Date: 6/17/21

Virtual Meeting

CATASTROPHE INSURANCE (C) WORKING GROUP
Monday, June 21, 2021
2:30 p.m. ET / 1:30 p.m. CT / 12:30 p.m. MT / 11:30 a.m. PT

ROLL CALL

Mike Chaney, Chair	Mississippi	Jerry Condon/Matthew Mancini	Massachusetts
James A. Dodrill, Vice Chair	West Virginia	LeAnn Cox	Missouri
Jimmy Gunn/Brian Powell	Alabama	Carl Sornson	New Jersey
Katie Hegland	Alaska	Timothy Johnson	North Carolina
Jimmy Harris	Arkansas	Tom Botsko	Ohio
Lynne Wehmueller	California	Cuc Nguyen	Oklahoma
George Bradner	Connecticut	David Dahl/Ying Liu/Van Pounds	Oregon
David Altmaier	Florida	David Buono	Pennsylvania
Colin M. Hayashida	Hawaii	Beth Vollucci	Rhode Island
Judy Mottar	Illinois	Will Davis	South Carolina
Travis Grassel	Iowa	David Combs	Tennessee
Heather Droge	Kansas	Mark Worman/J'ne Byckovski	Texas
James J. Donelon	Louisiana	David Forte	Washington
Joy Hatchette	Maryland		

NAIC Support Staff: Sara Robben

AGENDA

1. Discuss Referral from the Climate and Resilience (EX) Task Force— *Commissioner Mike Chaney (MS)* — Attachment One

2. Discuss Any Other Matters Brought Before the Task Force —*Commissioner Mike Chaney (MS)*

3. Adjournment

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Referral from Climate and Resiliency (EX) Task Force

MEMORANDUM

TO: Catastrophe Insurance (C) Working Group of the Property and Casualty Insurance (C) Committee

FROM: Raymond G. Farmer (SC), Co-Chair of the Climate and Resiliency (EX) Task Force
Ricardo Lara (CO), Co-Chair of the Climate and Resiliency (EX) Task Force
James J. Donelon (LA), Co-Vice Chair of the Climate and Resiliency (EX) Task Force

DATE: May 24, 2021

RE: Proposed Changes to the *Catastrophe Computer Modeling Handbook*

In 2020, the NAIC formed the Climate and Resiliency (EX) Task Force, with five workstreams to assist in carrying out the charges of the Task Force. The Technology Workstream was charged with applying technology, such as early warning systems and predictive modeling tools, to understand and evaluate climate risk exposures.

The Catastrophe Insurance (C) Working Group developed the *Catastrophe Computer Modeling Handbook* (*Catastrophe Handbook*) in 2010 with the purpose "to explore in some detail catastrophe computer models and to discuss issues that have arisen or can be expected to arise from their use." Further, the Catastrophe Insurance (C) Working Group has a charge to provide a forum for discussing various issues related to catastrophe modeling, and monitor issues that will result in changes to the Catastrophe Handbook. The Technology Workstream of the Climate and Resiliency (EX) Task Force met in an open meeting on May 7 to discuss the need for revisions to the Catastrophe Handbook.

The Technology Workstream requests that the Catastrophe Insurance (C) Working Group consider the need for revisions to the Catastrophe Handbook. During its open meeting, the Technology Workstream discussed several updates for the Working Group to consider.

First, the purpose of the Handbook, "to explore in some detail catastrophe models and to discuss issues that have arisen or can be expected to arise from their use," should be revisited to develop an understanding of how the Catastrophe Handbook is used currently and determine its practical use within the regulatory toolkit. Furthermore, the work should be coordinated with the Catastrophe Risk (E) Subgroup to understand the materials it is developing or otherwise making available to state insurance regulators regarding catastrophe models.

Second, the Catastrophe Handbook is currently limited to earthquake and hurricane. Catastrophe models have evolved to include many additional perils, which should be recognized in the revised Catastrophe Handbook. The questions for evaluating models in

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Section VII of the Catastrophe Handbook are of particular interest and should be updated to, at a minimum, include the wildfire questions described in the *Application of Wildfire Mitigation to Insured Property Exposure.*[1] The Working Group should consider questions specific to additional perils for which there are catastrophe models in use today including, but not limited to, flood. Furthermore, the questions should be denoted to clarify which should be directed to insurers versus catastrophe modelers.

Third, the Technology Workstream suggests the Working Group explore which catastrophe modelers have begun including climate data in their models. As model versions are updated regularly and advancements continue to evolve in this area, the Working Group should consider alternative formats for the Catastrophe Handbook to make more recent information available or otherwise consider more frequent updates to be made in the future.

Finally, it was noted during the Technology Workstream's meeting on May 7 that the American Academy of Actuaries (Academy) has developed guidance and education on catastrophe models, which the Working Group may wish to explore.

Since the Working Group is already charged to consider updates to the Catastrophe Handbook, a response to the Technology Workstream is not necessary. However, we welcome any questions or comments you may have about the request. Please direct questions or comments to Jennifer Gardner (NAIC) at *jgardner@naic.org*.

[1] NAIC Center for Insurance Policy and Research, Risk Management Services, and Insurance Institute for Business and Home Safety, *Application of Wildfire Mitigation to Insured Property Exposure*, November 2020, *https://content.naic.org/sites/default/files/cipr_report_wildfire_mitigation.pdf*

Catastrophe Modeling Handbook Presentation

ASOP 56 - Modeling

ACTUARIAL STANDARDS BOARD

Actuarial Standard
of Practice
No. 56

Modeling

Developed by the
Modeling Task Force of the
General Committee of the
Actuarial Standards Board

Adopted by the
Actuarial Standards Board
December 2019

Doc. No. 195

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APPENDIXES

ASOP No. 56—Doc. No. 195

December 2019

TO: Members of Actuarial Organizations Governed by the Standards of Practice of the Actuarial Standards Board and Other Persons Interested in Modeling

FROM: Actuarial Standards Board (ASB)

SUBJ: Actuarial Standard of Practice (ASOP) No. 56

This document contains ASOP No. 56, *Modeling*.

History of the Standard

The ASB first began work on a standard for modeling in the late 1990s. Motivated primarily to address the role catastrophe modeling of earthquakes and hurricanes played in casualty ratemaking, this work was focused on the use of specialized models where actuaries would have to rely on a model that was developed by professionals other than actuaries. As a result of this work, ASOP No. 38, *Using Models Outside the Actuary's Area of Expertise*, was approved by the ASB in June of 2000 with the scope of the standard limited to the Property/Casualty area of practice. Historically, ASOP No. 38 had been the only ASOP that specifically addressed modeling.

Recently, the number and importance of modeling applications in actuarial science have increased, with the results of actuarial models sometimes being reflected in financial statements.

Recognizing this trend, the ASB asked the Life Committee in 2010 to begin work on an ASOP focused on modeling. The Life Committee formed a task force to address this issue and, in February of 2012, a discussion draft titled *Modeling in Life Insurance and Annuities* was released and nineteen comment letters were received. The transmittal letter also mentioned that the scope might be expanded to all practice areas and asked for comments on this idea.

Based upon the feedback received, and numerous other discussions on the topic of modeling, in December of 2012 the ASB created two multi-disciplinary task forces under the direction of the General Committee: i) a general Modeling Task Force, charged with developing an ASOP to address modeling applications in all practice areas, and ii) a Catastrophe Modeling Task Force to consider expanding ASOP No. 38 to all practice areas while focusing exclusively on using catastrophe models. The membership of these task forces has experience in all actuarial practice areas, including enterprise risk management.

First Exposure Draft

The first exposure draft was released in June 2013 with a comment deadline of September 30, 2013. Forty-eight comment letters were received and considered in making changes that were reflected in the second exposure draft.

Second Exposure Draft

A second exposure draft was released in November 2014 with a comment deadline of March 1, 2015. Thirty-seven comment letters were received and considered in making changes that were reflected in the third exposure draft.

Third Exposure Draft

A third exposure draft was released in June 2016 with a comment deadline of October 31, 2016. Twenty-eight comment letters were received and considered in making changes that were reflected in the fourth exposure draft.

Fourth Exposure Draft

A fourth exposure draft was released in December 2018 with a comment deadline of May 15, 2019. Twenty-six comment letters were received and considered in making changes that were reflected in this final ASOP. For a summary of the issues contained in these comment letters, please see appendix 2.

Notable Changes from the Fourth Exposure Draft

Notable changes made to the fourth exposure draft are summarized below. Additional changes were made to improve readability, clarity, or consistency.

1. Section 3.1.6(b), Margins, was deleted because it did not provide sufficiently clear guidance. While margins are appropriately used, or even required, for certain intended purposes, margins are inappropriate and not used for other intended purposes.

2. "Hold-out data" in predictive modeling was defined and added to the list of items that may be included in the model output validation in section 3.6.2(b).

3. The term "parameter" was eliminated from section 3 of the ASOP, referencing it only within the definition of "assumption" because the two terms often are synonymous and the guidance often was identical.

As a next step, the ASB will review the previously approved but pending ASOP No. 38, *Catastrophe Modeling (for All Practice Areas)*, for any changes necessitated by this ASOP and take appropriate action.

The ASB thanks everyone who took the time to contribute comments and suggestions on the exposure drafts.

The ASB also thanks former task force member Aaron R. Weindling for his assistance during the earlier drafting of this standard.

The ASB voted in December 2019 to adopt this standard.

ASOP No. 56—Doc. No. 195

Modeling Task Force

Dale S. Hagstrom, Chairperson

Maryellen J. Coggins	Stephen Mildenhall
Julie H. Fried	Judy K. Stromback
Kenneth R. Kasner	

General Committee of the ASB

Margaret Tiller Sherwood, Chairperson

Ralph S. Blanchard III	Susan E. Pantely
Andrew M. Erman	Judy K. Stromback
Dale S. Hagstrom	Hal Tepfer
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Kathleen A. Riley, Chairperson

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Mita D. Drazilov	Patrick B. Woods

The Actuarial Standards Board (ASB) sets standards for appropriate actuarial practice in the United States through the development and promulgation of Actuarial Standards of Practice (ASOPs). These ASOPs describe the procedures an actuary should follow when performing actuarial services and identify what the actuary should disclose when communicating the results of those services.

ASOP No. 56—Doc. No. 195

ACTUARIAL STANDARD OF PRACTICE NO. 56

MODELING

STANDARD OF PRACTICE

Section 1. Purpose, Scope, Cross References, and Effective Date

1.1 Purpose—This actuarial standard of practice (ASOP or standard) provides guidance to actuaries when performing actuarial services with respect to designing, developing, selecting, modifying, using, reviewing, or evaluating **models**.

1.2 Scope—This standard applies to actuaries in any practice area when performing actuarial services with respect to designing, developing, selecting, modifying, or using all types of **models**. For example, an actuary using a **model** developed by others in which the actuary is responsible for the **model output** is subject to this standard.

If the actuary's actuarial services involve reviewing or evaluating **models**, the reviewing or evaluating actuary should be reasonably satisfied that the actuarial services were performed in accordance with this standard. The reviewing or evaluating actuary should apply the guidance in this standard to the extent practicable within the scope of the actuary's assignment.

The guidance in this ASOP applies to the actuary when, in the actuary's professional judgment, reliance by the **intended user** on the **model output** has a material effect for the **intended user**. This judgment should be made within the context of the use of the **model output** and the needs of the **intended user**, based on facts known by the actuary at the time the actuarial services are performed. For example, actuarial services performed in relation to pension plan contribution and cost projection **models**, insurance pricing **models**, predictive **models**, reserving **models**, and insurance company financial planning **models** may require application of the guidance in this ASOP. In assessing materiality, the actuary should be guided by ASOP No. 1, *Introductory Actuarial Standard of Practice*, section 2.6.

The guidance in this ASOP does not apply to the actuary when performing services with respect to individual pension benefit calculations and nondiscrimination testing, as described in section 1.2 of ASOP No. 4, *Measuring Pension Obligations and Determining Pension Plan Costs or Contributions*.

This standard only applies to the extent of the actuary's responsibilities. The actuary's responsibilities may extend to performing actuarial services related to an entire **model** or to only a small portion of a **model**.

Other ASOPs may provide guidance for actuarial services that involve **models**. If the actuary determines that the guidance from another ASOP conflicts with the guidance of this ASOP, the guidance of the other ASOP will govern.

If the actuary departs from the guidance set forth in this ASOP in order to comply with applicable law (statutes, regulations, and other legally binding authority), or for any other reason, the actuary should refer to section 4. If a conflict exists between this standard and applicable law, the actuary should comply with applicable law.

1.3 Cross References—When this ASOP refers to the provisions of other documents, the reference includes the referenced documents as they may be amended or restated in the future, and any successor to them, by whatever name called. If any amended or restated document differs materially from the originally referenced document, the actuary should consider the guidance in this ASOP to the extent it is applicable and appropriate.

1.4 Effective Date—This ASOP is effective for work performed on or after October 1, 2020.

Section 2. Definitions

The terms below are defined for use in this actuarial standard of practice and appear in bold throughout the ASOP.

2.1 Assumption—A type of explicit **input** to a **model** that is derived from **data**, represents possibilities based on professional judgment, or may be prescribed by law or by others. When derived from **data**, an **assumption** may be statistical, financial, economic, mathematical, or scientific in nature, and may be described as a **parameter**.

2.2 Data—Facts or information that are either direct **input** to a **model** or inform the selection of **input**. **Data** may be collected from sources such as records, experience, experiments, surveys, observations, benefit plan or policy provisions, or **output** from other **models**.

2.3 Governance and Controls—The application of a set of procedures and an organizational structure designed to reduce the risk that the **model output** is not reliably calculated or not utilized as intended.

2.4 Hold-out Data—A subset of **data** that is withheld intentionally when developing a predictive **model** so that the **model** may be validated later with **data** that were not used to develop the **model**.

2.5 Input—**Data** or **assumptions** used in a **model** to produce **output**.

2.6 Intended Purpose—The goal or question, whether generalized or specific, addressed by the **model** within the context of the assignment.

2.7 Intended User—Any person whom the actuary identifies as able to rely on the **model output**.

2.8 Model—A simplified representation of relationships among real world variables, entities, or events using statistical, financial, economic, mathematical, non-quantitative, or scientific concepts and equations. A **model** consists of three components: an information **input** component, which delivers **data** and **assumptions** to the **model**; a processing component, which transforms **input** into **output**; and a results component, which translates the **output** into useful business information.

2.9 Model Risk—The risk of adverse consequences resulting from reliance on a **model** that does not adequately represent that which is being modeled, or the risk of misuse or misinterpretation.

2.10 Model Run—The process of transforming a particular set of **input** to a particular set of **output** in a **model**. A **model run** could include the whole transformation process or part of the process, as applicable.

2.11 Output—The results of a **model** including, but not limited to, point estimates, likely or possible ranges, **data** or **assumptions** (as **input** for other **models**), behavioral expectations, or qualitative criteria on which decisions could be made.

2.12 Overfitting—A situation where a **model** fits the **data** used to develop the **model** so closely that prediction accuracy materially decreases when the **model** is applied to different **data**.

2.13 Parameter—A type of statistical, financial, economic, mathematical, or scientific value that is used as **input** to certain types of **models**. Examples of **parameters** include expected values in probability distributions and coefficients of formula variables. Some types of **models**, such as predictive or statistical **models**, produce estimates of **parameters** as **output**, which may be used as **input** to other **models**.

Section 3. Analysis of Issues and Recommended Practices

3.1 Model Meeting the Intended Purpose—The actuary should understand the **model's intended purpose**.

3.1.1 Designing, Developing, or Modifying the Model—When the actuary designs, develops, or modifies the **model,** the actuary should confirm, in the actuary's professional judgment, that the capability of the **model** is consistent with the **intended purpose**. Items the actuary should consider, if applicable, include but are not limited to the following:

a. the level of detail built into a **model**;

b. the dependencies recognized; and

c. the **model's** ability to identify possible volatility of **output**, such as volatility around expected values.

3.1.2 Selecting, Reviewing, or Evaluating the Model—When selecting, reviewing, or evaluating the **model**, the actuary should confirm that, in the actuary's professional judgment, the **model** reasonably meets the **intended purpose**.

3.1.3 Using the Model—When using the **model**, the actuary should make reasonable efforts to confirm that the model structure, **data**, **assumptions**, **governance and controls**, and **model** testing and **output** validation are consistent with the **intended purpose**.

3.1.4 Model Structure—The actuary should assess whether the structure of the **model** (including judgments reflected in the **model**) is appropriate for the **intended purpose**. The actuary should consider the following, as applicable, for a particular **model**:

a. which provisions and risks specific to a business segment, contract, or plan, if any, or interactions more broadly, are material and appropriate to reflect in the **model**;

b. whether the form of the **model** is appropriate, such as a projection **model** (deterministic or stochastic), statistical **model**, or predictive **model**;

c. whether the use of the **model** dictates a particular level of detail, for example, whether grouping **inputs** will produce reasonable **output**, or whether a certain level of detail in the **output** is needed to meet the **intended purpose**;

d. whether there is a material risk of the **model overfitting** the **data**; and

e. whether the **model** appropriately represents options, if any, that could be reasonably expected to have a material effect on the **output** of the **model**. Examples include call options on fixed income assets, policyholder surrender options, and early retirement options.

3.1.5 Data—The actuary should use, or confirm use of, **data** appropriate for the **model's intended purpose** and should refer, as applicable, to ASOP No. 23, *Data Quality*, when selecting, reviewing, or evaluating **data** used in the **model**, either directly or as the basis for deriving, estimating, or testing **assumptions** used in the **model**.

3.1.6 Assumptions Used As Input—For **models** that use **assumptions** as **input**, the actuary should use, or confirm use of, **assumptions** that are appropriate given the

model's intended purpose. The following guidance applies for **models** that use **assumptions** as **input**:

a. Setting Assumptions—When setting **assumptions** for which the actuary is taking responsibility, the actuary should consider using the following **data** or information:

   1. actual experience properly modified to reflect the circumstances being modeled, to the extent actual experience is available, relevant, and sufficiently reliable;

   2. other relevant and sufficiently reliable experience, such as industry experience that is properly modified to reflect the circumstances being modeled, if actual experience is not available or relevant, or is not sufficiently reliable;

   3. future expectations or estimates, including those derived from market **data**, when available and appropriate; and

   4. other relevant sources of **data** or information.

b. Range of Assumptions—The actuary may consider using a range of **assumptions** and, if so, whether the number of **model runs** analyzed reflects a set of conditions consistent with the **intended purpose**.

c. Consistency—Where appropriate, the actuary should use, or confirm use of, **assumptions** for the **model** that are reasonably consistent with one another for a given **model run**.

   If the actuary is aware of material inconsistencies among **assumptions** used by the actuary in the **model**, the actuary should disclose the inconsistencies and known reasons for the inconsistencies. In the case of **assumptions** prescribed by applicable law, the actuary's disclosure may be limited to identifying the possibility of an inconsistency with other **assumptions**.

d. Appropriateness of Input in Current Model Run—Where practical and appropriate, the actuary reusing an existing **model** should evaluate whether **input** unchanged from a prior **model run** is still appropriate for use in the current **model run**. For example, **models** used in financial reporting may offer opportunities to compare **assumptions** to emerging experience in the aggregate.

e. Reasonable Model in the Aggregate—The actuary should assess the reasonability of the **model output** when determining whether the **assumptions** are reasonable in the aggregate. While **assumptions** might appear to be reasonable individually, conservativism or optimism in multiple **assumptions** may result in unreasonable **output**.

3.2 Understanding the Model—When expressing an opinion on or communicating results of the **model**, the actuary should understand the following:

a. important aspects of the **model** being used, including but not limited to, basic operations, important dependencies, and major sensitivities;

b. known weaknesses in **assumptions** used as **input**, known weaknesses in methods or other known limitations of the **model** that have material implications; and

c. limitations of **data** or information, time constraints, or other practical considerations that could materially impact the **model's** ability to meet its **intended purpose**.

3.3 Reliance on Data or Other Information Supplied by Others—When relying on **data** or other information supplied by others, the actuary should refer to ASOP No. 23 and ASOP No. 41, *Actuarial Communications*, for guidance.

3.4 Reliance on Models Developed by Others—If the actuary relies on a **model** designed, developed, or modified by others, such as a vendor or colleague, and the actuary has a limited ability either to obtain information about the **model** or to understand the underlying workings of the **model**, the actuary should disclose the extent of such reliance. In addition, the actuary should make a reasonable attempt to have a basic understanding of the **model**, including the following, as appropriate:

a. the designer's or developer's original **intended purpose** for the **model**;

b. the general operation of the **model**;

c. major sensitivities and dependencies within the **model**; and

d. key strengths and limitations of the **model**.

When relying on **models** developed by others, the actuary should make practical efforts to comply with other applicable sections of this standard.

3.5 Reliance on Experts—The actuary may rely on experts in the fields of knowledge used in the development of the **model**. In determining the appropriate level of reliance, the actuary may consider the following:

a. whether the individual or individuals upon whom the actuary is relying are experts in the applicable field;

b. the extent to which the **model** has been reviewed or validated by experts in the applicable field, including known material differences of opinion among experts concerning aspects of the **model** that could be material to the actuary's use of the **model**;

c. whether there are industry or regulatory standards that apply to the **model** or to the testing or validation of the **model**, and whether the **model** has been certified as having met such standards; and

d. whether the science underlying the expertise is likely to produce useful **models** for the **intended purpose**.

When relying on experts, the actuary should disclose the extent of such reliance.

3.6 Evaluation and Mitigation of Model Risk—The actuary should evaluate **model risk** and, if appropriate, take reasonable steps to mitigate **model risk**. The type and degree of **model risk** mitigation that is reasonable and appropriate may depend on the following:

a. the **model's intended purpose**;

b. the nature and complexity of the **model**;

c. the operating environment and **governance and controls** related to the **model**;

d. whether there have been changes to the **model** or its operating environment; and

e. the balance between the cost of the mitigation efforts and the reduction in potential **model risk**.

3.6.1 Model Testing—For a **model run** or set of **model runs** generated at one time or over time that is to be relied upon by the **intended user**, the actuary should perform sufficient testing to ensure that the **model** reasonably represents that which is intended to be modeled. **Model** testing may include the following:

a. reconciling relevant **input** values to the relevant system, study, or other source of information, addressing and documenting the differences appearing in the reconciliation, if material;

b. checking formulas, logic, and table references;

c. running tests of variations on key **assumptions** used as **input** to test that changes in the **output** are consistent with expectations given the changes in the **input** (i.e., sensitivity testing); and

d. reconciling the **output** of a **model run** to prior **model runs**, given changes in **data**, **assumptions**, formulas, or other aspects of the **model** since the prior **model run**.

3.6.2 Model Output Validation—The actuary should validate that the **model output** reasonably represents that which is being modeled. Depending on the **intended purpose**, **model output** validation may include the following:

a. testing, where applicable, preliminary **model output** against historical actual results to verify that modeled **output** would bear a reasonable relationship to actual results over a given time period if **input** to the **model** were set to be consistent with the conditions prevailing during such period;

b. evaluating whether the **model** applied to **hold-out data** produces **model output** that is reasonably consistent with **model output** developed without the **hold-out data**, as may be used for predictive **models**;

c. performing statistical or analytical tests on **model output** to assess their reasonableness;

d. running tests of variations on key **assumptions** to test that changes in the **output** are consistent with the expectations given the changes in the **input**; and

e. comparing **model output** to those of an alternative **model**(s), where appropriate.

3.6.3 Review by Another Professional—The actuary may consider obtaining a review by another qualified professional, depending upon the nature and complexity of the **model**.

3.6.4 Reasonable Governance and Controls—The actuary should use, or, if appropriate, may rely on others to use, reasonable **governance and controls** to mitigate **model risk**.

3.6.5 Mitigating Misuse and Misinterpretation—The actuary should refer to the guidance in ASOP No. 41, in particular sections 3.4.1 and 3.7, to mitigate possible misuse and misinterpretation of the **model**.

3.7 Documentation—The actuary should consider preparing and retaining documentation to support compliance with the requirements of section 3 and the disclosure requirements of section 4. If preparing documentation, the actuary should prepare such documentation in a form such that another actuary qualified in the same practice area could assess the reasonableness of the actuary's work. The degree of such documentation should be based on the professional judgment of the actuary and may vary with the complexity and purpose of the actuarial services. In addition, the actuary should refer to ASOP No. 41, section 3.8, for guidance related to the retention of file material other than that which is to be disclosed under section 4.

Section 4. Communications and Disclosures

4.1 Required Disclosures in an Actuarial Report—When issuing an actuarial report under this standard, the actuary should refer to ASOP Nos. 23 and 41. In addition, the actuary should disclose the following in such actuarial reports:

a. the **intended purpose** of the **model**, as discussed in section 3.1;

b. material inconsistencies, if any, among **assumptions**, and known reasons for such inconsistencies, as discussed in section 3.1.6(c);

c. unreasonable **output** resulting from the aggregation of **assumptions**, if material, as discussed in section 3.1.6(e);

d. material limitations and known weaknesses, as discussed in section 3.2;

e. extent of reliance on **models** developed by others, if any, as discussed in section 3.4; and

f. extent of reliance on experts, if any, as discussed in section 3.5.

4.2 Additional Disclosures in an Actuarial Report—The actuary should include the following, as applicable, in an actuarial report:

a. the disclosure in ASOP No. 41, section 4.2, if any material **assumption** or method was prescribed by applicable law;

b. the disclosure in ASOP No. 41, section 4.3, if the actuary states reliance on other sources and thereby disclaims responsibility for any material **assumption** or method selected by a party other than the actuary; and

c. the disclosure in ASOP No. 41, section 4.4, if, in the actuary's professional judgment, the actuary has otherwise deviated materially from the guidance of this ASOP.

4.3 Confidential Information—Nothing in this ASOP is intended to require the actuary to disclose confidential information.

Appendix 1

Background and Current Practices

Note: This appendix is provided for informational purposes and is not part of the standard of practice.

Background

Actuaries frequently use models to analyze uncertain outcomes, with every discipline relying on a broad range of modeling applications, ranging from simple spreadsheets to complex capital models. Actuaries have used models for a variety of purposes including to help explain a system, to study the effects of different parts of a system, to predict the behavior of a system, to predict the behavior of people, to derive estimates, or to inform decisions. The importance of modeling in actuarial science has continued to increase, with results of models sometimes being reflected in financial statements.

A model is only an approximation of reality, however, and not reality itself. Therefore, even a model that is prudently developed and carefully used does not eliminate inherent uncertainty and variability, and actual results may differ, sometimes significantly, from outcomes suggested by the model.

Current Practices

Actuaries use many types of models, ranging from projection models to statistical models and predictive models. Some models evolve through a life cycle consisting of: (1) a specification phase, (2) an implementation phase, and (3) a production phase, which consists of one or more model runs. Other models evolve through a life cycle of: (1) a specification phase, (2) an iterative, assumptions estimation phase, and (3) an output evaluation, validation, and selection phase. For other models, combinations of functionally similar phases may exist.

Appropriate model governance and controls are important when using models. Examples of model governance and controls include the following:

- limitations on access to use and modify the model (that is, restricting access to model input, model programming code and calculations, and model output);
- confirmation that model output is reproducible upon rerun (if the model allows for such reproducibility);
- implementing a model change management process;
- specification, documentation, and programming standards for the model;

- procedures for secure back-up of the media storing the programming code and data;

- appropriate staff training or cross-training for continuity of use and mitigation of key-person risk;

- plans for periodic consideration of the organization's continued ability to access and maintain the model, including data, software, staff, hardware, and any vendor relationships; and

- plans for periodic review of the assumptions, functionality, and methodology.

Appendix 2

Comments on the Fourth Exposure Draft and Responses

The fourth exposure draft titled *Modeling* was approved by the ASB in December 2018 with a comment deadline of May 15, 2019. Twenty-six comment letters were received, some of which were submitted on behalf of multiple commentators, such as by firms or committees. For purposes of this appendix, the term "commentator" may refer to more than one person associated with a particular comment letter. The Task Force and General Committee carefully considered all comments received, and the ASB reviewed (and modified, where appropriate) the changes proposed by the General Committee.

Summarized below are the significant issues and questions contained in the comment letters and the responses to each. Minor wording or punctuation changes that were suggested but not significant are not reflected in the appendix, although they may have been adopted.

The term "reviewers" includes the Task Force, General Committee, and the ASB. Unless otherwise noted, the section numbers and titles used below refer to those in the fourth exposure draft, which are then cross referenced with those in the final ASOP.

GENERAL COMMENTS	
Comment Response	One commentator suggested that the uses of "any" when in the context of what an actuary should do or should consider, and other similar references, may be onerous to actuaries in practice, and recommended their elimination. The reviewers agree and made the change.
Comment Response	One commentator suggested retaining a definition of "simple model" conceptually similar to what was included in the third exposure, with the suggested enhancement of modifying "transparent and can be predicted" to "transparent or can be predicted" to improve its usefulness and clarity. The reviewers note the concept of "simple model" has been previously addressed and made no change.
Comment Response	One commentator suggested that the standard include a definition of and guidance for ongoing model performance monitoring. While the reviewers agree with the concept of ongoing performance monitoring within a formalized model risk management program, the reviewers disagree with the suggestion for this ASOP and therefore did not make the change.
SECTION 1. PURPOSE, SCOPE, CROSS REFERENCES, AND EFFECTIVE DATE	
Section 1.1, Purpose	
Comment Response	One commentator suggested that sections 1.1, Purpose, and 1.2, Scope, should include explicit reference to mitigating model risk since it is a key area of focus on the modeling process and there is an explicit section of the ASOP exposure draft dedicated to this practice. The reviewers believe the guidance is appropriate and therefore made no change.

Section 1.2, Scope	
Comment	One commentator suggested that "responsible" should be replaced by "accountable" since it implies ownership – and the use of this term is more consistent with that used in the insurance industry to indicate appropriate ownership.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator recommended the use of the words "rely" and "reliance" be clarified as the terms are rather subtle given that some users of models consider the use of a model as reliance even when it is the user's own model.
Response	The reviewers believe the guidance is appropriate and therefore made no change.
Comment	One commentator suggested that the standard be applied only to financial reporting models and perhaps enterprise risk models.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested that the guidance for an actuary reviewing or evaluating models is not clear as to whether it is the model itself that is being reviewed or evaluated (which is what the text seems to literally suggest), or whether it is the use of the model that is being reviewed.
Response	The reviewers clarified the guidance.
Comment	One commentator disagreed with the exclusion of the concept of a "simple model" from the fourth exposure draft and recommended that the scope explicitly exclude simple calculations.
Response	The reviewers disagree with the suggestion and, therefore, did not make the change. The reviewers refer the commentator to section 1.2, Scope, including the definition of "model," when considering the applicability of the guidance in the ASOP.
Comment	One commentator suggested certain references to "use" might be confusing, in particular: 1) When the actuary's "use" of a model is not for the purpose of reviewing the model itself but only for the purpose of reviewing or using the output. In this instance, the standard should explicitly state that the actuary should not be charged with applying this standard, and 2) in the second paragraph that states the reviewing or evaluating actuary should "use the guidance in this standard to the extent practicable within the scope of the actuary's assignment" and in third paragraph that appears to use "rely" and "use" interchangeably.
Response	The reviewers agree with the potential confusion that might arise with the word "use" in the second and third paragraphs, and replaced these two references to "use" in section 1.2, Scope to improve clarity. However, the reviewers believe the guidance in the second paragraph is appropriate and therefore made no change in response to that part of the comment.
Comment	Two commentators suggested that the first sentence in the fifth paragraph seems unnecessary and suggested eliminating that sentence. One commentator also suggested beginning the paragraph with the current third sentence.
Response	The reviewers agree and made the change.

Comment Response	One commentator thought the example, "For example, actuarial services performed in relation to pension plan contribution and cost projection models…may require application of the guidance in this ASOP" was confusing. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 1.4, Effective Date	
Comment Response	Once commentator believes that the effective date language needs to be more descriptive because as written, it leaves many questions related to when the model was run, selected, developed, or when model results were communicated. The reviewers note that ASOPs apply to the actuary performing the actuarial services, and the effective date applies to "work performed [by the actuary] on or after...." Therefore, the reviewers made no change in response to this comment.
SECTION 2. DEFINITIONS	
Comment Response	One commentator suggested adding definitions for "testing," "validation," and "limitations." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.1, Assumption	
Comment Response	One commentator suggested that the definition of section 2.1, Assumption, be changed to note that an assumption can be produced as output from another model. Alternatively, the definitions of data and parameter in sections 2.2 and 2.12, respectively, could be changed to remove any reference to these items being produced from other models. The reviewers agree, made changes to the definitions of "assumption," "parameter," "input," and "output," and removed references to "parameter" within section 3 of the ASOP to improve clarity.
Comment Response	One commentator question whether assumptions are always input into a model versus incorporated into the model operations or methodology. In an effort to improve clarity and in response to this comment, the reviewers revised the definition of "assumption" to "a type of explicit input…" thus differentiating between explicit and implicit assumptions.
Section 2.2, Data	
Comment Response	One commentator requested examples of data that can be input to a model in the same way that examples of parameters are provided in that section since data are often refreshed with each model run while parameters and assumptions often remain unchanged from one run to the next. While the reviewers did not make the specific recommended edit, the reviewers made changes to the definitions of "assumption," "parameter," "input," and "output," and removed references to "parameter" within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested that the drafted definition is too vague and general with respect to the kinds of data the ASOP addresses and suggested the definition be limited to quantitative or numerical data. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.3, Governance and Controls	
Comment Response	One commentator suggested that a more descriptive definition would be "The application of a set of procedures and an organizational structure designed so that intended users can have confidence that the model output is reliably calculated and utilized as intended." The reviewers clarified the language.

Comment Response	One commentator suggested defining “governance” and “controls” separately since they have different meaning. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.4, Input (now section 2.5)	
Comment Response	One commentator suggested the definition of input is very broad, and that input to a model can be in the form of 1) assumptions, 2) data, or 3) parameters. While each term is defined separately later in the document, the user must glean that they are not overlapping elements of input. The reviewers agree, made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested adding the following sentence after the current sentence: “Input may include assumptions, data, and parameters.” The reviewers agree in part, made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Section 2.5, Intended Purpose (now section 2.6)	
Comment Response	One commentator suggested clarifying whether a model can have more than one intended purpose, perhaps treating each intended purpose as a separate model, even where they have a common processing component. This approach will reinforce the need to assess the appropriateness of a combination of specific processing components, data, assumptions, parameters and output for each intended purpose. The reviewers believe the guidance is appropriate and therefore made no change.
Comment Response	One commentator understood the definition for all roles other than when the actuary is the model developer and suggested that there should be a consideration of other purposes to be efficient with modeling efforts and less siloed in approach. The reviewers disagree and therefore made no change.
Section 2.6, Intended User (now section 2.7)	
Comment Response	Three commentators suggested replacing “actuarial findings” with “model’s output” (which is defined in this ASOP while “findings” are not). The reviewers agree and made the change.
Comment Response	One commentator suggested replacing the word “actuarial findings” with “output of an actuarial model.” The reviewers agree in part and replaced “actuarial findings” with “model output.”
Comment Response	One commentator noted the definition is too broad as it describes an actuary as “able” to rely, and suggested alternatives of “likely” or “expected.” The reviewers disagree and therefore made no change.
Comment Response	One commentator suggested that, while the definition is identical to that contained within ASOP No. 41, *Actuarial Communications*, the use of “able” and “identifies” in the definition may cause confusion, and suggested the alternative “Any person whom the actuary has indicated is permitted to rely on the actuarial findings.” The reviewers disagree and therefore made no change.
Section 2.7, Model (now section 2.8)	
Comment Response	One commentator sought feedback regarding the definition of “model” in the context of several examples. The reviewers note that the ASOPs are principle-based and believe the current language covers these issues at the appropriate level of detail. Therefore, no change was made in response to this comment.

Comment Response	One commentator suggested adding the caveat from the background section of appendix 1 to the definition of a "model" to emphasize that a model is not bad or inaccurate just because a model did not match actual experience, namely: "A model is only an approximation of reality, not the reality itself, and the differences between the model and actual experience, by themselves, do not indicate a flawed model or noncompliance with standards." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that the definition of a "model" is very broad and recommended defining the "processing component" to enable differentiation between simple calculations and a "model." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested removing the reference to "simplified" as it seems unnecessarily restrictive. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that the definition is too broad as it could be interpreted to include any actuarial service other than individual benefit calculations and recommended that the definition should also describe what is not a model, such as nondiscrimination testing. The reviewers believe the definition of "model" is appropriate but note that section 1.2 was modified to exclude nondiscrimination testing.
Comment Response	One commentator suggested that the definition be changed to include "contractual" as a type of input and suggested adding "actuarial" to the list. In addition, the commentator suggesting adding a new definition for "system" as referenced in the definition. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested separating the "results component" from the model definition because the use of "results" in section 2.10, Output, appears to be inconsistent with the "results component" as described in this definition and the definition of output allows that such output could be used as input to other models. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested changing "to predict the behavior of a system, or to derive estimates and guide decisions" to "to predict the behavior of a system, to derive estimates of a system, or to guide decisions," because the former could imply "guiding decisions" and "deriving estimates" should always be considered together. The reviewers note that the last sentence in the definition was removed.
Comment Response	One commentator suggested that the definition and section 1.2, Scope, were unclear, and thus it was difficult to evaluate the remainder of the exposure draft. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Comment Response	One commentator suggested the definition was unclear as to what types of models were addressed by the ASOP, and recommended that the ASOP specifically refer to quantitative or numerical models with respect to data, parameters, input and output, and that the scope of the "models" covered by the ASOP should be limited to quantitative models (for example, estimates) or perhaps other types of models based directly on quantitative values and explicitly exclude algorithmic decision making and other forms of artificial intelligence. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.8, Model Risk (now section 2.9)	
Comment Response	One commentator suggested that the definition include specific guidance on the use of the term, namely that "model risk" is not intended to include the likelihood that actual results of most all models will often differ, perhaps materially, from that produced by the Model's output, and recommended that, at a minimum, the sentence from the second paragraph (if not, the entire paragraph) in the "Background" section of this ASOP be made an integral part of the ASOP: "Even a model that is prudently developed and carefully used does not eliminate inherent uncertainty and variability, and actual experience may differ, sometimes significantly, from the estimates derived from the model results," ideally, within this definition. As an alternative, the ASOP could add an additional definition for "model outcome risk." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggesting adding the consequence of model risk to the definition, namely that "Model risk can lead to financial loss, poor business and strategic decision making, or damage to ... reputation." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested rewording for better clarity as follows: "The risk of adverse consequences resulting from reliance on a model that does not adequately represent that which is being modeled or the risk of misuse or misinterpretation." The reviewers agree and made the change in response to this comment.
Section 2.9, Model Run (now section 2.10)	
Comment Response	Two commentators sought clarification on what a model run constitutes, with one commentator recommending calling the collection of all simulations for a stochastic model as one model run to improve clarity. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggesting replacing "selection of input" with "set of input." The reviewers agree and made the change.
Section 2.10, Output (now section 2.11)	
Comment Response	One commentator suggested that the four possible uses of output (i.e., point estimates, ranges, parameters for other models, or qualitative criteria for making decisions) fail to capture the use of a model for explaining a system or predicting its behavior. The reviewers agree and added "behavioral expectations" to the definition.

Comment Response	One commentator noted that section 2.10, Output, only mentions parameters as output that might be used as input to other models, while different sections of the proposed ASOP also mention data and assumptions as possible model outputs that can be used as input to other models. The reviewers agree, made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested eliminating “qualitative criteria on which decisions could be made,” which is vague and may include unintended application of the ASOP. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.11, Overfitting (now section 2.12)	
Comment Response	Three commentators suggested adding “materially” to the phrase “prediction accuracy decreased” to allow for the actuary to determine whether that decrease is large enough to cause concern. The reviewers agree and made the change.
Comment Response	One commentator suggested that including “may decrease” in place of “decrease” seems more appropriate since the guidance in section 3.14 uses the words “should consider.” The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested including a definition of underfitting as well as adding more descriptive examples for both overfitting and underfitting. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 2.12, Parameter (now section 2.13)	
Comment Response	One commentator suggested that to further distinguish parameter from data, it would be helpful to state, “Parameters often consist of product features that are used to configure a model for specific blocks of business. Unlike data, they typically remain constant from run to run, unless the model’s scope is expanded to include new products.” While the reviewers did not make the specific recommended edit, the reviewers made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Comment Response	One commentator recommended further differentiating between a parameter used as an input to a model and that used as output from a model (for example, “input parameter” and “output parameter”). While the reviewers did not make the specific recommended edit, the reviewers made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested adding the phrase “that is not data or assumptions” after “contractual input” in the first sentence. The reviewers removed the reference to the term “contractual” within the definition of “parameter,” and revised the definitions of “assumptions,” “input,” and “output” to improve clarity.
Comment Response	One commentator shared an analysis of the definitions and use of the terms “parameter,” “assumptions,” “input” and “output,” and stated that it is not clear how “parameters” are distinguishable from other “assumptions” or “data.” The reviewers agree, made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.

Comment Response	One commentator observed that the definition of parameter appeared to be a subset of assumptions and recommended considering language to highlight that assumptions/methods may be used to develop the parameters used in the model. The reviewers agree in part, made changes to the definitions of “assumption,” “parameter,” “input,” and “output,” and removed references to “parameter” within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested adjusting the definition to restrict it to quantitative values. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
SECTION 3. ANALYSIS OF ISSUES AND RECOMMENDED PRACTICES	
Section 3.1, Model Meeting the Intended Purpose	
Comment Response	One commentator noted that actuaries will often “repurpose” models for different intended purposes and suggested that the ASOP explicitly require the actuary developing, selecting, or evaluating the model to identify and document the specific purposes or ranges of parameters/inputs, etc., for which the model is valid/applicable and require actuaries to identify what aspects of the model would need to be adjusted to eliminate model limitations. The commentator also suggested that actuaries developing models should anticipate modeling changes that will develop in the near future to avoid having rigid models. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 3.1.1, Designing, Developing, or Modifying the Model	
Comment Response	One commentator suggested that this section should speak directly to modeling choices. Where the design of a model includes significant modeling choices (for example, simplifications, approximations), the actuary should understand the rationale and/or justification for the choices made. Where an actuary is responsible for designing, developing, or modifying a model, the actuary should consider whether developmental testing is needed to assess the appropriateness of significant modeling choices. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator noted that the meaning of “dependencies recognized” is not clear and requires additional explanation. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator noted that it may not be clear what the actuary is looking for in terms of “consistency with the intended purpose” when discussing the volatility of the expected values and that it’s not clear what “dependencies” are, in particular whether the term is referencing the dependencies among models or consistency of the model with its data, assumptions & parameters (A&P), and methods. In addition, the commentator suggested that a definition of dependencies would be helpful. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing the phrase “include but are not limited to” with “for example” since such a replacement would reduce the chance of misinterpretation of the guidance in terms of what the actuary is obliged to do. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Section 3.1.2, Selecting, Using, Reviewing, or Evaluating the Model (now titled, Selecting, Reviewing, or Evaluating the Model). ***Note: Changes to old section 3.1.2 have been incorporated into new section 3.1.3, Using the Model, as referenced below.***	
Comment Response	One commentator noted that the initial input as well as revisions to input need to be consistent with the intended purpose, and therefore recommended removing the words "any revisions to." The reviewers agree and made the change, which appears in new section 3.1.3.
Comment Response	One commentator noted general agreement, with the exception of "governance and controls," which in many situations will be set at a firm-wide level and are not available for an actuary's review (for instance, when an actuary uses its firm's actuarial valuation software). Further, although the commentator agrees that governance and controls may affect the actuary's ability to rely on the model, the commentator does not believe these factors would affect the model's inherent consistency with its intended purpose, and suggested the ASOP should contain a separate section describing what an actuary should consider with respect to governance and controls for models. The reviewers believe the guidance, which now appears in new section 3.1.3, is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator noted confusion with the use of "output are consistent with the intended purpose," and that the use of "consistent" might result in confusion between sections 3.1.1 and 3.1.2. Further, the commentator suggested the word "validation" should be replaced with "testing" given that the term "validation" is a very particular word for many companies and usually corresponds to Independent Model Validation. The reviewers believe the guidance, which now appears in new section 3.1.3, is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing "confirm the model reasonably meets the intended purpose ..." with "review that the model is reasonable with respect to meeting the intended purpose ..." In addition, the commentator suggested replacing "to ensure that any revisions to the input and ... are consistent with the intended purpose." with "to consider whether the revisions to the input and ... are consistent with the intended purpose." The reviewers clarified the guidance.
Comment Response	One commentator suggested replacing the word "ensure" with "validate" and sought an example for what "the standard require(s) with respect to the determination of reasonability." The reviewers clarified the guidance and replaced the word "ensure" with "use or confirm" in new section 3.1.3.
Section 3.1.3, Understanding the Model (now section 3.2)	
Comment Response	One commentator suggested replacing "results of the model," with "output" as defined in section 2, requested clarification of "methods" in paragraph b, and suggested removing "time constraints" in paragraph c. The reviewers believe the guidance is appropriate and therefore made no change in response to these comments.
Comment Response	One commentator asked whether the actuary should also understand the appropriate use of the model. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator did not think this paragraph should be limited to when the actuary is expressing an opinion on or communicating results of the model and suggested "rewording would be helpful here." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Comment Response	One commentator expressed uncertainty regarding the meaning of "dependencies," and questioned whether "methods" meant the model "methodology" or whether it meant the methods used to develop the A&P. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing section 3.1.3 with the following: "When providing actuarial services which depend significantly on the use of one or more models, the actuary should understand the important aspects of each model being used, such as: a. basic operation of the model, significant dependencies and sensitivities among variables or parameters, input and output, in the model; b. significant known limitations with respect to assumptions and parameters used as input, with respect to the data, information or methods used to build, calibrate, test or validate the model, or with respect to other considerations known to pose material implications when using the model or interpreting model output; and c. significant limitations with respect to a material impact affecting the ability of the model to meet its intended purpose due to other practical considerations, such as data issues, incomplete information, time constraints, etc." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 3.1.4, Model Structure	
Comment Response	One commentator recommended removing the examples in 3.1.4(e), suggesting that they are not "useful or necessary." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that this section should clarify when the actuary should make this assessment, such as when designing, developing, modifying, selecting, using, reviewing, or evaluating a model, or only when doing some of those actions. In addition, the commentator requested further clarification on the meaning of "judgments reflected in the model" and recommended the removal of "the structure of" from the stem as it would not change the guidance and could prevent confusion/misinterpretation. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator questioned why only overfitting is considered, and suggested consideration of parsimony, identifiability, goodness of fit, theoretical consistency and predictive power given that overfitting is just one of many types of error that would result in deteriorating a model's predictive power. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested including definitions for "projection model," "statistical model," and "predictive model." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing the current statement "whether the model is overfitting the data" with "whether the model is overfitting or underfitting the data" to fully capture the bias/variance tradeoff instead of focusing solely on overfitting. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Comment Response	One commentator suggested using "structure" instead of "form" for consistency with the title of 3.1.4, Model Structure. The reviewers disagree and therefore made no change.
Comment Response	One commentator suggested replacing should "consider" in section 3.1.4 with "evaluate and document," and suggested adding wording that requires actuary to indicate how, if at all, modeling of these provisions, risks and interactions are simplified and therefore appropriate only in certain situations. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested adding the word "product" to the list in section 3.1.4(a), adding "or type" after "whether the form" to better reflect the reference to projection, statistical, predictive models, and whether "model requirements" may be necessary in section 3.1.4(c). The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested rewording of section 3.1.4, subsections a, d, e as follows: "(a) whether there are specific provisions and risks reflected in the model which are material and appropriate to the use of the model, for example, differences by business segment, contract or plan; (d) whether there is a significant and material risk of overfitting the model with the available data; (e) whether the model appropriately reflects the existence of significant options or features, which may apply, that could be reasonably expected to have a material effect on the output of the model. Examples include call options on fixed income assets, policyholder surrender options, and early retirement options." The reviewers clarified the language regarding overfitting the model but made no change in response to the other comments.
Section 3.1.5, Data	
Comment Response	One commentator suggested that the actuary should consider what transformations of input data and assumptions, if any, are required and how these affect results. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 3.1.6, Assumptions and Parameters Used As Input (now section 3.1.6, Assumptions Used As Input)	
Comment Response	One commentator believes that it is "unnecessary, confusing and burdensome to include assumptions setting guidance in this standard, given the Assumptions ASOP currently under development, and given the many other ASOPs that provide assumption setting guidance for certain activities." The reviewers believe the guidance is appropriate and therefore made no change related to this comment. This ASOP may not reference another ASOP that continues to be within the exposure process.
Comment Response	One commentator suggested adding "As" to the beginning of the stem of section 3.1.6, to read, "As for models that use assumptions and parameters as input...." In addition, the commentator noted that assumption setting and parameterization of assumptions should be mentioned separately for clarity as they are different activities and imply different risks. While the reviewers did not make the specific recommended edit, the reviewers made changes to the definitions of "assumption," "parameter," "input," and "output," and removed references to "parameter" within section 3 of the ASOP to improve clarity.
Comment Response	One commentator suggested the addition of an example of a model that does not use assumptions or parameters as input. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Section 3.1.6(a), Setting Assumptions and Parameters (now section 3.1.6[a], Setting Assumptions)	
Comment Response	One commentator stated that it should be a criterion that the actuary document assumptions appropriately or ensure that assumptions provided by others are documented as such. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested referring to ASOP No. 25, *Credibility Procedures*, when discussing using actual experience to the extent it is "relevant and sufficiently reliable" within section 3.1.6(a)(1). The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested adding a fifth line item to section 3.1.6(a), namely "prescribed assumptions set by law" and "prescribed assumptions set by another party" (as used in ASOP No. 27, *Selection of Economic Assumptions for Measuring Pension Obligations*, and ASOP No. 35, *Selection of Demographic and Other Noneconomic Assumptions for Measuring Pension Obligations*) (for example, accounting assumptions), and assumptions developed with the opinion of experts. In addition, the commentator does not believe that the actuary should be required to assess whether assumptions that include prescribed assumptions set by law or prescribed assumptions set by another party are reasonable in the aggregate. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested changing the title of section 3.1.6(a) from "Setting Assumptions and Parameters" to "Setting Assumptions or Parameters" because the former could imply both are required, and adding reasonableness of individual assumptions or parameters that could have a material impact on model results to section 3.1.6(a) since reasonableness in aggregate is mentioned in 3.1.6(f). The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggesting rewording section 3.1.6(a)(1) to be "actual experience adjusted to current conditions where applicable, to the extent that adjustments to the data are considered to be available, relevant, and sufficiently reliable;" and requested a definition of "market data." While the reviewers did not make the specific changes suggested, the reviewers replaced "It" with "actual experience" in section 3.1.6(a), Setting Assumptions, to improve clarity.
Section 3.1.6(b), Margins	
Comment Response	Several comments were received on the guidance or necessity of section 3.1.6(b), Margins. In response, the reviewers removed section 3.1.6(b), Margins.
Section 3.1.6(c), Range of Assumptions and Parameters (now Section 3.1.6[b], Range of Assumptions)	
Comment Response	One commentator suggested that it is not clear what is meant by a range of assumptions and parameters in section 3.1.6(c) and offered a number of alternative of the meaning of the phrase. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator questioned why the number of model runs was relevant to the range of assumptions and parameters. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

<table>
<tr><td colspan="2">Section 3.1.6(d), Consistency (now section 3.1.6[c], Consistency)</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested changing the phrase “…possibility of an inconsistency…” to “…potential of an inconsistency…”

The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested that just requiring the actuary to “use or confirm use” is very weak guidance, and that the standard should use "not unreasonably inconsistent" in order to indicate that consistency in this context is subject to considerable judgment.

The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.</td></tr>
<tr><td colspan="2">Section 3.1.6(e), Appropriateness of Input in Current Model Run (now section 3.1.6[d], Appropriateness of Input in Current Model Run)</td></tr>
<tr><td>Comment

Response</td><td>One commentator stated agreement with 3.1.6(e), and suggested the addition, perhaps in a separate paragraph, that the model itself (not just the input) should be evaluated.

The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested clarifying the following “… reusing an existing model…” given that the term “reusing” can also be interpreted as using an existing model for a different purpose while the intention here seems to be around using a model with updated data.

The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.</td></tr>
<tr><td colspan="2">Section 3.1.6(f) Reasonable Model in the Aggregate (now section 3.1.6[e] Reasonable Model in the Aggregate)</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested that it would be helpful to provide an example of a situation where assumptions which are reasonable individually can produce output which is unreasonable in the aggregate, and recommended adding guidance around appropriate potential actions if the actuary determines this to be the case.

The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.</td></tr>
<tr><td>Comment

Response</td><td>One commentator noted that the determination on the reasonability of a model in the aggregate as well as the assumptions and parameters in the aggregate would typically involve examining the reasonability of the output of the model in making such a determination, and suggested articulating the importance of considering the reasonability of the output in making the determination of the reasonability of the model in the aggregate as well as the reasonability of the parameters and assumptions in the aggregate.

The reviewers agree and added “the reasonability of the model output when determining” after “assess.”</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested rewording section 3.1.6(f) as follows: "The actuary should assess whether the assumptions and parameters are reasonable in the aggregate. The actuary should consider those assumptions and parameters which might appear to be reasonable individually, but would produce unreasonable output, due to conservatism or optimism in multiple assumptions and parameters."

The reviewers agree and made changes similar to those suggested to improve clarity.</td></tr>
<tr><td colspan="2">Section 3.2, Reliance on Data or Other Information Supplied by Others (now section 3.3, Reliance on Data or Other Information Supplied by Others)</td></tr>
<tr><td>Comment

Response</td><td>One commentator suggested adding the title of ASOP No. 23 consistent with the title of ASOP No. 41.

The reviewers note that the ASOP follows an approved style guide. Since the title of ASOP No. 23, Data Quality, had been previously mentioned, no further reference is required for subsequent mentions.</td></tr>
</table>

Section 3.3, Reliance on Models Developed by Others (now section 3.4, Reliance on Models Developed by Others)	
Comment Response	One commentator suggested that the actuary also consider the experience and qualifications of the colleague/vendor. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that to the extent the actuary relies on testing performed by others, the actuary should also make a reasonable attempt to understand testing that has been performed on the model, i.e., implementation testing as well as any developmental testing. In addition, the commentator suggested that actuary who relies on a model built by a vendor or other developer is still responsible for ensuring the model is appropriate given its intended purpose and that results of any ongoing performance monitoring processes should be added to the list items to examine and understand. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that this section would lead to a tremendous amount of additional, unnecessary work, and potential litigation risk if the work is not performed, such as when relying upon centralized valuation systems implemented and tested by others. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested removing the last sentence in the section as it is somewhat ambiguous and could leave open to interpretation which sections of the standard are applicable, and that the detailed sub-bullets 3.3(a)-(d) seem sufficient. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator noted that it isn't clear whether the intent is that the actuary should disclose reliance if they can do neither, or if they can do one but not the other, and that it is not clear whether "a limited ability … to understand the underlying workings of the model" would include a situation where the actuary cannot review programming but can understand what the model is intended to produce and can verify reasonableness and recommended clarification. The reviewers agree with the suggestion that the actuary may have a limited ability to either "obtain information about the model or to understand the underlying workings of the model" or both. The reviewers added "either" to improve clarity. Otherwise, the reviewers believe the guidance is appropriate and made no further change.
Comment Response	One commentator recommended that a new sentence be added after the listing, "The actuary should continually evaluate model results in light of emerging experience to determine that the model is still appropriate for its intended purpose." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator objected to permitting actuaries to rely upon models which they do not fully understand and feels this violates Precept 1 of the *Code of Professional Conduct* and diminishes our profession. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Section 3.4, Reliance on Experts (now section 3.5, Reliance on Experts)	
Comment Response	One commentator expressed no significant concerns with section 3.4, however noted that it will become cumbersome, confusing, and misleading in certain circumstances when the expert is employed by the same firm as the actuary. As a result, the commentator recommended that the requirement to disclose the extent of any reliance be limited to situations where the experts were not employed by the actuarial firm issuing the report. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested removing the last sentence, "The actuary should disclose the extent of any such reliance," because section 4.1(f) already lists the disclosure requirement for 3.4. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 3.5, Mitigation of Model Risk (now section 3.6, Evaluation and Mitigation of Model Risk)	
Comment Response	One commentator recommended including a statement that model materiality is an important consideration in actions the actuary should take to mitigate model risk. The more material the impacts of a model can have on the company financial statements, capital positions, or management action, the more actions the actuary should take to mitigate the model risk. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator stated that the actuary should use judgment when assessing mitigation efforts as compared to model risk, and that the level of model risk mitigation should be commensurate with the perceived or actual level of risk associated with the use of the model. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator believes that "evaluate" implies a quantitative process and recommended replacing "evaluate" with a term such as "understand." The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested changing the title of section 3.5 from "Mitigation of Model Risk" to "Evaluation and Mitigation of Model Risk" given the guidance. The reviewers agree and made the change.
Comment Response	One commentator suggested changing 3.5(d) to read "whether there have been any changes to the model or its operating environment" for consistency. The reviewers agree and made the change.
Comment Response	One commentator recommended the inclusion of guidance related to when and how often the actuary should an actuary evaluate model risk. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing 3.5(d) with the following: "(d) whether there have been significant changes to the model or to the underlying environment, conditions, experience, or process for which the model was designed; and" While the reviewers did not make the specific changes suggested, the reviewers replaced "modeling" with "operating" environment to improve clarity.

Section 3.5.1, Model Testing (now section 3.6.1, Model Testing)	
Comment	One commentator suggested that section 3.5.1, Model Testing, should include reference to sensitivity testing given that it is an important part of model testing.
Response	The reviewers agree and added "running tests of variation on key assumptions used as input to test that changes in the output are consistent with expectations given the changes in the input (sensitivity testing)."
Comment	One commentator suggested that it should be clearer that "reconciling," means that the values are input correctly in to the model or modeling software, and not just that the input data before it is loaded in to the model reconciles to the source data given that if someone reconciles that initial data before it is loaded in to a model reconciles with the admin system, but then loads it in to the model incorrectly, it is a source of model risk.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested that section 3.5.1(b) deserves more attention as this is often the most time-consuming element of model testing and recommended stating that the actuary should consider what the major modeling methodology choices and simplifications are, as well as determine the best way to appropriately test formulas.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested adding in a new section 3.5.1(c): "Performing sample runs of individual model points to validate application of model logic and inputs" and shifting the existing 3.5.1(c) to 3.5.1(d).
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator sought clarification on how the actuary's responsibility for testing the model would differ between a "model run" and a "set of model runs generated at one time or over time." In addition, the commentator suggested moving "data" to appear before "input," and changing the definition of "model" to reference "formula" instead of "processing component" given that the term is more intuitive.
Response	The reviewers agreed with moving the reference to "data" to be before "assumptions" but did not make other changes in response to this comment.
Comment	One commentator suggested renaming these sections 3.5.1 and 3.5.2 to "model integrity testing" and "model output validation."
Response	The reviewers agree that section 3.5.2, Model Validation, should be renamed to Model Output Validation, but did not change the title of section 3.5.1.
Comment	One commentator sought clarification on the determination of materiality in section 3.5.1(a), and on the difference between testing and validation.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator noted that sections 3.5.1 (a)-(c) could be considered model controls and governance, and not necessarily model testing.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Section 3.5.2, Model Validation (now section 3.6.2, Model Output Validation)	
Comment	One commentator sought clarification on the term "Model Validation," and how the use of term in the ASOP differs from the use of that same term under SR 11-7: Guidance on Model Risk Management.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested that section 3.5.2 should include and reference the concept of an "effective challenge," and that the intensity and effort of the challenge should be commensurate with the risk and materiality of the model.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested adding an additional item under 3.5.2 related to predictive models, namely, "For predictive models, testing should include running the developed model against a hold-out dataset, not used to develop the model, to verify that modeled output would bear a reasonable relationship to actual results from the hold-out data." In addition, the commentator suggested adding a definition of "hold-out data" such as: "Hold-out data – typically a random subset of the data being modeled. Hold-out data is not used to create the model itself, but rather, used to validate that the model that was built is truly predictive when applied to a previously unseen set of data."
Response	The reviewers agree that changes were appropriate and modified the language in this section and added a definition of "hold-out data."
Comment	One commentator suggested changing "The actuary should take appropriate steps to validate" to "The actuary should validate" for greater clarity.
Response	The reviewers agree and made the change.
Comment	One commentator suggested that section 3.5.2 be called Model Testing, given that Validation has a specific connotation to many companies that is not meant by what is being described.
Response	The reviewers modified the title of section 3.5.2 from Model Validation to Model Output Validation.
Section 3.5.3, Review by Another Professional (now section 3.6.3, Review by Another Professional)	
Comment	One commentator recommended striking section 3.5.3 since actuaries can always consider having another professional review their work and the section provides no guidance and is not needed.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator questioned when it would be appropriate to not obtain such a review and suggested that the word "may" be replaced by "should" or removing the sentence altogether.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment	One commentator suggested replacing section 3.5.3 with the following: The actuary may consider obtaining a review by a second, qualified professional. Use of another review would increase depending upon the nature and complexity of the model as well as with the materiality of the intended use(s)."
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Section 3.5.5, Mitigating Misuse and Misinterpretation (now section 3.6.5, Mitigating Misuse and Misinterpretation)	
Comment	One commentator suggested that section 3.5.5 is already handled in the stem of 3.5 and recommended that this section be removed.
Response	The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Comment Response	One commentator noted the reference in section 3.5.5 to sections 3.4.1 in ASOP No. 41 but noted there is no section 3.4.1 in ASOP No. 41. The reviewers note that section 3.4.1 in ASOP No. 41 is titled “Uncertainty or Risk.”
Comment Response	One commentator suggested mentioning the headings/titles of the section in other ASOPs in addition to the section numbers when they are being used as reference in case that the section numbers got changed in another ASOP for any reason. The reviewers note the standard follows an approved style guide and made no change in response to this comment.
Section 3.6, Documentation (now section 3.7, Documentation)	
Comment Response	One commentator suggested that the section should be more specific about what to document, with documentation best practices including the documentation of inputs, calculations – including key methodology choices (including simplifications and approximations), outputs, intended purpose, use limitations, and ongoing performance monitoring processes, model testing (including any developmental testing) and validation. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	Three commentators suggested strengthening the guidance by replacing “should consider” with “should.” The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested that the provision that the documentation could allow that another actuary qualified in the same practice area “assume the assignment if necessary” could be onerous in many cases and recommended that the ASOP should not expand upon general documentation requirements as the provision in the draft ASOP - that “another actuary qualified in the same practice area could assess the reasonableness of the actuary’s work”- is sufficient. The reviewers agree and deleted “or could assume the assignment if necessary.”
SECTION 4. COMMUNICATIONS AND DISCLOSURES	
Section 4.1, Required Disclosures in an Actuarial Report	
Comment Response	One commentator recommended changing the section name to “Disclosures in an Actuarial Report” since the use of “required” in the title is confusing given the guidance that the actuary “should disclose,” and recommended adding any unreasonable, unexplained variances from recent ongoing performance monitoring processes (addressed in a recommended new section 3.5.6) should be added to the list of items that should be disclosed. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator suggested replacing 4.1(d) with “d. unreasonable output resulting from the aggregation of assumptions and parameters used as input, if material, as discussed in section 3.1.6(f).” The reviewers agree with the concept and modified the language accordingly.
Comment Response	One commentator recommended changing “material limitations” to “material limitations, important aspects and weaknesses” to ensure disclosures cover all related items discussed in section 3.1.3. The reviewers agree in part and added “and known weaknesses” after “material limitations.”
Comment Response	One commentator suggested adding a clarification as to whether the “experts” in section 4.1(f) refer to outside experts or both outside and in-house experts. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

ASOP No. 56—Doc. No. 195

Comment Response	One commentator noted that not all items in section 3.3 are covered by the disclosures in section 4.1, namely key methods and A&P and model testing (sensitivities). The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator recommended that it be made clear that the ASOP does not require an actuarial report with respect to the models used by the actuary. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.
Comment Response	One commentator proposed removing section 4.2 as section 4.1 already requires compliance with the disclosure standards of ASOP No. 41. The reviewers believe the guidance is appropriate and therefore made no change in response to this comment.

Uses of Catastrophe Model Output—American Academy of Actuaries

JULY 2018

USES OF CATASTROPHE MODEL OUTPUT

American Academy of Actuaries
Extreme Events and Property Lines Committee

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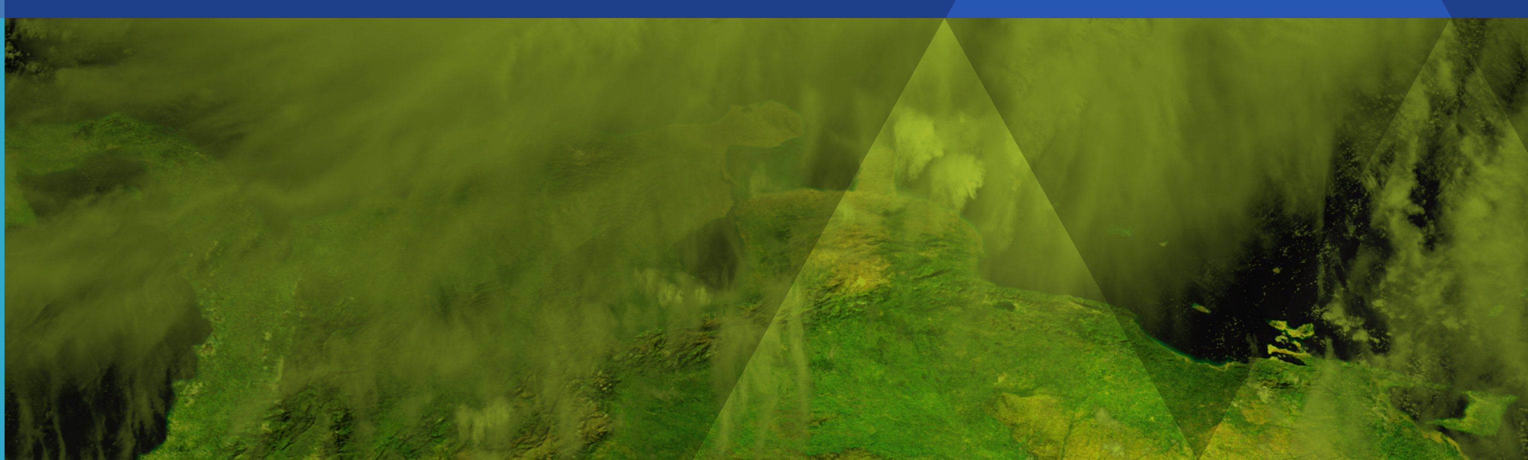

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The American Academy of Actuaries is a 19,000-member professional association whose mission is to serve the public and the U.S. actuarial profession. For more than 50 years, the Academy has assisted public policymakers on all levels by providing leadership, objective expertise, and actuarial advice on risk and financial security issues. The Academy also sets qualification, practice, and professionalism standards for actuaries in the United States.

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Contents

Executive Summary

Historical information is generally insufficient for predictions related to future catastrophes. As a result, catastrophe modeling—which is more accurate, stable, and flexible—has been developed. Catastrophe models have become an important element in actuarial practice. This paper reviews four basic uses: ratemaking, loss mitigation, risk selection, and reinsurance. The review uses four of the many possible events as illustrations: Hurricane Wind, Storm Surge, Inland Flood, and Tornado and Straight Line Wind.

As these models proliferate, various organizations have established requirements governing their use. American Academy of Actuaries members are required to follow applicable actuarial standards of practice (ASOPs)[1] as adopted by the Actuarial Standards Board. Regulatory and standard-setting bodies—most notably the Florida Commission on Hurricane Loss Projection Methodology and the National Association of Insurance Commissioners—have taken a lead in analyzing the appropriateness of catastrophe models.

Models dealing with different catastrophes have several similar components:

1. Probability of the particular catastrophe occurring;
2. Intensity of the catastrophe;
3. Corresponding damage; and
4. Allocation of loss amounts among the various impacted entities.

Each of these components becomes a module in a catastrophe model.

In the first module, a mathematical simulation with a large number of iterations is undertaken. The process produces probabilities of the event occurring, and is concerned with answering the question: What is the chance of this event occurring?

The second module concerns the intensity of the occurrence. It answers the question: What are event conditions (such as windspeed or water depth) inside the footprint (the area impacted by the event)?

The third module quantifies the impact of the event on the structures (and related property, such as building contents). It answers the question: How badly damaged is the insured structure?

1 Actuarial Standards Board; Actuarial Standards of Practice; available at http://www.actuarialstandardsboard.org.

The final allocates the damage among various parties (policyholder, insurance company, reinsurer) according to the terms of the insurance contract.

Models can be used in many applications. Common areas include ratemaking, risk selection, mitigation, and reinsurance. Expected losses, along with the associated volatility, are key building blocks in these and many other areas. Among other things, more accurate premiums can be determined, the potential benefit of mitigation features can be quantified, and changes to exposure characteristics and policy terms can be assessed.

Both state and federal public policymakers are using catastrophe models to address public policy issues. These efforts include analysis of the size of potential loss, the cost of a potential loss, appropriateness of territory and classifications, mitigation efforts, and insurance coverage modifications.

Catastrophe models offer many advantages compared to historical loss-based projections. Like any tool, understanding both their capabilities and shortcomings is of paramount importance.

Purpose

This paper is intended to provide an overview of how catastrophe models have developed and demonstrate how catastrophe model output can be used in selected actuarial tasks.

Much has been written about catastrophe models used for insurance. Modelers have published detailed information related to specific models including how they were developed and validated. High-level summaries have come out of the insurance sector's comparisons of output from model to model and to historical events. Practitioners have published papers highlighting and others discussing specific aspects of using model output for a given task. This paper was developed to help fill the gap between overviews and detailed description by describing some practical applications.

Catastrophe models were initially developed to address the shortcomings inherent in using historical data to project potential losses from infrequent, severe events that impacted many properties that were not geographically diverse. Knowledge about and acceptance of these models by risk-bearing entities and regulators have expanded along with the development of more and increasingly sophisticated models.

Model use has become required in many areas beyond those considered "traditional" areas of actuarial practice. These uses demonstrate the power and pervasiveness of models. Some of these are described in the Governance and Public Policy Uses section of this paper, while others have been espoused by the private market.

Also included are concrete examples of how expected losses and related metrics from catastrophe models can be used by private insurance companies, public policy experts, and others. Four basic use cases—ratemaking, loss mitigation, underwriting or risk selection, and reinsurance—are developed for four types of catastrophic events:

- Hurricane Wind (does not include tropical storms or Storm Surge)
- Flood: Storm Surge
- Flood: Inland
- Tornado and Straight-Line Wind (Tornado/SLW)

These types of events were selected as useful illustrations. Models also exist for many other causes of loss (earthquake, severe convective storm, wildfire, pandemic, etc.)

Appendices to this paper provide additional details on how the examples were developed.

Introduction

In perils where losses are dominated by reasonably predictable and frequent events, actuaries can use recent historical loss experience, adjusted for inflation and other appropriate changes, to estimate future losses. Where losses are infrequent events, such as those that arise from catastrophes, the available historical information may not be sufficient to reliably predict future loss potential. This problem has led to the development of sophisticated loss simulation models for perils such as hurricane, earthquake, and flood.

The actuarial profession has recognized the limitations of relying on historical data and has taken steps to incorporate model analyses into their work. Model development, expanding and enhancing their uses, and understanding their current and future potential contributions to analyses will continue for the foreseeable future.

History

Catastrophe modeling combines natural science with risk management practices, using computer power. Since the 1800s, property insurers have been visualizing exposure by mapping covered property. Likewise, scientists have been measuring wind speed and ground motion since the 1800s. In recent decades, many studies have been published asserting theories about the causes and expected frequency of natural disasters. "These two separate developments—mapping risk and measuring hazard—came together in a definitive way in the late 1980's and early 1990's" to create catastrophe models.[2] Increasing computer capabilities in that period were critical to model development.

Commercial modeling software was developed to estimate the potential cost of natural disasters. Initially, the use of these models was limited. However, in 1989, the $4 billion price tag for Hurricane Hugo and $6 billion for the Loma Prieta earthquake helped increase attention given to catastrophe models. In 1992, Hurricane Andrew ($15.5 billion) clarified the critical need to manage risk and the importance of catastrophe models. A few hours after Hurricane Andrew struck southern Florida, one of the modelers shared its real-time modeling estimate of $13 billion. Hurricane Andrew losses led to nine insurance company insolvencies.[3]

2 *Catastrophe Modeling: A New Approach to Managing Risk*; edited by Patricia Grossi and Howard Kunreuther; 2005.
3 Ibid.

The insurance industry's use of catastrophe models to estimate potential future catastrophe losses has gained momentum and has become a standard risk management practice. Several additional factors contributed to the advancement of the catastrophe models. The primary driver was the realization that commonly used actuarial methods relying on five to 25 years of historical catastrophe losses were inadequate for pricing and risk management. Combined with the substantial improvement in computing power and sophistication, models became the tool of choice for helping to manage catastrophic risk.

The continuing development and increasing reliance on catastrophe models is evidence of their value and suggests catastrophe models are here to stay and will continue to play an important role in measuring catastrophe risk.

Governance of Models

Catastrophe models have expanded into many areas of actuarial practice and are available for an increasing number of perils and potentially impacted regions. As the use of and reliance on catastrophe models has increased, the need for appropriate guidance and oversight has also increased. Various requirements have been established to govern the use of models. In addition, indirect oversight is occurring through scrutiny of models and model results by the business parties involved. Model analyses and output are required by various entities.

The American Academy of Actuaries and insurance regulatory bodies have developed requirements and guidance for actuaries in their development, use, and reliance on catastrophe models. Enterprise Risk Management (ERM), rating agencies, and state insurance regulators mandate certain model output to be provided for use in evaluation of risk-bearing entities. Reinsurers and capital markets rely on the standard language and definitions developed by modelers, and the output is key in designing products, defining terms, and negotiating costs. The reliance on model metrics creates an incentive for robust, current, and useful model results. While this is true for any tool used to manage risk, the level of financial impact and inability to ascertain the "right" answer result in application of additional scrutiny.

Actuarial Standards of Practice

All actuaries who are members of the U.S. actuarial organizations that have adopted the Code of Professional Conduct are required to follow actuarial standards of practice (ASOPs), which are established by the Actuarial Standards Board. The ASOPs provide guidance for what an actuary should consider, document, and disclose when performing an actuarial assignment. Actuaries may wish to review the applicability guidelines for assistance in determining standards of practice relevant to the task being performed. Specifically focused on catastrophe model use are:

- ASOP No. 38, *Using Models Outside the Actuary's Area of Expertise (Property and Casualty)*, provides guidance to an actuary in using models that incorporate specialized knowledge outside of the actuary's own area of expertise.
- ASOP No. 39, *Treatment of Catastrophe Losses in Property/Casualty Insurance Ratemaking*, indicates that an actuary should consider models based on noninsurance data when available historical insurance data does not sufficiently represent the exposure to catastrophe losses. In addition, this ASOP provides guidance for acceptable use of such models.

Florida Commission on Hurricane Loss Projection Methodology.

In the 1995 Florida Legislative session, the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM) was created to evaluate hurricane models. "The Legislature specifically determined that reliable projections of hurricane losses for residential property insurance are necessary to assure rates are neither excessive nor inadequate, and that computer modeling has made it possible to improve upon the accuracy of hurricane loss projections."[4] The FCHLPM's remit was expended in 2014 to include the flood peril.

The FCHLPM publishes standards and related information in salient scientific disciplines as well as supporting activities such as software and security. The information submitted to the FCHLPM by the modeling firms is reviewed by an independent panel of experts. A company submitting a rate filing for residential property insurance in the state of Florida that relies on the results of a hurricane model is limited to those models that have been found acceptable by the FCHLPM. Several other states have interrogatories or questionnaires related to catastrophe models used in rate filing indications. Many of the states exposed to hurricanes request information about the FCHLPM review of any hurricane model used. Models that have been approved by the FCHLPM have been more likely to be found acceptable by other states than are non-FCHLPM accepted models.

4 Florida Commission on Hurricane Loss Projection Methodology website: www.sbafla.com/methodology.

The National Association of Insurance Commissioners

The National Association of Insurance Commissioners (NAIC), representing the nation's state, territorial, and possession insurance regulators, certifies insurance regulatory sections of state government as being in compliance with its model laws (through an accreditation process), which creates an incentive for local regulators to follow what the NAIC has adopted. One requirement is assuring that companies have sufficient capital to withstand adverse events. While the review and determination of financial stability is up to a company's domiciliary state regulator, the NAIC has published a property/casualty risk-based capital (RBC) formula that quantifies many of the risks facing companies and relates it to solvency levels. One of the factors in the formula is catastrophic losses, and probable maximum losses (PMLs) at specified levels are required as input to this formula. Model use and results are also required in the completion of an Own Risk and Solvency Assessment (ORSA), which is a key part of Enterprise Risk Management (ERM)—discussed in more detail below).

The NAIC also offers educational sessions related to various topics of interest, including catastrophe models. It has provided a list of questions state regulators might ask.

Insurance regulators and policymakers recognize the importance of promoting insurance markets and supporting the use of models when historical data is limited or non-predictive of the future. For example, in 2015 the Florida Legislature wanted to stimulate growth of private flood insurance as an alternative to the National Flood Insurance Program (NFIP). The Florida Legislature passed a statute allowing private insurance companies to write flood insurance, beyond what can be offered via the NFIP's Write-Your-Own program. The Florida Office of Insurance regulation continues to review flood product and rate filings; however, insurance companies can introduce flood coverage without sharing specific details about how the flood rates were determined. The statute indicates that in 2025, insurance companies will be required to submit details of their models. This illustrates a recognition by regulators of the importance of models and how the regulatory environment can stimulate insurance coverage for a product that insurers have been historically reluctant to write. As mentioned above, the FCHLPM is responsible for developing flood standards designed to assure regulators that the flood models being used are accurate and reliable.

Enterprise Risk Management

Enterprise Risk Management (ERM) is defined as "*[T]he discipline by which an organization in any industry assesses, controls, exploits, finances and monitors risks from all sources for the purpose of increasing the organization's short- and long-term value to its stakeholders.*"[5]

Companies are becoming increasingly aware of the need for systematic evaluation of the risks faced. ERM is useful for any enterprise and is not limited to insurance-related entities. Many companies have departments dedicated to evaluation of risk. Such evaluations for property/casualty insurance companies often rely heavily on catastrophe models. Simulations can increase a company's understanding of the range of possibilities, concentration of risk, exposure overall, and the impact of any risk-transference mechanisms. The importance of catastrophe models in assessing an insurance company's risk is substantiated by rigorous use of models by reinsurers and rating agencies. The reinsurers' and rating agencies' reliance on such models also provides a form of governance of the models used, since more useful models provide superior understanding of catastrophic risk.

As catastrophe models continue to develop and their use expands and deepens, direct and indirect requirements and influences are likely to become more sophisticated.

5 Actuarial Standard of Practice No. 46, *Risk Evaluation in Enterprise Risk Management.*

Model Overview and Components

While each peril model reflects multiple factors specific to the peril being modeled, catastrophe models have similar components:

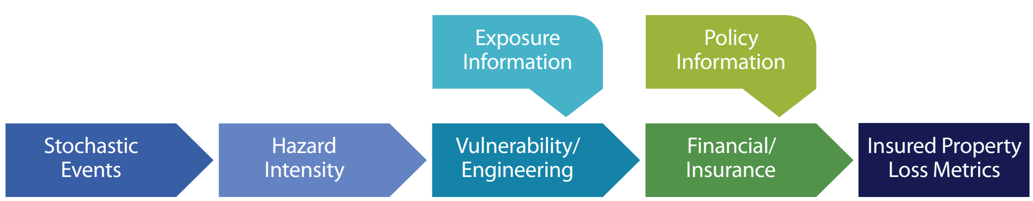
Stochastic Event Generation. Contains event information generated by the model, including probability of occurring (known as event rate), or the sequence of the event within the simulated year.

Hazard/Local Intensity. Local intensity of the event; what conditions are inside the event footprint. For example, inundation depth of a flood, wind speed of a hurricane, or ground movement accelerations of an earthquake.

Vulnerability/Engineering. How the intensity impacts the structure and contents. The salient structure characteristics are specific to a peril, although some (such as the age of a building) are likely to be applicable to many perils.

Financial/Insurance. How the loss is allocated among those responsible for payment. Applies the insurance contract terms to the loss, assigning portions of the amount to policyholders (via deductibles), insurance, and reinsurance companies.

The modules listed proceed sequentially. Each module creates data. Some key information is passed on to the next module to enable the process to continue. Some module output is useful on its own for validation and other purposes. The flowchart below illustrates how the model components interact.



The first stage of catastrophe modeling is to generate a stochastic event set, which is a database of simulated events. The events follow logical scientific rules related to the type of event. Each event is characterized by a probability of occurrence (event rate) and geographic area affected. Thousands of possible event scenarios are simulated, based on realistic parameters and historical data, to probabilistically model what could happen in the future.

The hazard component of catastrophe models quantifies the severity of each event in a geographical area, once the event has occurred. An event footprint is generated, which is a spatial representation of hazard intensity from a specific event. For example, the model calculates the peak wind speeds at each location affected by the storm for hurricane wind.

Catastrophe models capture property vulnerability. Mean damage ratios (MDRs) are losses expressed as a percent of value, for a given hazard level (e.g., ground motion or wind speed) and location. These are the average percentages of damage that are expected for a structure with the characteristics input into the model. The uncertainty around the estimated property loss (sometimes referred to as secondary uncertainty) is often expressed in terms of a standard deviation or a coefficient of variation (CV). Standard deviations are used in the examples in this monograph.

Finally, a financial or insurance module quantifies the financial consequences of each event from various financial perspectives. The policy terms such as deductibles, limits, and reinsurance are applied to the damage from each insured property from the vulnerability model to calculate the allocation of the loss amount.

While some analysis settings can be selected by the user (such as whether demand surge will apply), most of the model workings have been developed by the modeling company scientists and can't be altered. Users must input information about the policies potentially impacted and characteristics about each property. Individual policies, groups of policies (termed portfolios), and subsets of portfolios can be analyzed.

Use Cases

This section gives explanations and numeric examples of how catastrophe model output can be used in several typical actuarial tasks. A hypothetical set of policies in the state of Florida was defined for use in this paper and used as input to a catastrophe model. Details on this portfolio of policies and on the model settings used can be found in the appendices.

Ratemaking. The annual cost of catastrophic events needs to be determined because most policy terms are for a year. Models generate Average Annual Loss (AAL) for each insured property. The cost of an insurance policy is comprised of AAL, expenses, and risk load. Appropriate reinsurance costs must be included, and their assignment to an expense category depends on what those costs consist of and how they are treated by the primary company. The examples, which use a methodology chosen for its simplicity, does not include reinsurance costs. The risk load depends on the variability (i.e., standard deviation or CV) or uncertainty in the loss estimates. The premiums developed in this paper are for the catastrophe peril risk only and do not contemplate any non-catastrophe causes of loss.

Underwriting and Risk Selection. Nearly any property can be insured if an appropriate rate can be calculated and charged. However, an insurance company must consider the financial health of its entire book of business, and some risks are a better component for any given portfolio than others. In addition, companies typically specialize in types of property and/or geographic areas. So, while a price that is commensurate with expected loss is critical, there are other factors to be taken into consideration. The impact of adding a given property to what an insurer already has on its books depends not only on the individual property, but also on how that property's potential for loss interacts with existing policies. Measures such as Probable Maximum Losses (PML) are considered. A PML, also known as a Return Period Loss (RPL), gives two pieces of information—an amount and a probability. It is an amount that is expected to be exceeded with a given probability by an event or in a year. For example, a 100-year occurrence PML of $6 million ($6M) means that there is a 1-in-100 (1 percent) chance of a loss of at least $6M.

Loss Mitigation. Some characteristics that modelers have included have been shown to lessen the severity of loss. The impacts of these mitigation features can be evaluated by seeing how AALs and other measures react to the presence or absence of these features. Cost/Benefit tradeoffs can be evaluated. Strategies to encourage desired choices can be tied to potential loss dollar changes.

Catastrophe Reinsurance. Many insurance companies will themselves buy insurance (called catastrophe reinsurance) to assist in paying losses following a catastrophic event. In the case of a catastrophic event, insurance companies (primary insurers) are likely to quickly need large sums of money—more than what makes sense to accumulate. Because model output uses language and metrics that have become common among primary insurers, reinsurers, and others, transactions can be efficiently analyzed and terms agreed upon. Many reinsurers and reinsurance contracts are not focused on individual properties or everyday losses, but instead look at providing loss coverage to portfolios of policies. This allows primary companies to protect themselves from extreme events in accordance to their risk tolerance.

Ratemaking

Determine Rate Level

The ratemaking formula and assumptions used here are based on methods used by many property/casualty insurers. Simplifying assumptions have been made to facilitate understanding and highlight model output use. The price of insurance is based on the sum of three basic components. Companies may subdivide these three components and categorize the total premium in various ways. However, the basic principle is the same, which is to calculate the premium that is sufficient to cover expected loss, expenses, and risk load:

$$\text{Premium} = \text{AAL} + \text{Expense Load} + \text{Risk Load}$$

Catastrophe models are essential to calculate AAL and risk load. As noted above, AAL stands for Average Annual Loss; it is the expected loss per year, averaged over many years. AAL is calculated as the annualized cost of all potential stochastic events in a year:

$$AAL = \sum_{i} p_i L_i$$

Where: p_i is the annual probability of an event(i) occurring, and L_i is the expected loss of the event.

To adequately insure a risk, an insurer must commit a certain level of capital beyond the expected annual loss to cover the potential for catastrophic loss. This risk load should be sufficient to cover the cost of capital including a profit provision. Because catastrophe risk is volatile, the risk load can be multiples of AAL. The higher the volatilities, the higher the likelihood of insolvency, therefore the higher the risk load. There are different ways to develop the risk load. The standard deviation of the modeled losses (σ) is commonly used.

$$\sigma = \sqrt{\sum_i (p_i L_i^2) - AAL^2}$$

Table 1 shows the rate per $1,000 of building coverage for our portfolio of hypothetical policies for hurricane wind losses. It is shown as AAL / $1,000 building coverage. Tables 2, 3, and 4 show the same information for Tornado/Straight-Line Wind, Inland Flood, and Coastal Storm Surge. Nine counties in Florida and the entire state are shown to illustrate the potential variation of the costs. Insurance companies may use higher resolutions such as ZIP code or smaller grids in a rating plan to recognize the variations in the results.

The 27 percent expense load used in this example was judgmentally selected. An average building coverage limit of $207,500 is used in developing premium examples. The risk load is presumed to include a provision for profit.

TABLE 1 Hurricane Wind Rate and Premium Example

County	Modeled Gross Hurricane Wind Loss$ Per $1000 Cov A	Selected Risk Load (Standard Deviation)	Expense Load $	Hurricane Wind Premium $ Per $1000 Cov A	Hurricane Wind Premium $ for $207.5K Cov A Home
(A)	(B)	(C)	(D) = ((B)+(C))/.73-((B)+(C))	(E) = (B)+(C)+(D)	(F) = (E) * 207.5
Monroe	13.82	27.65	15.34	56.81	11,788.23
Broward	5.54	11.08	6.15	22.77	4,723.82
Palm Beach	5.26	10.51	5.83	21.60	4,482.44
Miami-Dade	7.60	15.21	8.44	31.25	6,484.54
Hillsborough	0.75	1.51	0.83	3.09	641.70
Orange	0.36	0.72	0.40	1.48	306.28
Okeechobee	1.91	3.81	2.11	7.83	1,624.67
Duval	0.25	0.49	0.27	1.01	209.96
Sarasota	1.74	3.48	1.93	7.14	1,481.68
Statewide	2.64	5.29	2.93	10.86	2,253.96

TABLE 2 Tornado/Straight-Line Wind Rate Premium Example

County	Modeled Gross Tornado/Straight-Line Wind Loss$ Per $1000 Cov A	Selected Risk Load (Standard Deviation)	Expense Load $	Tornado/Straight-Line Wind Premium $ Per $1000 Cov A	Tornado/Straight-Line Wind Premium $ for $207.5K Cov A Home
(A)	(B)	(C)	(D) = ((B)+(C))/.73-((B)+(C))	(E) = (B)+(C)+(D)	(F) = (E) * 207.5
Monroe	0.02	0.01	0.01	0.05	9.76
Broward	0.06	0.03	0.04	0.13	27.52
Palm Beach	0.08	0.04	0.04	0.16	33.49
Miami-Dade	0.06	0.03	0.03	0.12	24.84
Hillsborough	0.17	0.08	0.09	0.34	71.14
Orange	0.20	0.10	0.11	0.41	85.57
Okeechobee	0.13	0.06	0.07	0.26	54.25
Duval	0.16	0.08	0.09	0.32	67.18
Sarasota	0.13	0.06	0.07	0.26	53.90
Statewide	0.14	0.07	0.08	0.28	58.92

TABLE 3 Inland Flood Rate and Premium Example

County	Modeled Gross Inland Flood Loss$ Per $1000 Cov A	Selected Risk Load (Standard Deviation)	Expense Load $	Inland Flood Premium $ Per $1000 Cov A	Inland Flood Premium $ for $207.5K Cov A Home
(A)	(B)	(C)	(D) = ((B)+(C))/.73-((B)+(C))	(E) = (B)+(C)+(D)	(F) = (E) * 207.5
Monroe	0.18	0.28	0.17	0.63	131.29
Broward	0.65	0.98	0.61	2.24	465.14
Palm Beach	0.56	0.84	0.52	1.92	398.48
Miami-Dade	0.97	1.45	0.90	3.32	687.94
Hillsborough	0.25	0.38	0.23	0.86	178.72
Orange	0.40	0.59	0.37	1.36	281.65
Okeechobee	1.02	1.53	0.94	3.48	722.78
Duval	0.69	1.03	0.64	2.36	489.99
Sarasota	0.15	0.23	0.14	0.52	107.20
Statewide	0.59	0.89	0.55	2.04	422.64

TABLE 4 Storm Surge Rate and Premium Example

County	Modeled Gross Storm Surge Loss$ Per $1000 Cov A	Selected Risk Load (Standard Deviation)	Expense Load $	Storm Surge Premium $ Per $1000 Cov A	Storm Surge Premium $ for $207.5K Cov A Home
(A)	(B)	(C)	(D) = ((B)+(C))/.73-((B)+(C))	(E) = (B)+(C)+(D)	(F) = (E) * 207.5
Monroe	2.05	3.08	1.90	7.02	1,457.25
Broward	0.32	0.48	0.30	1.10	227.97
Palm Beach	0.05	0.07	0.04	0.17	34.25
Miami-Dade	0.23	0.34	0.21	0.79	162.97
Hillsborough	0.07	0.10	0.06	0.23	47.10
Orange*	—	—	—	—	—
Okeechobee*	—	—	—	—	—
Duval	0.70	1.05	0.65	2.40	498.68
Sarasota	0.26	0.39	0.24	0.89	184.26
Statewide	0.27	0.40	0.25	0.91	189.01

*These counties are inland, and not exposed to coastal storm surge.

Determine Risk Relativities and Rating Factors

An insured risk's potential insured loss propensity in a catastrophic event varies by many factors, including geographic location, physical characteristics of the building, and policy terms. Catastrophe models can be used to determine the impact of each rating factor, such as construction, year built, occupancy, and territory relativities.

Deductible Relativities

A deductible is the amount "deducted" from an insured loss before payment is made. Deductibles have been an essential part of insurance contracts for many years and are a sharing of the risk between the insurance company and the policyholder. When repairing a damaged home or replacing personal possessions, the amount of the deductible would come out of policyholder's own pocket.

Deductible relativities can be estimated by models using gross losses (loss after application of the deductible) divided by ground up losses (total amount of loss without any adjustments).

$$\text{Deductible loss elimination ratio} = 1\text{- (Gross Loss/Ground Up loss).}$$

Deductible relativity examples for 2 percent deductibles for Hurricane Wind, Tornado/Straight-Line Wind, Inland Flood, and Storm Surge are shown in tables 5 through 8. Two percent deductibles are standard in Florida for hurricane wind and are shown here for the other perils for comparison.

For hurricane wind deductible relativities in Table 5, non-coastal counties, such as Orange and Okeechobee, have higher deductible loss elimination ratios than coastal counties. This is because coastal regions experience higher wind speeds and losses are more likely to be severe, so deductibles tend to be a smaller portion of the overall loss. Because inland counties' hurricane wind losses are likely to be lower, deductibles tend to be a higher percentage of overall loss.

TABLE 5 Hurricane Wind Deductible Loss Elimination Ratio

County	Avg Hurricane Wind Ground Up AAL $	Avg Hurricane Wind Gross AAL $ @2% Deductible	2% Deductible Hurricane Wind Loss Elimination Ratio
(A)	(B)	(C)	(D) = 1-(C)/(B)
Monroe	3,577.20	2,868.47	19.8%
Broward	1,704.98	1,149.46	32.6%
Palm Beach	1,636.70	1,090.73	33.4%
Miami-Dade	2,190.53	1,577.90	28.0%
Hillsborough	365.76	156.15	57.3%
Orange	274.57	74.53	72.9%
Okeechobee	796.42	395.34	50.4%
Duval	182.22	51.09	72.0%
Sarasota	629.12	360.54	42.7%
Statewide	885.65	548.46	38.1%

TABLE 6 Tornado/Straight-Line Wind Deductible Loss Elimination Ratio

County	Avg Tornado/ Straight-Line Wind Ground Up AAL $	Avg Tornado/ Straight-Line Wind Gross AAL $ @2% Deductible	2% Deductible Tornado/Straight-Line Wind Loss Elimination Ratio
(A)	(B)	(C)	(D) = 1-(C)/(B)
Monroe	5.56	4.75	14.6%
Broward	15.80	13.39	15.2%
Palm Beach	18.98	16.30	14.1%
Miami-Dade	14.28	12.09	15.4%
Hillsborough	40.24	34.62	14.0%
Orange	47.58	41.64	12.5%
Okeechobee	29.64	26.40	10.9%
Duval	37.39	32.70	12.6%
Sarasota	30.27	26.23	13.4%
Statewide	33.00	28.67	13.1%

TABLE 7 Inland Flood Deductible Loss Elimination Ratio

County	Avg Inland Flood Ground Up AAL $	Avg Inland Flood Gross AAL $ @2% Deductible	2% Deductible Inland Flood Loss Elimination Ratio
(A)	(B)	(C)	(D) = 1-(C)/(B)
Monroe	55.37	38.34	30.8%
Broward	172.41	135.82	21.2%
Palm Beach	148.83	116.36	21.8%
Miami-Dade	250.88	200.88	19.9%
Hillsborough	64.38	52.19	18.9%
Orange	101.51	82.24	19.0%
Okeechobee	269.06	211.05	21.6%
Duval	164.52	143.08	13.0%
Sarasota	40.17	31.30	22.1%
Statewide	151.07	123.41	18.3%

TABLE 8 Storm Surge Deductible Loss Elimination Ratio

County	Avg Storm Surge Ground Up AAL $	Avg Storm Surge Gross AAL $ @2% Deductible	2% Deductible Storm Surge Loss Elimination Ratio
(A)	(B)	(C)	(D) = 1-(C)/(B)
Monroe	469.04	425.52	9.3%
Broward	70.67	66.57	5.8%
Palm Beach	10.56	10.00	5.3%
Miami-Dade	50.50	47.59	5.8%
Hillsborough	15.38	13.75	10.6%
Orange	—	—	—
Okeechobee	—	—	—
Duval	159.58	145.62	8.8%
Sarasota	58.88	53.81	8.6%
Statewide	60.48	55.19	8.7%

Geographic Location Relativities

The propensity for catastrophe damage depends highly on geographic locations. Models can be used to determine the location relativities under various resolutions. The relative frequency and severity of events are critical to determining rating territories, rate levels, and underwriting/risk selection criteria. The granularity of the meaningful variation is different for the various perils. For example, storm surge damage is generally more severe for properties closest to the coast. However, depending on the elevation, the expected damage can be quite different for areas near each other. Table 9 shows the geographic relativities for selected counties in Florida for Hurricane Wind, Tornado/Straight-Line Wind, Inland Flood, and Coastal Storm Surge risks.

TABLE 9 Territory Relativities

County	Hurricane Wind Gross Avg AAL $	Hurricane Territory Relativities	Tornado/ Straight-Line Wind Avg Gross AAL $	Tornado/ Straight-Line Wind Territory Relativities	Inland Flood Avg Gross AAL $	Inland Flood Territory Relativities	Storm Surge Avg Gross AAL $	Storm Surge Territory Relativities
(A)	(B)	(C) = (B)/ Statewide(B)	(D)	(E) = (D)/ Statewide(D)	(F)	G) = (F)/ Statewide(F)	(H)	(I) = (H)/ Statewide(H)
Monroe	2,868.47	5.230	4.75	0.166	38.34	0.311	425.52	7.710
Broward	1,149.46	2.096	13.39	0.467	135.82	1.101	66.57	1.206
Palm Beach	1,090.73	1.989	16.30	0.568	116.36	0.943	10.00	0.181
Miami-Dade	1,577.90	2.877	12.09	0.422	200.88	1.628	47.59	0.862
Hillsborough	156.15	0.285	34.62	1.207	52.19	0.423	13.75	0.249
Orange	74.53	0.136	41.64	1.452	82.24	0.666	—	—
Okeechobee	395.34	0.721	26.40	0.921	211.05	1.710	—	—
Duval	51.09	0.093	32.70	1.140	143.08	1.159	145.62	2.638
Sarasota	360.54	0.657	26.23	0.915	31.30	0.254	53.81	0.975
Statewide	548.46	1.000	28.67	1.000	123.41	1.000	55.19	1.000

Underwriting and Risk Selection

Insurance premiums commensurate with risk are critical to a robust insurance market and to the continuing ability of companies to remain solvent and provide needed protection to policyholders. Besides the business need for accurate premiums, insurance premiums that reflect risk can inform individuals as to how safe or exposed they are and can promote mitigating behavior. Along with adequate rates, companies monitor how much business they write and their aggregate exposure to loss from extreme events. For catastrophic events, this can be critical because many properties may be damaged from one event. Insuring 1,000 homes around the state of Florida may not be problematic while insuring 1,000 homes in the coastal Miami-Dade area may expose the company to an unacceptable level of loss. Managing aggregate risk minimizes the risk of insolvency. In addition, minimizing the concentration of risk may help reduce reinsurance costs and limit the number of claims following an event to a manageable level.

Risk selection initially was used as a binary decision tool—a property was acceptable to insure based only on its characteristics, or it was not acceptable. Catastrophe models also allow a property to be evaluated based on its risk in the context of a company's entire book of business. In some cases, catastrophe models may also facilitate premium changes or coverage adjustments to make the premium commensurate with the associated risk. Rather than yes/no decisions, these coverage and premium adjustments allow previously uninsurable properties to obtain coverage. More accurate premiums can be determined and charged for all risks.

Loss Metrics for an Insured Property at an Individual Location

Underwriters and risk selection algorithms can use many metrics, or combinations of them, to provide additional information to help understand the risk for an individual insured property location. Models consider both environmental and building characteristic variables to provide information relevant to the property being reviewed. Companies may set up guidelines around various ranges of these metrics, with these ranges set based on the risk tolerance that the company has decided to follow. A few examples of these metrics are:

1. AAL/TIV: The ratio of the AAL to the Total Insured Value (TIV) provides a metric that shows the long-term risk at a location. This can be useful in evaluating how properties that are close geographically can have significantly different expected losses AAL. Some examples are given in the tables that follow. Because all our hypothetical policies have been defined as having the same TIV, the division to put our metrics on a comparable basis is not needed.

Tables 10 through 13 demonstrate the importance of accurate detailed geographic information. For each catastrophic peril, ZIP-level AALs vary significantly from state-level, and location-level information within a ZIP also varies. This can be helpful in determining, for example, how large rating territories should be. In the tables below, Inland Flood and Storm Surge show the widest ranges of AAL values, compared to Tornado/Straight-Line Wind. One possible conclusion could be that differentiating Tornado/Straight-Line Wind loss potential by territory does not add much value. Inland Flood loss potential appears to be concentrated in fewer than a third of the locations within one ZIP code. Comparing this information to a map would be informative and could provide additional information besides proximity to a water source.

Other metrics besides AAL provide more depth, and it should be emphasized that relying solely on information such as that shown in the tables is not recommended. In addition, the ZIP codes shown below were selected to illustrate the variability among loss costs.

TABLE 10 **Hurricane Wind AAL**

ZIP Code	# Locations	Average AAL	Lowest AAL	Highest AAL
(A)	(B)	(C)	(D)	(E)
32327	121	$156.83	$85.20	$505.54
All (Statewide)	100,000	$885.65	$61.07	$5,931.26

TABLE 11 **Inland Flood AAL**

ZIP Code	# Locations	Average AAL	Lowest AAL	Highest AAL
(A)	(B)	(C)	(D)	(E)
32043	155	$218.86	$0.00	$9,927.00
32043	105 of the 155	$0.00	$0.00	$0.00
All (Statewide)	100,000	$151.07	$0.00	$21,632.46

TABLE 12 **Storm Surge AAL**

ZIP Code	# Locations	Average AAL	Lowest AAL	Highest AAL
(A)	(B)	(C)	(D)	(E)
34689	123	$403.51	$0.00	$4,708.26
34689	3 of 123	$0.00	$0.00	$0.00
All (Statewide)	100,000	$60.48	$0.00	$19,686.13

TABLE 13 **Tornado / Straight-Line Wind AAL**

ZIP Code	# Locations	Average AAL	Lowest AAL	Highest AAL
(A)	(B)	(C)	(D)	(E)
32534	79	$81.09	$75.11	$117.70
All (Statewide)	100,000	$33.00	$1.88	$157.78

2. PML/TIV ratio: The ratio of a PML at a specified return period, to the TIV gives an indication of the possible severity at a location. Combining this view with locations that have similar AAL/TIV ratios gives an indication of the variability of risk at a location.

Hurricane wind example: Here are two locations from different parts of the state with similar AALs but different 250-year PML/AAL ratios. As this example shows, a location in ZIP code 32053 has a slightly higher AAL, but the PML for ZIP code 32311 has a PML that is 20 percent larger (suggesting higher loss potential from extreme events).

TABLE 14 **Hurricane Wind PML/TIV**

ZIP Code	AAL	250-year PML	PML / AAL
(A)	(B)	(C)	(D)
32053	$98.16	$5,024.54	51.19
32311	$91.88	$6,025.14	65.58

Portfolio Metrics

It can be instructive to see how adding or removing a property affects PML for a book of business. A property could have a relatively high AAL, but if it's in an area with low concentration in the current book, and doesn't impact the total book's PML and resulting reinsurance costs, the property could still be acceptable to an insurer, especially if capital allocated to writing property insurance is limited. Another way that some companies do this is to review their Tail Value at Risk (TVaR). Like the PML process, a company may review its TVaR to see if adding locations has a significant impact on the tail/extreme risk at various return periods.

An extension of the process described above is portfolio optimization. In this process, the insurance company chooses the modeled metric that is important to it, and then builds a geographically distributed portfolio that optimizes that metric relative to premium or insurance values (exposure). For example, if a company has the capital allocated to be able to write $100 million in premiums in a state, it may design a portfolio that minimizes a specified return period PML (like a 100-year PML).

Consider two separate insurance carriers in a state having similar 100-year PMLs, even though they have very different distribution of risk across the state. Both are considering acquiring a portfolio of locations. However, given their different current distributions, the acquisition could cause significantly different marginal changes to their PMLs.

Mitigation

Mitigation involves efforts to prevent hazards from developing into disasters and to reduce the effects of disasters when they occur. There are many different types of mitigation efforts. Some apply to individuals and some to communities, and they can be structural (e.g., window shutters, flood levees) or nonstructural (e.g., land-use planning). In all these situations, catastrophe models can help quantify the costs and benefits.

In the case of an individual structure, mitigation decisions often occur when insurance for the home is purchased. As an example, consider a hypothetical homeowner in Monroe County, Florida, who is debating whether to install hurricane shutters on her home. From Table 1 in the Ratemaking section above, she would be considering a premium (based on the hypothetical portfolio) of $11,788 for hurricane wind coverage. A catastrophe model used to calculate the premium can also be used to explore the savings from installing shutters. The following table shows output of this analysis.

TABLE 15 Hurricane Wind Shutter Impact on AAL

County	Hurricane Wind Gross AAL $ Without Shutter	Hurricane Wind Gross AAL $ With Shutter	Hurricane Shutter Discount
(A)	(B)	(C)	(D) = 1-(C) /(B)
Monroe	2,872.35	2,479.14	13.7%
Broward	1,377.11	1,154.62	16.2%
Palm Beach	1,170.99	970.26	17.1%
Miami-Dade	1,732.43	1,459.86	15.7%
Hillsborough	169.17	131.77	22.1%
Orange	77.21	54.90	28.9%
Okeechobee	420.06	326.71	22.2%
Duval	53.94	39.41	26.9%
Sarasota	440.52	363.29	17.5%
Statewide	483.87	398.29	17.7%

Recalculating the premium to reflect the hurricane wind savings would proceed as follows:

AAL with savings = (Col C from Table 15, per thousand) + Risk Load Expenses (Col C from Table 1), loaded for expenses.

$$= ((2{,}479 \,/\, 207.50) + 27.65) \,/\, (1-0.27) = \$54.23 \text{ per thousand}$$

Compared to the calculated Hurricane Wind premium per thousand from Table 1 of $56.81, this results in savings of 4.5% (54.23/56.81 -1). The premium savings would be 0.045 x $11,788.23 = $534.

The company may decide to adjust loss elimination ratios (LER) and expenses for mitigated properties as well. To the degree expenses vary with claim costs, additional savings could be realized. LERs could be increased or decreased. Because there tend to be more minor losses than extreme losses, more relative weight would be in the LER.

A community can also use a catastrophe model to weigh public policy decisions. Because a model can easily be applied to groups of individual risks, it can help a community understand aggregate costs and benefits stemming from a widespread implementation of a mitigation effort (e.g., a building code change).

As part of its review, the Florida Commission on Hurricane Loss Projection Methodology requires catastrophe modeling firms to make extensive regular submissions which, among many other things, must include the modeling firm's measurement of various mitigation measures. A copy of the relevant table for the model used in this paper from the April 2017 submissions is shown in Appendix 2. The first few rows are reproduced here to demonstrate the high level of detail that a catastrophe model can provide policymakers. With aggregated calculations like those used in the individual case above, a community can use these rates to measure the effect of mitigation efforts on its housing stock.

Figure 1: Response to FCHLPM Form V-2

INDIVIDUAL MITIGATION MEASURES			PERCENTAGE CHANGES IN DAMAGE* (REFERENCE DAMAGE RATE - MITIGATED DAMAGE RATE) / REFERENCE DAMAGE RATE * 100									
			FRAME STRUCTURE					MASONRY STRUCTURE				
			WINDSPEED (MPH)					WINDSPEED (MPH)				
			60	85	110	135	160	60	85	110	135	160
	REFERENCE STRUCTURE		0	0	0	0	0	0	0	0	0	0
ROOF STRENGTH	*BRACED GABLE ENDS*		15.1%	14.6%	12.4%	9.9%	4.8%	13.6%	13.4%	11.6%	9.4%	5.9%
	HIP ROOF		19.0%	18.2%	15.5%	12.5%	6.2%	17.3%	16.8%	14.5%	11.9%	7.5%
ROOF COVERING	*METAL*		-8.7%	-8.6%	-7.3%	-5.7%	-2.7%	-8.1%	-8.3%	-7.1%	-5.6%	-3.4%
	ASTM D7158 CLASS H SHINGLES (150 MPH)		1.9%	1.9%	1.6%	1.2%	0.6%	1.7%	1.7%	1.5%	1.2%	0.7%
	MEMBRANE		-5.2%	-5.1%	-4.3%	-3.4%	-1.6%	-5.0%	-5.1%	-4.4%	-3.5%	-2.1%
	NAILING OF DECK	8d	1.9%	1.9%	1.6%	1.2%	0.6%	1.7%	1.7%	1.5%	1.2%	0.7%

Reinsurance

Reinsurance and other risk transfer mechanisms play a valuable role in the insurance market. The risk of insolvency increases for primary insurance companies when many policies are likely to have a claim at the same time. For many types of claims, the correlation between policies is low (e.g., slip-and-fall claims). However, catastrophes increase the likelihood of many claims in close geographic proximity occurring all at once. Primary insurance companies manage this exposure by transferring the risk to other parties. Other parties with less concentrated exposure (e.g., investors or reinsurers with worldwide portfolios) are in a better position to manage this risk. This process expands the capacity of the insurance market by adding capital and efficiently managing risk.

Reinsurance pricing for catastrophe losses relies heavily on model results. Clearly defined measures and terms facilitate communication and negotiation of contract terms between various parties.

For example, a catastrophe reinsurance contract may cover losses between the 100-year and 250-year PMLs for specific causes of loss. As stated earlier, a PML or Return Period Loss is an amount that is expected to be exceeded by an event with a given probability. Table I6 shows 100-year and 250-year PMLs for our hypothetical policies for each of our four causes of loss. The probabilities in column (B) are the reciprocals of the Return Period years, (e.g., 1.0% = 1 / 100 and 0.4% = 1 / 250.) The PMLs in columns (C) through (G), shown in millions USD, are the model-generated expected loss amounts. As shown in Table 16, there is a 1.0% chance of hurricane wind causing damage costing at least $1,315 million, and a 0.4% chance of hurricane wind causing damage of at least $1,902 million. As expected, lower probabilities are associated with higher PMLs. For our hypothetical group of policies, at the probabilities shown, Hurricane Wind is likely to cause the most severe loss, followed by Inland Flood, Storm Surge (Coastal Flood), and finally Tornado/Straight-Line Wind.

TABLE 16 **PML Amounts in $ millions by Peril**

Return Period	Probability	Hurricane Wind	Flood Inland	Flood Storm Surge	Tornado/ SLW	All Causes Combined
(A)	(B)	(C)	(D)	(E)	(F)	(G)
100-year	1.0%	1,315	202	97	37	1,458
250-year	0.4%	1,902	384	157	52	2,031

Although AALs are additive, PMLs are not. Note that the PML for All Causes Combined is less than the sum of the PMLs from each cause of loss. To illustrate why PMLs are not additive, consider the probability that a one in 100-year event occurs for each cause of loss. The probability that all causes have a one in 100-year event in the same year is much less than 1 percent; therefore, the sum of the one in 100-year PMLs is associated with a much longer return period.

A reinsurance company may decide to sell coverage for a loss of at least $1,315M up to $1,902M to a primary company for wind damage from hurricane wind. This layer can be evaluated based on the AALs and standard deviations. Reinsurance pricing discussions often begin with the AAL plus a factor times the standard deviation for the layer. The factors used vary over time and under differing circumstances, but for a given layer at a fixed point in time, factors from similarly exposed companies and/or similar market conditions can serve as useful benchmarks.

Table I7 shows AALs, standard deviations, and coefficients of variation for the 100-year PML to the 250-year PML layer for the same causes of loss as in Table 16. The probability of reaching an amount of loss that activates the reinsurance coverage, called the layer retention, is 1.0 percent, and the probability of a loss using the entire layer, known as hitting the layer limit, is 0.4 percent.

TABLE 17 **Layer Statistics for 100- to 250-year PML**

	Hurricane Wind	Flood Inland	Flood Storm Surge	Tornado/ SLW	All Causes Combined
(A)	(B)	(C)	(D)	(E)	(F)
AAL in layer 100-year to 250-year	3,412	248	161	0	3,821
Standard Deviation in layer 100-year to 250-year	39,649	8,385	2,652	0	43,441
Coefficient of Variation 100-year to 250-year layer	11.6	33.8	16.5	na	11.4

Table 18 adds a layer covering expected losses in the 250-year to the 500-year return periods. Note that as the probability of loss to a layer decreases, the AAL also decreases and the coefficient of variation increases. This makes intuitive sense by recognizing:

- the probability of a loss in the 100- to 250-year layer return period is 1.0 percent;
- the probability of a loss in the 250- to 500-year layer return period is 0.4 percent; and
- layers with less frequent occurrences are less predictable, thus, volatility is higher.

TABLE 18 **Layer Statistics for 100- to 250- and 250- to 500-year PMLs**

	Hurricane Wind	Flood Inland	Flood Storm Surge	Tornado/ SLW	All Causes Combined
(A)	(B)	(C)	(D)	(E)	(F)
AAL in layer 100-year to 250-year	3,412	248	161	0	3,821
Standard deviation in layer 100-year to 250-year	39,649	8,385	2,652	0	43,441
Coefficient of Variation in layer 100-year to 250-year	11.6	33.8	16.5	na	11.4
AAL in layer 250-year to 500-year	1,348	35	64	0	1,448
Standard deviation in layer 250-year to 500-year	23,863	1,808	1,548	0	25,331
Coefficient of Variation in layer 250-year to 500-year	17.7	51.7	24.2	na	17.5

Reinsurance costs are often negotiated and can be influenced by market conditions. More judgment is applied to pricing reinsurance compared to primary coverage. Pricing and availability of coverage is information that is disseminated throughout the market. Catastrophe modeling provides an important source of quantitative information to evaluate risk and objectively evaluate reinsurance pricing. Moreover, catastrophe modeling provides quantitative information to financial markets in developing catastrophe bonds and other risk-linked securities.

Florida Hurricane Catastrophe Fund

Following Hurricane Andrew in 1992, the state of Florida created the Florida Hurricane Catastrophe Fund (FHCF) in a special legislative session to "provide a stable and ongoing source of reimbursement to insurers for a portion of their catastrophic hurricane losses; (to) create additional insurance capacity sufficient to ameliorate the current dangers to the state's economy and to the public health, safety, and welfare." (F.S. 215.555). The Fund operates as an independent state-run reinsurer for primary insurance companies selling residential property insurance in the state. Each company must participate in the Fund, but can select from various participation percentages. The Fund's capacity, retention, and limits are set by statute, and are adjusted annually based on specified Fund and market demographics. Statewide capacity was originally set to $17 billion for a hurricane season, and was later amended to include an additional $17 billion for a subsequent season, based on exposure growth and capacity.

The FHCF is required to use the results of all models found acceptable by the Florida Commission on Hurricane Loss Projection Methodology in determining the premiums charged to participants.

Public Policy and Catastrophe Models

The value of catastrophe models is recognized by public policymakers and those who provide them with analyses. As mentioned above, the Florida Hurricane Catastrophe Fund is required to use FCHLPM's approved models in its determining the premium it charges to participants.

On the federal level, the Congressional Budget Office's September 2017 study "The National Flood Insurance Program: Financial Soundness and Affordability"[6] made use of models in quantifying its analyses and conclusions. The Federal Emergency Management Agency is working with a private catastrophe modeling firm to "leverage a probabilistic modeling approach to assess the flood program's overall risk and potential payouts to property owners. The model will also be used to help the NFIP evaluate actuarially sound rates for its policies and to assess the impacts of major flooding events in real time."

All the use cases cited above, as well as many other applications, can inform public policy issues. Some policy questions that can be addressed include:

1. What is the probability of an event occurring that is too big for an entity to handle?
2. Do the premiums reflect an actuarially sound estimate of the expected value of all future costs associated with an individual risk transfer?
3. Have appropriate rating territories and classifications been identified?
4. Are there mitigation features that would reduce the costs to the entity in an advantageous cost/benefit way?
5. Are there reasonable coverage modifications (such as increasing deductibles) that could be useful?

Improvements in federal, statewide, and regional programs require the cooperation of several stakeholders. Objective quantification of potential losses can facilitate these efforts. Mitigation features, once identified and deemed feasible, can eventually become standards. One such example is the Insurance Services Office's Building Code Effectiveness Grading Schedule (BCEGS®).[7] Building codes and their enforcement can be considered in catastrophe models. For example, it was discovered that a significant amount of the damage from Hurricane Andrew could have been avoided if the building codes in effect had been more rigorously enforced. Hurricane models highlighted the pervasiveness of the issue, demonstrated the cost savings that could be generated, and facilitated decisions to improve building codes.

6 Congressional Budget Office; "The National Flood Insurance Program: Financial Soundness and Affordability"; September 2017.
7 ISO Mitigation; "What Determines a Municipality's Code Effectiveness Classification?"; Undated.

Advantages and Limitations of Historical Data and Catastrophe Models

Limitations of relying on historical data

1. Frequency and severity of catastrophe activity has not been constant over time. Climate conditions and sea surface temperatures, among other things, influence tropical cyclone activities. Although far better understood than in the previous century, there is still much that remains unknown about tropical cyclones. How much reliance is appropriate for data from past cycles and how long do those cycles tend to last? Damaging earthquake activity occurrence data is even sparser. The last major earthquakes in the New Madrid seismic zone happened in 1811 and 1812. Clearly, five to 25 years' experience is not nearly enough to evaluate the expected catastrophe costs.

2. In addition to limitations associated with historical frequency and severity, the attributes of historical events may be quite different from future events. Storm surge heights and the resulting damage from Hurricane Katrina, Hurricane Ike, Superstorm Sandy, and Hurricane Harvey were much greater than what would be expected from a surge estimation strictly tied to a wind event. Because this is a relatively recent recognition, historical records are unlikely to provide helpful experience that accurately separates wind and surge.

3. Geographical patterns and physical characteristics of the historical record do not reflect the full range of possible catastrophe events. Many areas may not have had any historical losses at all, but are clearly at risk. For example, a Texas 150-year experience period does not include a Category 5 hurricane. As a result, the frequency and severity of such an event would not be anticipated in the loss experience. Inland flood has catastrophic event potential across large areas, but there are usually specific places within those areas that experience a loss. Focusing on historical damage would overstate the loss potential in some areas and understate the potential in areas that are in very close proximity and equally likely to experience a loss.

4. Property distributions and characteristics have changed. Population has increased in high-risk areas near the coast, lakes, and rivers. Housing units have grown significantly in high-risk areas during the last few decades. Construction methods and building codes have changed. Modern building codes require wind- and water-resistive design elements that will reduce the likelihood of damage in the catastrophe. Historical

losses based on old exposure distribution can't be used without appropriate actuarial adjustments. Adjustments based on assumptions introduce more uncertainties to the process.

5. Many important property characteristics are not available in historical records. Expected catastrophe loss is highly dependent on a property's specific characteristics. Flood loss, for example, is affected by elevation, proximity to rivers or oceans, whether the building site is on the ground or on stilts, the bathymetry or contour of the ocean floors, the local flood mitigation features, etc. It is likely that two houses next to each other may have very different damage ratios from the same flood event due to their unique characteristics. This type of information may not have been collected in the past, and may not lend itself to reliable reconstruction.

6. Claim payment records may be limited or inaccurate and claim practices may have changed over time. In addition, exposure information related to the claim may not have been kept. Exposure information about properties exposed to loss but not damaged or having only negligible damage (especially below the deductible) may not be available. Understandably, claims adjusters focus on making policyholders whole following an event and may not be as meticulous as they might otherwise be in their documentation.

7. Information related to older events is not always reliable. Extreme events might have damaged or destroyed instruments. Events that occurred where the population was sparse or limited may have only the most general information recorded or may not have been noted at all. The exposure information related to the insured losses may not contain information that allows matching to claim payments, and, as noted above, exposure information for properties that did not suffer damage may not have been kept.

8. For these reasons and others, while historical data does bring valuable insight about catastrophe losses, it is insufficient in many cases to make proper projections for future catastrophe losses. This has led to extensive efforts to develop catastrophe models, which are a better alternative for estimating catastrophe losses.

Advantages of Using Catastrophe Models

Catastrophe models overcome the limitations of the historical records in several ways.

1. Catastrophe models simulate significantly more realistically plausible events than are contained in the historical record. Catastrophe simulation models use a database of scenario events that are designed to be comprehensive and realistic. The frequency of each event is calibrated to reflect the scientific view of the likelihood of that event. For example, if a coastal segment has experienced more Category 3 storms than category 4 or 5 storms, then the event database will take this into account. Category 3 storms would make up a bigger portion of the storms affecting the area in the model analysis. These event parameters are smoothed to minimize the gaps in the historical records. Similar scientific knowledge is incorporated into each of the model modules as appropriate.
2. Catastrophe models allow users to import and analyze the current exposure and settlement terms, therefore avoiding the pitfalls in adjusting historical experience to reflect changes in the number, types, and values of structures exposed to the hazard. The models can also account for changes in building practices, building code, and loss-mitigation features.
3. Catastrophe models are updated regularly and often. This enables catastrophe models to incorporate the most advanced science in meteorology, hydrology, seismology, statistics, and structural engineering into the models. Catastrophe models incorporate the most current information on land use/land cover, surface roughness, soil type, flood defense, flood control measures, ZIP code boundary, etc.
4. Catastrophe models allow the insurance industry to develop forward-looking views. It allows users to analyze "what if" scenarios to assess the impact of certain catastrophe risk management strategies.
5. Catastrophe models encourage sensitivity testing, which leads to more frequent and thorough testing. These analyses can provide valuable information about characteristics to investigate more thoroughly, provide additional viewpoints to consider, and stress-test scenarios.
6. There are several catastrophe models available to the insurance industry. Having several viewpoints can provide additional, valuable information related to risk management.

Limitations of Catastrophe Models

1. There are significant uncertainties around model estimates and large ranges of output values among different models. Many assumptions are involved in creating catastrophe models. A large range of output does not mean that any model is inaccurate or unreliable. The uncertainty is, to a large degree, expected, and its sources understood by actuaries. Uncertainties in alternate methods of estimating catastrophe damage are likely to be even larger and more difficult or impossible to quantify. However, a wide range of model output can cause concerns with consumers, regulators, and executives.
2. Collecting important building characteristics is not an easy task for an insurance company and may require a substantial financial output before any benefit is realized.
3. There may be damage or causes of loss that happen due to or concurrent with a catastrophic event that are not included in model output. These need to be treated separately. This is not usually problematic, but does emphasize the importance of understanding what the model assumptions are.
4. Model changes with software update can cause stability concerns. As science continues to evolve, and more data becomes available, modeling vendors have opportunities to incorporate new sciences and learnings into the models. As a result, the industry may experience large swings in the estimates from year to year. However, these changes are far smaller than what could happen when relying on historical experience.
5. Given the complexity of catastrophe models, using models requires either reliance on a company's reinsurance broker or other third party, or significant investment in training, software, and hardware to develop and maintain internal expertise.
6. While the technical documentation of the models is available to users for their general knowledge, some core assumptions are considered proprietary and are not readily accessible to users. A catastrophe model is developed by a group of scientists (meteorologist, seismologist, hydrologist, statisticians, engineers, actuaries, computer scientist, etc.) with specialized knowledge in different fields. It is not an easy task for model users to develop even a basic understanding of the model, as required by U.S. actuaries' standards of practice.[8]
7. Catastrophe models are tools to help insurers assess and understand catastrophe risks. Like other tools, catastrophe models have limitations. Due to the uncertainties discussed above, it is impossible and unrealistic to expect a catastrophe model to produce perfect answers. However, this is not a reason to discredit a modeling approach, as relying solely on historical records is less reliable.

8 ASOP No. 38, Op. cit.

Summary

Use of computer models to estimate catastrophe losses for the insurance industry has gained momentum and has become a standard risk management practice. Hurricane Andrew in 1992 highlighted the shortcomings of processes used up until that time and how those shortcomings could create problems for the industry. Hurricane and earthquake models were introduced first to the market, followed by severe convective storm, wildfire, flood, terrorism, and pandemics. Several factors contributed to the advancement of the catastrophe models. The primary driver was the realization that the unpredictability of catastrophe events and limitations of traditional actuarial methods that rely on five to 25 years' historical records were not adequate to plan for future extreme events. Combined with the substantial improvement in computing power and sophistication, models became the tool of choice for managing catastrophic risk.

This monograph is offered to provide the reader with an overview of how actuaries use catastrophe model output for various analyses. Examples based on defined exposure input for selected causes of loss provide insight into these applications and show uses of modeled output.

Appendix 1
Hypothetical Policies and Model Settings

Construction of Hypothetical Policies

We distributed 100,000 single-residential policies geographically throughout the state of Florida, representing approximately 1 percent of the market's policy count.[9] The 100,000 policies were assigned to ZIP codes in proportion to the population of that ZIP.[10] Random parcels within the ZIP were assigned to each policy that had been allocated to that ZIP. The building value for each structure is $207,500.[11] Appurtenant structure values were 10 percent of building value ($20,750); Contents coverage value was set to 50 percent of building value ($103,750); and Additional Living Expense was 20 percent of building coverage, or $41,500. Each policy had a 2 percent blanket deductible (2 percent of the sum of all coverages combined, applied against losses from all coverages combined). Note that Florida requires 2 percent of building value be offered, and that choice is virtually universal in the admitted market in that state.

Construction, year of construction, and foundation type were left as default values. No basement or NFIP coverage was assumed to exist.

Model Settings

CoreLogic's RQE (Risk Quantification and Engineering) catastrophe model was used to generate the metrics shown in the tables.

Settings were selected that are, in the authors' experience, typical for model use. The expected losses include potential impacts of demand surge. All residential property coverages were included: Building, Appurtenant Structures, Contents, and Additional Living Expense. Except where otherwise indicated, the expected losses are ground-up, occurrence losses.

9 SNL data
10 IRS data
11 Median value per Zillow.com

Appendix 2
2017 Florida Hurricane Mitigation Measures

INDIVIDUAL MITIGATION MEASURES			PERCENTAGE CHANGES IN DAMAGE* (REFERENCE DAMAGE RATE - MITIGATED DAMAGE RATE) / REFERENCE DAMAGE RATE * 100									
			FRAME STRUCTURE					MASONRY STRUCTURE				
			WINDSPEED (MPH)					WINDSPEED (MPH)				
			60	85	110	135	160	60	85	110	135	160
	REFERENCE STRUCTURE		0	0	0	0	0	0	0	0	0	0
ROOF STRENGTH	BRACED GABLE ENDS		15.1%	14.6%	12.4%	9.9%	4.8%	13.6%	13.4%	11.6%	9.4%	5.9%
	HIP ROOF		19.0%	18.2%	15.5%	12.5%	6.2%	17.3%	16.8%	14.5%	11.9%	7.5%
ROOF COVERING	METAL		-8.7%	-8.6%	-7.3%	-5.7%	-2.7%	-8.1%	-8.3%	-7.1%	-5.6%	-3.4%
	ASTM D7158 Class H Shingles (150 MPH)		1.9%	1.9%	1.6%	1.2%	0.6%	1.7%	1.7%	1.5%	1.2%	0.7%
	MEMBRANE		-5.2%	-5.1%	-4.3%	-3.4%	-1.6%	-5.0%	-5.1%	-4.4%	-3.5%	-2.1%
	NAILING OF DECK	8d	1.9%	1.9%	1.6%	1.2%	0.6%	1.7%	1.7%	1.5%	1.2%	0.7%
ROOF-WALL STRENGTH	CLIPS		17.8%	17.1%	14.6%	11.6%	5.8%	16.2%	15.8%	13.7%	11.1%	7.1%
	STRAPS		17.8%	17.1%	14.6%	11.6%	5.8%	16.2%	15.8%	13.7%	11.1%	7.1%
WALL-FLOOR STRENGTH	TIES OR CLIPS		4.6%	4.6%	3.9%	3.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%
	STRAPS		4.6%	4.6%	3.9%	3.0%	1.4%	0.0%	0.0%	0.0%	0.0%	0.0%
WALL-FOUNDATION STRENGTH	LARGER ANCHORS OR CLOSER SPACING		0.0%	0.0%	0.0%	0.0%	0.0%	-	-	-	-	-
	STRAPS		4.6%	4.6%	3.9%	3.0%	1.4%	-	-	-	-	-
	VERTICAL REINFORCING		-	-	-	-	-	-	-	-	-	-
OPENING PROTECTION	WINDOW SHUTTERS	PLYWOOD	12.1%	12.0%	10.1%	7.9%	3.8%	11.0%	11.0%	9.4%	7.6%	4.7%
		METAL	12.1%	12.0%	10.1%	7.9%	3.8%	11.0%	11.0%	9.4%	7.6%	4.7%
	DOOR AND SKYLIGHT COVERS		21.8%	20.6%	17.7%	14.3%	7.2%	19.9%	19.2%	16.6%	13.6%	8.7%
	WINDOW	IMPACT RATED	10.6%	10.5%	8.9%	7.0%	3.3%	9.7%	9.8%	8.4%	6.7%	4.1%
	ENTRY DOORS	MEETS WINDBORNE DEBRIS REQUIREMENTS	10.6%	10.5%	8.9%	7.0%	3.3%	9.7%	9.8%	8.4%	6.7%	4.1%
	GARAGE DOORS		10.6%	10.5%	8.9%	7.0%	3.3%	9.7%	9.8%	8.4%	6.7%	4.1%
	SLIDING GLASS DOORS		18.8%	18.0%	15.4%	12.3%	6.2%	17.3%	16.8%	14.5%	11.9%	7.5%
	SKYLIGHT	IMPACT RATED	13.8%	13.5%	11.4%	9.0%	4.4%	12.3%	12.2%	10.5%	8.5%	5.3%
MITIGATION MEASURES IN COMBINATION			PERCENTAGE CHANGES IN DAMAGE* (REFERENCE DAMAGE RATE - MITIGATED DAMAGE RATE) / REFERENCE DAMAGE RATE * 100									
			FRAME STRUCTURE					MASONRY STRUCTURE				
			WINDSPEED (MPH)					WINDSPEED (MPH)				
			60	85	110	135	160	60	85	110	135	160
STRUCTURE	MITIGATED STRUCTURE		27.2%	25.6%	22.0%	17.8%	9.1%	25.2%	24.0%	20.8%	17.2%	11.1%

* Note: Larger or closer spaced anchor bolts: not currently distinguished in the model, as other aspects are deemed more important; also difficult to ascertain vertical reinforcing for masonry walls: this feature is accounted for through the selection of the base structure; vertically reinforced masonry walls are considered by the CoreLogic model as Reinforced Masonry (RM).

The input one-minute sustained 10-meter wind speeds were assumed to be over-water and were converted to over-land peak gust wind speeds using the minimum direction-dependent roughness length for the ZIP Code centroid and the model's standard gust factor formulation.

Source: FCHLPM; CoreLogic

Appendix 3
Disclaimers

This paper is not intended to be an interpretation of the actuarial standards of practice and is not meant to be a codification of generally accepted or appropriate actuarial practice. Actuaries are not in any way bound to comply with this paper or to conform their work to the practices described herein.

The use of the CoreLogic RQE model does not imply any recommendation or preference of that model over any other model.

The results shown in this paper have been derived as described. While accurate based on the exposures and assumptions described here, they are not realistic quantifications of expected loss and are not meant to be used for any purpose other than illustration.

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Introduction

The Academy has long been the most reliable and credible source of objective, independent, and nonpartisan information about actuarial matters that can and do affect public policy decisions in the U.S. We have long sought to provide an objective voice about matters related to risks from climate, which is an area that can only benefit from objective and independent actuarial analysis. We are now releasing the Actuaries Climate Risk Index (ACRI) to provide that objective and independent analysis to assist in answering the question: Are the extreme weather conditions that result from a changing climate producing increased property losses?

The findings contained in version 1.0 of the ACRI are the culmination of years of research. We are presenting them now in the spirit of objective, transparent scientific inquiry and statistical rigor. This release is not a political statement. We fully understand and have heard from some who would prefer that actuaries make a political statement. This is not the Academy's mission or undertaking.

This project could not have happened without the tireless and dedicated work of Steve Jackson, Ph.D., the Academy's assistant director for research (public policy), as well as the members of the Climate Index Working Group. Many thanks for all their efforts to bring this project to fruition.

Release of version 1.0 of the ACRI is one that we and we anticipate other stakeholders will continue to build upon with the same objective, transparent inquiry and rigor; such is the nature of scientific investigation.

We welcome feedback and suggestions for enhancements. Please email acri@actuary.org with your thoughts.

Yours sincerely,

D. Joeff Williams	Shawna Ackerman
Academy President	Academy Past President

Executive Summary

In November 2016, the American Academy of Actuaries, the Canadian Institute of Actuaries, the Casualty Actuarial Society, and the Society of Actuaries launched the Actuaries Climate Index (ACI). The ACI provides an objective indicator of the frequency of extreme weather events and the extent of sea level change for 12 regions in the United States and Canada. This index is updated four times a year. Reflecting on the results of the ACI invites us to ask the question: Is there a statistical relationship between the weather components of the Actuaries Climate Index and damages to life and property caused by severe weather? This paper summarizes research to model this relationship. The Actuaries Climate Risk Index (ACRI) was developed from this model. This new index, the ACRI, is intended to measure the change in damages resulting from environmental conditions in excess of those observed in the reference period, as measured by the ACI.

In undertaking this effort, the American Academy of Actuaries is mindful of the results and the messages offered by prior research. First, that losses due to extreme weather events are large and increasing, yet most of the losses are due to increasing wealth and population yielding increased exposure to risk. Second, that estimates of loss due to extreme weather have been, are, and are likely to be very imprecise, yet imprecise results may be useful.

The examination began by looking at the relationship between environmental variables, as captured in the ACI components, and losses captured in publicly available databases that matched the ACI's geographic and time reference periods. For the United States, the SHELDUS[1] database (built largely with data from the National Oceanographic and Atmospheric Administration [NOAA] Storm Database) was identified as the most appropriate set of data. For Canada, the Major Storms database was identified as the best available dataset to use for the analysis. However, due to the limited number of events covered by the Canadian database, it was decided for version 1.0 of the ACRI to restrict attention to the United States and its seven regions. Moreover, the model thus far has only been developed to quantify impacts on property losses, although the same framework is believed likely to perform similarly for deaths and injuries.

1 Spatial Hazard Events and Losses Database for the United States.

To find the best correlation between weather variables and property losses, the impact of inflation, exposure, region, and seasonality have been controlled for. The Academy has have analyzed a dependent variable expressing losses in dollars and have treated each month of each year for each region as a separate observation. To allow for non-linearity in relationships between weather conditions and losses, to allow for interaction among weather conditions, and to mitigate the impact of the highly skewed distribution of losses, a model has been estimated in which both independent and dependent variables are log-transformed. To identify statistically significant parameters, the Academy used backward regression on the dependent variable and the ACI to select the best estimated model in which all parameters were statistically significant at the 90 percent confidence level.

Based on this estimated relationship between the ACI and losses, the ACRI is calculated as the difference in modeled losses due to ACI components being above (or below) their reference period mean values. In order to exclude the impact of changes in exposure on the ACRI, the reference period mean modeled losses are exposure-adjusted. The resulting ACRI totals $24 billion during the post-reference period, 1991–2016, equal to approximately 3.3 percent of the exposure-adjusted losses during that period.

The model has a large amount of uncertainty, because each region-month currently only has 56 data points on which to base the parameters, 30 points during the reference period and 26 points subsequent to the reference period. The Academy has estimated uncertainty in two ways. Based on the intrinsic uncertainty associated with the regression estimates from which the ACRI is built, a 90 percent confidence interval is estimated around the best estimate for total ACRI losses of $16 billion to $36 billion. However, the broader, extrinsic uncertainty associated with only having one "draw" of the weather distributions, both for the reference and the post-reference periods, has been estimated using a stochastic model of synthetic datasets based on randomly selected observations from the original data. With this broader definition of uncertainty, it is estimated that a 90 percent confidence interval for total ACRI losses stands at $2 billion to $45 billion. Of course, even these two measures of uncertainty are somewhat uncertain. There are several ways in which these confidence intervals for both intrinsic and extrinsic uncertainty could have been created, and different methods might produce materially different estimates.

Weaknesses and limitations are outlined throughout this documentation that serve as cautionary notes, pointing to the need to interpret these current results in light of their inherent uncertainty. Chief among these limitations are:

- As noted, while the model has an r-squared of 0.62 on log-transformed values, the r-squared on dollars of modeled and actual losses is only 0.03.
- The model performs most dependably at the national level, less so at the regional level (mean r-squared equals 0.36), and even less well at the region-month level (r-squared equals 0.24).
- The ACI metrics used in the model are averaged over large geographic areas, while the most damaging events are concentrated in much smaller areas.
- The ACI metric for wind, based on average monthly wind speeds in these large geographic areas, is not shown by the model to be a close estimate of large losses, which are driven primarily by windstorms.
- Equation coefficients are quite inconsistent from one month to the next in a given region, which does not provide a logical explanation for the ACRI values.

These weakness and limitations also spur the Academy to proceed to version 2.0 of both the ACI and the ACRI to seek better data and develop more effective metrics and more robust analysis. Others are encouraged to build on this work by conducting research using weather metrics and proprietary insurance company loss data, which would be available in precise geographic detail.

Actuaries Climate Risk Index: Preliminary Findings

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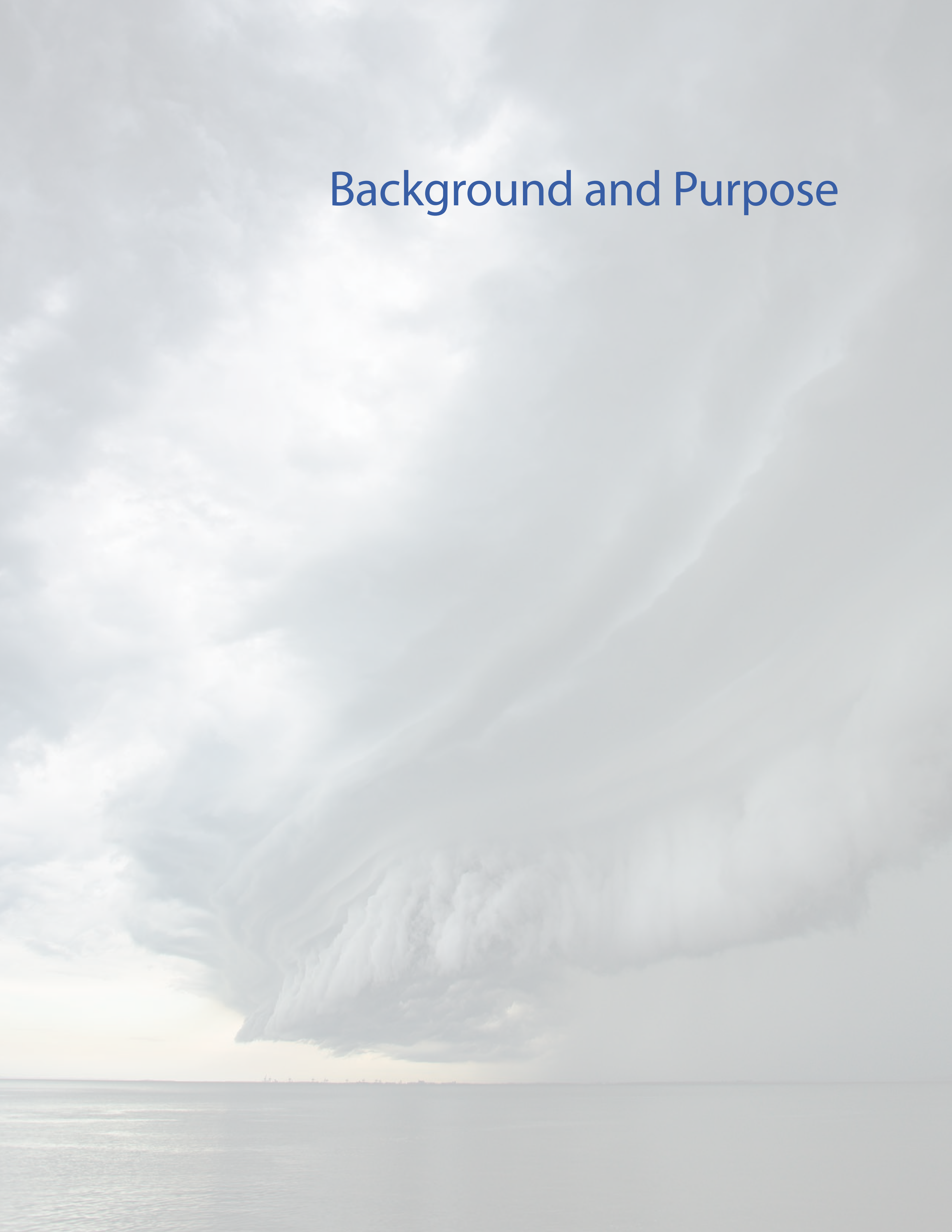
Background and Purpose



Background

In November 2016, the American Academy of Actuaries, the Canadian Institute of Actuaries, the Casualty Actuarial Society, and the Society of Actuaries ("the ACI Actuarial Associations") introduced the Actuaries Climate Index (ACI). The ACI provides an objective indicator of the frequency of extreme weather events and the extent of sea level change. The six components of the ACI are drought, precipitation, high temperature, low temperature, sea level, and high winds. The data for each category are standardized in respect to a reference period, 1961–1990, and those standardized values are combined to produce the ACI. On the ACI website (actuariesclimateindex.org), both the components' index values and the composite index value (an amalgam of the components) are provided for seven regions within the U.S. and five regions within Canada, as well as for both countries as a whole. The website also documents the methodology and data used to develop the indexes. The data is updated quarterly and presented both monthly and by meteorological season.

The ACI documents the variation in a set of extreme weather and hydrologic measures across time and place. Having the ACI invites us to ask the question: How much damage is done to life and property when the distribution of environmental events differs from those observed during a reference period, 1961–1990? The Actuaries Climate Risk Index (ACRI) seeks to answer that question. Based on identified relationships between the atmospheric and hydrologic conditions assessed in the ACI and data on harm to people and damages to properties due to climate-related events, the ACRI is intended to estimate the impacts resulting from environmental conditions in excess of (or below) the average in the reference period. Just as the ACI reports values monthly and by season for each of seven regions in the U.S. and five regions in Canada, the ACRI aims to also reflect the damage done monthly and by seasons in the same regions.

In November 2015, the ACI Actuarial Associations received a report commissioned from Solterra Solutions describing a procedure for creating the ACRI. Data from the ACI was combined with data from the SHELDUS database on losses from storm events in the U.S., and from the Major Storms database in Canada, to assess relationships between environmental conditions and losses. For each region, Solterra looked for the best fit between an element of the ACI (e.g., wind) and losses from associated events (e.g., floods). Based on the set of best-fitting regressions, Solterra created an index for the ACRI that allowed information from the different regions, based on different environmental conditions, to be combined. While never endorsed by the ACI Actuarial Associations, nor launched on the ACI website, this method was the basis for numerous presentations in recent years. This index will be referred to as ACRI version 0.1.

After identifying weaknesses in version 0.1 and receiving peer review inputs from the Institute and Faculty of Actuaries (U.K.), the Academy decided to create version 1.0, responding to the five main limitations in the regressions that serve as the ACRI's foundation version 0.1:

1. Introduce control for the risk exposure and other intervening factors in the modeling of the relationship between weather and hydrologic conditions and losses;
2. Find statistically significant relationships that accounted for a reasonable share of the variation observed;
3. Move from a 1-10 scale to a dollar scale;
4. Look at regressions that included multiple environmental variables simultaneously rather than one variable at a time; and
5. Improve the analysis of heat-related losses.

ACRI version 1.0 uses the same data sources that Solterra used for ACRI version 0.1, which are still considered the best readily available databases.

As the Intergovernmental Panel on Climate Change (IPCC) noted in its 5th Assessment in 2014, "Studies analyzing changes in climate variables and insured losses in parallel are still rare."[2] But, as the Government Accountability Office (GAO) concluded in its 2017 analysis of climate change and economic losses, "Methods used to estimate the potential economic effects of climate change in the United States—using linked climate science and economics models—are based on developing research. The methods and the studies that use them produce imprecise results because of modeling and other limitations but can convey insight into potential climate damages across sectors in the United States."[3]

This paper will discuss the most closely related comparable efforts, but, attempting to create a sustainable index that can be easily updated quarterly and that is reflecting damages from extreme or moderately extreme environmental conditions at the regional level within the U.S. and Canada has not been done before. The Academy intended to build ACRI 1.0 using the best practices developed for similar efforts. This version of the ACRI is expected to be updated to version 2.0 as soon as the Academy can explore additional data sources, environmental metrics, and methods of analysis.

The following sections describe in detail the methodology, choices made, and data used to create ACRI version 1.0.

2 IPCC, 2014: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

3 GAO 17-720, "GAO Highlights," 2017.

Normally, building indexes involves four tasks:

1. Deciding what modeling approach to use;
2. Deciding what data to use;
3. Modeling the relationship between climate events and damage in a robust manner; and
4. Constructing the index (or versions of the index).

However, given the novelty of this effort and the limited relationships found, two more tasks are added as follows:

5. Subjecting results on the relationship between environmental conditions and damages to deeper scrutiny;
6. Examining other models of the relationship between weather conditions and damages.

Purpose

The Actuaries Climate Risk Index (ACRI) is intended to provide an actuarial perspective on impact on property and human death/injury of extreme or moderately extreme environmental conditions.

Using measures of four categories of weather conditions, the ACRI is built upon a modeling of the relationship between those changing climate conditions and the damage done by climatological events. Controlling for risk exposure and regional and seasonal factors, the ACRI produces a measure of the effect on economic losses of deviations from benchmark climate conditions in each region, in each season.

A robust version of the ACRI might be useful to different audiences in different ways:

- For the **general public**, the ACRI can provide a means to understand to what extent extreme climate events and their increasing frequency have been correlated with economic losses, allowing for a greater understanding of the impact of climate on costs involved.
- For **public policymakers**, the ACRI can provide a measure that may be useful in leveraging the costs of prevention and mitigation policies.
- For **public and private decision-makers**, it can provide a base for planning the capacity to assume larger risks associated with changes in environmental conditions.
- For **actuaries**, the ACRI can provide insight into the risks potentially associated with extreme or moderately extreme climate events. Information on potential losses due to the increasing frequency or severity of extreme events helps with setting parameters for those losses in stochastic models used to project possible losses in the future. New considerations for increasing contingency margins could also result. However, by nature an index such as the ACRI provides information at a macro level but not at the level of granularity that is required for reserving or pricing. For these purposes, actuaries would need to adapt the ACRI methodology by incorporating more specific information about environmental conditions and insurance claims related to a specific purpose.

While ACRI 1.0 provides estimates of the impact of extreme environmental conditions, and assessments of the uncertainty there of, it is not the robust version that is sought.

The conclusions of prior research have been considered in presenting the ACRI 1.0 and the results of this analysis:

- Losses due to extreme weather events are large and increasing; a recent study by the Universal Ecological Fund (FEU) estimated that between 2007 and 2017, annual losses from extreme weather events in the United States averaged $42 billion.[4]
- Most of the losses are due to increasing wealth and population yielding increased exposure to risk; as the IPCC 2014 Report concludes: "Economic costs of extreme weather events have increased over the period 1960–2000. … However, the greatest contributor to increased cost is rising exposure associated with population growth and growing value of assets."[5] One of the few studies that has sought to quantify the relative impacts of climate events and exposure on observed, as opposed to future, losses for the United States as a whole over a long period of time concluded: "[T]he increase in losses due to socio-economic changes was approximately three times higher than that due to climate-induced changes."[6]
- Estimates of loss due to extreme weather have been, are, and are likely to be very imprecise; as the GAO concluded from its review of prior research seeking to assess the economic impacts of climate change and discussions with experts, "the methods produce imprecise results."[7] As elaborated by Schmidt et al., "[I]t is generally difficult to obtain valid quantitative findings about the role of socio-economics and climate change in loss increases. This is because of criteria such as the stochastic nature of weather extremes, a shortage of quality data, and the role of various other potential factors that act in parallel and interact."[8]
- Imprecise results may be useful. As the GAO noted, imprecise results "can convey useful insight into broad themes about potential climate damages across sectors in the United States. For example, according to several experts interviewed, these methods can provide valuable research information about the potential magnitude of economic effects and potential areas of greatest concern, including where assets may be at greatest risk. Some other experts told us that using the methods can help identify areas where additional research would be most useful."[9]

4 Sir Robert Watson, Dr. James J. McCarthy and Liliana Hisas, "The Economic Case for Climate Action in the United States," Universal Ecological Fund (FEU), September 2017.
5 IPCC, 2014: *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
6 Schmidt, Silvio; Kemfert, Claudia; Höppe, Peter (2008): "The impact of socio-economics and climate change on tropical cyclone losses in the USA, DIW Discussion Papers, No. 824, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin.
7 U.S. GAO, "Climate Change: Information on Potential Economic Effects Could Help Guide Federal Efforts to Reduce Fiscal Exposure," September 2017.
8 Schmidt, op. cit.
9 U.S. GAO, "Climate Change: Information on Potential Economic Effects Could Help Guide Federal Efforts to Reduce Fiscal Exposure," September 2017.

Overview of Models of Weather-Related Risks to Property and Lives

There are at least four types of models that attempt to relate extreme climate events to socioeconomic harm. First are the catastrophe models now routinely used by insurers to estimate the property insured losses that are likely to occur as a result of natural disasters such as earthquake, flood, convection and snowstorms, etc. Second are the integrated models that underline IPCC's periodic assessments. Third are the social-cost-of-carbon models that were used by the Interagency Working Group on Social Cost of Greenhouse Gases (United States Government) to try, among other things, to provide metrics for evaluating environmental regulations, based on the economic damage done by increasing levels of greenhouse gases. Fourth are the models used to generate the Disaster Risk Index for the United Nations Development Programme (UNDP), which aims to assess the number of deaths resulting from natural catastrophes, taking into account the varying levels of socioeconomic development in different countries.

Catastrophe models proceed in three stages to estimate the likely costs of natural disasters.[10] In the first stage, the probabilities of certain events occurring at certain magnitudes and/or frequencies are calculated. As a second step, the physical damage that would occur in a particular region if it were subjected to a certain magnitude of events is estimated, given the characteristics of both the built and the natural environment. Finally, in the third stage, the insured losses that would occur given specifics insurance protection and conditions are estimated. This type of model requires detailed data not available for the ACRI intended purposes.

The integrated models used by the IPCC rely on underlying research that establishes likely consequences of particular climate events on particular outcomes.[11] The models then aim to integrate the consequences of these various events, taking into account the interactions among the climatological events and, in principle, among the effects—interactions which might either increase or decrease the magnitude of impacts. In the context of ACRI, the limitation of these models is that they depend on establishing a very large number of relationships between discrete past and future environmental events and discrete past and future harms in a large number of locations. These integrated models also depend on establishing or assuming the interactions among causes and effects and again, in ways that might differ in different locations. As the ACRI is intended to be an objective, retrospective measure of the relationship between environmental effects and economic losses, this type of model was put aside.

10 See AIR description or RMS description of Catastrophe Modeling.
11 See Intergovernmental Panel on Climate Change, *Fifth Assessment Report*, 2014, Chapter 10, page 681.

Social-cost-of-carbon models estimate the harm done by the increases in surface temperature driven by the increases in the level of greenhouse gases over a reference period point in time.[12] These models are built on substantial underlying research on the impact of temperature on various elements of the ecosystem and the socioeconomic environment. They also include varying degrees of interaction effects among the varying ecological and socioeconomic elements. Given that these models are forward-focused and depend on strong underlying research, they do not fit the purposes for which the ACRI is being developed.

Finally, models aiming to broadly assess the impact of extreme events for large numbers of countries are exemplified by the Disaster Risk Index developed for the UNDP. The general objective here was to develop a method of estimating how many deaths would occur in each country based on climate-related natural disasters given the socioeconomic status of the country. Compared to the previous three classes of models, this is a simpler modeling effort aiming to broadly illustrate the impact of varying socioeconomic conditions on the relationship between natural disasters and lives lost. While the ACRI aims to assess damage to property as well as number of deaths for two countries, the Academy concluded that the general objective of the Disaster Risk Index is similar to that of the ACRI.

Leveraging these developed models while keeping in mind the specific objectives underlying the ACRI model, the relationship, if any, between environmental conditions and economic losses or deaths from environmental events is defined in the following general functional form:

Equation (A) Loss = f(Risk Exposure, Environmental conditions, Geography, Season)

12 See the 2016 update to the Technical Documentation of the SOC models.

Data Used in Constructing the ACRI

The model requires data on damages due to environmental events given risk exposure, geographic variability, and seasonality. Those factors—risk exposure, geography, and season—set the value and resilience of the built environment, and therefore might shape the relationship between environmental conditions and losses observed.

Economic Damages: While insurers have accurate data on covered losses (both in property and life insurance) generated by insured climate events, their data do not include losses that were not covered, and, as a result, provide an incomplete picture of the damage done. Further, the data is generally proprietary.

For the United States, the NOAA Storm Events Database documents:

> "The occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce; Rare, unusual, weather phenomena that generate media attention, such as snow flurries in South Florida or the San Diego coastal area; and Other significant meteorological events, such as record maximum or minimum temperatures or precipitation that occur in connection with another event."[13]

The SHELDUS database[14] builds upon the foundations of the NOAA Storm Events data and, especially for the years prior to 1996, supplements that data with occasional additional reports.

While the NOAA database contains information on more than 50 types of incidents, the SHELDUS database reduces that to 18 categories, of which 17 are relied on for the ACRI: Avalanche, Coastal, Drought, Flooding, Fog, Hail, Heat, Hurricane/Tropical Storm, Landslide/avalanche, Lightning, Severe Storm/Thunder Storm, Tornado, Tsunami, Volcano,[15] Wildfire, Wind, and Winter Weather. For each event, in addition to the date and location of the event, the database reports estimates for property damage, crop damage, lives lost, and injuries. Because these categories do not match exactly the ACI weather event types, the Academy decided to examine the relationship between all ACI components and all losses (from these specified sources) in modeling. As a result, the measure of losses for a particular region in a particular month is the sum of all damage done from all reported events, in constant 2016 dollars.[16]

13 NOAA Storm Events Database.
14 SHELDUS Database.
15 Losses from volcano eruptions will be excluded in loss totals in the next iteration of this analysis. Overall, volcanos accounted for less than 1 percent of the reported losses over the time period, 1961–2016. Geophysical losses were excluded.
16 Controlling for inflation was approximated by using constant 2016 U.S. dollars. This year was selected because it was the most recent year for which ACI and loss data existed when modeling began.

The SHELDUS database has advantages as well as disadvantages. The advantages include: data coverage from the present back to before 1961, the starting point for the ACI reference period;[17] coverage of losses from a wide range of weather event types; losses are designated at the county level; losses include property losses, crop losses, lives lost, and injuries sustained. Disadvantages include: concerns about the completeness of reporting of events, especially prior to 1996; and concerns about the reported losses. Property losses for hurricanes and wildfires are less than those reported by the Insurance Industry Institute.[18] Nonetheless, of the publicly available databases, the SHELDUS database (or the NOAA Major Storms Database on which SHELDUS is largely based) is the best for the ACRI's purposes.

For Canada, the best source of comparable data is the Canadian Disaster Database (CDD), which

> "contains detailed disaster information on more than 1000 natural, technological and conflict events (excluding war) that have happened since 1900 at home or abroad and that have directly affected Canadians. The CDD tracks 'significant disaster events' which … meet one or more of the following criteria: 10 or more people killed; 100 or more people affected/injured/infected/evacuated or homeless; an appeal for national/international assistance; historical significance; or significant damage/interruption of normal processes such that the community affected cannot recover on its own."[19]

While this database contains information on almost 60 categories of disasters, 13 of them are "Meteorological/Hydrological." Of those, 10 of which were selected that are most likely to result from the categories of climate events incorporated into the ACI: Cold Event, Drought, Flood, Heat Event, Hurricane/Typhoon/Tropical Storm, Storm Surge, Storms and Severe Thunderstorms, Tornado, Wildfire, and Winter Storm. As with the data for the U.S., the damage done by all of these events have been added together into a single measure for a given region in a given month. Unfortunately, during the entire time period covered by the analysis, 1961–2016, there were only 275 region-months in Canada (of 3,360 region-months) with nonzero losses.[20] This small quantity of data made it impossible to estimate credible relationships for the Canadian regions using the same model as in the U.S. Because of this data constraint, ACRI 1.0 is focused solely on the United States.

17 Availability of data was a major factor in setting 1961 as the beginning of the reference period for the ACI.
18 Calculations by author from SHELDUS data compared, for example, to losses cited in "Facts + Statistics: Wildfires," Insurance Industry Institute (accessed Dec. 19, 2019), and "Facts + Statistics: Hurricanes," Insurance Industry Institute (accessed Dec. 19, 2019). More generally, issues with the reliability of SHELDUS data (compared to that of other databases) is well covered in: "When Do Losses Count? Six Fallacies of Natural Hazards Loss Data," Melanie Gall, Kevin A. Borden, and Susan L. Cutter, *Bulletin of the American Meteorological Society*, June 2009.
19 Canadian Disaster Database.
20 The limited number of reported losses in Canada is due to the definition of "disasters," compared to the tracking of storms and weather events in the US data. In contrast to Canada, fewer than 8 percent of region-months in the U.S. had zero losses; more than 92 percent had nonzero losses.

Risk Exposure: Adapting a well-established method proposed by Collins and Lowe,[21] the value of property at risk of damage in each region in the U.S. in each month has been approximated. On the assumption that residential property value is correlated with total property value, the ACRI uses median house prices multiplied by the number of housing units, which is available from the Census Bureau on an annual basis at the state level. That data has been aggregated to the region level, as defined for the ACI, and interpolated to obtain values for each month. Exposures are then expressed in constant 2016 U.S. dollars.[22]

Environmental Conditions: While constructing the ACI, the ACI Actuarial Associations evaluated many sources of environmental data and many ways to construct indicators of extreme weather events.[23] In that process, they settled on indicators for six categories of weather and hydrologic events: Drought, Precipitation, High Temperature, Low Temperature, Sea Level, and Wind. To combine information about these disparate categories into a single index (the ACI), the ACI Actuarial Associations decided to standardize the individual measures by relating the raw measure to the mean and standard deviation of that measure for a particular region and a particular month during a reference period, from 1961–1990.

Because the manner in which ACI components capture weather and hydrologic "extremes" is highly relevant to the way in which the meaning of the ACRI is interpreted, it is important to detailed here how they were constructed. Consider T90, the indication of temperatures above the 90th percentile, keeping in mind that all components were constructed the same way.

T90 is a temperature metric included in the GHNCNDEX dataset24 and is equal to the percentage of days in a month for which the temperature of the day falls above the 90th percentile of the distribution of daily high temperatures during the reference period. It is tabulated for each month and for each region over the 1961–1990 time period. A separate temperature distribution is used for each of the 12 calendar months and for each geographic location.

21 Douglas Collins and Stephen Lowe, Collins (2001). "A macro validation dataset for U.S. hurricane models." Casualty Actuarial Society, *Winter Forum*, pp. 217–52.

22 This was one of eight measures of exposure that was tested, and which improved the correlation of estimates most. The other seven were Population; Housing Units; Total Income, computed by multiplying each county's per capita income by its population, and then summing across all counties in an ACI region; Net Worth, computed from national net worth by assuming that wealth is proportional to the population in each region; Net Worth, computed from national net worth by assuming that wealth is proportional to the number of housing units in a region; Fixed Assets and Consumer Durable Goods, computed from national data by assuming proportionality with number of housing units in a region; Value of Housing Stock, equal to Median house price * number of housing units, using national-level house price data; Value of Housing Stock, equal to Median house price * number of housing units, using state-level house price data.

23 See the *Actuaries Climate Index Development and Design* for details on data sources and measurement techniques.

24 Global Historical Climatology Network (GHCN) Daily, from the NOAA Satellite and Information Service, is an integrated database of daily climate summaries from land surface stations across the globe. The grids each cover a surface area of 2.5 degrees longitude by 2.5 degrees latitude. GHCNDEX is a dataset based on GHCN Daily. It provides gridded, station-based indices of temperature- and precipitation-related climate extremes and was developed by the Climate Change Research Centre and the Australian Research Council's Centre of Excellence for Climate System Science. (Donat, M.G., L.V. Alexander, H. Yang, I. Durre, R. Vose, J. Caesar, "Global Land-Based Datasets for Monitoring Climatic Extremes," *Bulletin of the American Meteorological Society*, July 2013.)

The GHCNDEX data is geographically "gridded." The grid consists of pairs of latitude and longitude points with 2.5 degrees of spacing between them. Each of the ACI's geographic regions contains numerous GHCNDEX's grid points. The T90 data for these grid points is averaged across each ACI's geographic region separately for each of the 12 calendar months, thus producing 12 time series for each region. Each of these monthly time series is then standardized by region by (i) subtracting the region's mean value of T90 computed across the 1961–1990 reference period, and (ii) by dividing the result by the region standard deviation of T90 computed across the reference period. A positive standardized value indicates that a particular T90 value is above the reference period mean, while a negative value indicates that it is below the reference period mean.

If the reference period means of the ACI components represent the cutoff between ordinary and extreme in weather conditions, that would allow us to interpret without qualification positive values of the ACI as extreme and the impact of those positive values as the impact of extreme weather conditions. Unfortunately, it is not quite that simple. If a month has 30 days, then, on average, 3 of those days should exceed the 90th percentile temperature during the reference period. But, that means that some months within a time series will have 0, 1, or 2 days and others will have 4, 5, 6 or more days exceeding the 90th percentile temperature. If the reference period percentage of days above the 90th percentile is defined as the average of all months including those with fewer and those with more than the average, the reference period will capture extreme conditions in certain ways, but not in others. In other words, T90 captures the number of days which exceed the 90th percentile of the temperature distribution, thus providing an initial basis for measuring extreme conditions. But, when results are averaged across all months, both extreme months and non-extreme or ordinary months are included—thus moderately extreme weather conditions are being measured rather than extreme weather conditions. In this paper, references to "extreme" or "unusual" weather conditions indicate these "moderately extreme" conditions which the ACI currently captures.

While different data or different measures of climate events for the ACRI could have been sought, it seemed closest to the intent of the ACRI to rely as much as possible on the same data and the same measures as were (and are) created for the ACI. While models were tested on standardized data and other data sources were explored, the results obtained were not as strong as those obtained using the unstandardized measures of extreme or moderately extreme climate events underlying ACI and were sufficient for ACRI version 1.0. It should be noted that this version of the ACRI does exclude two of the six ACI-measured conditions: Sea Level and Continuous Dry Days (Drought). Sea Level was excluded because it was not measured for one of the U.S. regions; only those measures which existed for all regions were included. Moreover, preliminary analyses did not indicate very much explanatory power was lost by the exclusion of Sea Level.[25] Continuous Dry Days was excluded because it is the only element in the ACI that comes from annual data and is then interpolated to obtain monthly values. Perhaps due to the relative infrequency of the data, this variable also proved, in preliminary analyses, to be without significant explanatory power.

Geography: Because the relationship between extreme weather events and property losses varies by geographic region, the ACRI controls for geographic variability by estimating the parameters for each region separately.

Seasonality: Explicitly represented in the ACRI model Equation (A), seasonal effects—where, for example, high temperatures are more likely to cause damage during summer months than during winter months—is implicit in the definition of hazards introduced by Peduzzi in the Disaster Risk Index modeling.[26] Rather than combining the measures for losses, exposure, geography, and seasonality into a single hazard measure, months of the year are used as a way to control for the seasonal variation in damage resulting from environmental conditions. The ACRI controls for exposure, geography, and seasonality by estimating parameters separately for each region-month combination, while including exposure as an independent variable in the model.[27]

25 Sea level was primarily removed because of its absence from one of the ACI regions. If it can be incorporated into future versions of the ACRI, sea level may well have significant impacts.
26 P. Peduzzi, H. Dao, C. Herold, and F. Mouton, "Assessing global exposure and vulnerability towards natural hazards: the Disaster Risk Index," *Natural Hazards and Earth System Sciences*, (2009) 9, 1149–1159.
27 For some univariate and bivariate views of the data elements, see Appendix 1.

Modeling the Data

To assess the relationship between weather and losses described in Equation (A) above, the ACRI relies on the formulation of Peduzzi,[28] shown in Equation B:

(B) $\text{Loss} = I * \text{Exposure}^{e} * \text{Precipitation}^{p} * \text{Low Temperature}^{l} * \text{High Temperature}^{h} * \text{Wind}^{w}$

Where:

Loss: Property losses in dollars for a particular region in a particular month;

I: Intercept which scales losses to account for factors other than those included in the model;

Exposure: an estimate of the property value at risk in a given region in a given month;

Precipitation (Rx5Day): the maximum 5-day precipitation in the month;

Low Temperatures (T10): the change in frequency of colder temperatures below the 10th percentile, relative to the reference period of 1961 to 1990;

High Temperatures (T90): the change in frequency of warmer temperatures above the 90th percentile, relative to the reference period of 1961 to 1990;

Wind: Daily average wind speed measurements are converted to wind power, which is proportional to the cube of the wind speed. Wind power is used because impacts from high winds (i.e., damages) have been shown to be more closely related to the cube of wind speed. The procedure used for temperatures is followed, by finding the 90th percentile of wind power for each month or season and subtracting the 90th percentile of wind power for that month over the reference period.

$^{e,\, p,\, l,\, h,\, w}$: If statistically significant, these are the exponents corresponding to the independent variables and reflect the sensitivity of loss to changes in these variables.

Taking the natural log of both sides of equation (B) does not change the equality and produces an equation estimable by linear regression, as shown in equation (C):

28 P. Peduzzi, op cit.

$$\text{(C)} \quad Ln(Loss) = ln(I) + e*ln(Exposure) + p*ln(Precipitation) + l*ln(Low\ Temperatures) + h*ln(High\ Temperatures) + w*ln(Wind).$$

The log transformation of the dependent variable, Loss, is useful, given the distribution of Losses. Examination of that distribution revealed a significantly positively skewed distribution, as seen in Table 1 below.[29] To reduce the skew while preserving as much as possible of the remaining characteristics of the distribution, the log transformation is a common procedure. The resulting distribution, also shown in Table 1, is materially less skewed.

Table 1: Distributions of Monthly Losses, Original and Log-Transformed

	Loss ($)	Ln(Loss) ($)
Min	0	0
Median	5,479,140	16
Mean	139,947,401	19
95th	355,898,211	20
99th	2,173,762,739	21
Max	92,905,914,368	25
Skewness	42.80	-1.66
Coefficient of Variation	11.86	0.35

The parameters of equation (C) for each region-month have been estimated over the time period 1961–2016, using a pooled cross-sectional time series analysis. In this form of estimation, an assumption was made that excluded factors have a common distribution of impacts in all region-months. This effect is captured by a shared error term and by a general intercept for the equation as a whole. But, the Academy further assumes that all of the included variables—both weather-related and exposure—have impacts specific to the particular region-month. Dummy variables were used for both intercepts and slopes to pool the region-months into a single equation and have used backwards regression (with a 90 percent confidence level) to identify statistically significant parameters. The model estimated, with its dummy variables for each region, is as follows:

29 For more detailed analysis of the Loss variable, see Appendix 1.

(D) $Ln(Loss) = Dum_{11}*ln(I_{11}) + \ldots + Dum_{712}*ln_{(I712)} +$

$Dum_{11}*e_{11}*ln(Exposure) + \ldots + Dum\ *e_{712}*ln(Exposure) +$

$Dum_{11}*p_{11}*ln(Precipitation) + \ldots + Dum_{712}*p_{712}*ln(Precipitation) +$

$Dum_{11}*l_{11}*ln(Low\ Temperatures) + \ldots + Dum_{712}*l_{712}*ln(Low\ Temperatures) +$

$Dum_{11}*h_{11}*ln(High\ Temperatures) + \ldots + Dum_{712}*h^{712}*ln(High\ Temperatures) +$

$Dum_{11}*w_{11}*ln(Wind) + \ldots + Dum_{712}*_{w712}*ln(Wind).$

Where:

$I_{11} \ldots I_{712}$: Intercept for region 1, month 1 … region 7, month 12 which scales losses to account for factors other than those included in the model;

e_{11} **…** e_{712}**:** If statistically significant, these are the estimated exponents for region 1, month 1 … region 7, month 12 for exposure, and similarly for the four weather components.

The pooled, cross-sectional model produced an r-squared of 0.63, an adjusted r-squared of 0.62, and a Durbin-Watson statistic of 1.76.[30] However, a measure of heteroskedasticity proposed by MacKinnon and White indicated rejection of the null hypothesis of homoskedasticity at the 99.99 percent confidence level.[31] As a result, the equation was re-estimated with a consistent, adjusted covariance matrix, as suggested by MacKinnon and White. The results reported are those derived from these corrected estimates.

The corrected, pooled, cross-sectional model produced an r-squared of 0.62 and an adjusted r-squared of 0.61. When the parameters estimated from the pooled data are applied to the data by region, the mean r-squared for the seven regions is 0.36. In other words, about 60 percent of the explained variation in losses occurs within regions while the other 40 percent of the variation is explained by differences across regions. When those same parameters are applied to the data by region-month, with 56 observations per sub-sample (one for each year, 1961–2016), the mean r-squared is 0.24. These results, at different levels of observation, suggest the model is strong at the national level, a little weaker at the regional level, and weaker still at the region-month level.

30 The Durbin-Watson statistic indicates a likelihood of positive serial correlation (probability of rejecting the null hypothesis = 0.0001). With a first order autocorrelation of 0.12, the Academy elected to use the Cochrane-Orcutt procedure to correct for this autocorrelation. The modeled values from the corrected regression produce an r-squared of 0.99 when regressed against the modeled values from the original estimation, a result that suggests that serial correlation is not a material issue. In addition to the Durbin-Watson test and evidence of heteroskedasticity discussed in the text immediately following this note, results were examined as closely as possible for other violations of assumptions as suggested by Nau's Regression Diagnostics. Not surprisingly, there are some observations exercising undue influence. Otherwise, the results are well-behaved according to Nau's recommended tests.

31 James G MacKinnon and Halbert White, "Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties" *Journal of Econometrics*, Volume 29, Issue 3, September 1985, Pages 305-325 (https://doi.org/10.1016/0304-4076(85)90158-7).

A detailed summary of the methods used to estimate Equation D, as well as the methods used to calculate the ACRI and to assess its uncertainty, are presented in Appendix 2.

The parameter results are presented in Appendix 3 and summarized in Table 2. There are several noteworthy features of these parameter results. For the four climate conditions, there are 336 possible slope estimates (four climate conditions* seven regions * 12 months); of those, 25 percent are statistically significant. For the four climate conditions, the respective percentage of region-months which are statistically significant are: 54% (Rx5Day), 12% (T10), 19% (T90), and 15% (Wind).[32] For those region-months with statistically significant slopes, the average parameters, respectively, for the four weather conditions are 4.13 (Rx5Day), 1.12 (T10), 1.11 (T90), and 2.80 (Wind). Finally, across all region-months, whether estimated parameters are statistically significant or equal to zero, the average parameters for the four weather conditions are 2.21 (Rx5Day), 0.13 (T10), 0.21 (T90), and 0.43 (wind). In three different ways, among the weather elements. Precipitation (Rx5Day) is the most important factor driving results, with Wind also important.

Table 2: Summary of Parameter Estimates Significant at the 90% Confidence Level
(based on estimates for 84 region-months)

	Statistically Significant	Average Value for Region-Months With Statistically Significant Values	Average Value for All
Exposure	70%	1.84	1.29
Rx5Day	54%	4.13	2.21
T10	12%	1.12	0.13
T90	19%	1.11	0.21
Wind	15%	2.80	0.43

It is worth noting that with an r-squared of 0.62, there is still significant unexplained variation. It is also worth noting that the included variables might also be capturing effects of excluded variables that are correlated with included variables. In particular, note that the parameter estimates for exposure (displayed in Appendix 3) could reflect non-exposure-related issues that, like exposure, change across time. For example, consider the fact that the completeness of the data has increased across time. This measurement problem could boost the exposure exponent, even if the problem is unrelated to exposure.

32 For comparison, exposure is significant in 70 percent of the region months.

Constructing the ACRI

The ACRI intends to describe the losses that resulted from unusual levels of precipitation, temperature, and wind compared to the reference period, 1961–1990. In other words, if one asks how much loss (in 2016 dollars) occurred in a particular region in a particular month in a particular year between 1961 and 2016, the ACRI can answer that by looking directly at the data on losses from NOAA. If an observer then wants to ask how much of that loss (again in 2016 dollars) occurred as a result of unusual environmental conditions, estimates for Equation (D) provide an answer to that question.

Ideally, the ACRI would satisfy the following criteria in its construction:

- the sum of ACRI for each region-month during reference period equals zero. In the same way that the reference period creates a baseline for the evaluation of changes in weather in the ACI, the reference period ought to create a baseline for the losses associated with weather conditions;
- the ACRI for each region-month for which ACI elements are statistically insignificant equals zero. If weather is not statistically significant, then no losses should be attributable to weather in the ACRI;
- the partial correlation of ACRI and Exposure for each region-month equals zero (i.e., controlling for ACI). ACRI should not reflect changes in exposure, only changes in weather;
- the ACRI should be expressed in dollars;
- finally, there should be no artefactual bias either upward or downward in the estimated ACRI.

For each region-month-year, the parameter estimates produce a modeled value of losses. To produce a value for the ACRI, from the modeled loss is subtracted that loss which would have occurred had environmental conditions not been unusual. There are two ways in which the losses associated with "usual" conditions might be estimated. First, using the parameter estimates from Equation (C), for each region-month in each year the modeled losses can be calculated if the value of each weather condition equaled its reference period average. To calculate the ACRI for a particular region-month-year, simply subtract the modeled losses under reference period mean weather conditions from the modeled losses with observed weather conditions. These values are then aggregated by month, season, or year, to produce ACRI estimates of losses due to unusual environmental conditions.

Unfortunately, the non-linearity of the estimating equation builds an upward artefactual bias into this estimating method. With exponents greater than 1 (which is generally the case in the estimates), a weather condition 10 percent above average will produce more than a 10 percent increase in losses, while a weather condition 10 percent below average will produce less than a 10 percent decrease in losses. In this way, average weather conditions in two months (one above by 10 percent and one below by 10 percent) will produce more losses than average weather conditions in each of the two months would.

A second method avoids this bias due to non-linearity. In this method, the average losses modeled during the reference period, 1961–1990, are calculated for a particular region-month.[33] These losses represent the losses that are estimated by the ACRI model with the distribution of weather conditions which were observed in a region-month during the reference period. That average reference period loss is then taken as the estimate of the losses expected in a region-month experiencing the "usual" weather of the reference period. The ACRI is then calculated by subtracting from the modeled losses for a region-month in a given year the reference period average modeled loss for that region-month.

However, the ACRI measured in this way captures some of the impact of exposure changes in addition to the impact of changes in weather patterns. It also reflects, in undiscernible ways, differences in resilience. If, over time, some regions are adopting measures (e.g., enhanced building codes) to reduce losses due to extreme weather events, this estimating method, which assumes constant parameters over time, will be underestimating the impact of weather early in the time period and overestimating the impact in later years. As Bouwer notes: "[T]he potential effects of past risk-reduction efforts on the loss increase are often ignored, because data that can be used to correct for these effects are not available."[34] With currently available data, no method presents itself to adjust for changes in resilience; however, the ACRI has incorporated an adjustment for changes in exposure.

33 Before averaging, the ln(Loss) is converted into dollars through exponentiation.
34 Laurens M Bouwer, "Have Disaster Losses Increased due to Anthropogenic Climate Change," *Bulletin of the American Meteorological Society*, January 2011.

In order to control for the impact of increases in exposure, the reference period average modeled losses have been exposure-adjusted before subtracting them from the modeled losses for a particular region-month-year. When exposure-adjusting the reference period averages, the logic of the model might suggest adjusting only those region-months that produced statistically significant estimates for exposure. However, accepting that some (or all) of the 30 percent of region-months without statistically significant parameters might have been misestimated, the Academy has chosen to exposure-adjust all region months. Compared to the unadjusted total ACRI, the adjustment of all region-months reduces the total by twice as much as would the adjustment only of those region-months with statistically significant parameter values.[35]

Table 3 calculates for the post-reference period, 1991–2016, for the USA as a whole and for its seven ACI regions the sum of all ACRI losses and displays them alongside the observed losses as well as the exposure-adjusted losses. Several noteworthy points arise. First, in the post-reference period, 1991–2016, an estimated total of $24B of losses are attributable to unusually high precipitation, extreme temperatures, and high winds.[36] Further, those losses attributable to unusual environmental conditions amount to approximately 5 percent of the $493B in observed losses during that same period, and 3.3 percent of the exposure-adjusted losses. The vast majority of the ACRI total losses originate in the Southeast Atlantic region, which experienced ACRI losses of $22B in the post-reference period, out of a total of $278B observed losses (8 percent) and $421B in exposure-adjusted losses (5 percent). Of the other six regions, three reveal no material impact from extreme weather (ALA, CWP, and MID), one had somewhat less loss as a result of changes in weather conditions (CEA), and two had modest losses (SPL and SWP).

35 Without adjustment for changes in exposure, the ACRI total estimate is approximately $74 billion. With the adjustment for all region-months implemented, that total decreases to $24 billion. If the adjustment were only applied to region-months with statistically significant parameters for exposure, the ACRI total would be approximately $50 billion.

36 Precipitation and wind increase, on average, relatively small amounts after the reference period, although volatility increases somewhat more. The losses result from the high sensitivity to those changes.

Table 3: ACRI Losses, Observed Losses, Exposure-Adjusted Losses, by Region, 1991–2016, (in billions)

	ACRI	Observed Losses	Exposure-Adjusted Losses
USA	$23.78	$493.61	$711.95
ALA	$0.01	$0.51	$0.72
CEA	-$3.00	$51.53	$60.71
CWP	-$0.16	$5.39	$8.19
MID	$0.28	$57.07	$79.54
SEA	$22.42	$277.65	$420.84
SPL	$2.69	$65.81	$92.18
SWP	$1.55	$35.65	$49.77

Figure 1 displays annual totals for the USA for ACRI, observed losses, and modeled losses. A close relationship exists between modeled losses and the ACRI; this makes sense given the method used to generate the ACRI. The modeled losses match imperfectly the observed losses in two ways: 1) the modeled losses are substantially less than the observed losses; and 2) in most years, the peaks in the ACRI do not match peaks in observed losses. In most of those cases, the observed losses are elevated when the ACRI peaks, but not necessarily at their peaks. While there is no guarantee that ACRI peaks and those of observed losses should correspond exactly, that certainly would be a prior expectation.

Figure 1: ACRI, Modeled Losses, Observed Losses: Annual Totals, 1961–2016; USA

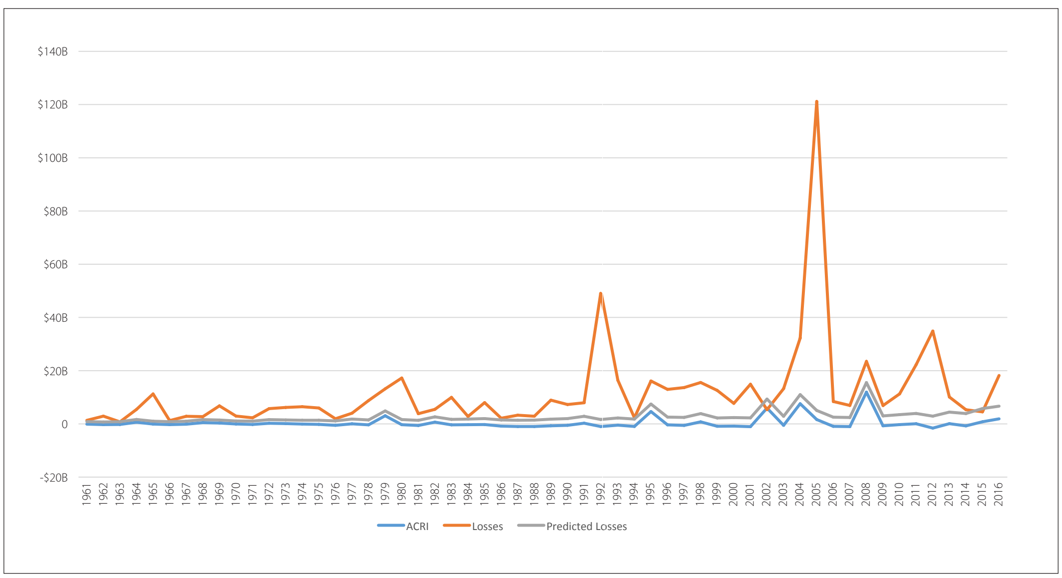
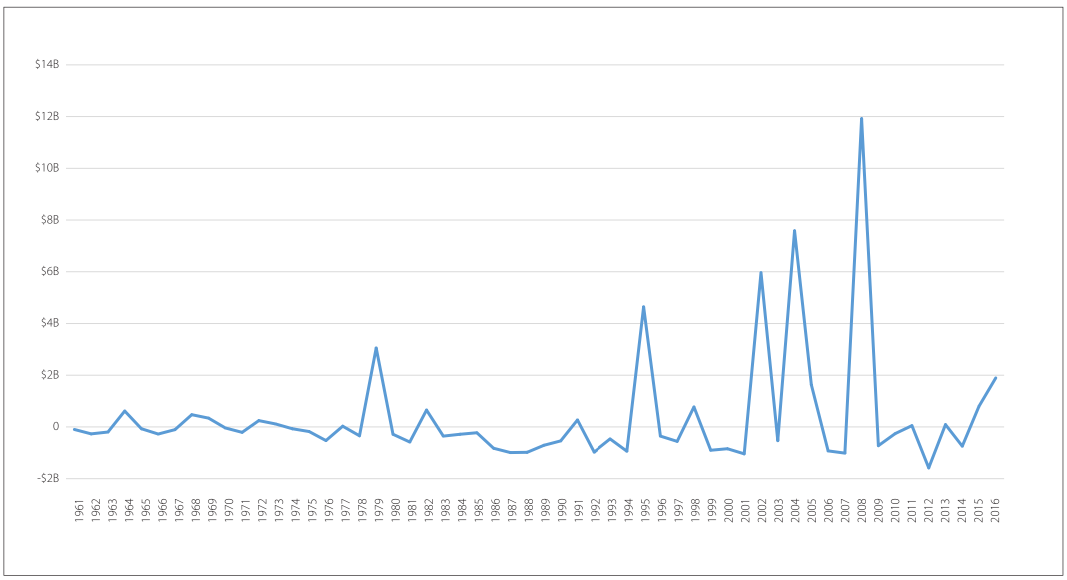


Figure 2 isolates the graph of the ACRI (the same one shown in Figure 1); separated in this way, the movement of the ACRI is more plainly visible. If we look first at the ACRI during the 30-year reference period (1961–1990), we see that on one occasion the ACRI exceeded $3B, reaching a high of $3.1B in 1979. On 22 occasions, the ACRI was negative, and on the seven occasions (other than 1979) when the ACRI was positive, it was less than $620 million. In the 26-year period since 1990, we see four occasions when the ACRI exceeded $3.1B, the highest of those being greater than $11B. The ACRI is still negative 15 times since 1990, indicating that weather conditions less extreme than during the reference period reduced losses. In sum, the ACRI in the period since 1990 reaches higher heights, reaches those heights more frequently, and dips down to negative levels frequently, if not quite so frequently as during the reference period. This describes a pattern of both increasing values of the ACRI and increasing volatility.[37]

Figure 2: ACRI: Annual Totals, 1961–2016; USA

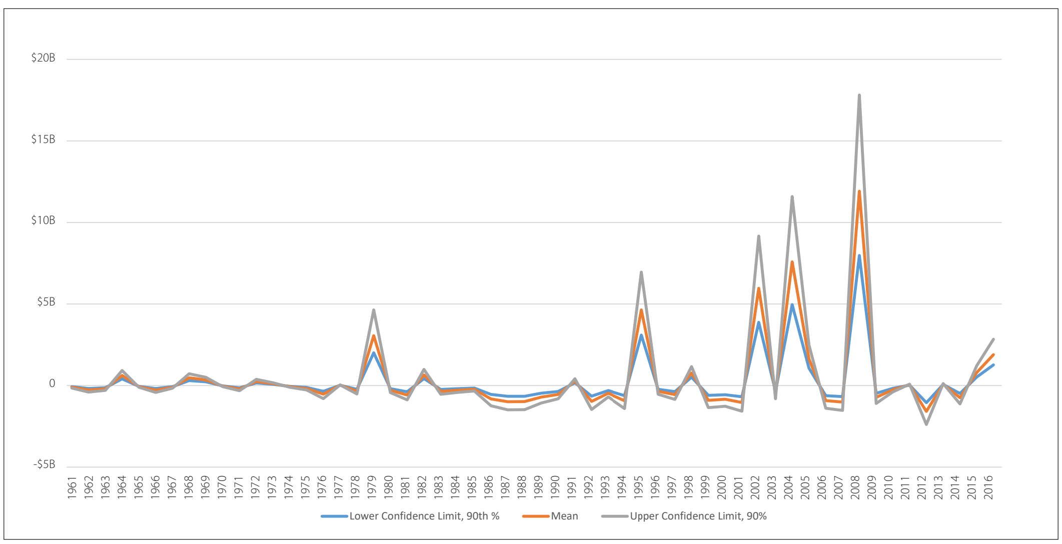


37 It is important to recall that at least some of the increase in the ACRI is due to increasing exposure.

This line showing ACRI losses may suggest more certainty than the Academy believes appropriate. There are many sources of uncertainty surrounding these estimates; some of those sources are internal to the calculations, and some are external (including data sources, singularity of very large losses, and the possibility that the results hinge on unusual characteristics of the observed weather distributions). To gauge the uncertainty with which the estimates ought to be viewed, that uncertainty has been assessed in two ways. The first way sought to gauge the intrinsic uncertainty—the uncertainty that attaches to any regression results based on the uncertainty of the fitted equation. The second sought to gauge the extrinsic uncertainty, particularly that which follows from the particularities of the distribution of weather events presented historically.

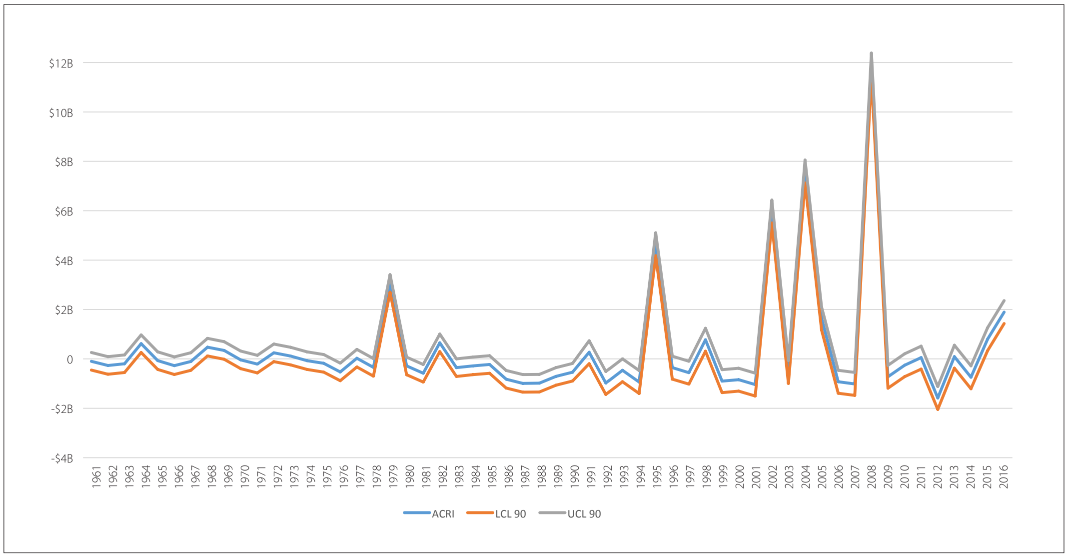
Figure 3 shows the ACRI graph bounded by the upper and lower limits of the 90th percent confidence interval.[38] This interval only reflects the uncertainty due to the probabilistic errors associated with the regression method employed here. Figure 4 shows the ACRI graph bounded by the 90th percent confidence intervals generated by a stochastic model based on alternative distributions of observations drawn from the historical record. For both of these techniques, see Appendix 2 for more details on the procedures followed.

Figure 3: ACRI, 1961–2016, Across All Regions and Months With 90% Confidence Level, Based on Intrinsic Uncertainty



38 The 90th percentile confidence interval for the ACRI was calculated by using the 90th percentile limits for the modeled values from the underlying estimates of the relationship between the weather metrics and losses. These confidence intervals are themselves subject to uncertainty, as they could be constructed in several different ways.

Figure 4: ACRI, 1961–2016 Across All Regions and Months With 90% Confidence Level, Based on Extrinsic Uncertainty



These results show good reason to be cautious in attaching too much significance to the precise values estimated. With intrinsic uncertainty accounted for, only 11 of the 26 post-reference period years are likely, at the 90 percent confidence level, to exhibit a positive ACRI. When accounting for the extrinsic uncertainty, only eight of the 26 post-reference years are likely to have positive values for the ACRI. Yet, the years that *are* positive are relatively large. Hence, it is useful to return to the breakdown for the regions and the country as a whole of ACRI totals for the entire post-reference period, as shown in Table 3. Table 4 shows those same values, but now with Lower and Upper confidence limits, from both internal and external assessments.

Table 4: ACRI Losses by Region, With Confidence Intervals (in billions)

	1991–2016	Intrinsic, Lower Limit	Extrinsic, Lower Limit	Intrinsic, Upper Limit	Extrinsic, Upper Limit
USA	$23.78	$15.72	$2.42	$35.98	$45.15
ALA	$0.01	$0.00	-$0.06	$0.01	$0.08
CEA	-$3.00	-$4.47	-$3.65	-$2.01	-$2.35
CWP	-$0.16	-$0.23	-$3.82	-$0.10	$3.51
MID	$0.28	$0.20	-$1.26	$0.39	$1.82
SEA	$22.42	$14.82	$10.90	$33.91	$33.94
SPL	$2.69	$1.79	-$15.66	$4.05	$21.03
SWP	$1.55	$1.02	-$0.19	$2.33	$3.29

This table illuminates the caution with which these estimates might best be treated. Taking only intrinsic uncertainty into account, one might conclude with 90 percent confidence that the U.S. as a whole and five of the seven regions had positive losses in the period 1991–2016 due to increases in the extremity of weather events compared to the reference period. However, taking extrinsic uncertainty into account, one might only conclude with 90 percent confidence that the U.S. and one of the seven regions had positive losses.

Throughout the process of estimating the relationship between weather and losses, and extending to the analysis of ACRI, the results are more certain at the national level than at the region level, and more certain at the region level than at the region-month level. Estimations at the region-month level with log-log transformed variables that exhibit a mean RSQ of 0.26, and an RSQ approaching 0 when transformed into dollars, produce estimates with lots of room for error. While each estimate might be far off in dollars from observed losses, the results in which higher levels of aggregation are more certain than lower levels suggests that at least some of the errors are the result of predictable over- and underestimation of particular observations.

Assessing the Modeled Relationship

The relationship modeled between the ACI components and property losses is the basis for the calculation of the ACRI. The credibility of the ACRI depends, in large part, upon the credibility of the modeled relationship. Going beyond the standard tools used to assess the validity of least squares regression models (primarily the significance tests for the parameters), it is important to illuminate as much as possible the extent and the limits of the robustness of this model. Throughout this estimation effort, the Academy has been trying to balance a set of conflicting objectives: a model robust with respect to both time and place, sensitive to both low-medium values of losses as well as to the extreme values in the loss distribution. The results in this section of the paper shed light on how successful we have been.

While r-squared is a reasonable, if statistically problematic,[39] yardstick for the ACRI model, the conventional r-squared reported examines all cases. As a result, it combines the effects which the model estimates within regions with some part of the differences across regions. To see whether the model is robust enough so that its explanatory power remains when the r-squared at the level of each region is examined, Table 5 shows the r-squared from the estimated model for each of the seven regions in the U.S., as well as for the U.S. as a whole. It has already been noted that the mean r-squared for the regions is a little more than half of the r-squared for the nation as a whole. What we see beyond that is that the range of r-squareds runs from a low of 0.24 to a high of 0.49, with only one region, ALA, exhibiting r-squared below 0.30. These regional results suggest that the model is similarly effective in most regions, with some small variation.

Looking at the results in another way, the r-squareds have been recalculated not in terms of Ln(Loss) (observed vs. modeled) but rather, in terms of the original Losses in dollars. When this is done, the r-squareds decline precipitously (as seen in the final row of Table 5). This difference is a measure of the impact of a log transformation on a highly skewed dependent variable. It indicates that the current state of the ACRI modeling captures a good deal of the variation in losses as long as those losses are log-transformed.

39 R-squared is potentially problematic in two senses. First, it is problematic because r-squared has no defined statistical distribution; as a result, it is impossible to identify a confidence level for r-square. Another problem with r-squared, in this application, is that r-squared increases with the number of variables. Adjusted r-squared would mitigate this problem. However, given that either when the sample is taken as a whole, or when region-months are considered as units within the sample, the number of estimators is less than 10 percent of the number of cases, the adjusted r-squared is never more than 0.02 less than r-square.

Table 5: R-Squared by Region, Ln(Loss) and Loss in $

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, Ln(Loss)	0.22	0.36	0.26	0.50	0.39	0.47	0.32	0.36	0.62
R-Squared, Loss in $	0.00	0.02	0.00	0.07	0.02	0.07	0.14	0.05	0.03

Are these results being dominated by extreme values in the loss distribution? While the values of loss have been log transformed, with the effect of trimming in the most extreme values, those highest values are still significantly higher than the median values. As one can see in Table 1, the median Ln(loss) is 16, while the value of the largest Ln(loss) is 25. Table 6 repeats the r-squared by region from Table 5 and adds a new row reporting the r-squareds calculated post-regression without the inclusion of the top 1 percent of observations. Clearly, the results are not being heavily influenced by the extreme values in the loss distribution. On average, the regions decline by 1 percent, while the U.S. as a whole does not decline. It is clear that estimating the relationship with a log-transformed dependent variable has made it so that those cases have the same impact on the regression as all others.

Table 6: R-Squared by Region, Ln(Loss): Whole Sample and Bottom 99 Percent

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, All	0.22	0.36	0.26	0.50	0.39	0.47	0.32	0.36	0.62
R-Squared, Bottom 99%	0.24	0.35	0.26	0.50	0.34	0.47	0.31	0.35	0.62

Given that the pooled cross-section includes many effects—both explicitly and implicitly—the Academy also wanted to ensure that the multivariate correlations observed are due, at least in part, to the environmental conditions measured by the ACI components. It would be possible for the r-squareds to derive solely or primarily from cross-regional or cross-monthly differences in losses. Results in Table 7, in which both the r-squareds by region of the estimated equation and the equivalent r-squareds for an equation estimated without any ACI components are presented, suggest that differences in average losses across region-months is playing a major role. The r-squared for the U.S. as a whole drops from 0.62 to 0.54 without the ACI components, indicating that only 8 percent of the impact observed originates with the ACI components. In the regions, on average, a little more than half (56 percent) of the impact appears to be due to the climate index components, with the average regional r-squared declining from 0.36 to 0.16. While a larger impact of the ACI components would be desirable (especially on the national level) to assure us that the results do reflect, in part, the impact of the weather metrics, the substantial overall r-squared combined with statistically significant estimates (at the 90 percent confidence level) for one-quarter of the ACI component parameters indicates a relatively robust result.

Table 7: R-Squared by Region: With and Without ACI Components

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, With ACI	0.22	0.36	0.26	0.50	0.39	0.47	0.32	0.36	0.62
R-Squared, Without ACI	0.16	0.10	0.11	0.26	0.09	0.29	0.12	0.16	0.54

Finally, two tests of robustness of the results and a brief look at results by region-month. In Table 8, the Academy randomly split the sample of region-months in half, and estimated the relationship between losses and the ACI components. In almost every instance, the r-squareds for the two samples are similar to each other, and similar to the results for the whole sample. The r-squared for the U.S. is 0.63 for the whole sample, and 0.64 and 0.69 for the first and second random samples, respectively. The means of the regional r-squareds are also comparable, 0.36 vs. 0.43, with an r-squared of 0.37 for the sample as a whole.

Differences are observed in the parameter estimates. Only 54 percent of the parameters estimated as statistically significant in the first half of the sample are also significant in the second half, while 55 percent of the parameters estimated as significant in the second half are statistically significant in the first half as well. This lack of robustness across geography and seasonality is not surprising. Given the disproportionate impact of extreme values on the estimates, losses from a single major storm that appears in one-half of the sample and not the other can easily change results. This might serve to remind observers that these descriptive results do depend on losses as they occurred, with some very large losses having a large impact on the particular parameters estimated.

Table 8: Corrected for Heteroskedasticity
R-Squared by Region: Whole Sample, and Randomly Split Into Sample A and Sample B

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, Whole Sample	0.22	0.36	0.26	0.50	0.39	0.47	0.32	0.36	0.62
R-Squared, Random Sample A	0.32	0.32	0.37	0.60	0.41	0.48	0.40	0.41	0.67
R-Squared, Random Sample B	0.24	0.38	0.32	0.48	0.39	0.50	0.33	0.38	0.63

The second test of robustness looked to intertemporal robustness; namely, do estimates of the relationship based on one time period produce reasonable correlations between observed and modeled values in a different time period. Most of the work here uses in-sample estimates; estimates for the years 1961–2016 are based on parameters estimated on those same years. This intertemporal robustness test is looking at out-of-sample estimates. Specifically, the Academy has estimated parameters based on the time period, 1961–2015, and then examined the model estimates for 2016. The results reported in Table 9 show an r-squared for the USA as a whole that is a little less than one-third for the modeled 2016 relationship compared to that estimated for the whole sample reported above. The average for regional r-squareds (based on only 12 observations for each region in 2016) is similarly reduced, declining from 0.31 to 0.09. However, this average masks differences. For one regions (MID), the r-squared declines by roughly 50 percent when moving from in-sample to out-of-sample testing; for two regions (CWP and SEA), the r-squareds decline by roughly two-thirds for the out-of-sample test compared to the in-sample results; and for the four remaining regions, the out-of-sample results are more than 80 percent lower than the in-sample ones. This test indicates questions about the intertemporal stability of the estimates. While the Academy does not now nor intends in the future to use these estimates as the basis for predicting future outcomes, intertemporal stability would still be a desirable characteristic of the process used to generate ACRI values.

Table 9: R-Square by Region: Model Estimates for 2016 Based on 1961–2015 Estimates

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, 1961–2016	0.14	0.34	0.25	0.45	0.35	0.42	0.24	0.31	0.59
R-Squared, 2016, based on 1961–2015 estimates	0.02	0.06	0.08	0.22	0.12	0.07	0.03	0.09	0.20

Conclusion

This paper reports on progress made on the path to meeting the following goals:

- **To assist** policymakers, the public, and actuaries with an indication of the relationship between environmental conditions and damages;
- **To use the data** and defined components of the Actuaries Climate Index in the construction of the Actuaries Climate Risk Index, as much as possible; and
- **To create an index** which can be updated regularly and made accessible to all users via the website maintained by the Academy.

This paper also reflects the challenges that remain with the data used both for the ACI and the ACRI, the metrics underlying the ACI components, the modeling of the relationship between the ACI components and losses, and the construction of the ACRI. Given the identified sources of uncertainty in the current estimates, the work has not yet extended to produce ACRI estimates for losses of life and for injuries, nor develop an ACRI measure for Canada, although the plan in the future is to include those.

Much remains to be done to improve upon the ACI and the ACRI in versions 2.0 and beyond. While others have undertaken efforts similar in some respects to the ACI and ACRI, the differences in the sponsoring organizations' objectives for both indexes create novel challenges. While the IPCC and the U.S. National Climate Assessments aim at a goal related to that of the ACI, the focus of their efforts is both longer term and predictive. Unlike those efforts, the ACI aims to describe what has already happened and to update those descriptions quarterly. While the UNDP Disaster Index sought to establish a relationship between environmental conditions and economic losses, it did so with an annual national database. Moreover, while catastrophe models have become quite good at identifying relationships between certain extreme events and associated economic losses, their focus is on estimation and prediction, which is usually narrowly circumscribed both by types of event and geographic domain.

The ACRI, like the ACI, aims not to predict but to describe what has happened and to update those descriptions regularly. The ACRI also aims to apply to large regions within two countries (U.S. as outlined in this paper and Canada) with a common model. These projects—both the ACI and the ACRI—are inherently difficult.

To find the best correlation between weather variables and property losses, the impact of inflation, exposure, region, and seasonality has been controlled for. A dependent variable expressing losses in dollars was analyzed, and each month of each year for each region has been treated as a separate observation. To allow for non-linearity in relationships between weather conditions and losses, to allow for interaction among weather conditions, and to mitigate the impact of the highly skewed distribution of losses, a model has been estimated in which both independent and dependent variables are log transformed. To identify statistically significant parameters, backwards regression was used on the dependent variable and the ACI to select the best estimated model in which all parameters were statistically significant at the 90 percent confidence level. The pooled, cross-sectional model produced an r-squared of 0.62 with the log-transformed modeled values, although the r-squared for the dollar equivalents was 0.03. Once corrected for heteroskedasticity, the r-squareds remained largely unchanged.

Based on this estimated relationship between the ACI and losses, the ACRI was calculated as the difference in modeled losses due to ACI components being above (or below) their reference period mean values. In order to exclude the impact of changes in exposure on the ACRI, the reference period mean modeled losses have been exposure-adjusted. The resulting ACRI totals $24 billion during the post-reference period, 1991–2016.

The model has a large amount of uncertainty, because each region-month currently only has 56 data points on which to base the parameters: 30 points during the reference period and 26 points subsequent to the reference period. This uncertainty has been estimated in two ways. Based on the intrinsic uncertainty associated with the regression estimates from which the ACRI is built, a 90 percent confidence interval is estimated around the best estimate for total ACRI losses of $16 billion to $36 billion. However, the broader extrinsic uncertainty associated with only having one "draw" of the weather distributions, both for the reference and the post-reference periods, has been estimated using a stochastic model of synthetic datasets based on randomly selected observations from the original data. With this broader definition of uncertainty, a 90 percent confidence interval has been estimated for total ACRI losses of $2 billion to $45 billion.

Throughout this documentation, weaknesses and limitations are outlined that serve as cautionary notes, pointing to the need to interpret these current results in light of their inherent uncertainty. Chief among these limitations are:

- As noted, while the model has an r-squared of 0.62 on log-transformed values, the r-squared on dollars of modeled and actual losses is only 0.03.
- The model performs most dependably at the national level, less so at the regional level (mean r-squared equals 0.36), and even less well at the region-month level (r-squared equals 0.24).
- The ACI metrics used in the model are averaged over large geographic areas, while the most damaging events are concentrated in much smaller areas.
- The ACI metric for Wind, based on average monthly wind speeds in these large geographic areas, is not shown by the model to be very good estimates of large losses that are driven primarily by windstorms.
- Equation coefficients are quite inconsistent from one month to the next, in a given region, which does not provide a logical explanation for the ACRI values.

These weakness and limitations also suggest a direct proceeding to version 2.0 of both the ACI and the ACRI to seek better data and develop more effective metrics and more robust analysis. Others are encouraged to build on this work by conducting research using weather metrics and proprietary insurance company loss data, which would be available in precise geographic detail.

Appendix 1: Statistical Appendix

The tables below present data tabulations for each of the seven geographic regions. For each region, the results are tabulated across all 56 years and 12 months of data.

Table 10: Univariate Analysis: 99th Percentile / 50th Percentile

Region	Rx5day	Wind	T90	T10	Property Loss
ALA	2.2	2.1	4.1	6.3	3,133.9
CEA	2.1	2.4	3.1	3.3	175.1
CWP	2.7	2.3	3.0	4.0	1205.3
MID	1.8	2.1	3.5	3.6	130.0
SEA	1.6	2.2	3.4	3.2	281.6
SPL	2.0	2.0	2.7	3.1	104.0
SWP	2.7	2.9	2.7	3.2	443.9

Table 11: Univariate Analysis: Average / 50th Percentile

Region	Rx5day	Wind	T90	T10	Property Loss
ALA	1.07	1.05	1.21	1.39	434.0
CEA	1.04	1.03	1.12	1.14	14.7
CWP	1.07	1.04	1.14	1.23	82.6
MID	1.00	1.06	1.16	1.12	8.6
SEA	1.00	1.05	1.14	1.12	20.6
SPL	1.05	1.04	1.09	1.09	6.4
SWP	1.08	1.08	1.09	1.13	19.4

Table 12: Average Weather Metric 1991–2016 Divided by Average Weather Metric 1961–1990

Region	Rx5day	Wind	T90	T10
ALA	1.01	0.91	1.33	0.65
CEA	1.06	0.75	1.20	0.73
CWP	1.02	0.87	1.19	0.77
MID	1.05	1.16	1.06	0.87
SEA	1.03	0.94	1.20	0.80
SPL	1.04	1.09	1.15	0.86
SWP	0.98	0.81	1.32	0.76

Table 13: 90th Percentile of Weather Metric 1991–2016 Divided by 90th Percentile of Weather Metric 1961–1990

Region	Rx5day	Wind	T90	T10
ALA	1.02	0.94	1.31	0.70
CEA	1.05	0.94	1.17	0.81
CWP	1.00	0.87	1.16	0.80
MID	1.04	1.10	1.00	0.93
SEA	1.01	1.00	1.16	0.86
SPL	1.00	1.08	1.16	0.91
SWP	0.94	0.73	1.28	0.76

Table 14: Correlation of Weather Metric With Logged Loss

Region	Rx5day	Wind	T90	T10
ALA	6.6%	5.7%	13.6%	-7.6%
CEA	48.8%	15.9%	2.3%	-2.6%
CWP	26.8%	20.3%	15.5%	-0.4%
MID	54.1%	22.1%	4.3%	-4.2%
SEA	43.0%	32.3%	16.0%	-4.9%
SPL	49.5%	16.9%	1.4%	4.6%
SWP	24.6%	8.3%	12.0%	-1.1%

Table 15: Correlation of Weather Metric With Loss in Dollars

Region	Rx5day	Wind	T90	T10
ALA	-4.4%	-6.8%	-5.4%	1.4%
CEA	15.1%	1.4%	1.3%	-2.2%
CWP	7.4%	0.6%	0.4%	0.9%
MID	19.9%	8.2%	-3.0%	-3.1%
SEA	12.1%	7.5%	5.2%	-0.8%
SPL	22.0%	4.8%	2.0%	2.0%
SWP	14.5%	3.5%	9.0%	4.9%

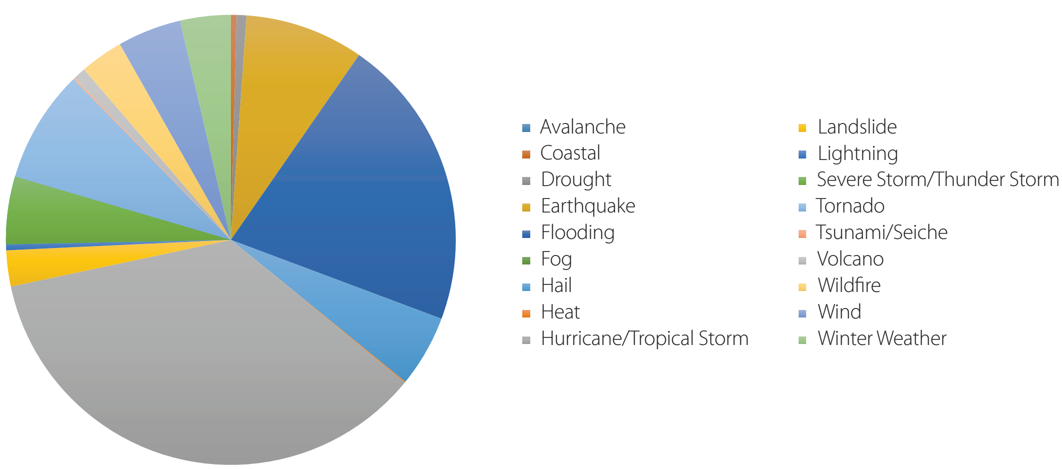
Table 16: Exposure in Year "Y" / Exposure in Year "X"

Region	2016 / 1961	2002 / 1975
ALA	9.25	2.42
CEA	3.61	1.91
CWP	8.09	2.83
MID	3.25	1.71
SEA	6.78	2.56
SPL	4.88	2.03
SWP	8.02	2.62
Note: The exposure data is in 2016 USD, so the ratios above capture real as opposed to nominal exposure growth.		

Table 17: Average Modeled Loss 1991–2016 Divided by Average Modeled Loss 1961-1990

Region	Loss	Loss / Exposure
ALA	5.64	1.93
CEA	0.34	-0.29
CWP	1.44	-0.28
MID	0.75	-0.01
SEA	2.86	0.48
SPL	1.32	0.07
SWP	2.25	0.29
Note: The estimates are in 2016 USD, so the ratios above reflect real as opposed to nominal changes.		

Figure 5: Distribution of Property Losses by Peril



Note that losses arising from volcanoes—which represent less than 1 percent of total property losses—were included in this analysis by mistake. This error, however, has no material effect on results.

Appendix 2: Procedures Used in Estimation of OLSQ Equation and ACRI Calculation

Estimation

The relationship between weather and losses is estimated in three steps, using data from seven U.S. regions, over each of the 12 months, over a 56-year period, from 1961 to 2016. The 30-year period from 1961 to 1990 is treated as the reference period; the 26 subsequent years are discussed as the post-reference period. Estimation was performed using SAS statistical software.

The exponential equation in Equ B as estimated by taking natural logarithms of all independent and dependent variables. For Losses, which sometimes have a value of 0, 1 was added to all dollar values of losses prior to transformation. When losses are restored to dollars by exponentiation, 1 dollar was subtracted.

In the first phase, four weather elements (Precipitation, High Temperatures, Low Temperatures and Wind), along with Exposure, were entered into an ordinary least squares (OLSQ) regression estimating equation with dummy variables for each region-month combination. A total of 420 variables were entered in this fashion (seven regions, 12 months, five variables). In addition to a global intercept, there was an intercept for each region-month. Backward, stepwise regression was then employed to eliminate variables not significant at the 90 percent confidence level.

In the second phase, the variables found to be significant in the first phase, were entered into an OLSQ regression. However, in this phase the covariance matrix was adjusted to correct for heteroskedasticity using the method describe by White (1980).[40] With the corrected covariances, tests of significance were repeated and some variables were identified as insignificant.

In the third phase, the variables continuing to be significant after correction for heteroskedasticity were entered into an OLSQ regression. This equation was used to produce the modeled values (and the confidence interval around those values), which were used as the basis for calculating the ACRI and its intrinsic confidence interval.

40 Halbert White, "A Heteroskedastic Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica* (48,4), May 1980.

Calculating the ACRI

First, all modeled losses were converted to dollars. Second, the average modeled loss for a particular region month over the 30-year reference period was calculated. This provides a baseline against which to measure subsequent losses; it is a baseline which controls, in a sense, for the distribution of weather and exposures in that region-month during the reference period.

The intention in the ACRI is to assess the losses that are due to differences between weather in the post-reference period and that which prevailed during the reference period. However, if the modeled losses in a particular post-reference period are compared to the reference period average, it will be the product of differences in both weather and exposure. In order to control for the effect of changes in exposure, and isolate the effect of changes in weather, the average modeled losses from the reference period are adjusted for changes in exposure. In particular, the average for a region-month are multiplied by the ratio of Exposure in a particular year to the average Exposure in that region-month during the reference period. For example, if the average modeled loss in a particular region-month was $1B during the reference period, and the average exposure for that region-month during the reference period was $1T, then if the ACRI is being calculated for a later period in which the exposure was $10T, one would treat $10B as the exposure-adjusted average modeled loss during the reference period for that region-month.

To calculate the ACRI for each region-month each year, the exposure-adjusted average modeled loss for the region-month was subtracted from the modeled loss for that region-month-year. Summing these values across all months and all years from 1991 to 2016 produced estimates of ACRI for each region in the post-reference period. Summing the individual ACRI values across all region-months in a given year produced estimates of the ACRI for each year.

Estimating the Uncertainty of the ACRI Estimates

Uncertainty of the ACRI has been estimated in two ways:

First, the intrinsic uncertainty of the ACRI estimates has been estimated. This is the uncertainty arising from the OLSQ method with the observed data. Using the standard error of the regression, the lower and upper limits for the 90 percent confidence level of each modeled loss have been derived. The lower limits of the modeled losses were then used to create a lower bound for the ACRI, following exactly the same steps to calculate the ACRI as described above, substituting the lower bound for the best estimate. Similarly, the upper bound of the ACRI confidence level has been calculated using the upper bound limits of the modeled losses. This produces the picture shown in Figure 3, with a fairly tight confidence band around the ACRI annual estimates.

Second, the extrinsic uncertainty of the ACRI estimates has been estimated. This is the uncertainty arising from reliance on a single observed distribution of weather events and losses. While this distribution is the only historical set of observations available, one could think of this set of observations as drawn from a larger pool of potential observations. This second estimate of uncertainty tries to capture this extrinsic source of uncertainty, while preserving as much as possible the structure of the observed data.

In order to accomplish this objective, a synthetic data set has been created with values for each region-month-year. To create the values for the 30 reference-period years for a particular region-month, one of the observations has been randomly selected from the reference period for that region-month and its values for weather and losses have been assigned to the first year. This process was then repeated for each of the 30 years, treating as the pool of possibilities the original 30 observations with replacement. In creating this synthetic set of values for the reference period, some observations may be excluded, and some included more than once. The same procedure was then done for the 26 post-reference period values for each region-month, drawing the synthetic values from the observed values in the post-reference period. Having created the synthetic data base for all regions, months, and years, the equations were then estimated in the three-phase process described above. Based on those results, the ACRI was then calculated for each region-month-year, also as described above.

Early attempts revealed that a single region-month—Alaska in April—often produced outlandish results, sometimes exceeding the total losses for all regions for all years by several orders of magnitude. This was the result of the region-month experiencing one large storm early in the reference period (and thus it became larger when exposure-adjusted). The doubling or the exclusion of this event caused enough differences in estimates for this region that the Academy excluded it from all calculations of uncertainty. No other region-month demonstrated any comparable volatility.

This process was repeated 30 times. This process generated a mean and a standard error for the annual total ACRI values, and for regional, post-reference period ACRI values, as shown in Figure 4 and Table 4. While more repetitions would have been desirable, the time required for this exercise was a limiting factor. However, plotting the mean and standard errors against the number of simulation runs indicates that both have begun to converge on their limiting values, as seen in figures 6 and 7 below. The values for the ACRI derived from the historical observations were combined with the standard errors derived from this method to produce a 90 percent confidence interval for the ACRI estimates based on extrinsic uncertainty.

Figure 6: ACRI USA Total, 1991–2016 Simulation Mean, v. # of Simulation Trials

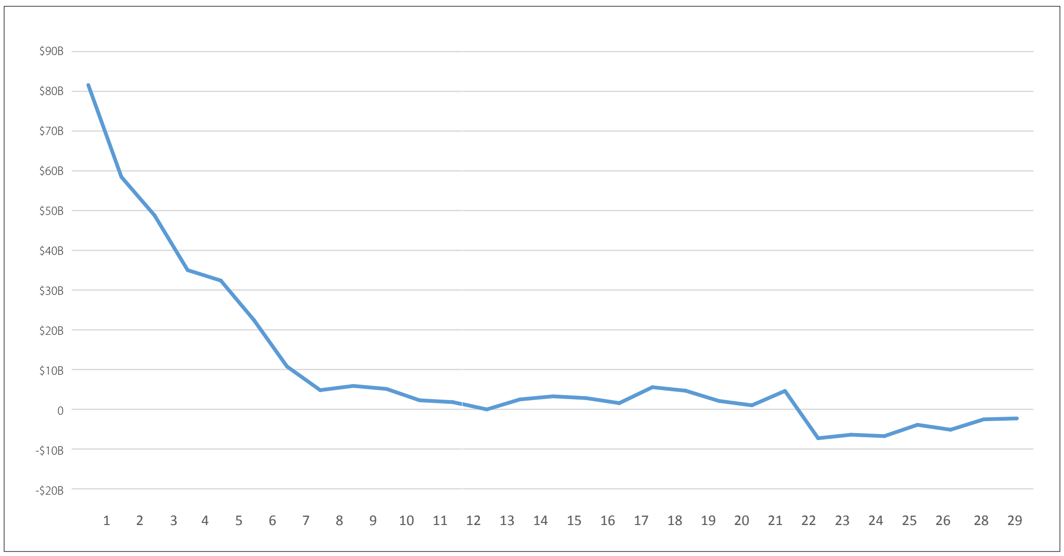
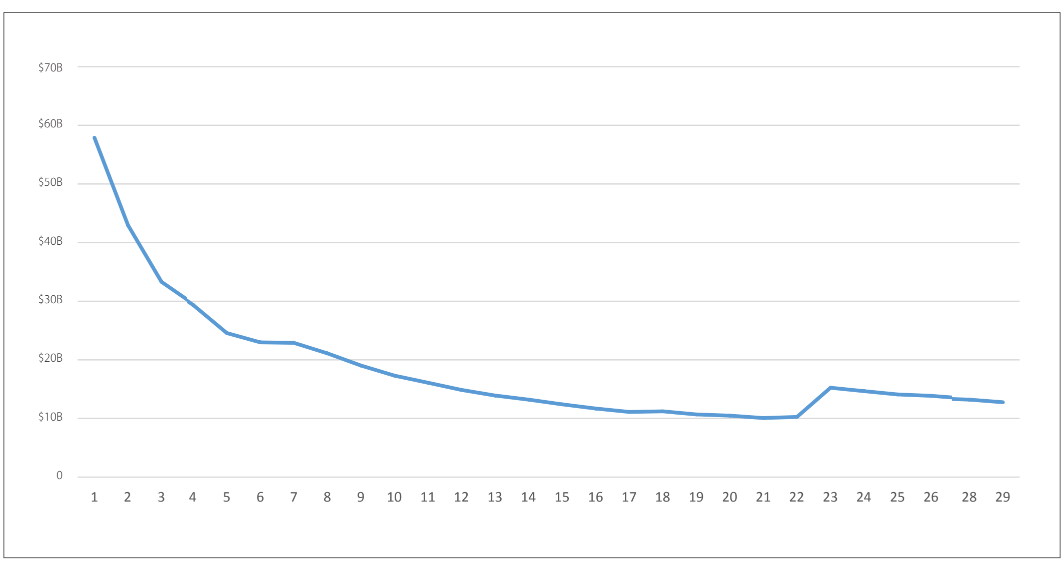


Figure 7: ACRI USA Total, 1991–2016 Simulation Standard Error, v. # of Simulation Trials



Appendix 3: Statistically Significant Parameters (90 Percent Confidence Level) For Equation D

	Region	ALA	CEA	CWP	MID	SEA	SPL	SWP
Variable	Month							
Intercept	0	-32.64	-32.64	-32.64	-32.64	-32.64	-32.64	-32.64
Intercept	1		37.17				-56.76	
Intercept	2	-72.80	38.53	-47.79	-93.33			
Intercept	3	38.40	36.04		36.36	50.66		
Intercept	4	-37.76	33.96		50.27			
Intercept	5	-73.68	37.33					
Intercept	6	-40.32	33.09			49.85	51.35	
Intercept	7	-104.16	49.72		50.56	49.69		
Intercept	8		34.99	45.93				
Intercept	9	-62.81	29.15			29.37	49.60	42.11
Intercept	10							-46.34
Intercept	11			-50.81			-43.57	
Intercept	12	-54.02	37.53	46.46			28.75	
Exposure	1	1.70		0.69	0.92	1.10	3.18	1.16
Exposure	2	4.40		2.52	4.23	1.61	1.40	1.33
Exposure	3			1.00			1.79	1.37
Exposure	4	2.99		1.06		1.24	1.84	1.51
Exposure	5	4.69		1.65	1.76	1.28	1.85	1.67
Exposure	6	3.23		1.21	1.32			1.70
Exposure	7	5.12		1.29			1.80	1.70
Exposure	8	1.58			1.74		1.79	1.71
Exposure	9	3.32		1.38	1.28			
Exposure	10	1.53	0.96	0.77	0.96	1.30	1.35	2.55
Exposure	11	0.96	0.95	3.53	1.02	1.57	2.56	1.45
Exposure	12	3.91			1.08	1.07		1.11
Rx5Day	1		3.17	6.88	6.19	4.48	2.23	4.17
Rx5Day	2		2.82	6.24	6.00		3.03	3.50
Rx5Day	3		3.39	5.07	3.66			1.63
Rx5Day	4		3.81	3.81		3.72		
Rx5Day	5		2.93			3.35		
Rx5Day	6		4.21	3.47	3.22			
Rx5Day	7							
Rx5Day	8		3.72			11.07		
Rx5Day	9	5.93	4.90		3.18	4.10		2.14
Rx5Day	10		4.02	4.66	5.35		3.28	2.83
Rx5Day	11	6.62	5.21		3.32		4.46	1.33
Rx5Day	12		2.85		4.83	4.43	3.47	3.25

	Region	ALA	CEA	CWP	MID	SEA	SPL	SWP
Variable	Month							
T10	1							
T10	2			0.84			0.91	0.89
T10	3			1.04				
T10	4							
T10	5							1.70
T10	6							
T10	7							
T10	8	4.80		2.01				
T10	9							
T10	10					-1.47		
T10	11							1.68
T10	12						-1.21	
T90	1						-1.78	
T90	2				-0.86			
T90	3	-1.67						-1.23
T90	4							
T90	5	1.17		1.12				
T90	6							
T90	7			1.19				
T90	8	3.79		2.96				
T90	9					1.69		
T90	10			2.12				
T90	11	2.32		3.07		1.19		3.73
T90	12	-1.04						
Wind	1						5.29	2.21
Wind	2				1.62		3.60	
Wind	3	3.98				1.67		
Wind	4							1.32
Wind	5							
Wind	6							
Wind	7							
Wind	8							
Wind	9							
Wind	10					2.92		
Wind	11		1.85			4.19		
Wind	12				2.72	1.72	3.36	

Appendix 4: Alternative Forms of the Model

In developing the model presented here, several functional forms have been explored for the estimating model, and others have been contemplated but not yet fully explored. In each case, other forms had weaknesses that seemed greater than those of the model presented. Without revisiting all of the analysis, consider next three illustrative forms accompanied by the reasoning that led the Academy to reject these forms in favor of the proposed model (Equation D).[41]

Loss per dollars of exposure was treated as the dependent variable in many efforts. When the same model estimated as Equation (C) but dividing Losses by Exposure before log-transforming was run, results similar to those presented in the body of the paper were obtained.

These results (see Table 19, R-Squared, Log-Log Form) reveal an r-squared for the U.S. as a whole of 0.46, and an r-squared dropping to 0.04 for the U.S. and to 0.06 for the mean of the regions when the exponentiated values of losses in dollars are correlated with modeled losses in dollars. These results are similar but inferior to the results presented in the paper.

Table 19: R-Squared by Region: Log-Log Transformed Model in Logged Units and in $

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	U.S.
R-Squared, Log-Log Form	0.13	0.33	0.33	0.48	0.39	0.48	0.26	0.34	0.46
R-Squared in $	0.00	0.02	0.00	0.16	0.04	0.10	0.08	0.06	0.04

In an effort to find a model where the r-squared would be higher in dollar-dollar correlations, a simple linear model was tried, without log-transformations. The dependent variable was dollars per dollar of exposure. But, because of the skewness of the distribution of losses, this variable was truncated at the 99th percentile, with values at the 99.5th percentile substituted. Results, shown in Table 20, show both strength and weakness relative to the model presented in the text.

Table 20: R-Squared by Region, Loss/Exposure and Loss in $

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	USA
R-Squared, Loss/Exposure	0.08	0.16	0.13	0.09	0.32	0.18	0.12	0.15	0.21
R-Squared, Loss in $	0.00	0.01	0.00	0.14	0.09	0.15	0.10	0.07	0.09

41 The results reported in this appendix do not include corrections for heteroskedasticity.

GLM models, commonly used in catastrophe modeling, aim primarily to estimate distributions of losses rather than to generate modeled values for particular observations. While in Version 2.0 of the ACRI this distributional approach may be pursued, and GLM and other models may be more useful, the current effort aimed to generate a fit to the data such that each region-month in each year had a reasonable model estimate of the observed loss (i.e., a classical regression fit). In exploring GLM models, given limitations from available technology,42 the Poisson distribution provides the best fit of the data. In the GLM model presented in Table 21, results assessed for the correlation of observed and modeled Loss/Exposure is similar to, and stronger in some respects, than the current Loss/Exposure proposed model. The same conclusion holds true when considering correlations in terms of dollar losses.

However, when looking at the correlations within region-months (for example, calculating the r-squared for January in Region 1, etc.), overfitting is immediately evident. Table 22 shows certain characteristics of the distribution of these 84 region-month r-squareds. Note that the 90th percentile cut-off for r-squareds among the region-months is 0.79 means that 10 percent of the region-months have r-squareds greater than 0.79. This is an implausible result without overfitting. The data possesses too much error and the relationships are sufficiently obscure that r-squareds above 0.4 or 0.5 ought to raise red flags. As a result of this overfitting, the Academy has put aside the GLM models for the current version of the ACRI.

Table 21: R-Squared by Region: GLM Model, in Loss/Exposure, and in $

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	U.S.
R-Squared, Loss/Exposure	0.33	0.30	0.38	0.33	0.34	0.27	0.44	0.34	0.33
R-Squared, Loss in $	0.01	0.05	0.01	0.49	0.08	0.20	0.32	0.16	0.09

Table 22: Distribution of R-Squareds, Loss/Exposure, GLM model, 84 Region-months

	R-Squared
Minimum	0.00
Median	0.19
Mean	0.30
80th Percentile	0.59
90th Percentile	0.79
Max	0.96
SWP	2.25

42 Work was done in SAS and R. Without programming proprietary density functions, work was limited to the distributions available.

Finally, in an effort to separate estimation of the frequency of losses from the severity of those losses, the Academy follows the example of Wanik (2012), who applied separate models to these two tasks in an effort to predict damages to an electric grid. Combining the results for frequency and severity would, in principle, produce a more refined picture of the relationship between ACI components and losses as a basis for creating the ACRI.

To estimate frequency, any region-month with any non-zero losses was coded a 1; all others were coded 0. A logistic regression with a probit transform was executed and the results were evaluated by comparing region-months that experienced (or did not) any losses with those region-months in which the estimated probability of experiencing any loss was greater (or less than) 50 percent. The results are reported in Table 23. On the face of it, these results are quite positive, with more than 92 percent of region-months correctly modeled (Yes-Yes and No-No in the table). The problem is that almost all cases where there were no losses are mismodeled as likely to have losses. In a sample where 92 percent of cases are positive, estimating that virtually all cases (99.70 percent) will be positive is an effective strategy for getting more than 90 percent correct estimates. This model is therefore not effectively discriminating between cases that will and will not have losses. This problem was exacerbated when also looking at the Canadian data, where 90 percent of the region-months had zero losses and virtually all region-months were modeled as zero losses. Again, the model is showing no ability to discriminate non-zero from zero-loss observations.

Table 23: Probit Regression Estimating Frequency of Observing Losses Percentage Correct and Incorrect Predictions

Predicted Probably of Losses	Observed Losses		
	Yes	No	Total
Yes (or >50%)	92.01%	7.70%	99.70%
No (or < 50%)	0.17%	0.13%	0.30%
Total	92.18%	7.82%	

For the U.S. as a whole, this problem is not very material given the limited number of observations with zero losses. Hence, estimates of conditional severity would be considered—that is, the relationship between ACI components and Loss/Exposure restricted to region-months with non-zero losses. However, the results of this model reported in Table 24 are not significantly different from those of the proposed model where the same model is applied to both non-zero and zero-loss observations. Simplicity, combined with the weakness of the frequency modeling, suggests using the unified model rather than a two-stage model attempted here.

Table 24: R-Squared by Region: Severity Model for Non-Zero Loss Region-Months

Region	ALA	CEA	CWP	MID	SEA	SPL	SWP	Mean	U.S.
R-Squared, non-zero losses, Loss/Exposure	0.15	0.17	0.14	0.09	0.33	0.18	0.09	0.17	0.23

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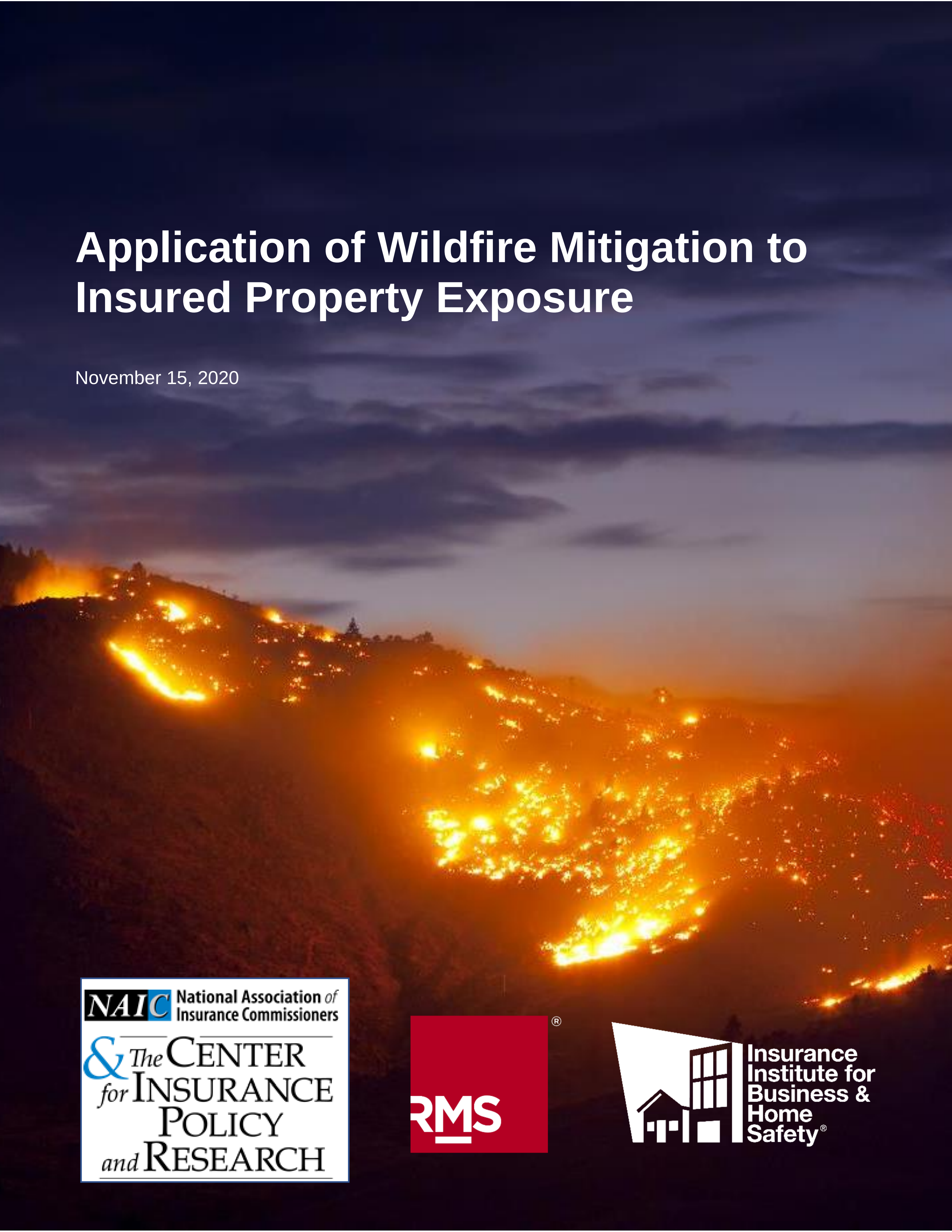
Application of Wildfire Mitigation to Insured Property Exposure – CIPR, RMS & IBHS

Application of Wildfire Mitigation to Insured Property Exposure

November 15, 2020



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Executive Summary

The recent wildfires across the Western U.S. have created an insurance crisis across several states. Homeowners are facing non-renewals or significantly increasing insurance premium rates, issues that put pressure on State Departments of Insurance and other state policymakers to act. Research by renowned organizations such as the *Insurance Institute for Building and Home Safety* (IBHS) and community mitigation programs such as *National Fire Protection Association's* (NFPA) *Firewise USA® Program* provide guidance on how to create more wildfire resilient communities. However, what is relatively unknown is whether these risk reduction actions are economically worth the effort and cost? Or which features are the most important from a relative investment return perspective?

Catastrophe modeling allows for a probabilistic assessment of wildfire risk, examining key location and community level attributes to determine potential insured property losses. These models calculate risk by looking at a range of factors such as topography, distance to vegetation, slope, and other location-specific information including roof system covering, roof vents, suppression, and accessibility conditions. Critically then, catastrophe models can reflect structure-specific and community level mitigation in loss estimates. This study is designed to demonstrate that learnings from building science research can be reflected in a catastrophe model framework in order to proactively inform decision-making around the reduction of wildfire risk for residential homeowners in wildfire zones.

To quantify the benefits of certain wildfire mitigation features, this study uses the *RMS North America Wildfire Model* to quantify hypothetical loss reduction benefits in nine communities across three Western States: California, Colorado, and Oregon. The simulated reduction in losses are compared to the costs of implementing associated mitigation measures. A straightforward benefit-cost methodology is applied to assess the economic effectiveness of the two overall mitigation strategies modeled – structural mitigation, and vegetation management.

We find that there are opportunities to significantly reduce this risk with the two stated mitigation strategies. Firstly, we show that structural modifications can reduce wildfire risk up to 40%, and structural and vegetation modifications combined can reduce wildfire risk up to 75% when simply moving to a well-built wildfire-resistant structure from a neutral property setting. Moreover, we determine that the losses avoided can be even more significant (e.g. 5 times greater) when compared to a highly flammable structure.

From a benefit-cost perspective, we demonstrate that for a number of the modelled locations, the relative risk reduction, if enabled within insurance products based on wildfire risk-based pricing, would provide economically effective incentives at promoting mitigation with pay-back periods from 10 to 25 years.

This study also concludes that the identification of locations where viable economic incentives are effective is complex, and will require insurance companies to invest in location specific data and new pricing approaches that leverage probabilistic methodologies that also incorporate risk reduction strategies as we have done here.

Finally, the authors emphasize that this study is an illustrative, foundational effort and further detailed research is necessary to illustrate specifically where and how economically effective wildfire mitigation could be applied in the context of insured property exposures. On its own, this study is neither comprehensive nor sufficient to create regulatory policy on this topic. Nonetheless, there is a definite and growing need for the type of analysis we have performed here to help to guide the implementation of wildfire risk reduction actions and to inform the policy discussion for how to make this happen in an economically efficient manner.

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Contents

The Case for Wildfire Mitigation – A Catastrophe Model Application

For homeowners in wildfire prone areas of the United States, as the underlying wildfire risk continues to increase, there are exacerbating pressures on the affordability and availability of homeowner's insurance. As evidence of this insurance dynamic in California, 2019 saw a 31 percent increase in non-renewals by insurance companies state-wide as compared to 2018, with more significant non-renewal increases in higher risk areas in the state, up to 203 percent (CDI, 2020). And this data follows the recent trend since 2010 in California "that homeowners' insurance coverage in the wildland-urban interface (WUI) is increasingly difficult to obtain and, if available, is unaffordable to many that need it." (CDI, 2018. pg. 1). Relatedly, since 2015 California FAIR Plan policies – the state insurer of last resort – have increased by 35 percent state-wide with up to 803 percent increases in higher wildfire risk areas such as the Southern Sierra (CDI, 2020). Continued population and WUI expansion, coupled with increased weather and climate drivers, will continue to aggravate this insurance dynamic.

Decreasing the risk of loss is a direct and likely expedient way to increase the availability and affordability of homeowner's insurance in wildfire-at-risk areas. Mitigating wildfire risk can involve several activities including enhanced building codes; land-use planning; environmental regulation; enhanced infrastructure; adoption of wildfire sensors; fire resistant individual property modifications; and community wide abatement. Understanding the relative value of each of these mitigation measures is critical toward their implementation. In this report we focus specifically on quantifying wildfire avoided losses due to the implementation of individual property modifications and community wide abatement of wildfire risk. By combining the determined avoided losses with costs to implement these activities we can determine the economic efficiency of property and community wildfire mitigation efforts.

Historically wildfire risk scores have been used by insurers to decide whether to renew or write new insurance policies in the WUI. However, they do not consider home & community mitigation efforts (Commission on Catastrophic Wildfire Cost & Recovery, 2018). However, catastrophe (CAT) models have the ability to reflect structure-specific and community level mitigation. Accordingly, we take a CAT modeling approach to quantify the benefits and costs of individual & community wide wildfire mitigation.

We use the *RMS North America Wildfire HD Model* applied to 1,161 individual structures in 9 community locations in the states of California, Oregon, and Colorado. The RMS wildfire model accounts for the latest wildfire mitigation science regarding structural and surrounding ignition zone modifications that can be made to a property and we utilize the modeling framework to quantify their impacts.

With these impacts quantified, a benefit-cost analysis has been completed to show how under some circumstances, wildfire mitigation is not only possible but economically feasible.

Wildfire Mitigation – Individual and Community Best Practices

The building science behind wildfire mitigation has been an active area of research for several decades. There are many mitigation programs developed and proposed in various areas. At the national level, the most prominent recommendations come from the collaboration between the Insurance Institute for Business and Home Safety (IBHS) and the National Fire Protection Association's (NFPA) Firewise USA® Program.

The following sections describe the physical attributes of homeowner wildfire risk identified by IBHS and the voluntary educational Firewise USA program designed to bring these techniques to the public.

Insurance Institute for Business and Home Safety (IBHS)

There are three main sources of ignition for structures stemming from the wildfire hazard:

- i) direct — flame in direct contact with a structure or accumulated embers on a structure;
- ii) indirect — flying embers ignite materials close to a home; and
- iii) radiant heat — heat from the fire causes materials to ignite.

A house, its roof, and its surroundings can be configured to defend against these three sources of ignition and hence the ways that a wildfire can attack a structure. By bringing the current state of science to bear, IBHS has identified eight critical parts of a home and its surroundings.

- Fuel management – Defensible space, combustibles around a home (home ignition zone)
- Fences
- Decks
- Building shape
- Walls
- Roofs
- Roof vents
- Eaves & overhangs

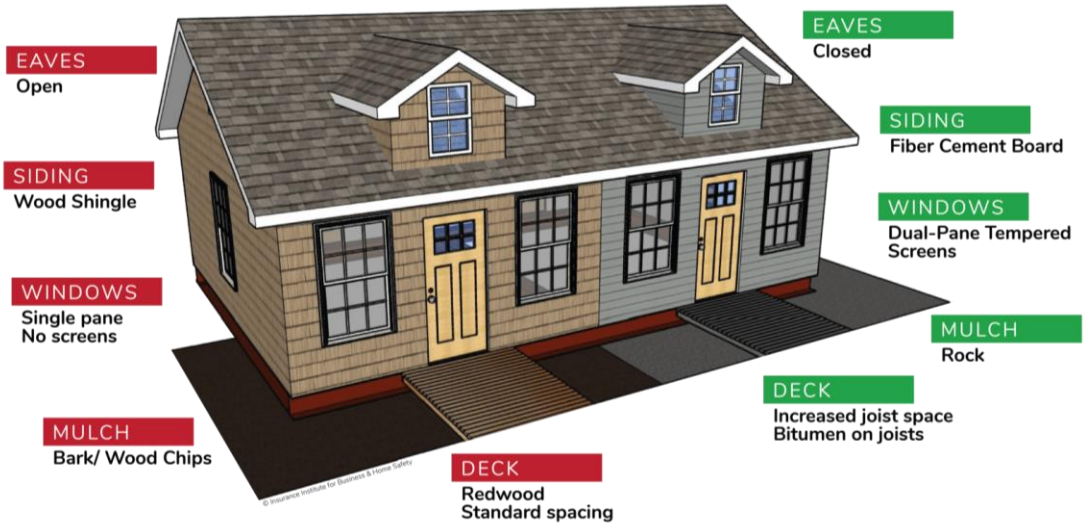
The vulnerability of a home or business can be reduced by adapting to the threat of wildfire for each of these eight components through making better material and building choices for each.

From these eight, the most critical actions for wildfire protection are **the roof, the defensible space/home ignition zone, decks, and vents.** This is the starting line for homeowners to reduce their risk and increase the chances for a home to survive should a wildfire threaten. This set of actions must be addressed and maintained before any other steps can have a meaningful impact.

- ROOF: A noncombustible roof covering and assembly is the first line of defense against ember attack during a wildfire. The roof material must have a fire rating from the Underwriters Laboratories testing program (Class A, B, and C). IBHS encourages homeowners to use a product or full roofing assembly that has a Class A rating when re-roofing. Nearly all asphalt shingles currently on the market have a stand-alone Class A rating. Approximately 75% of homes in the United States have asphalt shingle roofs.
- HOME IGNITION ZONE: This is the five- foot area extending outward from a home, sometimes referred to as the noncombustible zone[1]. The area is essential to stopping fire from spreading to a structure and stopping embers from igniting anything that may be immediately next to a home. The best practice is to avoid anything that can burn, but when used with gravel or rock ground cover/mulch, fire-resistant plants can help slow fire from spreading or reduce the intensity of fire in this area. Diligent maintenance of this area is vital
- DECKS: Decks are a common feature of suburban homes but unfortunately can be a vulnerable element that allows intense fire to spread quickly to a home. It is critical to keep areas underneath elevated decks clear of yard debris, firewood, and anything else that could ignite. Research has shown that fire can become very intense if the deck ignites and can easily spread toward the home. This also exposes the home not only to extreme heat, but also direct flame contact and burning embers from the deck itself. This area must also be vigilantly maintained for it to be effective.
- VENTS: Roof vents, gable vents, and crawl space vents are small but critical pieces of a home. During wildfires, wind-driven embers can easily enter a home though vents and ignite materials. A simple and cost-effective mitigation strategy is to ensure all vents have 1/8th inch or finer noncombustible (i.e. metal) mesh covering them. This will keep the larger, more energetic embers from entering. While maintenance is needed to keep vents clear of any debris, this is an easy but critical step in combating an ember storm

[1] [1] We note that NFPA defines the home ignition zone as the home itself and everything around it within 100 to 200 feet. NFPA has recently broken out the home ignition zone into sub-zones – the immediate zone is the five foot area; intermediate is 5-30 feet; extended zone is 30-100 feet (or more).

Figure 1: Comparison of Good (Green) and Bad (Red) House features to reduce Wildfire risk.



Source: IBHS

The wildfires of 2017–2018 across California were a stark reminder of what can happen when the ingredients for significant wildfires come together. There remains no better example of the damaging and deadly potential of wildfire than the Camp Fire of 2018. The 2017 and 2018 wildfires caused over $33 billion in losses and put damages on par with those from landfalling hurricanes and severe storms. IBHS analysed post-event data collected by CalFire from the fires of 2017-2018 to determine what factors are most critical to the damage level to the building. Looking at three important fires including Atlas, Thomas, and Tubbs, the five building and surrounding home features with the most relative importance were:

- Topography
- Vegetative clearance (i.e. defensible space)
- Roof material
- Siding material
- Vents / screens.

However, from these five factors, IBHS scientists found that only topography and defensible space were consistent predictors of home damage level. Other attributes of a home and its property varied in their level of importance from fire to fire. This suggests the need for a system of mitigation steps to be taken to protect a home.

And although defensible space was an important characteristic of homes that survived, well-maintained defensible space did not guarantee survivability in this fire. It was clear in some instances that rapid fire spread, under ideal conditions, defeated even well-maintained defensible space. Furthermore, some actions cannot be effectively applied in suburban communities because homes are closely spaced, or landscape designs have not historically considered the threat from wildfires.

In addition to steps property owners can take to protect their homes, actions at the neighborhood and community level can improve resilience for everyone. Because of the way wildfires spread, in some cases, a neighbor's actions or inactions could determine whether surrounding homes survive. In a closely spaced suburban environment, maintaining good defensible space must be a community-wide effort. Actions taken by neighbors are just as important as those taken by an individual property owner.

Homeowners associations (HOAs) also can play a large role in helping scale-up mitigation protections for individual homes. HOAs can develop and enforce architectural rules that are in alignment with the steps necessary to reduce the neighbourhood's vulnerability to fire, or less formally, provide forums for homeowners to share best practices. In addition, enforcement of maintenance practices is often easier at the small community scale. However, HOAs can also be a hindrance by restricting the use of building materials and landscaping that may be more fire resistant. Homeowners should be encouraged to share best-practices with their associations and explore serving on neighborhood boards. These actions at the community scale can also help reduce the need for firefighter intervention and allow these critical resources to be focused on containing a potential catastrophic wildfire.

National Fire Protection Association (NFPA) Firewise USA® Program

Initiatives such as NFPA's Firewise USA recognition program help strengthen the survivability of homes and neighbourhoods with hands-on efforts to reduce ignition risks and maintain buildings and landscapes with fire in mind. It is a voluntary program that provides a framework to help neighbours get organized, find direction, and act to increase the ignition resistance of their homes and community. The focus of this program is showing how we can stop the transition from the wildland fire to the W/UI fire and create ignition-resistant communities.

When individual homes ignite or a single wildland ignition occurs, local fire agencies' standard operating procedures (SOPs) are very effective. The success rate in containing these ignitions is routinely in the 98%-99% range. When ignitions occur in dense fuels (whether structural or vegetative) during periods of severe fire conditions, numerous homes may become involved. Rapidly spreading fire cannot be stopped and our suppression efforts are dramatically reduced. The world sees the resulting "wildland/urban fire disaster" on the evening news.

Standard fire suppression operations are largely ineffective against the most severe wildland fire behavior, driven by high winds and producing huge flames, along with intense heat and showering firebrands. The effectiveness of well-equipped fire departments is hampered to perform even the simplest task, like placing a hose stream on a flaming house. Often, during these situations fire fighters must "fall back" to implement their own necessary life safety procedures. Stopping the transition of a fire from natural fuels to built fuels (i.e. buildings) significantly reduces the likelihood of a disaster.

The Firewise USA® Recognition program is administered by the non-profit National Fire Protection Association (NFPA) and is co-sponsored by the USDA Forest Service, the U.S. Department of the Interior, and the National Association of State Foresters.

NFPA, as a non-profit that reaches out to consumers and the fire service, has partnered with the USDA Forest Service since 1986 on cooperative agreements to help reach the public with wildfire safety information and knowledge to reduce losses to life and property from wildfire. Firewise USA® was developed in acknowledgement that private residents often lacked knowledge about how to prepare homes and neighbourhoods to resist wildfire ignition, and that the fire service and government agencies could not require activity on private property. The program seeks to educate residents to help them realize their ownership of the risk and provides a path for them to take practical, science-based steps to reducing their individual and collective risk.

Started in 2002, the original pilot had 12 sites, 9 of which are still active. As of October 2020, there are 1782 active sites in 42 states. 55 percent of all participating sites are in the top 5 states of California, Colorado, Oregon, Washington, and Arizona. There are several steps to achieving national recognition:

- Completing a written wildfire risk assessment is the first step in becoming a nationally recognized Firewise USA® site. The community wildfire risk assessment is typically completed with the assistance of state forestry staff, local fire department, or a designated partner.
- Form a board/committee comprised of residents and other applicable wildfire stakeholders. This group will collaborate on developing the site's risk reduction priorities and they will develop a multiyear action plan based on the assessment, along with overseeing the completion of the annual renewal requirements. The board or committee can involve just homeowners or sometimes local fire staff
- Action plans are a prioritized list of risk reduction projects developed by the participant's board/ committee for their site. Plans include recommended home ignition zone projects, educational activities, and other stakeholder outreach efforts that the site will strive to complete annually or over multiple years.
- At a minimum, each site is required to invest the equivalent value of one volunteer hour per dwelling unit in risk reduction actions annually. A wide range of qualifying actions and expenditures (contractor costs, rental equipment, resident activities, grants, etc.) comprise the overall investment totals.
- Applicants begin the overall process by creating a site profile at: www.portal.firewise.org. The application is eligible for submission when the overall criteria is completed. State liaisons (assigned from state forestry agencies) approve applications with final processing completed by the National Fire Protection Association (NFPA).

The community wildfire risk assessment is an important step in the Firewise USA® recognition process. It is a tool to help residents and their community members understand their wildfire risk and engage them in risk reduction efforts.

The community wildfire risk assessment methodology that NFPA recommends speaks to the general conditions of the overall Firewise USA® site and does not provide details on each individual dwelling. The assessment should focus on:

- Vulnerability of homes to embers, surface fire, and crown fire
- Condition of the structures themselves
- Immediate hazards within the Home Ignition Zone on individual properties
- Concerns presented by common/open space areas or adjacent public lands

The assessment also considers factors that impact risk and influence fire behavior or structure ignitability:

- Structural characteristics (such as roofing, siding, and decks)
- Vegetation types
- Slope and aspect (direction a community faces - north, south, east, or west)
- Housing density

The recommendations provided by the completed assessment will be the board/committee's primary tool in determining action priorities within the site's boundaries, documented in their action plan. The Firewise USA® program requires assessments be updated at a minimum of every five years, and action plans be updated every three years.

Study Methodology

This study is a benefit-cost study based on notional risk assessments at sample communities in three states. The benefits of individual risk reduction are quantified using a catastrophe model which simulates millions of possible wildfire scenarios that could occur in the immediate future. The benefits are expressed as an average annual loss reduction. Costs associated with implementing one or more of the wildfire mitigation techniques in this study are referenced from published research studies. Finally, the benefit-cost ratio is developed by converting future loss reduction benefits into a present value and comparing them to mitigation costs.

This section describes the catastrophe model used in this study – the RMS North America Wildfire model - and the design of the study locations and mitigation scenarios investigated.

RMS North America Wildfire HD Model

Recent catastrophe events have highlighted the need across the (re)insurance industry for a new generation of quantification tools for wildfire risk. To that end, the RMS North America Wildfire HD Models have been developed to enable effective underwriting, portfolio management, and risk transfer use cases across the industry.

The four basic components of a catastrophe model are: hazard, exposure, vulnerability, and loss as depicted in Figure 2:

Figure 2: Basic Component of a Catastrophe Model.

Catastrophe models use synthetic events representing thousands of years of potential events to create analytics that can be used by the insurance industry. First, the model determines the risk of the hazard phenomenon, which in the case of a wildfire is characterized by heat, ember, and smoke hazard components. Next, the model characterizes the exposure by determining how many properties are at risk from the wildfire heat, ember, and smoke hazards.

The vulnerability module then quantifies the physical impact of the wildfire hazard phenomenon on the exposure at risk. Vulnerability is typically characterized as a mean damage ratio given a hazard level. Based on this measure of vulnerability, the financial loss to the property exposure is evaluated. Direct financial losses include the cost to repair and/or replace a structure, and also the anticipated increase in cost of material and workforce due to the demand surge in the aftermath of a major disaster.

The simulated losses for each event are then passed to a financial module which allocates loses to various parties in the risk transfer process – homeowners, insurers, and re-insurers (if applicable).

More specifically, the *RMS North America Wildfire Models* includes ground-up and temporal simulations of building-level losses per coverage and sub-peril, and includes:

- A simulation-based framework that enables millions of realizations of wildfire losses across thousands of simulated years
- A probabilistic approach to model the ignition and spread of wildfires, in addition to their associated ember and smoke footprints
- High-resolution geospatial data to resolve the high-gradient nature of the peril due to topography, fuel (type of vegetation), and weather parameter variations
- Multi-parameter vulnerability distributions to enable greater risk differentiation and reflect the behavior of wildfire claims in a realistic manner
- Flexible financial modeling to handle diverse temporal (hours clause) and spatial (distance clause) policy terms

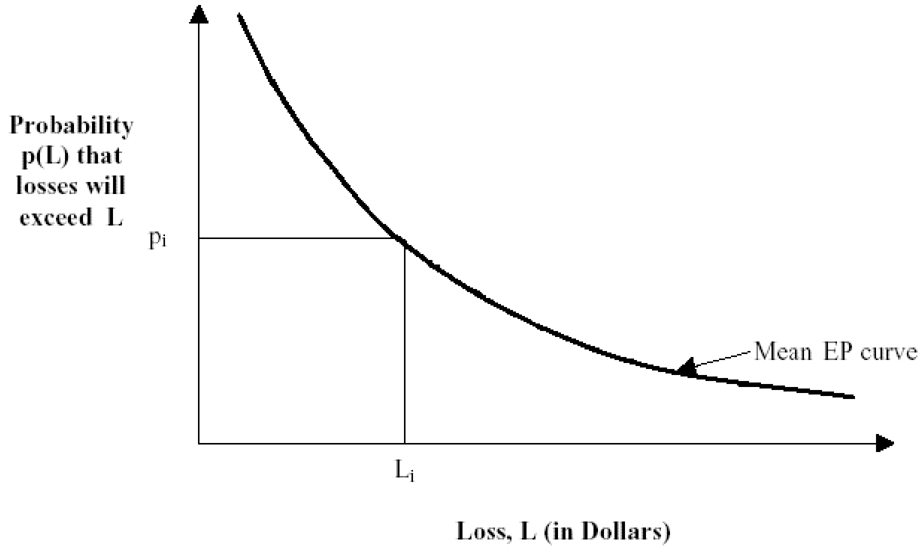
RMS derived the methodologies used in developing the wildfire model components in collaboration with researchers and experts in different areas of specialty including historical fire incidents datasets, fire occurrence modeling, fire spread, and damage mitigation. The model includes a comprehensive range of stochastic wildfire events, accounting for fire, ember, and smoke risk, over a wide geographic extent, at high resolution. The wildfire vulnerability module supports a comprehensive range of risk classes, which were calibrated using extensive claims data. In addition, the financial options enable users to explore sensitivity of loss results to various modeling assumptions.

Cat Model Ouptut: Exceedance Probability and Average Annual Loss

The stochastic event sent from the model can be sorted in such a way as to create an exceedance probability (EP) curve. This curve provides the probability of surpassing any loss level, expressing this probability in the form of a return period. Return periods are calculated by sorting the occurrence and yearly losses to create occurrence (OEP) and aggregate (AEP) curves, respectively. These curves are often used to look up key return period losses, such as 1 in 100 or 1 in 250, to help with solvency, rating agency evaluation, and reinsurance purchasing decisions.

For a given portfolio or structure at risk, an EP curve is a graphical representation of the probability p that a certain level of loss \$X will be surpassed. The x-axis measures the loss in dollars and the y-axis depicts the annual probability that losses will exceed a particular level. Figure 3 depicts a hypothetical mean EP curve where for a specific loss L_i, the likelihood that losses will exceed L_i is given by p_i.

Figure 3: Example of Mean Exceedance Probability Curve



(Source: Czajkowski et al., 2012)

The overall expected loss for the entire set of events, denoted as the average annual loss (AAL) is the sum of the expected losses of each of the individual events for a given year. The AAL is calculated by summing the product of each event loss and its corresponding frequency for all events in the stochastic set (here we model 50,000 events) for any specific location/building, account, or portfolio. It is graphically represented as the area underneath the EP curve.

Average Annual Loss (AAL), the averaging of all potential yearly losses into one average number, is one of the most frequently used outputs of the model. The AAL is calculated by summing the product of each event loss and its corresponding frequency for all events in the stochastic set for any specific location/building, account, or portfolio.

Risk reduction measures typically decrease the vulnerability and therefore reduce the expected loss. Graphically, mitigation shifts the EP curve down and to the left and therefore reduces the AAL value (i.e. decreases the area under the curve) as depicted in Figure 4.

Consequently, we express the benefits to mitigation in terms of average annual losses and loss cost – a normalized loss metric, which is defined as the average annual loss per $1000 of coverage (i.e., AAL / Total Insured Value x $1000).

For the three site locations in each state we first present the AAL from a neutral setting where there is no mitigation credit or penalty accounted for (to be describe below), and then represent the benefits to mitigation – structural and vegetation – as differences from this initial neutral AAL perspective.

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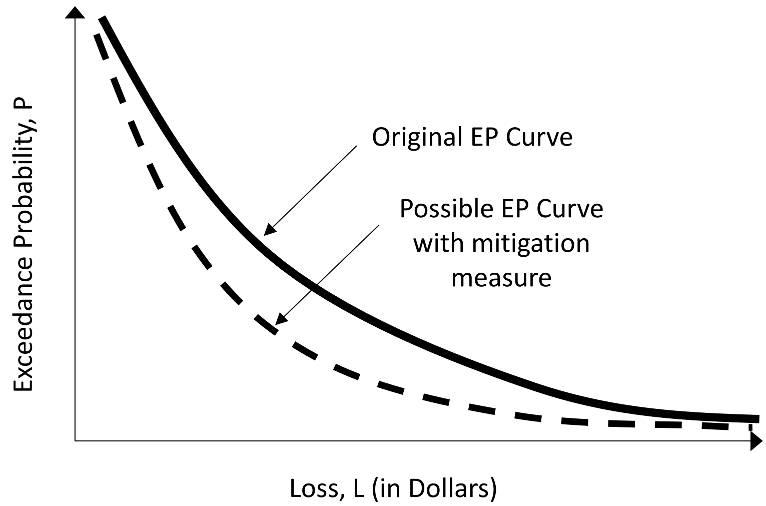
Figure 4: Exceedance Probability (EP) curve showing potential benefits of disaster risk reduction



Vulnerability and Structure Secondary Modifiers

As presented in the earlier section on wildfire mitigation best practices, recent work in the building science disciplines have shown that the factors most critical to the survivability of a structure include the site hazard parameters that affect localized hazard intensity as well as the various structural characteristics of the home such as roofing, siding, and decks. These wildfire mitigation aspects can be accounted for – their value and/or presence/lack of presence – in the RMS wildfire model hazard, exposure, and ultimately vulnerability components through exposure secondary modifier and site hazard data as we describe below.

The RMS North America Wildfire HD Models express damage to insured properties through vulnerability functions, also known as vulnerability curves or damage curves. Wildfire vulnerability functions consider the combined effect of probability of ignition to a structure when faced with radiant heat, flames, and embers, as well as the conditional damage once a structure is ignited. The model includes separate vulnerability functions for each hazard (i.e., direct flame and radiant heat, embers, and smoke). The model combines damage ratios for heat and ember to output the fire risk for every location. For analyses that include fire and smoke, the model combines damage from both sub-perils to determine the overall damage for each individual coverage (structure, contents, or business interruption).

An important aspect of modeling wildfire losses is recognizing that there is a possibility of structures surviving *within* the fire footprint as shown in Figure 5. Finding ways to increase the likelihood of survival is the whole point of adopting mitigation measures.

Figure 5: Example of Partially Damaged Structure following Wildfire

In the RMS North America Wildfire HD Models, damage curves for heat, ember and smoke represent the average vulnerability of a class of buildings for a specific combination of primary characteristics. The vulnerability of any individual building relative to others in that group depends on site-specific details as well as localized wildfire characteristics that can significantly alter the ignition probability as well as conditional damage. Users can model this variation in expected performance of individual buildings using secondary modifiers.

The North America Wildfire HD Models support 15 wildfire-specific secondary modifiers (Table 1) which affect loss estimates when the user specifies all the primary building characteristics (occupancy type, construction class, year built, and number of stories). Many of these modifiers (e.g., roof cover and roof shape) are commonly collected on homeowners policies and are used for risk assessment in other perils such as hurricane and hail. Others, such as slope setback and roof vents, may not be readily available at the point of underwriting but are commonly recorded during physical inspection of the property.

With heightened awareness of wildfire risk after recent catastrophe events and new research on roof materials, fire retardant gels, and suppression tactics, wildfire-resistant mitigation practices are now more commonplace. Thus, modeled secondary modifiers offer a convenient way to reflect location-level view of wildfire risk. We apply ten of these modifiers (described below) in our wildfire mitigation analysis.

Table 1: Mitigation Factors available in RMS Wildfire model.

Secondary Modifier	Description	Number of Options
Roof System Covering	▪ The flammability of roof cover is an important factor in structure ignitions. Users can specify either a roof cover material type, from which the model infers a typical flammability class or specify a fire rating class based on UL (Underwriter Laboratories) or FM (Factory Mutual Global) classifications	15
Roof Shape	▪ Roof Slope affects a building susceptibility to flames and radiant heat. It also affects the likelihood of embers to accumulate on the roof.	9
Roof Age or Condition	▪ Older roofs are more susceptible to ignition due to degradation of roof material and lower resistivity to heat and embers.	5
Roof Vents	▪ Roof vents allow embers and smoke to infiltrate the structure causing ignitions and, smoke damage. ▪ Wildfire resistive vents have been tested by research institutions such as IBHS and contain baffles impeding the direct flow of embers, or 1/8-inch diameter (or smaller) mesh screens, or both. ▪ Most exterior vents do not typically meet the “wildfire-resistant” classification. For example, large vents on the broad side of gabled roof structures are very vulnerable to ember attack. In addition, venting with no (or missing) louvers without the presence of screens are the most vulnerable.	6
Ember Accumulators	▪ Ember accumulators are areas on the building's roof and envelope that allow or encourage wind-borne embers to pile up and cause ignition of other combustible objects. These building features include inside corners, junctions between horizontal surfaces, and depressions such as stairwells.	4
Suppression	▪ Captures likelihood of localized suppression at the property based on specific measures that are either active (private fire protection) or passive (exterior sprinklers)	4
Sprinkler Presence	▪ Presence of interior sprinklers only can have some impact on reducing loss if the structure ignites. Note dedicated **exterior** sprinkler systems intended for wildfire applications are accounted for within the Suppression modifier.	3
Construction Quality	▪ Obvious signs of degradation can increase susceptibility to ember attacks.	3
Slope Setback	▪ Minimal (or no) setback includes homes built directly on slopes with sloped foundation or homes (and/or decks attached to structures) partially supported by elevated piers downslope. ▪ For homes built on slope or at top of slope, adequate structure set back is a minimum of 15 ft for single story and 30 ft for two-story; extended fuel modification (removing or modifying vegetation to minimize fire spread) on down-slope area approximately 150 ft from top of slope.	
Wall Cladding Type	▪ The flammability of wall cladding is an important factor in structure ignitions. ▪ Specify a wall cladding material type from which model infers a typical flammability class. Research demonstrates that the risk of structure ignitions from ember attack is substantially lower for siding that terminates at least a foot above ground.	13

Secondary Modifier	Description	Number of Options
Residential Appurtenant Structures	▪ Residential appurtenant structures refer to fences, carports, and screened enclosures that can readily ignite. ▪ When appurtenant structures are generally over 10 feet away from the main building, the model applies a credit.	16
Patio Deck	▪ Wooden deck patios on the exterior are a common source of structure ignitions from heat and embers during a wildfire.	5
Opening Heat Resistance	▪ Research shows that double pane glazing is more likely to resist radiant heat effects in a wildfire.	7
Accessibility Condition	▪ Ability of fire fighters to access the area within the vicinity of the structure can significantly affect the likelihood of structure survival in a wildfire. ▪ Communities that have implemented wildfire mitigation activities such as those suggest by NPFA Firewise USA® can be captured with an option in this secondary modifier.	5

Site Hazard Data – Fuel Type, Slope, Distance to Vegetation

The RMS North America Wildfire HD Models contains 72 million events each with a heat, ember, and a smoke footprint. Research has shown that local conditions in the immediate vicinity of a structure including fuel type, slope, and distance to vegetation are critical for estimating the likelihood of ignition during a wildfire from the combined effect of radiant heat, flames, and embers. In particular, the effect of heat footprints is highly dependent on these local conditions at a site.

The RMS wildfire model contains site hazard model-default values from the hazard lookup that users can override with location-level inputs on one or more of the landscape parameters to better reflect in-situ conditions. This is the primary mechanism for capturing the risk reduction associated with developing and maintaining a defensible space as described by IBHS above.

Users may provide local fuel type, slope, or distance to vegetation based on inspections done before or after binding a policy.

- Fuel Type - For instance, if there are changes in fuel landscape due to urbanization of land, clearing of a defensible space, or recently experienced wildfire, users can override the default fuel type to a value more representative of the current state of vegetation.
- Slope - In a similar vein, slope values in the geohazard layer reflect the average across a 50-m cell. However, the slope of terrain within a cell can vary, particularly at sites where properties are located, due to presence of hills or road cutbacks.
- Distance to Vegetation – this is how defensible space is captured in the model. Default distance to vegetation values are provided by RMS databases at a resolution of 50 m. These default values represent an average across a 50-m URG cell. As users collect high-fidelity data on defensible space around property risks, they can override model-default values with site-specific distance to

vegetation input, which can significantly impact the composite hazard index and resulting modeled losses.

The RMS model has 26 different fuel type classifications. For purposes of our analysis on 9 site locations in California, Oregon, and Colorado (to be described below), nine of these fuel type classifications are utilized in the wildfire model application as described in Table 2.

For this notional study, default values provided by the underlying hazard layer have been used although conditions within these communities may actually be different.

Table 2: Fuel Classes in RMS Wildfire Model used in study

RMS Ranked Fuel Value	Description
10	Grass – Short
20	Grass – Timber understory
40	Shrubs – Chaparral
50	Shrubs – Brush
60	Shrubs – Dominant brush, hardwood slash
80	Timber – Needle and leaf litter only
90	Timber – Hardwood litter and occasional dead-down material
100	Timber / Slash
101	Urban (non-burnable)

Study Locations

This study is a notional study of hypothetical risks spread throughout selected communities. In each state of California, Oregon, and Colorado we selected three site locations (i.e., community) that were relatively geographically proximate, but varied in their inherent wildfire risk being either high or medium wildfire risk. Furthermore, one of the three sites selected in each state is a current Firewise USA® site. In total, 1,161 locations were chosen across 9 communities as described in the following sections.

Within each community, the hypothetical homes are spread uniformly at 1 km intervals across the community, and a notional total insured value (TIV) appropriate to that community is assigned uniformly. Because the area of each community is different, the number of notional structures in each community is different, but the focus of this study is on the relative performance of homes under wildfire risk scenarios within each community. Note that comparisons between communities are possible through normalization of the data.

Total Insured Value for each structure is the sum of building value replacement cost, content value replacement cost, and one year of coverage for additional living expenses. These values are obtained from an RMS database on industry exposure and represent typical values as of 2018. Total Insured Value ranges from $325 thousand in Colorado City in Colorado to about $1.5 million in Cordillera, Colorado.

Every structure in this study is assigned the same set of primary characteristics which may or may not exist within the selected communities. Specifically, this study assumes the following:

- Construction class = wood frame.
- Occupancy = single-family residential.
- Number of stories = 1 story.
- Year of construction = year 2000; and
- Floor area = 2000 square feet.

California Communities

The three selected communities in California are provided in Table 3 and shown in Figure 6. These communities are all in Northern California as illustrated below (Figure 6) with Upper Deerwood being the Firewise community and Berry Creek and Oroville the non-Firewise communities which are close to the city of Paradise which was the location of 2018 Camp Fire.

As you can also see from the aerial view figures shown in Figure 7 to Figure 9, Upper Deerwood and Berry Creek are located in more wooded-type locations with Oroville more of a suburban location.

Across all three communities in California, there are a total of 284 structures included in our analysis – 67 in Upper Deerwood[2], 98 in Berry Creek, and 119 in Oroville. Notional Total Insured Values assumed for each community range from about $550 thousand to $790 thousand.

From the below table (Table 4) in terms of fuel type composition we see that Upper Deerwood has 66% of its structures in grass or shrubs, 25% in timber, and 9% urban fuel types. Berry Creek has 7% of its structures in grass or shrubs and 93% in timber fuel types. The Oroville suburb is a more urbanized development pattern with only 10% of its structures in grass or shrubs, 3% in timber, and 87% in urban fuel types.

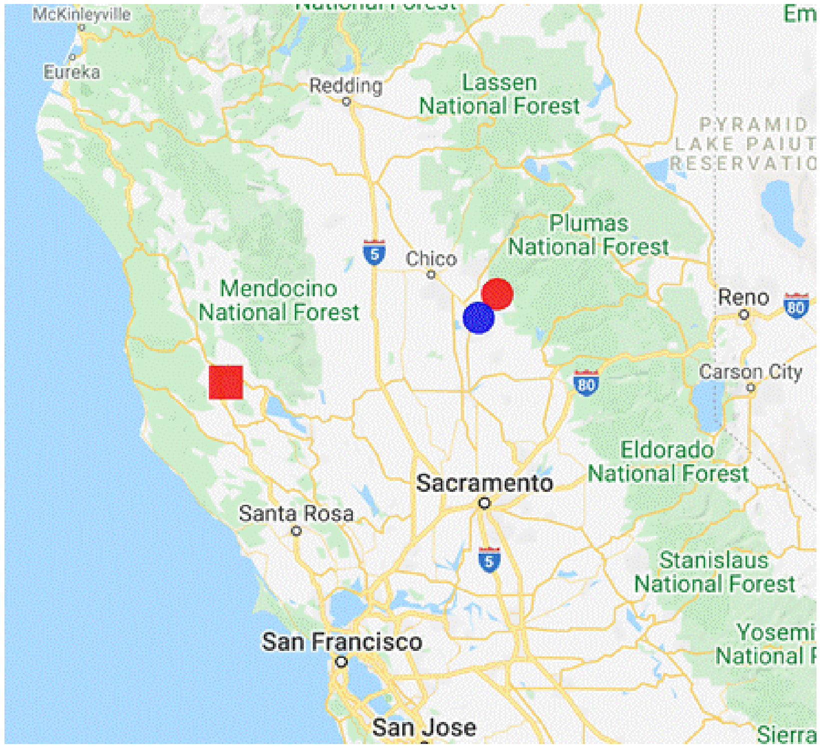
Only the urban locations in Upper Deerwood and Oroville have 160 feet or more of distance to the nearest vegetation, all others are assigned a distance to vegetation of 5 feet.

Table 3: California communities selected for study

Community Name	Latitude	Longitude	Number of Locations	Firewise	Risk	Notinoal Insured Value	Map
Upper Deerwood	39.18873	-123.17	67	Yes	High Risk	$789,573	Red Square
Berry Creek	39.63443	-121.405	98	No	High Risk	$558,650	Red Circle
Oroville	39.51285	-121.536	119	No	Medium Risk	$593,820	Blue Circle

[2] According to the 2019 Firewise Renewal Application there are 35 dwelling units in Upper Deerwood Site Location

Figure 6: Map of locations of California Communities in Study



(map source: https://mobisoftinfotech.com/tools/plot-multiple-points-on-map/)

Figure 7: Upper Deerwood sub-division community, aerial view

Figure 8: Berry Creek community, aerial view

Figure 9: Oroville sub-division community; aerial view

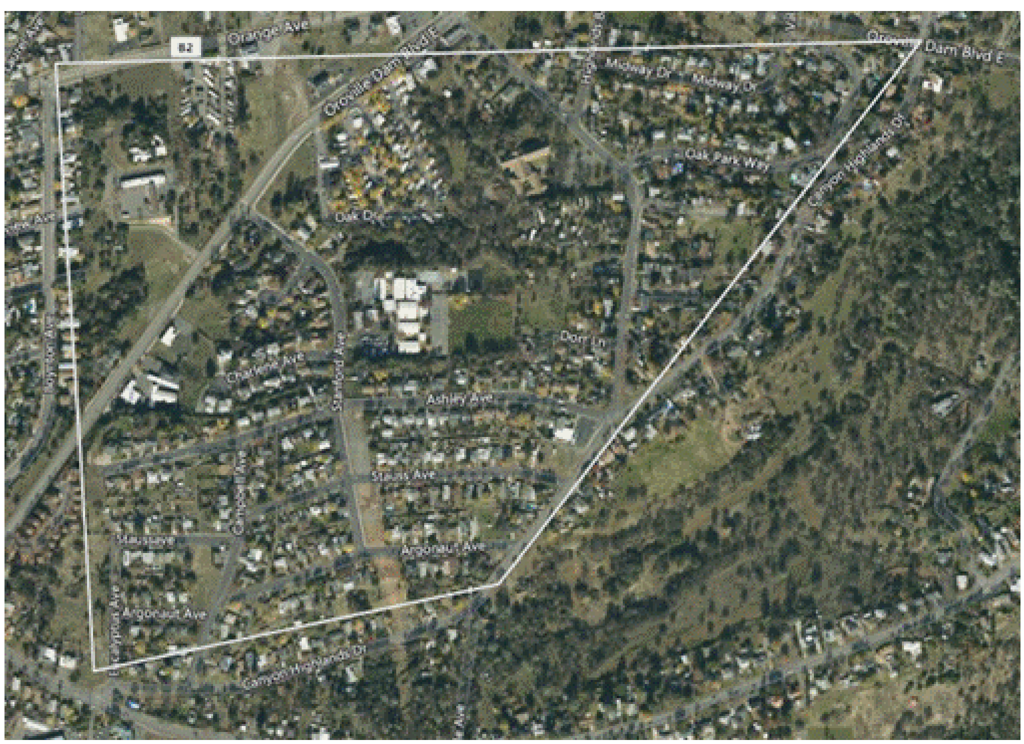


Table 4: Distribution of Fuel Types within Communities, California

Fuel Type		Upper Deerwood	Berry Creek	Oroville
10	Grass – Short	45%	-	1%
20	Grass – Timber understory	18%	5%	8%
40	Shrubs – Chaparral	-	1%	-
50	Shrubs – Brush	3%	-	1%
60	Shrubs – Dominant brush, hardwood slash	-	1%	-
80	Timber – Needle and leaf litter only	1%	10%	-
90	Timber – Hardwood litter and occasional dead-down material	18%	39%	3%
100	Timber / Slash	6%	44%	-
101	Urban (non-burnable)	9%	-	87%
	Total	**100%**	**100%**	**100%**

Oregon Communities

The three selected communities in Oregon are shown in Table 5 and shown in Figure 10. The Firewise community of Shadow Hills is located in the Southern Part of the state near to the Rogue River-Siskiyou National Forest, Brookings is in the Southwest corner of the state near to the California border, and Sweet Home being Southeast of Corvallis.

As you can see from the individual aerial view community maps (Figure 11, Figure 12, and Figure 13), Shadow Hills is in more wooded-type location, Brookings a mix of wooded and urban, and Sweet Home more of a suburban location.

Across all three communities in Oregon, there are a total of 309 structures included in our analysis – 157 in Shadow Hills[3], 79 in Brookings, and 73 in Sweet Home. Notional Total Insured Values assumed for each community range from about $380 thousand to $510 thousand.

In Table 6, in terms of fuel type composition we see that Shadow Hills has 34% of its structures in grass or shrubs, 60% in timber, and 6% urban fuel types. Brookings has 9% of its structures in shrubs, 23% in timber, and 68% in urban fuel types. Sweet Home has 4% of its structures in grass and 96% in urban fuel types.

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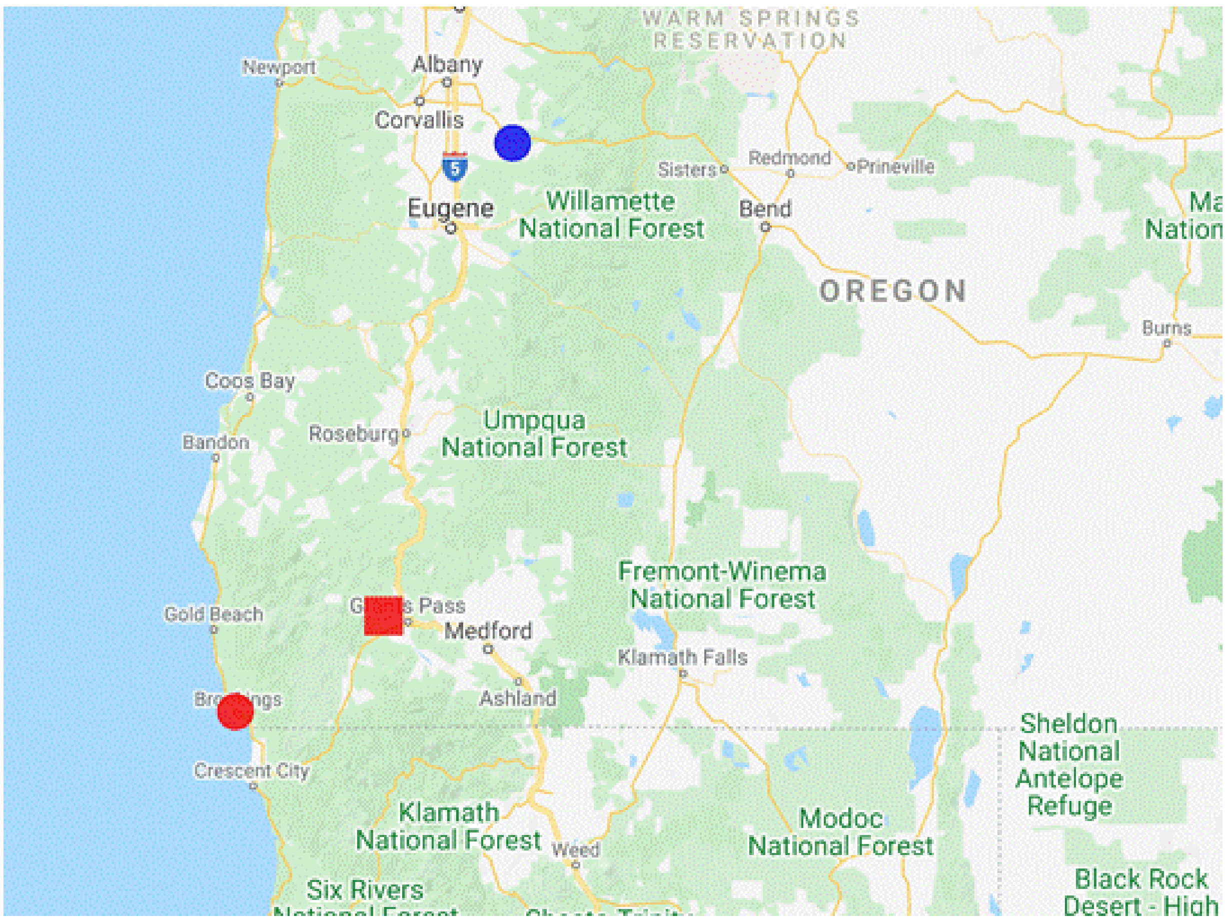
[3] From the Firewise Risk Assessment there are 12 dwelling units in their official Firewise community

Table 5: Oregon communities selected for study

Community Name	Latitude	Longitude	Number of Locations	Firewise	Risk	Notional Insured Value	Map
Shadow Hills	42.46689	-123.467	157	Yes	High Risk	$450,081	Red Square
Brookings	42.0633	-124.295	79	No	High Risk	$510,661	Red Circle
Sweet Home	44.39191	-122.738	73	No	Medium Risk	$378,665	Blue Circle

Figure 10: Map showing locations of Oregon communites in Study



(map source: https://mobisoftinfotech.com/tools/plot-multiple-points-on-map/)

Figure 11: Aerial view of Shadow Hills, Oregon

Figure 12: Aerial view of Brookings, Oregon

Figure 13: Aerial view of Sweet Home, Oregon

Table 6: Distribution of Fuel Type within Communities, Oregon

Fuel Type		Shadow Hills	Brookings	Sweet Home
10	Grass – Short	3%		3%
20	Grass – Timber understory	4%		1%
40	Shrubs – Chaparral			
50	Shrubs – Brush	28%	9%	
60	Shrubs – Dominant brush, hardwood slash			
80	Timber – Needle and leaf litter only	2%	8%	
90	Timber – Hardwood litter and occasional dead-down material	25%	15%	
100	Timber / Slash	32%		
101	Urban (non-burnable)	6%	68%	96%
	Total	**100%**	**100%**	**100%**

Colorado Communities

The three selected communities in Colorado are provided in Table 7 and shown in Figure 14. The Firewise community of Cordillera is in the White River National Forest West of Denver; Boulder Valley is West of Boulder in the Rocky Mountains; and Colorado City is Southwest of Pueblo in the Southern part of the state.

As you can also see from the aerial view maps in Figure 15 to Figure 17, Cordillera and Boulder Valley are in more wooded-type locations with Colorado City more of a suburban location.

Across all three communities in Colorado, there are a total of 568 structures included in our analysis – 341 in Cordillera[4], 85 in Boulder Valley, and 142 in Colorado City. Notional Total Insured Values assumed for each community range from about $325 thousand to $ 1.5 million.

In Table 8, in terms of fuel type composition we see that Cordillera has 64% of its structures in grass or shrubs, 31% in timber, and 5% urban fuel types. Boulder Valley has 28% of its structures in grass or shrubs and 72% in timber. Colorado City has 66% of its structures in grass and shrubs and 34% in urban fuel types.

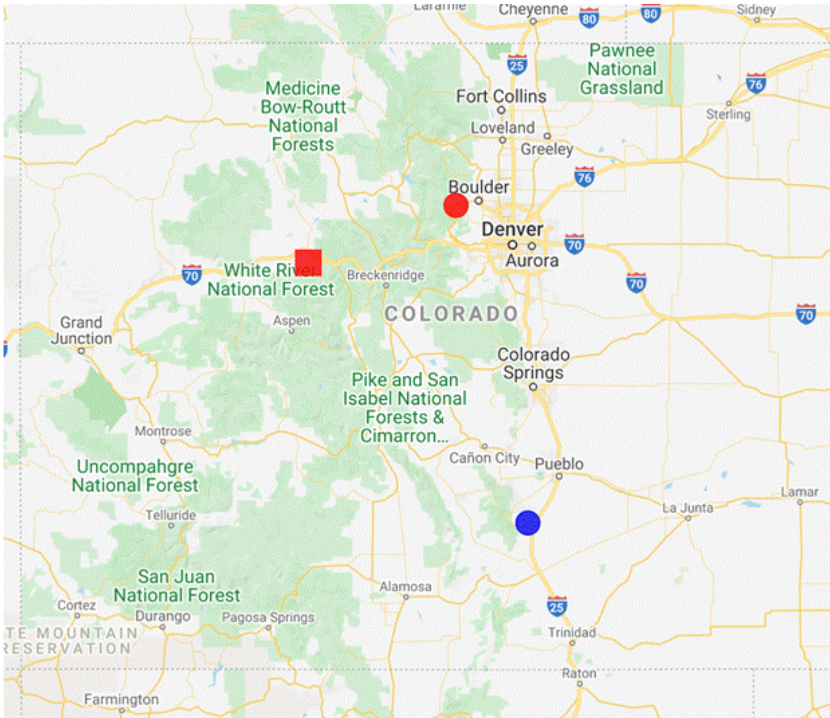
Only the urban locations in Cordillera and Colorado City have 160 feet of distance to the nearest vegetation, all others are assigned a distance of 5 feet.

Table 7: Colorado communites selected for study

Community_Name	Latitude	Longitude	Number of Locations	Firewise	Risk	Notional Insured Value	Map
Cordillera	39.62237	-106.674	341	Yes	High Risk	$ 1,489,947	Red Square
Boulder Valley	39.98445	-105.458	85	No	High Risk	$ 559,443	Red Circle
Colorado City	37.95177	-104.86	142	No	Medium Risk	$ 325,414	Blue Circle

[4] According to the 2019 Firewise application there are a total of 586 dwelling units in Cordillera.

Figure 14: Maps of locations of Colorado communities in study



(map source: https://mobisoftinfotech.com/tools/plot-multiple-points-on-map/)

Figure 15: Aerial view of Cordillera, CO community

Figure 16: Aerial view of Boulder Valley, CO community

Figure 17: Aerial View of Colorado City, CO community

Table 8: Distribution of Fuel Type within Communites, Colorado

Fuel Type		Cordillera	Boulder Valley	Colorado City
10	Grass – Short	49%		21%
20	Grass – Timber understory	5%	1%	8%
40	Shrubs – Chaparral			
50	Shrubs – Brush	6%	27%	27%
60	Shrubs – Dominant brush, hardwood slash	4%		9%
80	Timber – Needle and leaf litter only	15%	46%	
90	Timber – Hardwood litter and occasional dead-down material	12%	6%	
100	Timber / Slash	4%	20%	
101	Urban (non-burnable)	5%		35%
	Total	**100%**	**100%**	**100%**

Mitigation Scenarios

To assess the benefits to wildfire mitigation, we employ the RMS wildfire model on the 1,161 total structures that comprise our 9 site locations in California, Oregon, and Colorado.

For each structure in the selected site locations we perform five separate mitigation case runs of the model through site hazard and secondary modifier model selections that adjust the RMS vulnerability curves. We start with a neutral setting where all structural secondary modifiers are set to 0 = “unknown” such that there is no credit or penalty provided for the structural secondary modifier characteristics. Also, in the neutral setting the vegetation distance is taken as-is from the model-default distance to vegetation values which represent an average across a 50-m URG cell. As discussed in the location overview above, only the urban locations have distance to vegetation of 160 feet or more in this neutral setting, all other locations are determined to be at 5 feet.

Then two structural mitigation scenarios are applied, and then two additional vegetation management scenarios are applied so representative ranges of risk can be determined for the hypothetical community.

Structural Mitigation Scenarios

As described earlier, the RMS model includes several wildfire-specific secondary modifiers to capture the impact of additional building characteristics and mitigation measures on structure ignition and damage potential. As with other RMS peril models, the wildfire-specific secondary modifiers adjust the base heat, ember, and smoke vulnerability curves using credits and penalties for mean damage ratios. Through insights from detailed claims analyses and collaboration with research organizations such as the IBHS, RMS developed credit and penalty ranges for each modifier, which depend on specific building characteristics. Mean damage ration (MDR) credits and penalties in the model typically differ by occupancy group, construction class, number of stories, and hazard intensity. But as discussed above, we have normalized the primary characteristics of occupancy group, construction class, and number of stories for our analysis to allow for the MDR credits and penalties for the selected secondary modifiers to only vary by hazard intensity.

We perform two structural mitigation cases where we apply both structural maximum credits and structural maximum penalties by adjusting the associated secondary modifiers simultaneously for each structure. The options set for these secondary modifier adjustments are shown in Table 9 for each of the ten secondary modifiers discussed earlier that impact wildfire risk – roof system covering, roof shape, roof age, roof vents, ember accumulators, suppression, wall cladding, patio deck, opening heat resistance, and accessibility.

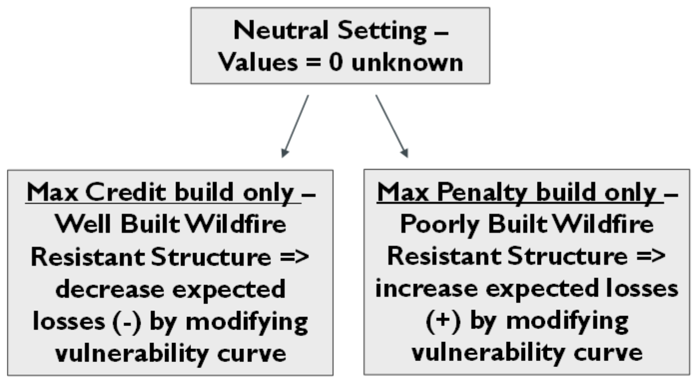
Table 9: Attributes used for the two Mitigation Cases

Variable	Max Credit Build Only	Max Penalty Build Only
Roof System Covering	2 - Metal sheathing with concealed fasteners	6 - Wood shakes
Roof Shape	2 - Flat roof without parapets	5 - Gable roof
Roof Age/Condition	1 – 0 to 5 years	4 - Obvious signs of deterioration and distress
Roof Vents	2 – None	5 - Wildfire Vulnerable Vents
Ember Accumulators	1 - None to few	3 – Abundant
Suppression	1 - Active Suppression	3 – None
Wall Cladding Type	9 – Stucco	3 –Wood
Patio Deck	1 - No deck present	2- Wood decking
Opening Heat Resistance	6 - All openings compliant with WUI code	1 - Single-pane windows and glass door
Accessibility	1 - Community designed or retrofit to be wildfire resistant / shelter-in-place	4 - Remote location with limited water supply and single access road

In essence, in comparison to a neutral structure we create a well-built wildfire resistant structure vs. a poorly constructed wildfire resistant structure as shown in Figure 18. For example, a well-built wildfire resistant structure has a flat metal roof that is less than 5 years of age, no ember accumulators, stucco walls, no wooden deck, openings that are WUI code compliant and is located in an active suppression community that is also designed or retrofitted to be wildfire resistant / shelter-in-place. Conversely, a poorly-constructed wildfire resistant structure has a gable shape wood shake roof that is quite aged and deteriorating, has wildfire vulnerable vents with abundant ember accumulators, wood cladding, wood decking, single-pane windows and is located non-active suppression community that is a remote location with limited water supply and a single access road.

Note, the accessibility secondary modifier is only applied to structures in our three Firewise communities. The well-built wildfire mitigation structure decreases expected losses and the poorly built wildfire structures increases expected losses.

Figure 18: Relationship of Structure Credit / Penalty Scenarios relative to Neutral Scenario

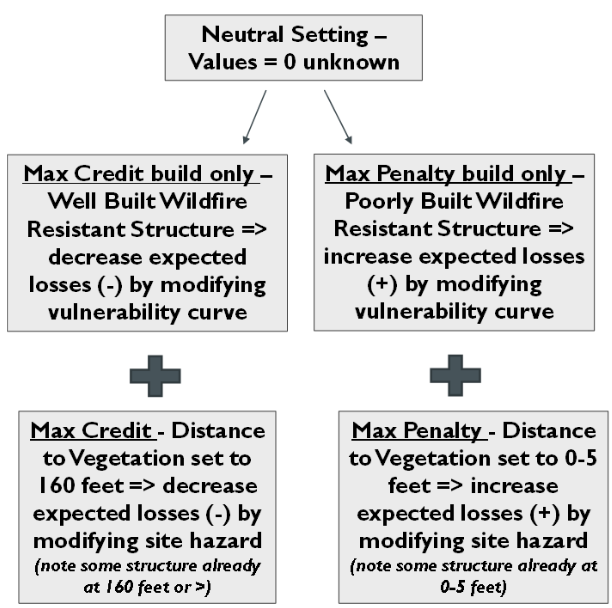


Vegetation Management Mitigation Scenarios

In addition to the structural credits and penalties, we also apply two vegetation mitigation cases where we apply both distance to vegetation maximum credits and distance to vegetation maximum penalties by adjusting the distance to vegetation data to 160 feet for the credit and 0 to 5 feet for the penalty respectively. For example, if from the neutral setting the vegetation distance is 0 to 5 feet representing an average across a 50-m cell that was collected for the structure and site, this is adjusted to 160 feet for the maximum credit. Likewise, if from the neutral setting the vegetation distance is 160 feet or greater representing an average across a 50-m cell, this is adjusted to 0 to 5 feet for the maximum penalty.

The vegetation credit scenario is only applied in addition to the structural credit, and the vegetation penalty is only applied in addition to the structural penalty as per Figure 19:.

Figure 19: Relationship of Structure Credit / Penalty Scenarios and Vegetation Mitigation relative to Neutral Scenario



Wildfire Mitigation Benefits

The following sections present the results of the catastrophe model simulations for the 5 mitigation scenarios described above. Commentary and analysis that put these results in context with prevailing insurance rates are presented by state and community.

California Community Mitigation Benefits

Comparison to Prevailing Insurance Premiums - California

For our three California communities of Upper Deerwood (67 structures), Berry Creek (98 structures), and Oroville (119 structures), the mean AAL across all structures in each community is $3,169, $637, and $35 respectively when all secondary modifiers have been set to the neutral setting. Therefore, on average, the wildfire risk in Upper Deerwood is 5 times greater than the wildfire risk in Berry Creek, and 90 times greater than the wildfire risk in Oroville.

As noted earlier, local conditions in the immediate vicinity of a structure including the fuel type are critical for estimating the likelihood of ignition during a wildfire. In Figure 20 we present the mean AAL by fuel type per community. In Upper Deerwood, AAL ranges from $1,971 for urban fuel type (9% of total structures) to $4,929 for timber/slash fuel type (6% of total structures). In Berry Creek, AAL ranges from $332 for grass-timber understory fuel type (5% of total structures) to $872 for timber/slash fuel type (44% of total structures). And finally, in Oroville AAL ranges from $18 for shrubs-brush fuel type (1% of total structures) to $47 for timber-hardwood litter fuel type (3% of total structures).

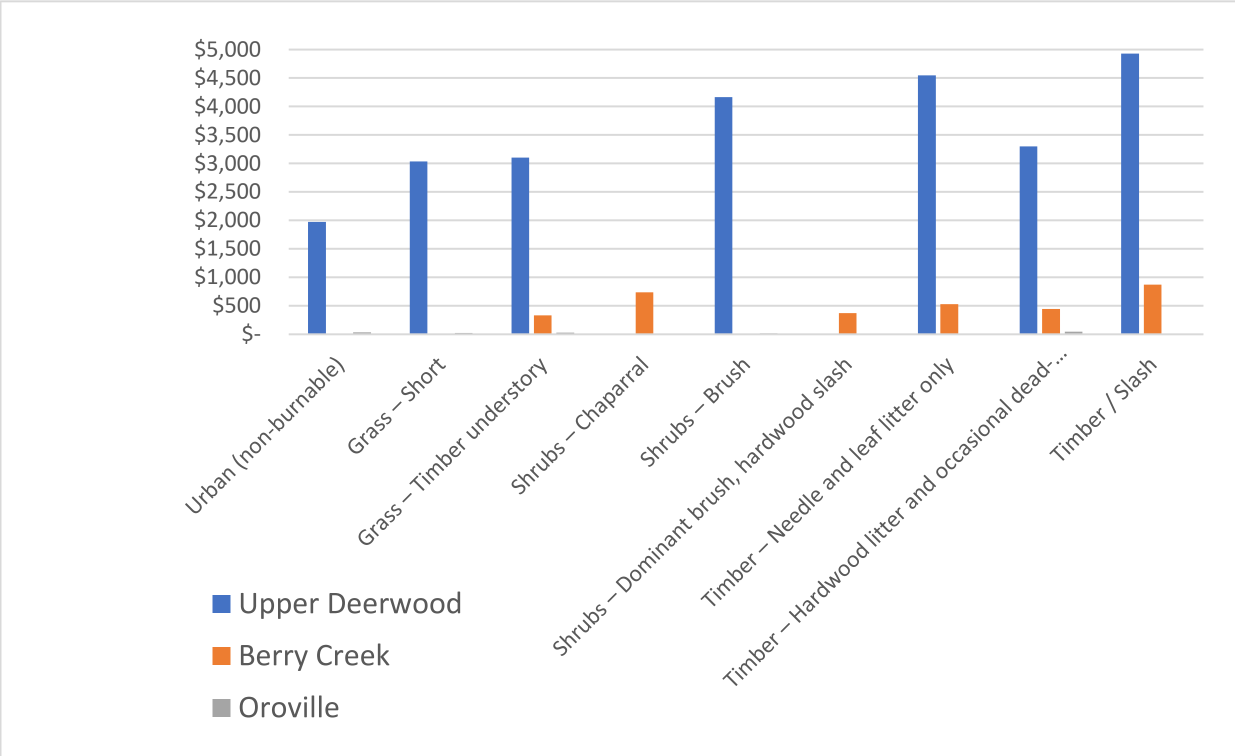
These determined AALs represent an unloaded premium for wildfire risk only. For relative comparison purposes, we pulled the California 2017 NAIC state-wide premium data in **Error! Reference source not found.**. In 2017, California HO-3 a verage premium values were $1,643 and California HO-5 average premium values were $2,595, both for exposure values $500,000 and over. These are the nearest NAIC premium values matching to our California communities modeled structure total insured value that ranges from $558,650 to $789,573.

Table 10: California Average Premium and Loss Cost for expsoure values $500,000 or more (NAIC 2017)

Policy Type	Average Premium	Loss Cost ($ / $1000)
HO-3	$1,643	$3.29
HO-5	$2,595	$5.19

Source (NAIC Premiums); Loss Cost = Premium / $500,000 * $1000

Figure 20: Average Annual Loss by Fuel Type for three communites in California



Thus, our determined wildfire AAL value per fuel type as a percentage of the California NAIC H0-3 state-wide average premium are: 120% to 300% in Upper Deerwood; 20% to 53% in Berry Creek; and 1% to 3% in Oroville. Of course, these NAIC premium values do account for more than just wildfire risk; they will cover other perils and also variable and fixed expenses. While it is unknown how much of the existing California 2017 premium accounts for wildfire risk, clearly our determined wildfire risk AAL represents a significant percentage of existing premiums in two of the three California communities.

For further comparative purposes we also collected 2017 and 2018 FAIR plan premiums and it is presented below. While we are able to collect FAIR plan premium data for comparative geographic areas utilizing zip codes, we are not able to collect it by the amount of coverage as is done with the NAIC data (e.g., $500,000 and over). From this information we see that FAIR plan premiums in our study areas – again not accounting for coverage amounts – are only greater than the NAIC state-wide data in Oroville ($1659 vs. $1643). Again, we can conclude that our determined wildfire risk AAL represents a significant percentage of existing FAIR plan premiums in two of the three California communities

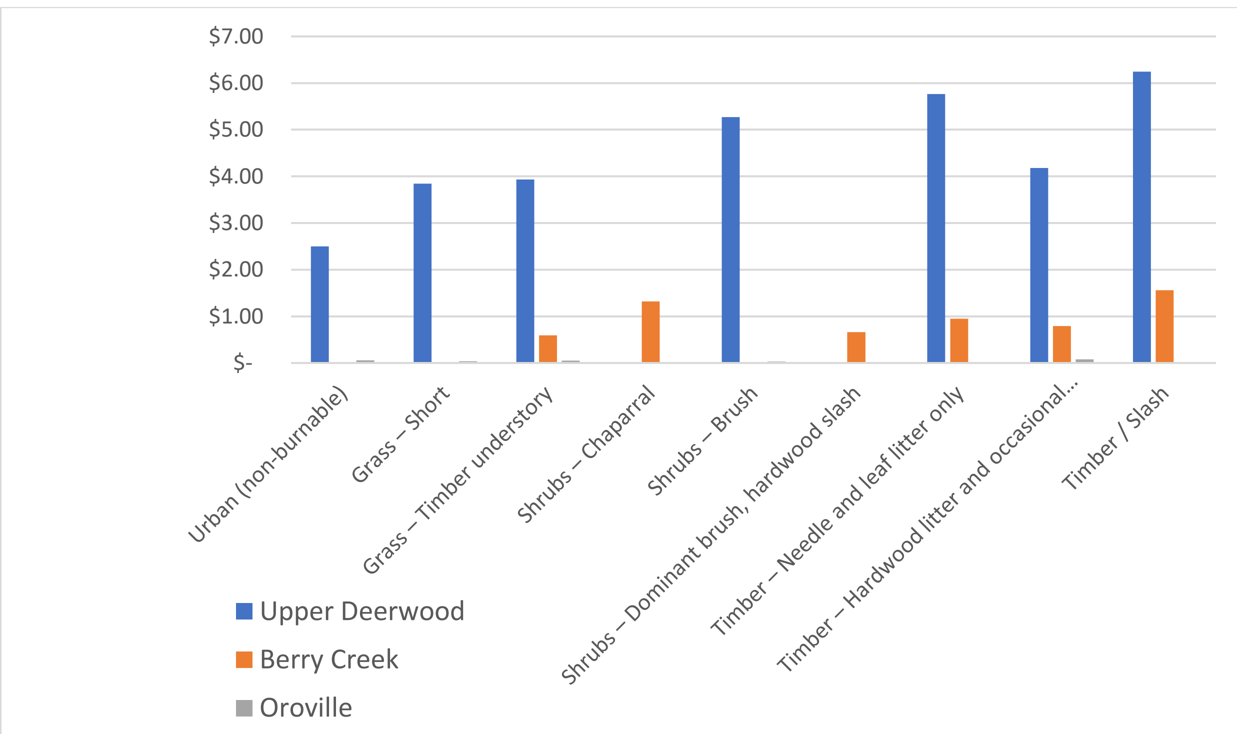
Table 11: Califonia FAIR Plan Average Premium for Selected Zip Codes

		Dwelling Fire - Owner-Occupied					
		2017			2018		
ZIP Code	City	Earned Premium	Earned Exposure	Average Premium	Earned Premium	Earned Exposure	Average Premium
95965	Oroville	$ 18,385	11	$ 1,659	$ 19,666	13	$ 1,573
95966	Oroville	$ 46,585	37	$ 1,253	$ 62,482	48	$ 1,295
	Oroville	$ 64,970	48	$ 1,347	$ 82,148	61	$ 1,352
95916	Berry Creek	$ 32,813	27	$ 1,204	$ 37,000	30	$ 1,223
95482	Ukiah	$ 21,573	16	$ 1,321	$ 33,546	26	$ 1,286

(Source: California Department of Insurance, personal communication)

All else being equal, AAL will be higher for larger TIV. To account for the TIV impact on our determined AAL we calculate the loss costs per $1000 of insurance coverage which is equal to the (AAL/TIV) * 1000. In Figure 21, we present the mean loss cost per $1000 of coverage by fuel type per community. In Upper Deerwood, loss costs per $1000 of coverage range from $2.50 for urban fuel type (9% of total structures) to $6.24 for timber/slash fuel type (6% of total structures). In Berry Creek, loss costs per $1000 of coverage range from $0.59 for grass-timber understory fuel type (5% of total structures) to $1.56 for timber/slash fuel type (44% of total structures). And in Oroville loss costs per $1000 of coverage range from $0.03 for shrubs-brush fuel type (1% of total structures) to $0.08 for timber-hardwood litter fuel type (3% of total structures).

Figure 21: Loss Cost per $1000 of Coverage (mean by number of structures)



Again, for relative comparison purposes, we determined a loss cost per $1000 of coverage from the California 2017 NAIC state-wide premium data (Table 10) . In 2017, California HO-3 loss costs per $1000 coverage were $3.29 and California HO-5 loss costs per $1000 coverage were $5.19, both for exposure values $500,000 and over.

Thus, our determined wildfire loss costs per $1000 of coverage values per fuel type as a percentage of the California NAIC H0-3 state-wide loss costs per $1000 of coverage are: 76% to 190% in Upper Deerwood; 18% to 48% in Berry Creek; and 0.9% to 2.4% in Oroville. While not as large a percentage as the AAL to premium values, again wildfire loss cost per $1000 coverage are still significant in two of the three California communities.

Normalizing associated with Loss Cost means that we can compare risks within and between the communities. In Figure 22 to Figure 24, the variation of the loss costs for each notional location are plotted with the same color ramp in the legend. These plots show that there are variations within the communities that are related to the nearby fuels, local topography, and distance to dense vegetation. These figures show that the level of risk in Oroville is an order of magnitude lower than the other high-risk communities, but the risk is not zero.

Potential for Extreme Wildfire Losses – California

The EP curve also provides the probability of surpassing any loss level, expressing this probability in the form of a return period. These metrics reveal the potential for very extreme events to wipe out entire communities like the situation in Coffey Park in 2017 or the Camp Fire in 2018. Average Annual Loss metrics can mask this potential because they weight the most extreme scenarios with extremely small likelihood of occurrence. Thus, it is useful to also examine the community EP curve to get a sense of how these ‘tail’ events contribute to the overall risk level.

Figure 22: Upper Deerwood sub-division community; Aerial view (left) and Loss Cost Map (Right)

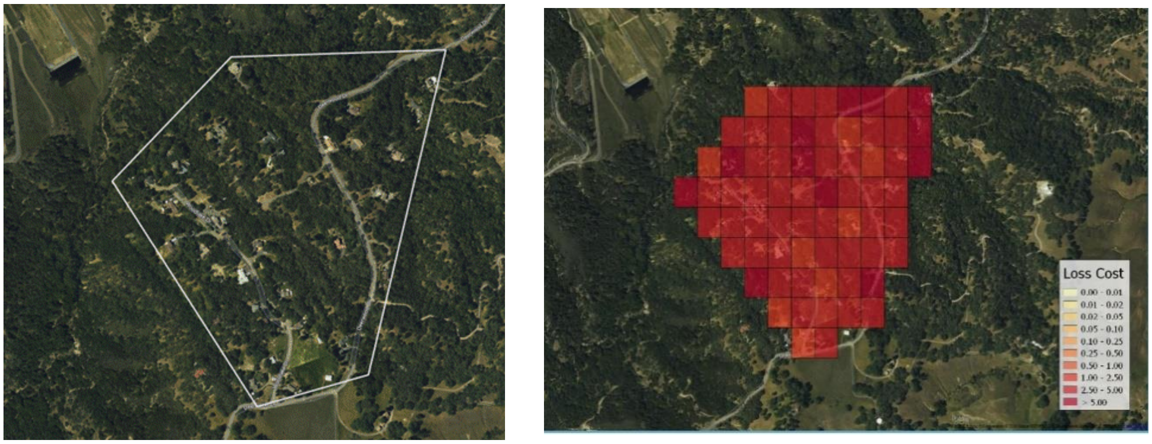


Figure 23: BerryCreek community; Aerial view (left) and Loss Cost Map (Right)

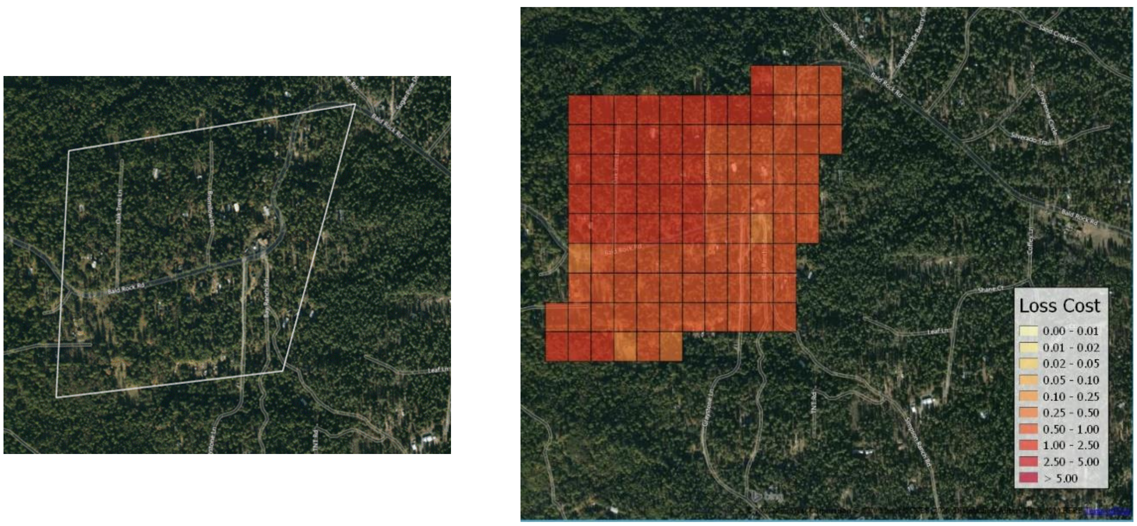
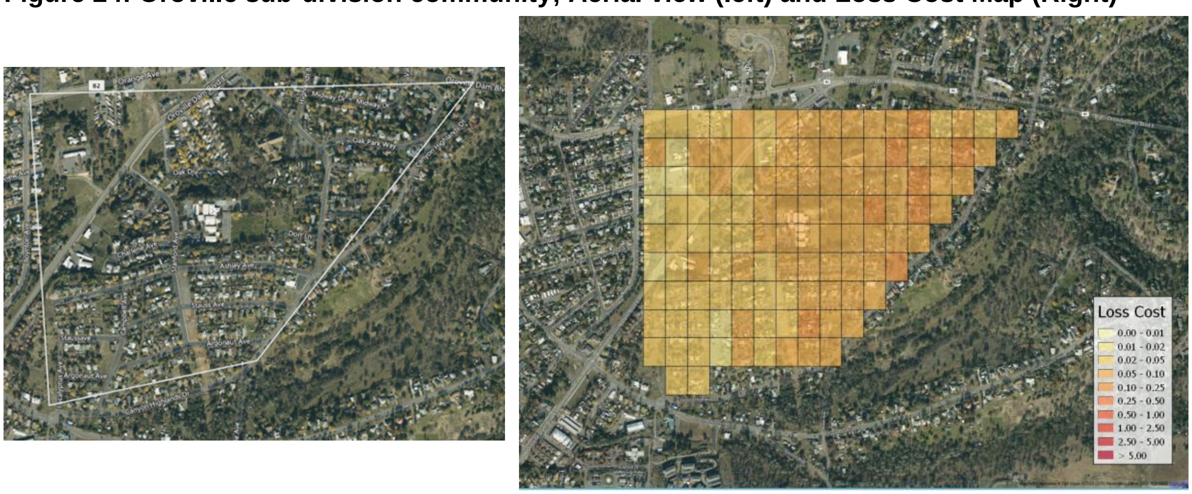


Figure 24: Oroville sub-division community; Aerial view (left) and Loss Cost Map (Right)



In the below table we present the various OEP return period (100, 250, 500, 1000 and 10,000 year) mean losses and losses per $1000 of coverage for each of the three California communities. We can see that the mean 1000 year return period loss in Upper Deerwood is approximately 63 percent of a total loss from the $789,573 TIV. Mean 1000 year return period losses are not as relatively high in Berry Creek and Oroville, but significant nonetheless at $119,808 and $1,626 respectively. Importantly, these tail return period losses highlight the potential significant impact of just one event occurring in a community, an aspect that is not as readily apparent from the AAL view of loss.

Table 12: Study Community Average Return Period (RP) Loss per structure and normalized Return Period Loss per $1000 coverage

Community / Return Period	Average RP Loss per Structure	Normalized RP Loss per $1000 Coverage
Upper Deerwood (FireWise)		
10,000 yr.	$666,777 of $790,000	844.48
1,000 yr.	$498,940	631.91
500 yr.	$424,667	537.84
250 yr.	$325,194	411.86
100 yr.	$86,242	109.23
Berry Creek		
10,000 yr.	$243,181 of $558,000	435.30
1,000 yr.	$119,808 of $558 k	214.46
500 yr.	$98,544	176.40
250 yr.	$72,431	129.65
100 yr.	$1,941	3.47
Oroville		
10,000 yr.	$57,537 of $593,000	96.89
1,000 yr.	$1,626 of $593 k	2.74
500 yr.	$921	1.55
250 yr.	$554	0.93
100 yr.	$245	0.41

Structural Mitigation Benefits - California

Given our neutral setting AAL results, we determine the structural maximum credit and the structural maximum penalty as differences from these values by adjusting the ten secondary modifiers (roof system covering, roof shape, roof age, roof vents, ember accumulators, suppression, wall cladding, patio deck, opening heat resistance, and accessibility) simultaneously for each structure in each community. The table below presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community.

Table 13: Credits and Penalties of the Structural Mitigation relative to Neutral Scenario for locations in various fuel classes.

Community / Fuel Type	STR Credit (%)	STR Penalty (%)	STR Credit ($)	STR Penalty ($)
Upper Deerwood (Firewise)				
Urban (non-burnable)	-37%	97%	-$720	$1,909
Grass – Short	-31%	81%	-$945	$2,457
Grass – Timber understory	-29%	78%	-$890	$2,411
Shrubs – Brush	-27%	72%	-$1,121	$3,015
Timber – Needle and leaf litter only	-18%	59%	-$822	$2,685
Timber – Hardwood litter and occasional dead-down material	-27%	73%	-$893	$2,398
Timber / Slash	-16%	50%	-$770	$2,454
Community Average	**-28%**	**76%**	**-$899**	**$2,409**
Berry Creek				
Grass – Timber understory	-37%	81%	-$121	$269
Shrubs – Chaparral	-39%	97%	-$287	$711
Shrubs – Dominant brush, hardwood slash	-38%	85%	-$139	$316
Timber – Needle and leaf litter only	-37%	95%	-$196	$505
Timber – Hardwood litter and occasional dead-down material	-38%	90%	-$168	$397
Timber / Slash	-33%	105%	-$289	$920

Community / Fuel Type	STR Credit (%)	STR Penalty (%)	STR Credit ($)	STR Penalty ($)
Community Average	**-35%**	**99%**	**-$222**	**$633**
Oroville				
Urban (non-burnable)	-15%	58%	-$5	$21
Grass – Short	-21%	62%	-$5	$13
Grass – Timber understory	-15%	58%	-$5	$18
Shrubs – Brush	-28%	92%	-$5	$16
Timber – Hardwood litter and occasional dead-down material	-12%	55%	-$6	$26
Community Average	**-15%**	**58%**	**-$5**	**$21**

Looking across all three communities we see that on average structural credits as a percentage difference from the neutral value AALs are significant ranging anywhere from 12 to 39 percent reductions in expected losses depending upon the fuel type. These percent differences are highest in Berry Creek (35% less on average), but certain fuel types in the other communities are comparable such as urban fuel types in Upper Deerwood (37% less on average) and shrubs-brush fuel types in Oroville (28% less on average).

Conversely, poorly built wildfire resistant structures suffer even more significant structural penalties as a percentage difference from the neutral value AALs. For example, Berry Creek penalties across all structure are 99 percent higher on average, whereas Upper Deerwood and Oroville are 76 percent and 58 percent higher on average, respectively. There is not one fuel type in any of our communities that does not incur at least a 50 percent penalty from the neutral value AALs when moving to a poorly built wildfire resistant structure.

Additionally, another way of thinking about these results is not just moving from an assumed CAT modeling neutral setting, but rather from a poorly built wildfire resistant structure to a well-built one. From this perspective, mean community AAL percent differences are 104 percent in Upper Deerwood, 134 percent in Berry Creek, and 73 percent in Oroville. Clearly, from an expected loss percentage reduction perspective substantial differences are achieved from this view for all three communities.

However, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In the below figure (Figure 25) we present the mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented in Table 13).

Figure 25: Mean Average Annual Loss Difference from Neutral case ($) by Community, California

Not surprisingly, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures happen where the wildfire risk is greatest in Upper Deerwood. Here, expected losses are on average $899 less from the neutral setting for well-built wildfire resistant structures. Conversely, poorly built wildfire structures in Upper Deerwood have mean AAL increases that are on average $2409 higher than the neutral setting. In total, moving from a poorly built wildfire resistant structure to a well-built one in Upper Deerwood saves on average $3307 annually in wildfire expected losses.

While AAL percent differences in Berry Creek were the largest for all three California communities, expected losses are on average $222 less from the neutral setting and AAL increases $633 more on average as compared to a neutral setting. Overall, moving from a poorly built wildfire resistant structure to a well-built one in Berry Creek saves on average $856 annually in wildfire expected losses. Given the relatively low neutral setting determined AAL in Oroville ($35), moving from a poorly built wildfire resistant structure to a well-built one in Oroville only saves on average $26 annually in wildfire expected losses.

Structural plus Vegetation Mitigation Benefits – California

In addition to the structural credits and penalties only, we also apply two distance to vegetation mitigation cases where we apply both distance to vegetation maximum credits (160 feet of defensible space) and distance to vegetation maximum penalties (less than 5 feet of defensible space). As described earlier, the vegetation credit is only applied in addition to the structural credit, and the vegetation penalty is only applied in addition to the structural penalty. The table below, Table 14, presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community. Note that in the table, “Veg Credit” values are the combined mitigation loss reductions of a well-built wildfire resistant structure with the additional distance to vegetation mitigation. And similarly, the “Veg Penalty” values are the combined mitigation penalties of a poorly built wildfire resistant structure with the additional distance to vegetation penalty applied. “STR Credits” and “STR Penalty” values are as they were in the Table 13 above.

Table 14: Credits and Penalties of the Structural and Vegetation Mitigation relative to Neutral Scenario for locations in various fuel classes.

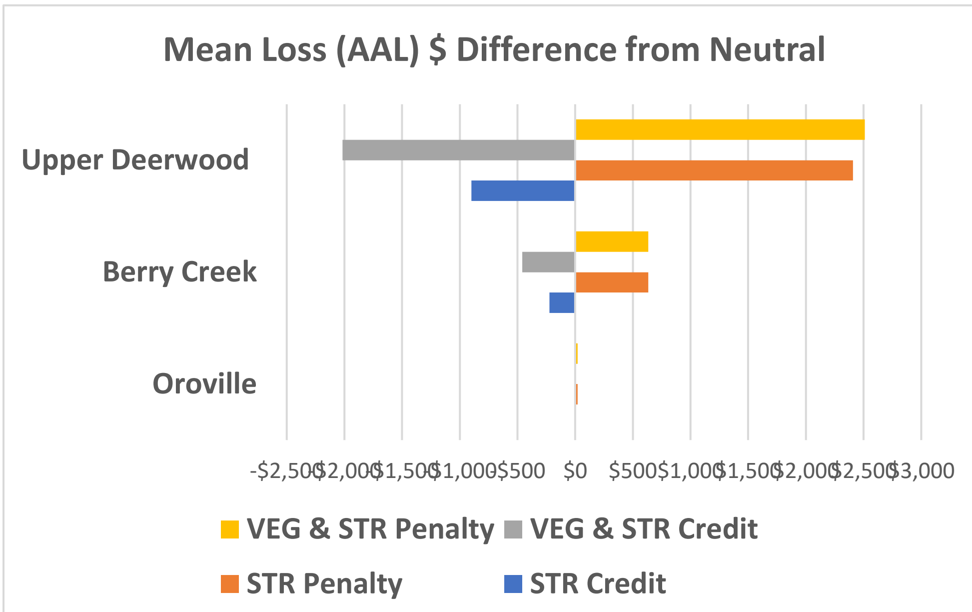
	VEG Credit	STR Credit	STR Penalty	VEG Penalty	VEG Credit	STR Credit	STR Penalty	VEG Penalty
Urban (non-burnable)	-39%	-37%	97%	155%	-$760	-$720	$1,909	$3,056
Grass – Short	-65%	-31%	81%	81%	-$1,973	-$945	$2,457	$2,457
Grass – Timber understory	-64%	-29%	78%	78%	-$1,989	-$890	$2,411	$2,411
Shrubs – Brush	-69%	-27%	72%	72%	-$2,884	-$1,121	$3,015	$3,015
Timber – Needle and leaf litter only	-76%	-18%	59%	59%	-$3,457	-$822	$2,685	$2,685
Timber – Hardwood litter and occasional dead-d	-65%	-27%	73%	73%	-$2,151	-$893	$2,398	$2,398
Timber / Slash	-64%	-16%	50%	50%	-$3,134	-$770	$2,454	$2,454
Upper Deerwood	**-64%**	**-28%**	**76%**	**79%**	**-$2,018**	**-$899**	**$2,409**	**$2,511**
Grass – Timber understory	-52%	-37%	81%	81%	-$173	-$121	$269	$269
Shrubs – Chaparral	-72%	-39%	97%	97%	-$533	-$287	$711	$711
Shrubs – Dominant brush, hardwood slash	-54%	-38%	85%	85%	-$200	-$139	$316	$316
Timber – Needle and leaf litter only	-68%	-37%	95%	95%	-$362	-$196	$505	$505
Timber – Hardwood litter and occasional dead-d	-62%	-38%	90%	90%	-$274	-$168	$397	$397
Timber / Slash	-78%	-33%	105%	105%	-$684	-$289	$920	$920
Berry Creek	**-72%**	**-35%**	**99%**	**99%**	**-$459**	**-$222**	**$633**	**$633**
Urban (non-burnable)	-15%	-15%	58%	62%	-$5	-$5	$21	$22
Grass – Short	-21%	-21%	62%	62%	-$5	-$5	$13	$13
Grass – Timber understory	-15%	-15%	58%	58%	-$5	-$5	$18	$18
Shrubs – Brush	-28%	-28%	92%	92%	-$5	-$5	$16	$16
Timber – Hardwood litter and occasional dead-d	-12%	-12%	55%	55%	-$6	-$6	$26	$26
Oroville	**-15%**	**-15%**	**58%**	**62%**	**-$5**	**-$5**	**$21**	**$22**

From these results we can ascertain the marginal value provided by the vegetation-based mitigation (i.e., building a defensible space around one’s home) in addition to the structural mitigation efforts that have already been afforded to the structure. In Upper Deerwood, the overall combined vegetation and structural percentage AAL reduction is 64 percent, with vegetation mitigation providing an additional 35 percent in mitigation benefits on average at the margin. In Berry Creek, the overall combined vegetation and structural percentage AAL reduction is 72 percent, with vegetation mitigation providing an additional 37 percent in mitigation benefits on average at the margin. However, in Oroville we determine no additional benefit on average in this community since the baseline distance to nearest vegetation is already at 160 feet or more for most homes given that 87 percent of the structures in our analysis are of an urban fuel type.

We can also examine the marginal impact of a vegetation penalty in addition to the structural penalties already in place. In this scenario, our AAL results show that an additional vegetation penalty makes little difference to expected losses. Only in Upper Deerwood was any additional impact determined moving from a 76 percent penalty on average for the poorly built wildfire resistant structure only to 79 percent with the additional poorly maintained distance to vegetation.

Again, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In the below figure (Figure 26) we present the structural and vegetation mitigation mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented in Table 14).

Figure 26: Mean Average Annual Loss Difference for Structural and Vegetation Credit/Penalty Scenarios



Not surprisingly again, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures with defensible space happen where the wildfire risk is greatest in Upper Deerwood. Here expected losses are on average $2018 less from the neutral setting with the additional vegetation mitigation representing $1119 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Upper Deerwood have mean AAL increases that are on average $2511 higher than the neutral setting with the vegetation penalty representing only $103 of this amount. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Upper Deerwood saves on average $4529 annually in wildfire expected losses.

In Berry Creek expected losses are on average $459 less from the neutral setting with the additional vegetation mitigation representing $237 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Berry Creek have mean AAL increases that are on average $633 higher than the neutral setting with the vegetation penalty not increasing this total amount. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Berry Creek saves on average $1092 annually in wildfire expected losses.

In Oroville, there is no meaningful difference in the vegetation mitigation results as compared to the structural only results.

Oregon Community Mitigation Benefits

Comparison to Prevailing Insurance Premiums - Oregon

For our 3 Oregon communities of Shadow Hills (157 structures), Brookings (79 structures), and Sweet Home (73 structures), mean AAL across all structures in each community is $310, $1,638, and $1 respectively when all secondary modifiers have been set to the neutral setting. Therefore, on average the wildfire risk in Brookings is 5 times greater than the wildfire risk in Shadow Hills, and 1,638 times greater than the wildfire risk in Sweet Home.

As noted earlier, local conditions in the immediate vicinity of a structure including the fuel type are critical for estimating the likelihood of ignition during a wildfire. In Figure 27 we present the mean AAL by fuel type per community (given the almost non-existent AAL in Sweet Home we only present data for Shadow Hills and Brookings). In Shadow Hills, AAL ranges from $102 for urban fuel type (6% of total structures) to $342 for timber/slash fuel type (33% of total structures). In Brookings, AAL ranges from $1,550 for urban fuel type (68% of total structures) to $2,173 for timber-hardwood litter fuel type (15% of total structures).

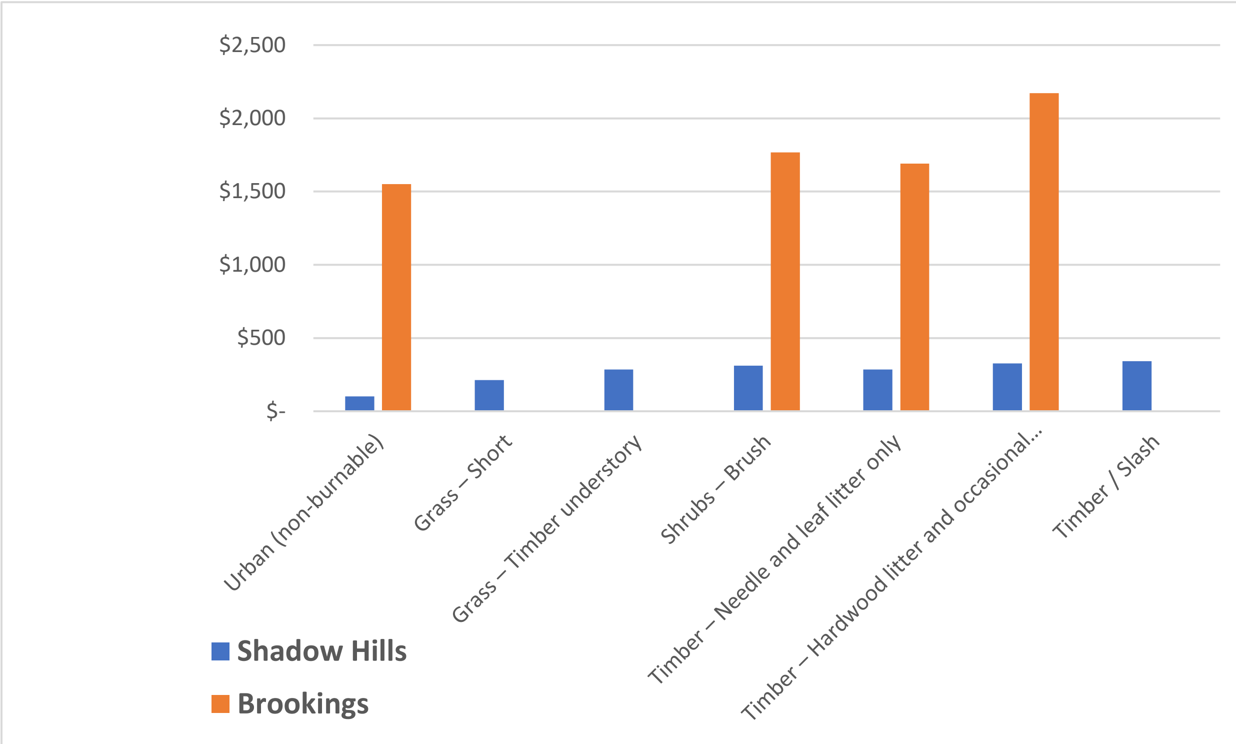
These determined AALs represent an unloaded premium for wildfire risk only. For relative comparison purposes, we pulled the Oregon 2017 NAIC state-wide premium data in Table 15Table 1. In 2017, Oregon HO-3 average premium values were $883 and Oregon HO-5 average premium values were $934, both for exposure values from $400,000 to $499,999. These are the nearest NAIC premium values matching to our Oregon communities modeled structure total insured value that ranges from $378,665 to $510,661.

Table 15: Oregon Average Premium and Loss Cost for expsoure values $400,000 to $499,000 (NAIC 2017)

Policy Type	Average Premium	Loss Cost ($ / $1000)
HO-3	$883	$1.96
HO-5	$934	$2.08

Source (NAIC Premiums); Loss Cost = Premium / $450,000 * $1000

Figure 27: Average Annual Loss by Fuel Type for each Community

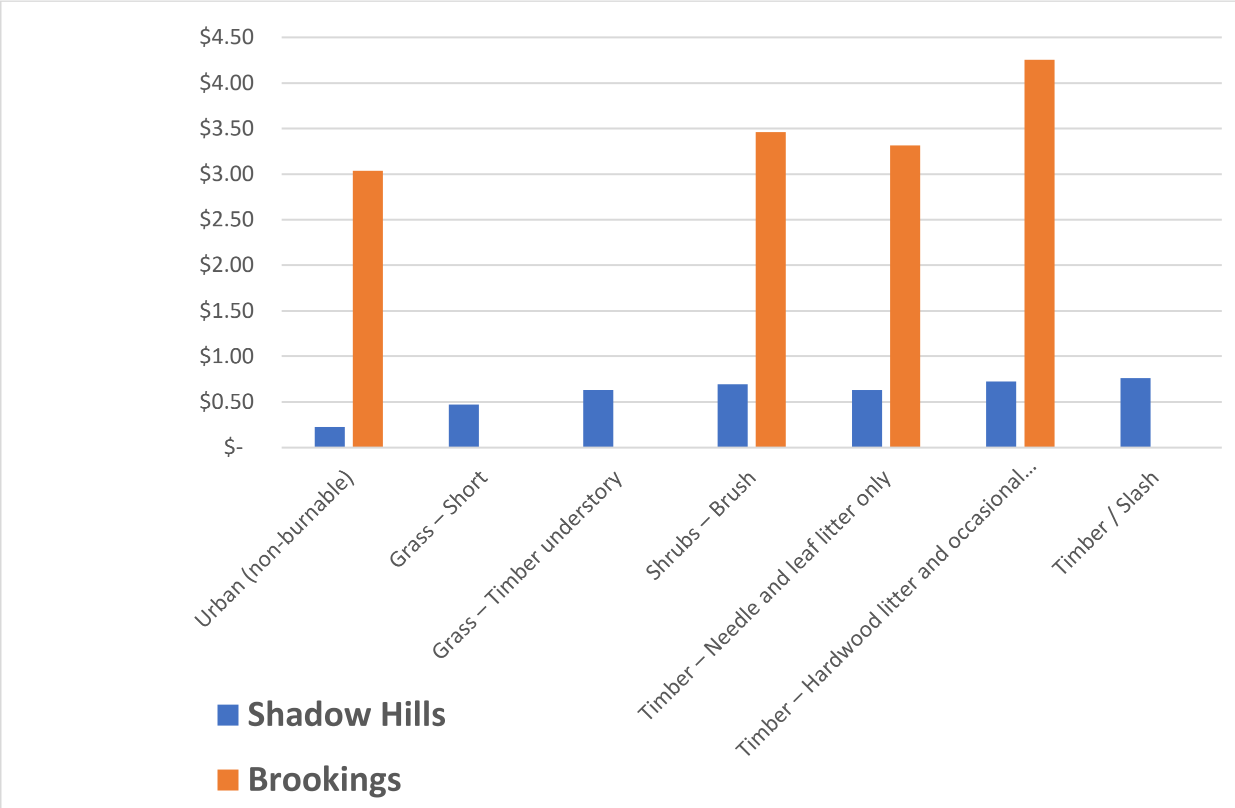


Thus, our determined wildfire AAL value per fuel type as a percentage of the Oregon NAIC H0-3 state-wide average premium are: 12% to 39% in Shadow Hills; and 176% to 246% in Brookings. Of course, these NAIC premium values do account for more than just wildfire risk. While it is unknown how much of the existing Oregon 2017 premium accounts for wildfire risk, clearly our determined wildfire risk AAL represents a significant percentage of existing premiums in two of the three Oregon communities.

All else being equal, AAL will be higher the larger is the TIV. To account for the TIV impact on our determined AAL we calculate the loss costs per $1000 of insurance coverage which is equal to the (AAL/TIV) * 1000. In Figure 28 we present the mean loss cost per $1000 of coverage by fuel type per community. In Shadow Hills, loss costs per $1000 of coverage range from $0.23 for urban fuel type (6% of total structures) to $0.76 for timber/slash fuel type (33% of total structures). In Brookings, loss costs per $1000 of coverage range from $3.04 for urban fuel type (68% of total structures) to $4.25 for timber-hardwood litter fuel type (15% of total structures).

Again, for relative comparison purposes, we determined a loss cost per $1000 of coverage from the Oregon 2017 NAIC state-wide premium data (Table 15). In 2017, Oregon HO-3 loss costs per $1000 coverage were $1.96 and Oregon HO-5 loss costs per $1000 coverage were $2.08, both for exposure values from $400,000 to $499,999.

Figure 28: Loss Cost per $1000 of Coverage for various Fuel Types for each Community



Thus, our determined wildfire loss costs per $1000 of coverage values per fuel type as a percentage of the Oregon NAIC H0-3 state-wide loss costs per $1000 of coverage are: 12% to 39% in Shadow Hills; and 155% to 217% in Brookings. While not as large a percentage as the AAL to premium values, again wildfire loss cost per $1000 coverage are still significant in two of the three Oregon communities

Normalizing associated with Loss Cost means that we can compare risks within and between the communities. In Figure 29 to Figure 31, the variation of the loss costs for each notional location are plotted with the same color ramp in the legend. These plots show that there are variations within the communities that are related to the nearby fuels, local topography, and distance to dense vegetation. These figures show that the level of risk in Sweet Home is extremely low, but the risk is not zero.

Potential for Extreme Wildfire Losses - Oregon

The EP curve also provides the probability of surpassing any loss level, expressing this probability in the form of a return period. Return periods are calculated by sorting the occurrence and yearly losses to create occurrence (OEP) and aggregate (AEP) curves, respectively. These curves are often used to look up key return period losses, such as 1 in 100 or 1 in 250, to help with solvency, rating agency evaluation, and reinsurance purchasing decisions. They can also be used to understand the tail risks of the loss distribution.

Figure 29: Shawdow Hills sub-division; Aerial view (left) and Loss Cost Map (Right)

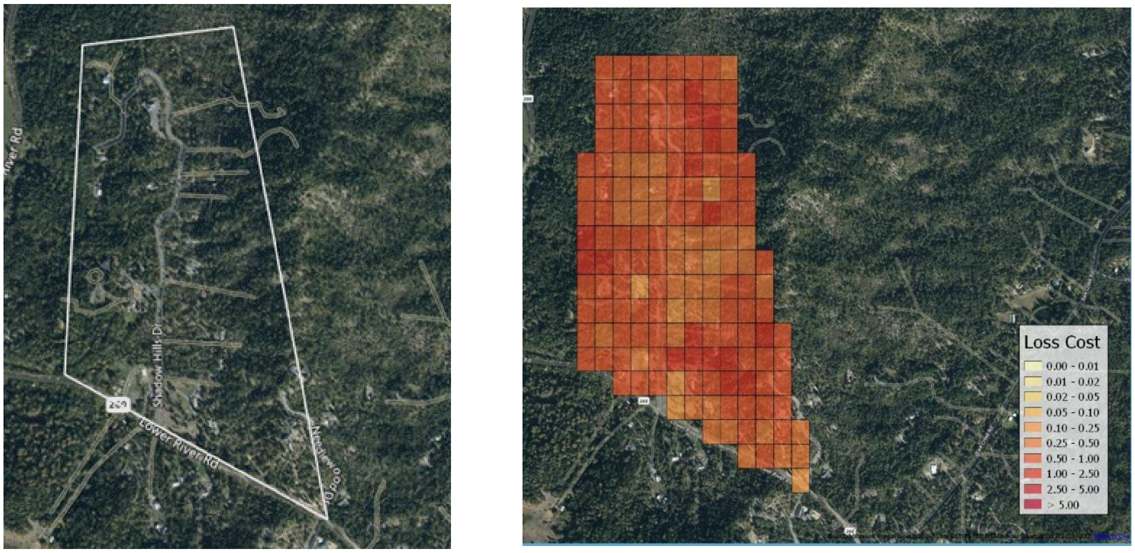


Figure 30: Brookings sub-division community; Aerial view (left) and Loss Cost Map (Right)

Figure 31: Sweet Home sub-division; Aerial view (left) and Loss Cost Map (Right)

In the below table we present the various OEP return period (100, 250, 500, 1000, and 10,000 year) mean losses and losses per $1000 of coverage for each of the three Oregon communities. We can see that the mean 1000 year return period loss in Brookings is approximately 61 percent loss from the $510,661 TIV. The mean 1000 year return period loss is not as relatively high in Shadow Hills, but significant nonetheless at $103,091. A 1000 year return period event in Sweet Home registers a loss of $208. Importantly, these tail return period losses highlight the potential significant impact of just one event occurring in a community, an aspect that is not as readily apparent from the AAL view of loss.

Table 16: Study Community Average Return Period (RP) Loss per structure and normalized Return Period Loss per $1000 coverage

Community / Return Period	Average RP Loss per Structure	Normalized RP Loss per $1000 Coverage
Shadow Hills (FireWise)		
10,000 yr.	$173,414 of $450,000	385.30
1000 yr.	$103,091	229.05
500 yr.	$68,152	151.42
250 yr.	$10,248	22.77
100 yr.	$684	1.52
Brookings		
10,000 yr.	$390,584 of $511,000	763.78
1000 yr.	$312,522	611.13
500 yr.	$269,296	526.60
250 yr.	$193,551	378.48
100 yr.	$15,945	31.18
Sweet Home		
10,000 yr.	$797 of $378,000	2.11
1,000 yr.	$208	0.55
500 yr.	$102	0.27
250 yr.	$34	0.09
100 yr.	$0	0.00

Structural Mitigation Benefits - Oregon

Given our neutral setting AAL results, we determine the structural maximum credit and the structural maximum penalty as differences from these values by adjusting the ten secondary modifiers (roof system covering, roof shape, roof age, roof vents, ember accumulators, suppression, wall cladding, patio deck, opening heat resistance, and accessibility) simultaneously for each structure in each community. The table below, Table 17, presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community.

Looking across all three communities we see that on average structural credits as a percentage difference from the neutral value AALs are fairly significant in two of the of three communities ranging anywhere from 19 to 36 percent reductions in expected losses depending upon the fuel type. These percent differences are highest in Shadow Hills (33% less on average), but certain fuel types in Brookings are comparable such as shrubs-brush fuel types (32% less on average).

Conversely, poorly built wildfire resistant structures suffer even more significant structural penalties as a percentage difference from the neutral value AALs. For example, Shadow Hills penalties across all structure are 104 percent higher on average, whereas Brookings are 80 percent higher on average.

There is not one fuel type in these two communities that does not incur at least a 58 percent penalty from the neutral value AALs when moving to a poorly built wildfire resistant structure.

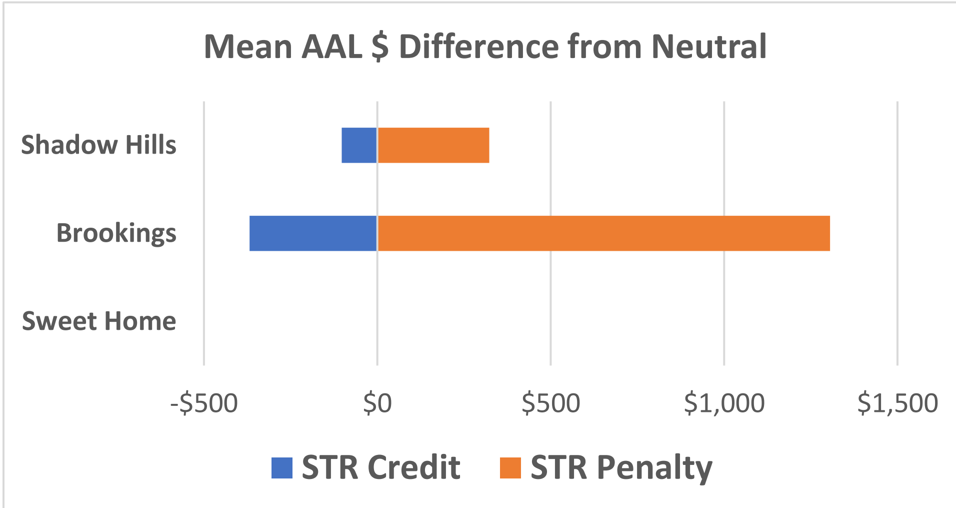
Additionally, another way of thinking about these percentage difference results is not just moving from an assumed CAT modeling neutral setting, but rather from a poorly built wildfire resistant structure to a well-built one. From this perspective, mean community AAL percent differences are 137 percent in Shadow Hills and 102 percent in Brookings. Clearly, from an expected loss percentage reduction perspective substantial differences are achieved from this view for these two communities.

However, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In Figure 32 we present the mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented in the Table 17).

Table 17: Credits and Penalties of the Structural Mitigation relative to Neutral Scenario for locations in various fuel classes

Community / Fuel Type	STR Credit (%)	STR Penalty (%)	STR Credit ($)	STR Penalty ($)
Shadow Hills				
Urban (non-burnable)	-33%	64%	-$33	$66
Grass – Short	-32%	93%	-$69	$197
Grass – Timber understory	-32%	97%	-$92	$278
Shrubs – Brush	-34%	104%	-$105	$326
Timber – Needle and leaf litter only	-36%	103%	-$103	$294
Timber – Hardwood litter and occasional dead-down material	-33%	104%	-$106	$338
Timber / Slash	-33%	108%	-$112	$369
Community Average	**-33%**	**104%**	**-$102**	**$322**
Brookings				
Urban (non-burnable)	-21%	83%	-$331	$1,281
Shrubs – Brush	-32%	84%	-$565	$1,483
Timber – Needle and leaf litter only	-24%	79%	-$399	$1,335
Timber – Hardwood litter and occasional dead-down material	-19%	58%	-$410	$1,267
Community Average	-22%	80%	-$368	$1,306
Sweet Home				
Urban (non-burnable)	-8%	0%	$0	$0
Grass – Short	-5%	1%	$0	$0
Grass – Timber understory	-6%	0%	$0	$0
Community Average	-7%	0%	$0	$0

Figure 32: Mean Average Annual Loss Difference from Neutral ($) by Community, Oregon



Not surprisingly, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures happen where the wildfire risk is greatest in Brookings. Here, expected losses are on average $368 less from the neutral setting for well-built wildfire resistant structures. Conversely, poorly built wildfire structures in Brookings have mean AAL increases that are on average $1,306 higher than the neutral setting. In total, moving from a poorly built wildfire resistant structure to a well-built one in Brookings saves on average $1,674 annually in wildfire expected losses.

While AAL percent differences in Shadow Hills were the largest for all three Oregon communities, expected losses are on average $102 less from the neutral setting and AAL increases $322 more on average as compared to a neutral setting. Overall then, moving from a poorly built wildfire resistant structure to a well-built one in Shadow Hills saves on average $425 annually in wildfire expected losses.

Structural Plus Vegetation Mitigation Benfits - Oregon

In addition to the structural credits and penalties only, we also apply two distance to vegetation mitigation cases where we apply both distance to vegetation maximum credits (160 feet of defensible space) and distance to vegetation maximum penalties (less than 5 feet of defensible space). As described earlier, the vegetation credit is only applied in addition to the structural credit, and the vegetation penalty is only applied in addition to the structural penalty. The table below, Table 18, presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community. Note that in the table, “Veg Credit” values are the combined mitigation loss reductions of a well-built wildfire resistant structure with the additional distance to vegetation mitigation. And similarly, the “Veg Penalty” values are the combined mitigation penalties of a poorly built wildfire resistant structure with the additional distance to vegetation penalty applied. “STR Credits” and “STR Penalty” values are as they were in Table 17 above.

Table 18: Credits and Penalties of the Structural and Vegetation Mitigation relative to Neutral Scenario for locations in various fuel classes

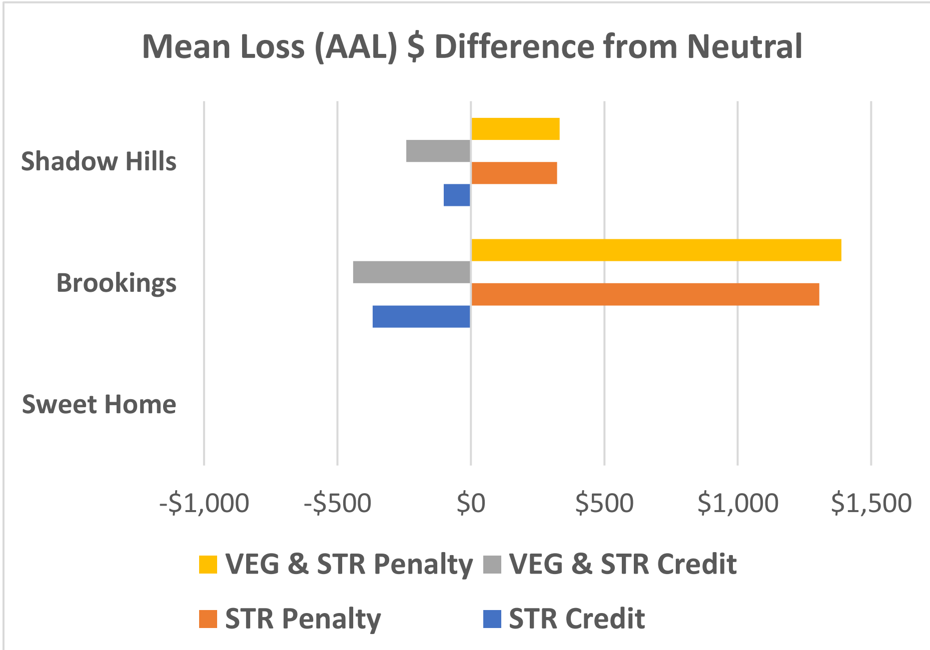
Fuel Type	VEG Credit	STR Credit	STR Penalty	VEG Penalty	VEG Credit	STR Credit	STR Penalty	VEG Penalty
Urban (non-burnable)	-35%	-33%	64%	247%	-$36	-$33	$66	$251
Grass – Short	-70%	-32%	93%	93%	-$149	-$69	$197	$197
Grass – Timber understory	-78%	-32%	97%	97%	-$221	-$92	$278	$278
Shrubs – Brush	-79%	-34%	104%	104%	-$246	-$105	$326	$326
Timber – Needle and leaf litter only	-75%	-36%	103%	103%	-$214	-$103	$294	$294
Timber – Hardwood litter and occasional dead-d	-79%	-33%	104%	104%	-$259	-$106	$338	$338
Timber / Slash	-79%	-33%	108%	108%	-$272	-$112	$369	$369
Shadow Hills	**-78%**	**-33%**	**104%**	**108%**	**-$242**	**-$102**	**$322**	**$333**
Urban (non-burnable)	-21%	-21%	83%	89%	-$332	-$331	$1,281	$1,387
Shrubs – Brush	-47%	-32%	84%	84%	-$830	-$565	$1,483	$1,483
Timber – Needle and leaf litter only	-31%	-24%	79%	79%	-$521	-$399	$1,335	$1,335
Timber – Hardwood litter and occasional dead-d	-37%	-19%	58%	64%	-$802	-$410	$1,267	$1,395
Brookings	**-27%**	**-22%**	**80%**	**85%**	**-$441**	**-$368**	**$1,306**	**$1,388**
Urban (non-burnable)	-8%	-8%	0%	0%	$0	$0	$0	$0
Grass – Short	-5%	-5%	1%	1%	$0	$0	$0	$0
Grass – Timber understory	-6%	-6%	0%	0%	$0	$0	$0	$0
Sweet Home	**-7%**	**-7%**	**0%**	**0%**	**$0**	**$0**	**$0**	**$0**

From these results we can ascertain the marginal value provided by the vegetation-based mitigation (i.e., building a defensible space around one's home) in addition to the structural mitigation efforts that have already been afforded to the structure. In Shadow Hills, the overall combined vegetation and structural percentage AAL reduction is 78 percent, with vegetation mitigation providing an additional 45 percent in mitigation benefits on average at the margin. In Brookings, the overall combined vegetation and structural percentage AAL reduction is 27 percent, with vegetation mitigation providing an additional 5 percent in mitigation benefits on average at the margin. However, in Sweet Home we determine no additional benefit on average in this community since the baseline distance to nearest vegetation is already at 160 feet or more for most homes given that 96 percent of the structures in our analysis are of an urban fuel type.

We can also examine the marginal impact of a vegetation penalty in addition to the structural penalties already in place. In this scenario, our AAL results show that an additional vegetation penalty makes relatively minimal difference to expected losses. In Shadow Hills penalties go from 104 percent penalty on average for the poorly built wildfire resistant structure to 108 percent with the additional poorly maintained distance to vegetation. In Brookings penalties go from 80 percent penalty on average for the poorly built wildfire resistant structure to 85 percent with the additional poorly maintained distance to vegetation.

Again, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In the below figure, Figure 33, we present the structural and vegetation mitigation mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented in Table 18 above).

Figure 33: Mean Average Annual Loss Difference from Neutral ($) by Community, Oregon



Not surprisingly again, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures with defensible space happen where the wildfire risk is greatest in Brookings. Here expected losses are on average $441 less from the neutral setting with the additional vegetation mitigation representing $73 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Brookings have mean AAL increases that are on average $1,388 higher than the neutral setting with the vegetation penalty representing only $82 of this amount. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Brookings saves on average $1,829 annually in wildfire expected losses.

In Shadow Hills expected losses are on average $242 less from the neutral setting with the additional vegetation mitigation representing $139 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Shadow Hills have mean AAL increases that are on average $333 higher than the neutral setting with the vegetation penalty only increasing this total amount by $11. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Shadow Hills saves on average $575 annually in wildfire expected losses. In Sweet Home, there is no meaningful difference in the vegetation mitigation results as compared to the structural only results.

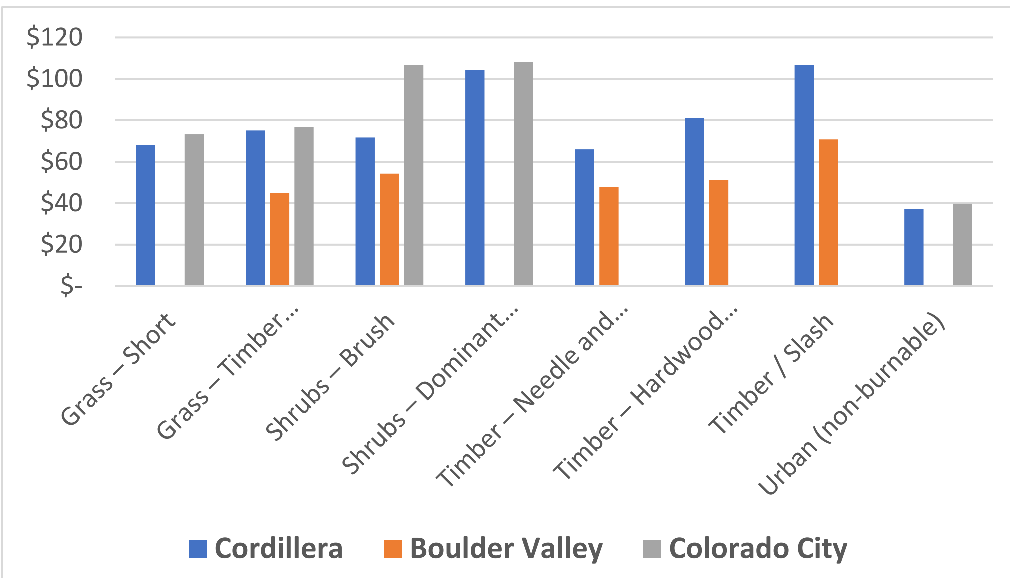
Colorado Community Mitigation Benefits

Comparison to Prevailing Insurance Rates - Colorado

For our 3 Colorado communities of Cordillera (341 structures), Boulder Valley (85 structures), and Colorado City (142 structures), mean AAL across all structures in each community is $71, $54, and $75 respectively when all secondary modifiers have been set to the neutral setting. Therefore, on average the wildfire risk in Cordillera is 1.3 times greater than the wildfire risk in Boulder Valley, and approximately equal to the wildfire risk in Colorado City.

As noted earlier, local conditions in the immediate vicinity of a structure including the fuel type are critical for estimating the likelihood of ignition during a wildfire. In Figure 34 we present the mean AAL by fuel type per community. In Cordillera, AAL ranges from $37 for urban fuel type (5% of total structures) to $107 for timber/slash fuel type (4% of total structures). In Boulder Valley, AAL ranges from $45 for grass-timber understory fuel type (1% of total structures) to $71 for timber/slash fuel type (20% of total structures). And in Colorado City AAL ranges from $40 for urban fuel type (34% of total structures) to $108 for shrubs-dominant brush, hardwood slash fuel type (9% of total structures)

Figure 34: Mean Average Annual Loss by Community, Colorado



These determined AALs represent an unloaded premium for wildfire risk only. For relative comparison purposes, we pulled the Colorado 2017 NAIC state-wide premium data in Table 19. In 2017, Colorado HO-3 average premium values were $2,466 and Colorado HO-5 average premium values were $2,921, both for exposure values $500,000 and over. These are the nearest NAIC premium values matching to our Colorado communities modeled structure total insured value that ranges from $325,414 to $1,489,947.

Table 19: Colorado Average Premium and Loss Costs for expposure values $500,000 or more (NAIC 2017)

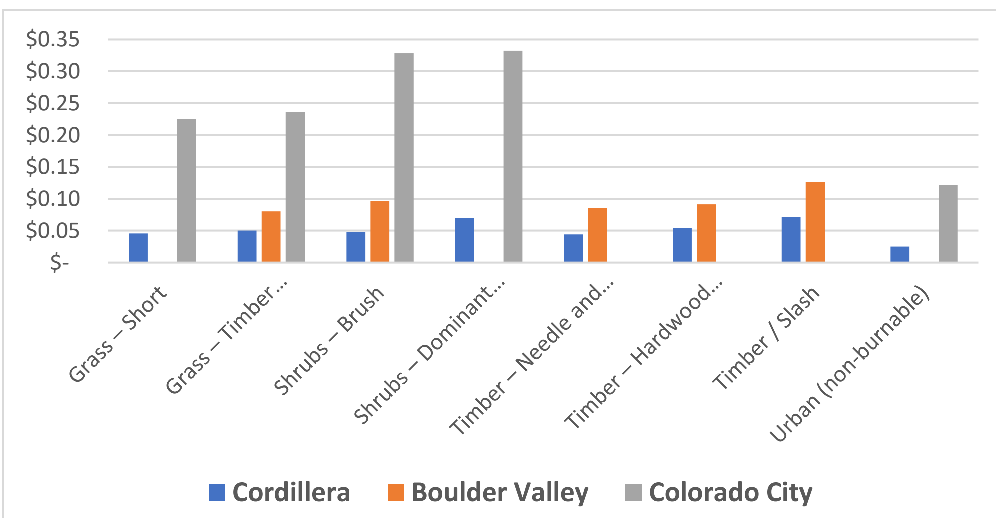
Policy Type	Average Premium	Loss Cost ($ / $1000)
HO-3	$2,466	$4.93
HO-5	$2,921	$5.84

Source (NAIC Premiums); Loss Cost = Premium / $500,000 * $1000

Thus, our determined wildfire AAL value per fuel type as a percentage of the Colorado NAIC H0-3 state-wide average premium are: 1.5% to 4.3% in Cordillera; 1.8% to 2.9% in Boulder Valley; and 1.6% to 4.4% in Colorado City. Of course, these NAIC premium values do account for more than just wildfire risk. While it is unknown how much of the existing 2017 premium accounts for wildfire risk, our determined wildfire risk AAL represents a relatively small percentage of existing premiums in all three Colorado communities.

All else being equal, AAL will be higher the larger is the TIV. To account for the TIV impact on our determined AAL we calculate the loss costs per $1000 of insurance coverage which is equal to the (AAL/TIV) * 1000. In Figure 35 we present the mean loss cost per $1000 of coverage by fuel type per community. In Cordillera, loss costs per $1000 of coverage range from $0.03 for urban fuel type (5% of total structures) to $0.07 for timber/slash fuel type (4% of total structures). In Boulder Valley, loss costs per $1000 of coverage range from $0.08 for grass-timber understory fuel type (1% of total structures) to $0.13 for timber/slash fuel type (20% of total structures). And in Colorado City loss costs per $1000 of coverage range from $0.12 for urban fuel type (34% of total structures) to $0.33 for shrubs-dominant brush, hardwood slash fuel type (9% of total structures). For our three Colorado communities, given the differences in TIV representing loss costs per $1000 coverage we see now that the mean wildfire risk in Colorado City compared to Cordillera is 4.8 times higher, not relatively equal as was the case with the mean AAL values.

Figure 35: Loss Cost per $1000 of Coverage by Fuel Type for Colorado communities



Again, for relative comparison purposes, we determined a loss cost per $1000 of coverage from the Colorado 2017 NAIC state-wide premium data (Table 19) . In 2017, Colorado HO-3 loss costs per $1000 coverage were $4.93 and Colorado HO-5 loss costs per $1000 coverage were $5.84, both for exposure values $500,000 and over.

Thus, our determined wildfire loss costs per $1000 of coverage values per fuel type as a percentage of the Colorado NAIC H0-3 state-wide loss costs per $1000 of coverage are: 0.5% to 1.5% in Cordillera; 1.6% to 2.6% in Boulder Valley; and 2.5% to 6.7% in Colorado City. Wildfire loss cost per $1000 coverage are still relatively insignificant in all three Colorado communities.

Normalizing associated with Loss Cost means that we can compare risks within and between the communities. In Figure 36 to Figure 38, the variation of the loss costs for each notional location are plotted with the same color ramp in the legend. These plots show that there are variations within the communities that are related to the nearby fuels, local topography, and distance to dense vegetation. As with the similar figures in California and Oregon presented earlier, the variations in loss cost within these communities highlight the need to use location specific data for pricing development.

Potential for Extreme Wildfire Losses - Colorado

The EP curve also provides the probability of surpassing any loss level, expressing this probability in the form of a return period. Return periods are calculated by sorting the occurrence and yearly losses to create occurrence (OEP) and aggregate (AEP) curves, respectively. These curves are often used to look up key return period losses, such as 1 in 100 or 1 in 250, to help with solvency, rating agency evaluation, and reinsurance purchasing decisions. They can also be used to understand the tail risks of the loss distribution.

Figure 36: Cordillera sub-division community; Aerial view (left) and Loss Cost Map (Right)

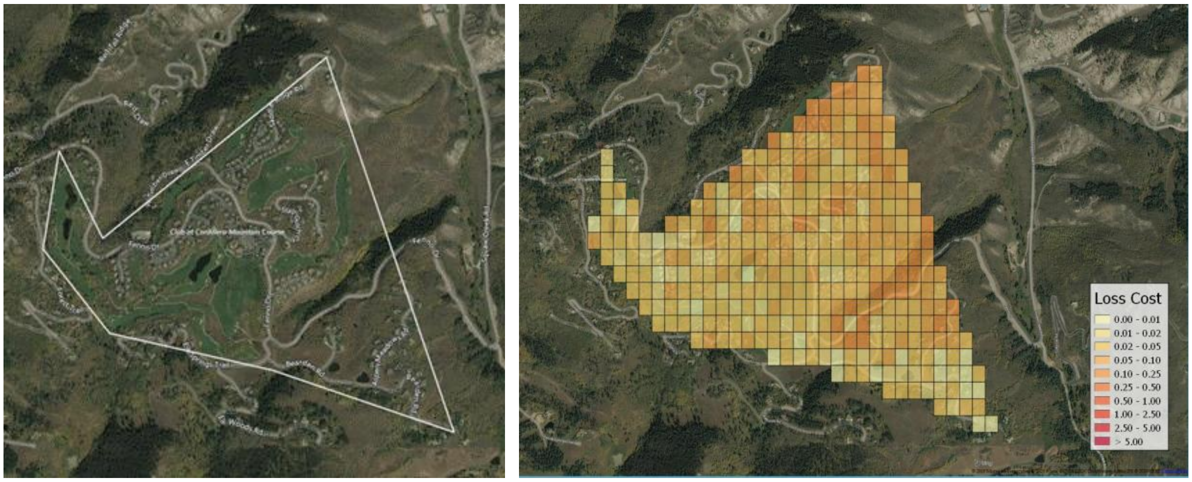


Figure 37: Boulder Valley sub-division community; Aerial view (left) and Loss Cost Map (Right)

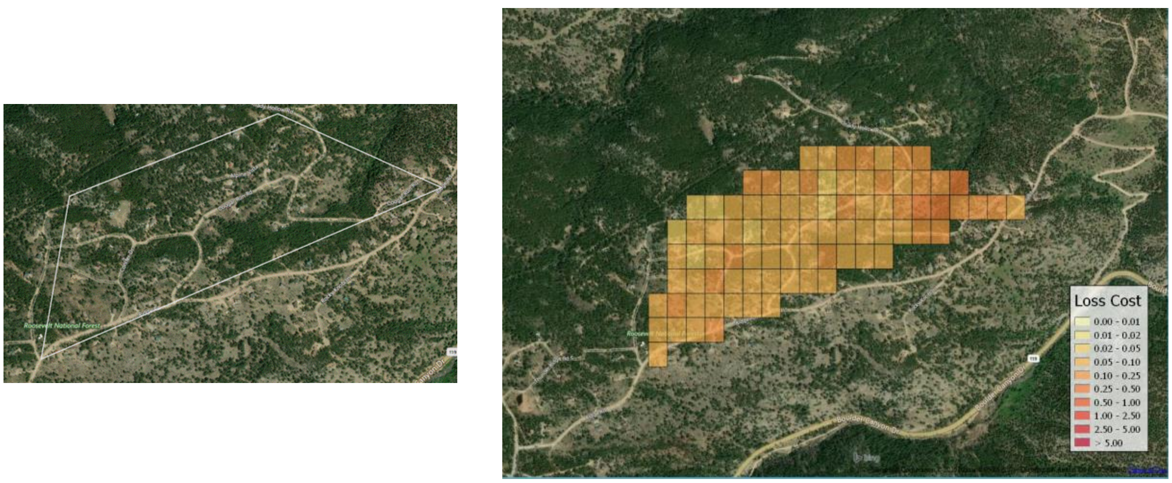
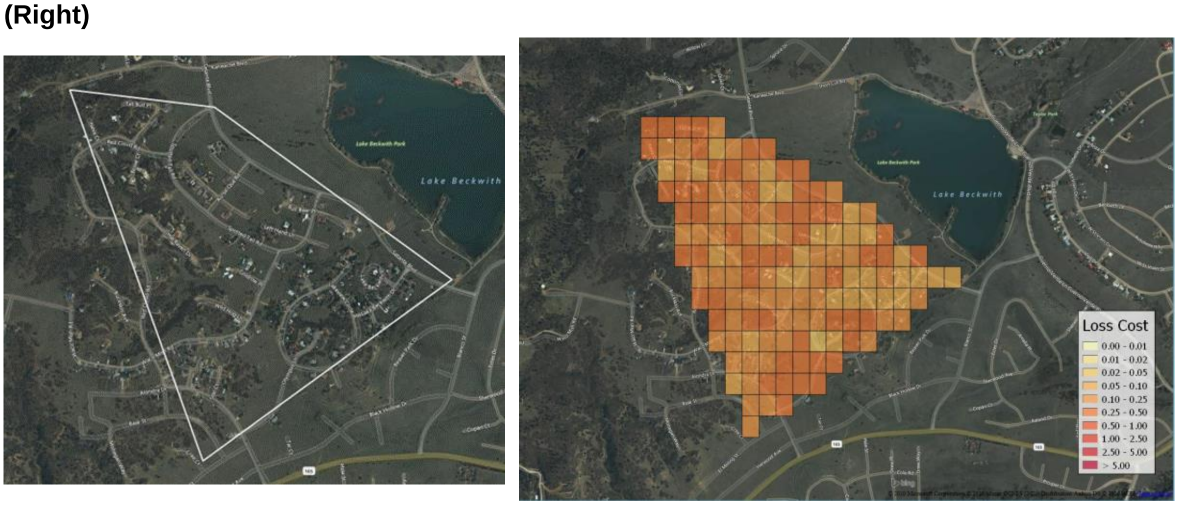


Figure 38: Colorado City sub-division community; Aerial view (left) and Loss Cost Map (Right)



In Table 20, we present the various OEP return period (100, 250, 500, 1000 and 10,000 year) mean losses and losses per $1000 of coverage for each of the three Colorado communities. We can see that the mean 1000 year return period loss in Colorado City is the most significant 1000 year return period loss at $30,708 which given TIV of $325,414 is a $94.37 loss per $1000 coverage. Boulder Valley mean 1000 year return period loss is $19,700 which given TIV of $559K is $35.21 loss per $1000 coverage. Importantly, these tail return period losses highlight the potential significant impact of just one event occurring in a community, an aspect that is not as readily apparent from the AAL view of loss. For example, the 10,000 year loss event in Cordillera has a normalized RP loss of $108 per thousand, whereas the loss cost (average annual loss / TIV) for Cordillera is a tiny amount of about $0.05 reflecting the possible but extremely rare likelihood of a very severe event.

Table 20: Typical Return Period Losses for community reported as loss per notional structure, and normalized loss.

Community / Return Period	Average RP Loss per Structure	Normalized RP Loss per $1000 Coverage
Cordillera (FireWise)		
10,000 yr.	$161,813 of 1,489,000	108.60
1,000 yr.	$919	0.62
500 yr.	$101	0.07
250 yr.	$0	0.00
100 yr.	$0	0.00
Boulder Valley		
10,000 yr.	$72,425 of $559,000	129.46
1,000 yr.	$19,700	35.21
500 yr.	$4,022	7.19
250 yr.	$322	0.57
100 yr.	$0	0.00
Colorado City		
10,000 yr.	$57,895 of $325,000	177.91
1,000 yr.	$30,708	94.37
500 yr.	$16,990	52.21
250 yr.	$278	0.85
100 yr.	$10	0.03

Structural Mitigation Benefits -Colorado

Given our neutral setting AAL results, we determine the structural maximum credit and the structural maximum penalty as differences from these values by adjusting the ten secondary modifiers (roof system covering, roof shape, roof age, roof vents, ember accumulators, suppression, wall cladding, patio deck, opening heat resistance, and accessibility) simultaneously for each structure in each community. The table below, Table 21, presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community.

Table 21: Credits and Penalties of the Structural Mitigation relative to Neutral Scenario for locations in various fuel classes

Fuel Type	STR Credit	STR Penalty	STR Credit	STR Penalty
Cordillera				
Urban (non-burnable)	-23%	33%	-$9	$12
Grass – Short	-34%	76%	-$23	$52
Grass – Timber understory	-36%	78%	-$27	$58
Shrubs – Brush	-36%	94%	-$26	$68
Shrubs – Dominant brush, hardwood slash	-37%	105%	-$38	$110
Timber – Needle and leaf litter only	-36%	93%	-$24	$62
Timber – Hardwood litter and occasional dead-down material	-37%	91%	-$30	$74
Timber / Slash	-36%	107%	-$39	$114
Community Average	**-35%**	**84%**	**-$25**	**$60**
Boulder Valley				
Grass – Timber understory	-40%	93%	-$18	$42
Shrubs – Brush	-41%	97%	-$22	$53
Timber – Needle and leaf litter only	-41%	92%	-$20	$44
Timber – Hardwood litter and occasional dead-down material	-41%	92%	-$21	$47
Timber / Slash	-41%	104%	-$29	$73
Community Average	**-41%**	**96%**	**-$22**	**$52**
Colorado City				
Urban (non-burnable)	-30%	58%	-$12	$23

Fuel Type		STR Credit	STR Penalty	STR Credit	STR Penalty
Grass – Short		-39%	91%	-$29	$67
Grass – Timber understory		-39%	91%	-$30	$70
Shrubs – Brush		-42%	103%	-$44	$110
Shrubs – Dominant brush, hardwood slash		-41%	106%	-$45	$114
	Community Average	**-39%**	**92%**	**-$29**	**$68**

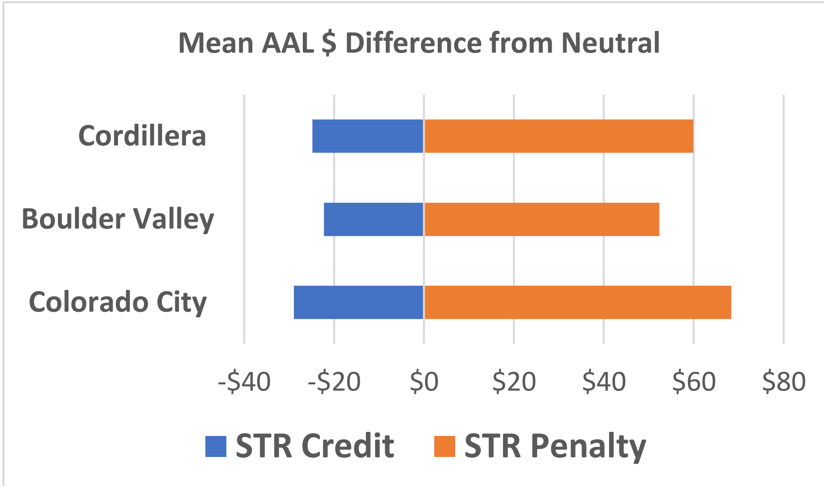
Looking across all three communities we see that on average structural credits as a percentage difference from the neutral value AALs are significant ranging anywhere from 23 to 42 percent reductions in expected losses depending upon the fuel type. These percent differences are highest in Boulder Valley (41% less on average), but certain fuel types in the other communities are comparable such as timber-hardwood litter fuel types in Cordillera (37% less on average) and shrubs-brush fuel types in Colorado City (42% less on average).

Conversely, poorly built wildfire resistant structures suffer even more significant structural penalties as a percentage difference from the neutral value AALs. For example, Boulder Valley penalties across all structure are 96 percent higher on average, whereas Cordillera and Colorado City are 84 percent and 92 percent higher on average, respectively. Outside of the two urban fuel type penalties in Cordillera and Colorado City (33 and 58 percent penalties), there is not one fuel type in any of our communities that does not incur at least a 76 percent penalty from the neutral value AALs when moving to a poorly built wildfire resistant structure.

Additionally, another way of thinking about these results is not just moving from an assumed CAT modeling neutral setting, but rather from a poorly built wildfire resistant structure to a well-built one. From this perspective, mean community AAL percent differences are 119 percent in Cordillera, 137 percent in Boulder Valley, and 130 percent in Colorado City. Clearly, from an expected loss percentage reduction perspective substantial differences are achieved from this view for all three communities.

However, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In the below figure, Figure 39, we present the mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented in the Table 21).

Figure 39: Mean AAL Difference from Neutral ($)



Not surprisingly, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures happen where the wildfire risk is greatest in Colorado City. Here, expected losses are on average $29 less from the neutral setting for well-built wildfire resistant structures. Conversely, poorly built wildfire structures in Colorado City have mean AAL increases that are on average $68 higher than the neutral setting. In total, moving from a poorly built wildfire resistant structure to a well-built one in Colorado City saves on average $97 annually in wildfire expected losses.

While AAL percent differences in Boulder Valley were the largest for all three Colorado communities, expected losses are on average $22 less from the neutral setting and AAL increases $52 more on average as compared to a neutral setting. Overall, moving from a poorly built wildfire resistant structure to a well-built one in Boulder Valley saves on average $75 annually in wildfire expected losses. In Cordillera, moving from a poorly built wildfire resistant structure to a well-built one saves on average $85 annually in wildfire expected losses.

Structural Plus Vegetation Mitigation Benefits - Colorado

In addition to the structural credits and penalties only, we also apply two distance to vegetation mitigation cases where we apply both distance to vegetation maximum credits (160 feet of defensible space) and distance to vegetation maximum penalties (less than 5 feet of defensible space). As described earlier, the vegetation credit is only applied in addition to the structural credit, and the vegetation penalty is only applied in addition to the structural penalty. Table 22 presents both the mean AAL percent difference and the mean AAL dollar value difference from the neutral setting results for all fuel types in each community as well as for the overall community. Note that in the table “Veg Credit” values are the combined mitigation loss reductions of a well-built wildfire resistant structure with the additional distance to vegetation mitigation. And similarly, the “Veg Penalty” values are the combined mitigation penalties of a poorly built wildfire resistant structure with the additional distance to vegetation penalty applied. “STR Credits” and “STR Penalty” values are as they were in Table 21.

From these results we can ascertain the marginal value provided by the vegetation-based mitigation (i.e., building a defensible space around one's home) in addition to the structural mitigation efforts that have already been afforded to the structure. In Cordillera, the overall combined vegetation and structural percentage AAL reduction is 66 percent, with vegetation mitigation providing an additional 32 percent in mitigation benefits on average at the margin. In Boulder Valley, the overall combined vegetation and structural percentage AAL reduction is 61 percent, with vegetation mitigation providing an additional 20 percent in mitigation benefits on average at the margin. In Colorado City, the overall combined vegetation and structural percentage AAL reduction is 70 percent, with vegetation mitigation providing an additional 31 percent in mitigation benefits on average at the margin.

We can also examine the marginal impact of a vegetation penalty in addition to the structural penalties already in place. In Cordillera penalties go from 84 percent penalty on average for the poorly built wildfire resistant structure to 89 percent with the additional poorly maintained distance to vegetation. In Brookings penalties are 96 percent on average for the poorly built wildfire resistant structure and remain at 96 percent with the additional poorly maintained distance to vegetation. However, in Colorado City penalties go from 92 percent penalty on average for the poorly built wildfire resistant structure to 125 percent on average with the additional poorly maintained distance to vegetation. We see the largest increase here with the urban fuel types moving from 58 percent to 228 percent penalties.

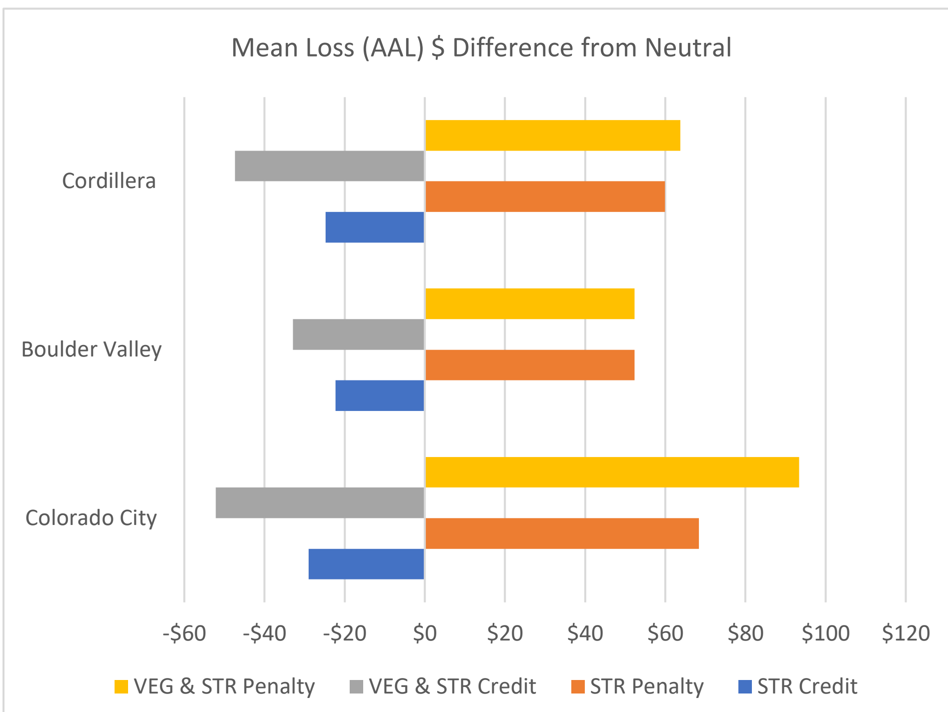
Table 22: Credits and Penalties of the Structural and Vegetation Mitigation relative to Neutral Scenario for locations in various fuel classes

Fuel Type	VEG Credit	STR Credit	STR Penalty	VEG Penalty	VEG Credit	STR Credit	STR Penalty	VEG Penalty
Urban (non-burnable)	-33%	-23.3%	33%	187%	-$12	-$9	$12	$70
Grass – Short	-62%	-33.7%	76%	79%	-$42	-$23	$52	$54
Grass – Timber understory	-62%	-35.5%	78%	78%	-$47	-$27	$58	$58
Shrubs – Brush	-72%	-36.5%	94%	94%	-$52	-$26	$68	$68
Shrubs – Dominant brush, hardwood slash	-78%	-36.6%	105%	105%	-$82	-$38	$110	$110
Timber – Needle and leaf litter only	-72%	-35.9%	93%	93%	-$48	-$24	$62	$62
Timber – Hardwood litter and occasional dead-d	-71%	-37.2%	91%	93%	-$58	-$30	$74	$75
Timber / Slash	-81%	-36.4%	107%	107%	-$87	-$39	$114	$114
Cordillera	**-66%**	**-35%**	**84%**	**89%**	**-$47**	**-$25**	**$60**	**$64**
Grass – Timber understory	-53%	-40%	93%	93%	-$24	-$18	$42	$42
Shrubs – Brush	-62%	-41%	97%	97%	-$34	-$22	$53	$53
Timber – Needle and leaf litter only	-57%	-41%	92%	92%	-$27	-$20	$44	$44
Timber – Hardwood litter and occasional dead-d	-55%	-41%	92%	92%	-$28	-$21	$47	$47
Timber / Slash	-66%	-41%	104%	104%	-$47	-$29	$73	$73
Boulder Valley	**-61%**	**-41%**	**96%**	**96%**	**-$33**	**-$22**	**$52**	**$52**
Urban (non-burnable)	-44%	-30.1%	58%	228%	-$18	-$12	$23	$91
Grass – Short	-69%	-39.2%	91%	91%	-$51	-$29	$67	$67
Grass – Timber understory	-70%	-39.4%	91%	108%	-$54	-$30	$70	$83
Shrubs – Brush	-79%	-41.6%	103%	104%	-$84	-$44	$110	$111
Shrubs – Dominant brush, hardwood slash	-79%	-41.2%	106%	112%	-$86	-$45	$114	$121
Colorado City	**-70%**	**-39%**	**92%**	**125%**	**-$52**	**-$29**	**$68**	**$93**

Again, while percent differences are a useful measuring stick, the actual dollar value differences these percent differences represent are even more critical for implementing wildfire mitigation measures given the implementation costs. In the below figure (Figure 40) we present the structural and vegetation mitigation mean AAL dollar value differences for all three communities from the neutral value setting AAL results (mean AAL dollar value differences by fuel type are also presented above in Table 22).

Not surprisingly again, we see that the largest AAL dollar value differences incurred from well-built wildfire resistant structures with defensible space happen where the wildfire risk is greatest in Colorado City. Here expected losses are on average $52 less from the neutral setting with the additional vegetation mitigation representing $23 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Colorado City have mean AAL increases that are on average $93 higher than the neutral setting with the vegetation penalty representing only $25 of this amount. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Colorado City saves on average $145 annually in wildfire expected losses.

Figure 40: Mean Loss (AAL) Difference from Neutral ($) – All Mitigation Cases



In Boulder Valley expected losses are on average $33 less from the neutral setting with the additional vegetation mitigation representing $11 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Boulder Valley have mean AAL increases that are on average $52 higher than the neutral setting with the vegetation penalty not increasing this total amount. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Boulder Valley saves on average $85 annually in wildfire expected losses. In Cordillera, expected losses are on average $47 less from the neutral setting with the additional vegetation mitigation representing $23 of this amount. Conversely, poorly built wildfire structures combined with poorly maintained defensible space in Cordillera have mean AAL increases that are on average $64 higher than the neutral setting with the vegetation penalty increasing this total amount by $4. In total then moving from a poorly built wildfire resistant structure with poorly maintained defensible space to a well-built one with well-maintained defensible space in Cordillera saves on average $111 annually in wildfire expected losses.

Benefit-Cost Analysis of Wildfire Mitigation

From an economic perspective, undertaking an action such as wildfire mitigation is considered worthwhile when the benefits are greater than the costs. Further, these benefits and costs can be accrued over different future time periods, where benefits and costs occurring in future periods need to be discounted to compute the present value. In a benefit-cost analysis (BCA), all costs and benefits accruing over time are monetized and aggregated so that they can be compared using the common economic efficiency criterion.

In general, if the stream of discounted benefits exceeds the stream of discounted costs (i.e., positive net present value economic benefits) a proposal is considered 'economically-efficient'. During the BCA, the total discounted benefits are divided by the total discounted costs. By definition, a benefit-cost ratio of 1 means that the expected discounted benefit of implementing the mitigation equals its cost. Any measure where a benefit-cost ratio is greater (less) than 1 is considered to be economically-efficient (not economically-efficient) and should (should not) be implemented as the benefits exceed (do not exceed) costs and a project thus adds (does not add) value to society.

To undertake a BCA of wildfire mitigation across different time horizons and discount rates as we do below, we first need to consider the costs of wildfire mitigation

Wildfire Mitigation Costs

Undertaking wildfire mitigation measures incurs an upfront cost. For existing residences, Headwaters Economics (Headwaters, 2018) estimated the costs of retrofitting the roof and exterior walls from a "typical" property to a wildfire resistant one. Costs were estimated for a 2,500-square-foot, single-story, single-family home representative of wildland-urban interface building styles in southwest Montana. The typical home was assumed to have an asphalt shingle roof, wood siding, dual-pane windows, and a wood deck. Wildfire-resistant materials were selected for similar aesthetics but also comply with wildfire-resistant building codes. Their estimated costs are presented in Table 23 which shows roof retrofit costs including roofing, vents, soffits, and gutters totalling $22,010. Retrofitting exterior walls including doors and windows is an additional $40,750 in costs. These retrofit costs would be best associated with the benefits of moving from a poorly built wildfire resistant structure to a well-built one from our catastrophe modeling results.

Table 23: Cost of Retrofitting Roof and Exterior Wall from Typical to Wildfire-resistant.

Roof	
Roofing	13,180
Vents	370
Soffit & Fascia	5,600
Gutters	2,860
Subtotal	**$22,010**
Exterior Walls	
Sheathing and Siding	20,580
Doors	8,120
Windows	12,050
Subtotal	**$40,750**

(Source: https://headwaterseconomics.org/wp-content/uploads/building-costs-codes-report.pdf)

IBHS also recently released retrofit cost estimates related to its recommended mitigation actions (IBHS, 2020). A cost range for each mitigation action is provided below. Costs of roofing, vents, and soffits comparable to the Headwaters study data would range from $12,200 to $30,200. Costs for replacing siding to stucco would be $20,000 to $30,000 as compared to the sheathing and siding costs of $20,580 from the Headwaters study. IBHS also included a cost for creating a defensible space around one's home ranging from $3000-$15,000. No primary characteristics were identified for these costs estimates.

Table 24: Costs of Wildfire Mitigation options from IBHS

Make sure your roof is fire-rated	Replacement cost of wood shake to asphalt comp class A roof:	$10,000–$25,000
Create a buffer around your home (0-5 foot home ignition zone)	Landscape cost using a contractor (labor included):	$3,000–$15,000
Add or upgrade your vent screens	Screen addition or replacement cost: (DIY)	$200
Replace combustible fencing or gates attached to the home		$500–$1,500
Replace your siding	Cost for replacing just the lowest one foot of siding:	$2,000–$5,000
	Cost for concrete-fiber board:	$8,000–$15,000
	Cost for stucco:	$20,000–$30,000
	Cost for brick or stone veneer:	>$40,000 (retrofit)
Enclose eaves	Boxed-in Eaves cost:	$500–$1,500
	Soffit cost:	$2,000–$5,000
Build a fire-resistant deck	Cost: For 500 sq ft deck, depending on complexity and footings	$9,000–$15,000
Upgrade windows	Cost: per window (including labor)	$500–$1,000

(Source: modified from https://disastersafety.org/wildfire/wildfire-ready/)

Lastly, the natural hazard mitigation saves 2019 report (MMC, 2019) provides the estimated costs to retrofit a building to comply with the International wildland-urban interface code's chapter 5 requirements of classes 1, 2, and 3 ignition resistant construction. These costs were split out for building and vegetation related mitigation. The geometric mean for class 1 or 2 ignition resistant construction is $72,000.

Table 25: Estimated Cost to Retrofit an Existing Home to Comply with the 2018 International Wildland-Urban Interface Code.

Mitigation	Class 1		Class 2		Class 3	
	Suburban	Rural	Suburban	Rural	Suburban	Rural
Building	$ 72,200	$80, 900	$64,200	$65,400	$3000	$3000
Vegetation	$5000	0	$2500	0	$1250	$1250
Total	$77,200	$,80,900	$66,700	$65,400	$4250	$4250
Average	$79,050		$66,050		$4250	

(Source: MMC, 2019 - Natural Hazard Mitigation Saves - https://cdn.ymaws.com/www.nibs.org/resource/resmgr/reports/mitigation_saves_2019/mitigationsaves2019report.pdf)

These three wildfire risk reduction cost studies show that the costs for retrofitting the structural and vegetative aspects from a "typical" property to a wildfire resistant one can range fairly significantly depending upon the risk reduction activity being undertaken and the assumptions of the property. Overall, the data provides costs on the low end of the spectrum from about $25,000 in total depending upon the activities (e.g., estimated derived by simply taking the low end of the range for all activities from IBHS) to the high-end totalling around $75,000.

Benefit-Cost Analysis Results

For our BCA, we utilize the determined average annual wildfire avoided losses moving from a poorly built wildfire resistant structure to a well-built wildfire resistant structure that we detailed earlier. These average annual avoided losses are for the structural only mitigation case as well as the structural and vegetation combined mitigation case (Table 26). We present the mean values by community in each state (note for Oregon, we do not present the Sweet Home community given the minimal values there that were <$1.00).

Given that these avoided losses are annual, we take them over time and discount them back to present value terms to compare to the upfront wildfire mitigation costs. We analyse results for 10, 25, and 50 year time horizons and with 1 and 3 percent assumed discount rates.[5] From the wildfire mitigation cost ranges discussed above, we run three costs scenarios: 1) low ($20,000 structural; $25,000 structural and vegetation); 2) medium ($40,000 structural; $50,000 structural and vegetation); and 3) high ($60,000 structural; $75,000 structural and vegetation).

Table 26: Mean Average Annual Loss Difference for Mitigation Cases by Community

Community	Structural Mitigation Loss Difference	Structural & Vegetation Mitigation Loss Difference
California		
Upper Deerwood	$ 3,307	$ 4,529
Berry Creek	$ 856	$ 1,092
Oroville	$ 26	$ 27
Colorado		
Cordillera	$ 85	$ 111
Boulder Valley	$ 75	$ 85
Colorado City	$ 97	$ 145
Oregon		
Shadow Hills	$ 425	$ 575
Brookings	$ 1,674	$ 1,829

[5] These values are in-line with the assumptions utilized in the Natural Hazard Mitigation Saves report that utilized up to 75 year time horizons as well 2.2, 3, and 7 percent discount rates.

Mean Benefit-cost ratios by cost scenario and community assuming the 1 percent discount case are presented for the structural mitigation cases only in Table 27 and the structural plus vegetation mitigation cases in Table 28. Cases that are considered economically-efficient for the community, on average, are highlighted with green shading.

Table 27: Mean Benefit Cost Ratios by Analysis Time (10,25,50 years) for Structural Mitigation Cases– 1% Discount

Community	Low Cost Scenario ($20,000 Structural)			Medium Cost Scenario ($40,000 Structural)			High Cost Scenario ($60,000 Structural)		
	10 year	25 Year	50 Year	10 year	25 Year	50 Year	10 year	25 Year	50 Year
California									
Upper Deerwood	1.6	3.6	6.5	0.8	1.8	3.2	0.5	1.2	2.2
Berry Creek	0.4	0.9	1.7	0.2	0.5	0.8	0.1	0.3	0.6
Oroville	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Colorado									
Cordillera	0.0	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.1
Boulder Valley	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0
Colorado City	0.0	0.1	0.2	0.0	0.1	0.1	0.0	0.0	0.1
Oregon									
Shadow Hills	0.2	0.5	0.8	0.1	0.2	0.4	0.1	0.2	0.3
Brookings	0.8	1.8	3.3	0.4	0.9	1.6	0.3	0.6	1.1

Table 28: Mean Benefit Cost Ratios by Analysis Time (10,25,50 years) for Structural+Vegetation Mitigation Cases– 1% Discount

Community	Low Cost Scenario ($20,000 Structural + $5000 Vegetation)			Medium Cost Scenario ($40,000 Structural +$10,000 Vegetation)			High Cost Scenario ($60,000 Structural+ $15,000 Vegetation)		
	10 year	25 Year	50 Year	10 year	25 Year	50 Year	10 year	25 Year	50 Year
California									
Upper Deerwood	1.7	4.0	7.1	0.9	2.0	3.6	0.6	1.3	2.4
Berry Creek	0.4	1.0	1.7	0.2	0.5	0.9	0.1	0.3	0.6
Oroville	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Colorado									
Cordillera	0.0	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.1
Boulder Valley	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.0
Colorado City	0.1	0.1	0.2	0.0	0.1	0.1	0.0	0.0	0.1
Oregon									
Shadow Hills	0.2	0.5	0.9	0.1	0.3	0.5	0.1	0.2	0.3
Brookings	0.7	1.6	2.9	0.3	0.8	1.4	0.2	0.5	1.0

Table 29: Benefit Cost Ratios for Medium Cost Scenario ($40,000 Structural; $10,000 Vegetation) – 3 % Discount Case

Community	Structural Mitigation BC Ratios			Structural & Vegetation Mitigation BC Ratios		
	10 year	25 Year	50 Year	10 year	25 Year	50 Year
California						
Upper Deerwood	0.7	1.4	2.1	0.8	1.6	2.3
Berry Creek	0.2	0.4	0.6	0.2	0.4	0.6
Oroville	0.0	0.0	0.0	0.0	0.0	0.0
Colorado						
Cordillera	0.0	0.0	0.1	0.0	0.0	0.1
Boulder Valley	0.0	0.0	0.0	0.0	0.0	0.0
Colorado City	0.0	0.0	0.1	0.0	0.1	0.1
Oregon						
Shadow Hills	0.1	0.2	0.3	0.1	0.2	0.3
Brookings	0.4	0.7	1.1	0.3	0.6	0.9

Mean Benefit Cost ratios for the medium cost scenario and community assuming the 3% discount case are presented in Table 29.

While results are dependent upon the specific time horizon and discount rate levels, in all presented cost scenarios we find at least two communities where wildfire mitigation is deemed to be economically efficient on average across the community (indicated by green shading with mean BC ratios > = 1.0). In our low-cost scenario (and 1% discount rate), for 10, 25, and 50 year time horizons both structural only as well as structural and vegetation wildfire mitigation are economically efficient on average in the Upper Deerwood California community. For Berry Creek California, economic efficiency for structural mitigation is achieved on average in the 50 year time horizon and also in the 25 and 50 time horizons for structural and vegetation mitigation. Lastly, in Brookings, Oregon economic efficiency is achieved on average for structural mitigation in the 25 and 50 year time horizon, and also in the 25 and 50 time horizons for structural and vegetation mitigation.

As mitigation costs increase we see from our medium and high costs scenario results that only Upper Deerwood California and Brookings Oregon achieve any economic efficient wildfire mitigation results on average in any of the 9 communities. And in the high cost scenario for Brookings Oregon this is only for the 50 year time horizon.

However, this does not mean that individual structures in these higher cost scenarios do not achieve economically efficient mitigation results. For example, in Berry Creek in the medium cost scenario (1% discount rate) and for a 25 year time horizon, 6 of the 98 structure in the community have a BC ratio > 1. Further, 29 of the 98 structures in the Berry Creek community have a BC ratio of 0.8 or greater in this scenario. Indicating that if actions could be taken to reduce the direct costs of mitigation to the property owner, even more properties would find wildfire mitigation to be economically worthwhile.

Policy Discussion

Policy Implications of Results in Context of 2020 Wildfires

For homeowners in wildfire prone areas of the United States, as the underlying wildfire risk continues to increase there are exacerbating pressures on the affordability and availability of homeowner's insurance. Unfortunately, the 2020 wildfire season shows no indication that this insurance affordability and availability issue will abate anytime soon. For example, 5 of the 6 largest wildfires in California history have occurred in the 2020 season. Similarly, in Colorado where three of the four largest wildfires in state history have ignited just since July[6], and in Oregon where the 2020 wildfires in the state are some of the most destructive on record.

Furthermore, many of the 2020 fires in California are burning in areas that have been impacted by wildfires in the past five years (Figure 41). With already 4 million acres burned in 2020 alone in California – more than three times the annual average acreage burned in the 2010s – and climate research suggesting that the average area of California that burns may increase by more than 75%, clearly there is a need for improved wildfire risk reduction activities to play a more prominent role moving forward.

This reality of course has not gone unnoticed by policymakers in our study locations. For example, in 2019 the Governor's Council on Wildfire Response was created in Oregon. As part of their 2019 issued recommendations report (Oregon 2019), one of the recommendations ranked very high is focused on risk mitigation incentives as it relates to property insurance. Specifically, the recommendation calls for – "Support and encourage insurance industry implementation of innovative policy changes and underwriting standards. These updates would motivate policy holders to make changes aligned with Oregon Cohesive Wildfire Strategies; to harden structures, provide for and maintain defensible space, create access for fire vehicles and evacuation routes."

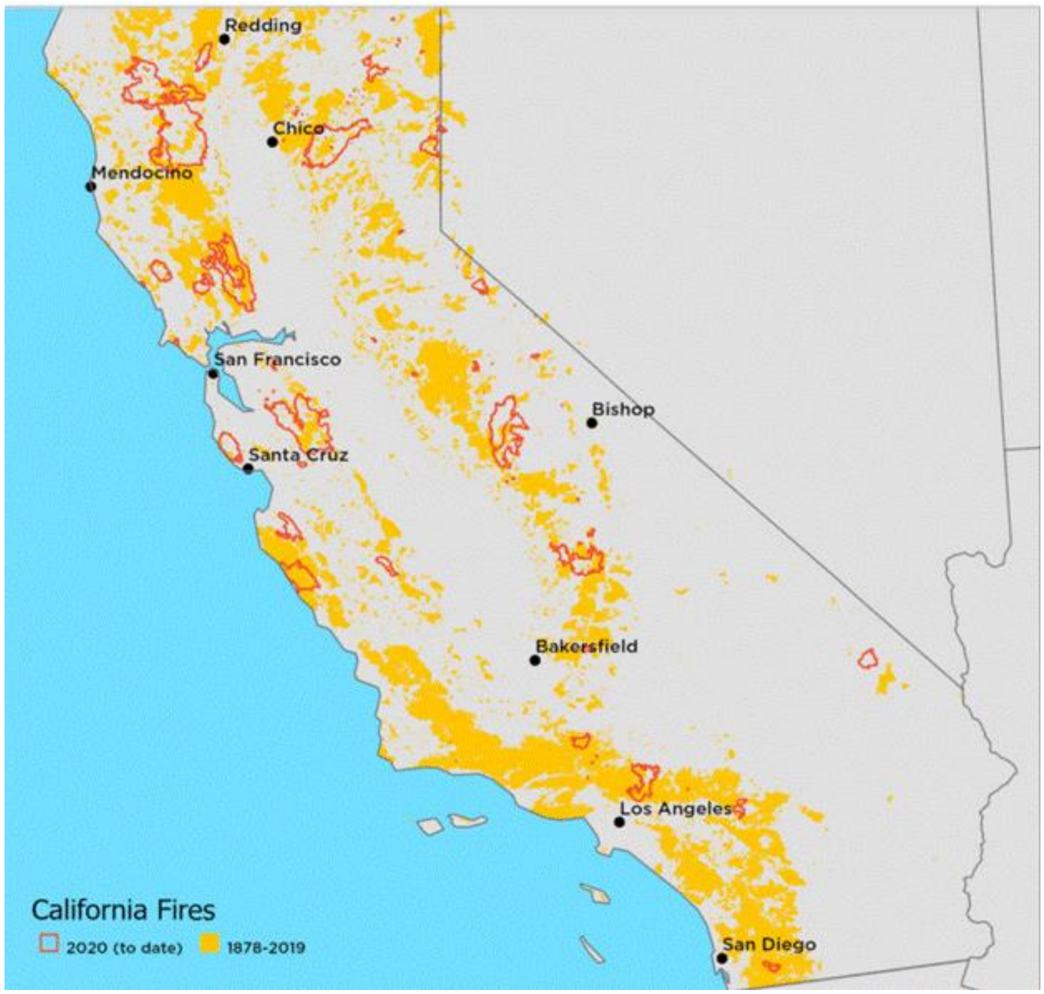
In California, the department of insurance has taken several actions since 2015 aimed at enhancing wildfire risk including developing incentives for homeowners to meet defensible space guidelines, alignment of a rating structure with IBHS risk-mitigation standards, and implementing community wide abatement programs (CDI, 2018). And as of the time of the writing of this report, California, Insurance Commissioner Ricardo Lara recently convened an investigatory hearing on Monday, October 19, 2020 to initiate a series of regulatory actions to include the following (CDI, 2020):

- Developing home-hardening standards that are consistent, based in fire science, and apply to all insurance companies.

[6] https://www.vox.com/2020/10/19/21522994/cameron-peak-calwood-colorado-wildfire-fire-record-east-troublesome-lefthand-canyon

- Giving transparency to consumers about their wildfire risk score and what they can do to reduce it. Insurance companies use wildfire risk scores to determine which homes they will write and the premium they charge.
- Creating insurance incentives recognizing home hardening, mitigation of properties, and community mitigation actions; and,
- Requiring that insurance companies seek adequate and justifiable rates to protect the solvency of the market

Figure 41: Map of 2020 Wildfires relative to historical footprints 1878-2019)



(Source: https://blog.ucsusa.org/kristy-dahl/5-of-californias-6-largest-fires-on-record-are-burning-now-the-astonishing-2020-wildfire-season-in-context)

Insurers have started to respond to the need for more homeowner risk reduction activities to take place as well. For example, again at the time of the writing of this report, on October 13, 2020 Mercury Insurance announced a new program the company is launching to help Californians better protect their homes and families if they live in areas prone to wildfires. Homeowners who take one or more steps to either harden their homes against wildfires or live in a community recognized by the

National Fire Protection Association® (NFPA) as a Firewise USA® site will be eligible to receive discounts of up to 18 percent. [7]

Clearly, there is a need for the type of analysis we have performed here to help to guide the implementation of such wildfire risk reduction actions as we have modeled and to inform the policy discussion for how to make this happen in an economically efficient manner.

And this need is immediate in communities we have selected for this analysis such as Berry Creek California where this risk is unfortunately something they have had to directly deal with in 2020. Berry Creek had the highest number of homes destroyed (1,147) and people killed (15) in the North Complex West Zone fire in September 2020[8] (Figure 42)

Figure 42:Comparioson of Aerial views of Berry Creek after the North Complex Fire 2020.

Source: https://www.mercurynews.com/2020/09/19/watch-officials-post-dramatic-drone-videos-before-and-after-photos-fire-devastation-near-berry-creek/

We do note that for our BCA analysis we have calculated only the direct economic benefits stemming from wildfire risk reduction and not considered other direct benefits (e.g., reduced fatalities and injuries), nor have we looked at the indirect economic benefits such as the savings in the costs of permanently relocating

7 (https://www.prnewswire.com/news-releases/mercury-insurance-launches-programs-to-help-california-homeowners-with-wildfire-risk-301149746.html#:~:text=FAIR%20Plan%20coverage.-,Mercury%20Insurance%20is%20one%20of%20the%20first%20companies%20to%20offer,portion%20of%20their%20insurance%20policy)

8 https://www.latimes.com/california/story/2020-09-22/the-people-in-this-california-town-have-much-to-begin-with-fire-took-it-away) and https://www.sacbee.com/news/california/fires/article245722090.html

residents, or related health impacts from wildfire exposure. Furthermore, wildfire risk reduction costs for new construction would be significantly lower than for existing construction, which could make mitigation of new homes much more appealing.

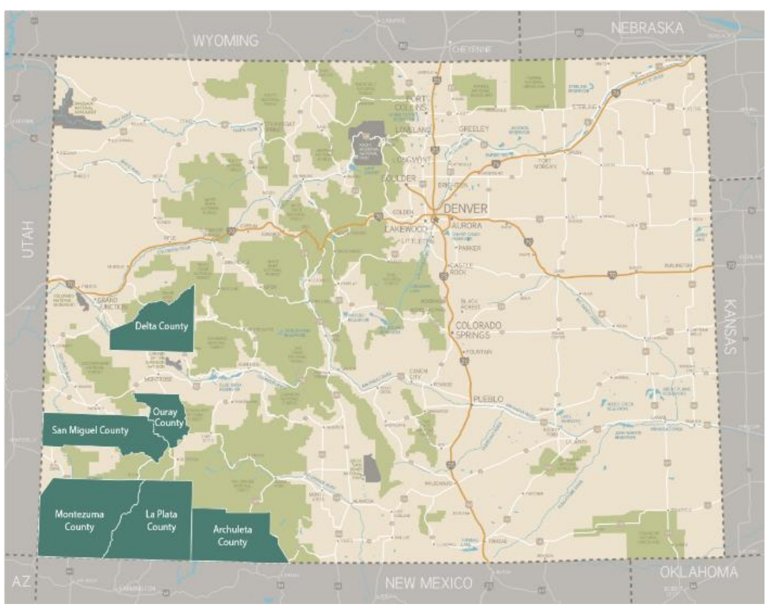
Wildfire Risk Perception and Mitigation: Recent Research

While understanding the economic efficiency of wildfire risk reduction activity is critical for informing related policy making, homeowner behavior driven by perceptions of wilidfire risk can also be a key determinant of mitigation uptake. Here, we provide an overview of research reports by scientists affiliated with the Wildfire Research Team (WiRē), an interdisciplinary collaboration on community adaptedness to wildland fire based in Colorado. The WiRē consortium was formed to integrate local social science with wildfire education and mitigation. The group's research outputs combine two main forms of data collection:

- Rapid wildfire risk assessments, in which professionals rate the relative risk of a given property within its community based on factors including building materials, nearby vegetation, fire fuel, land topography, and fire department access.
- Social surveys of approximately 2,000 residents in the professionally-assessed communities to investigate their perceptions of wildfire risk, risk mitigation behaviors, and responses to incentives to mitigate risk.

An overview of key takeaways from these reports is described below in order to highlight central areas of discussion and lessons applicable for insurance regulators facing ongoing wildfire risk - particularly to consider the role of risk perception in wildfire risk reduction uptake.

Figure 43: Wildfire risk assessment data came from interrelated studies conducted in 6 counties in western Colorado: Archuleta, Delta, La Plata, Montezuma, Ouray, and San Miguel.



Homeowners' perception of risk is complicated and multidirectional.

Risk perception is influenced by numerous factors, including first-hand experience of wildfire or evacuation. While perceiving that they face wildfire risk can motivate people to undertake mitigation activities, such as clearing brush, completing mitigation activities can also make people expect their risk will be somewhat alleviated. Research by Meldrum et al. (2019) "suggests that residents conduct mitigation in the expectation that doing so will lower the chance that a fire burns on their property and that doing so will also reduce their home's vulnerability if that occurs" (p.13).

The researchers also found that people living in areas exposed to wildfire hazards largely understand their risk and make decisions based not only on their complicated risk perceptions but also factors that stand in the way of taking action and beliefs about how effective such efforts will be. Barriers to action include a lack of options for brush removal, time to work on outdoor mitigation projects, and money to complete such projects.

Relevance to insurance regulation: Information alone is not enough to motivate people in high-risk areas to take mitigation action. Homeowners understand wildfire risk but face other constraints. Outreach efforts should focus not only on providing information but also helping residents overcome barriers to mitigation, for example by offering cost-sharing programs or aiding elderly residents unable to complete work on their own.

Compared to professional evaluation, people generally underestimate their property's wildfire risk.

In a study comparing professional and homeowner assessments, residents generally rated their property more favorably related to risk factors such as fire-safe building materials and ease of access to their property for first responders. Trained professionals generally rated nearby vegetation as more dense, dangerous topography closer to structures, and the overall slope of property steeper than respondents did.

Relevance to insurance regulation: Professional assessment should be paired with self-assessment to help residents objectively evaluate the wildfire dangers they face. Insurance companies should conduct regular on-site inspections and help residents understand their property's particular issues, outlining steps toward mitigation.

Wildfire mitigation must be a community effort.

A majority of residents had spoken with their neighbors about wildfire. Those who had were more likely to maintain defensible space around their home and have a more fire-proof structure. In contrast, people who said their neighbors had dense vegetation around their homes had little defensible space on their own property. The upshot? Neighborhood relationships may contribute to increased community-wide wildfire mitigation efforts.

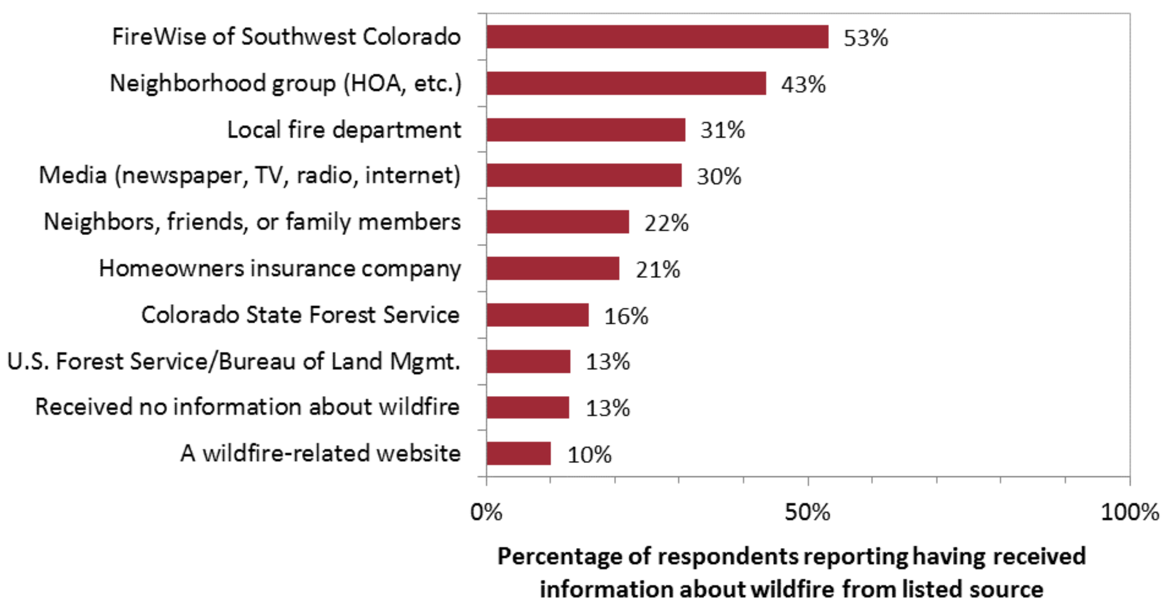
Relevance to insurance regulation: Organizations seeking to influence wildfire mitigation should focus on community-wide efforts to achieve wider results and help build relationships with positive spill over effects. Initiatives such as community chipper days could bring neighbors together to promote mitigation while helping them overcome stated barriers such as a lack of options for yard waste removal.

Information gap:

Compared with other sources of information, consumers reported receiving a relatively small amount of wildfire risk information from their homeowners insurance company. Meldrum et al. (2018) found that only a fifth of respondents reported getting information from their insurance company, whereas more than half had received information from FireWise of Southwest Colorado. Other key information sources were neighborhood groups such as HOAs, the local fire department, and local media.

Relevance to insurance regulation: An opportunity exists for homeowners insurance companies to expand or initiate wildfire education. Companies could model efforts on initiatives such as State Farm's support of NFPA's Wildfire Community Preparedness Day campaign, which provides community-based education on topics such as how to reduce combustible material around vulnerable homes and offers residents the chance to talk to local firefighters about community preparedness.

Figure 44:Comparison of effectivness of information channels in communicating wildfire risk.



Source: Meldrum, J. R., Brenkert-Smith, H., Wilson, P., Champ, P. A., Barth, C. M., & Boag, A. (2018). Living with wildfire in Archuleta County, Colorado: 2015 data report.

Challenges to creating Insurance discounts

Insurance products can be used to provide clear signals to policy holders about effective ways to reduce risk, and they have been applied in various ways in other catastrophe perils like hurricane risk with some success (RMS, 2010). For wildfire, one of the objectives of this report is to provide indicative proof points that the risk curve for this peril can be modified enough to suggest that primary insurance companies could design products to highlight these risk reduction signals. And while we have illustrated this, there are significant limitations to underscore when reviewing the relativities provided in this report that include the following:

- Location / Communities selected in this report are not selected to be representative of an average case, nor even upper/lower range of possible mitigation relativities possible. These are indicative, hypothetical examples only. Possible ranges of mitigation relativity may be smaller, or larger, than reported in this report for each state.
- The notional structure represented in the 'neutral' cases is a hypothetical mix of attributes across the region and may not even exist within the studied communities. The 'neutral' cases here are not indicative of any base rate case for a given insurance company in the state.
- No site-specific information was collected for these communities so even making conclusions that the risk is a given community is adequate to cover the wildfire risk quantified by the model cannot be made from this study.
- The model results in this study represent 'technical premium' - no consideration variable or fixed loss costs have been made in these simple assessments.

What makes wildfire different from other natural catastrophe perils is the hyper-local nature of the hazard gradient. Results and mitigation relativities will vary widely within distances as short as a few hundred meters.

As insurance regulators consider how to let mitigation signals be incorporated into insurance rates if at all, we encourage insurance regulators to consider the learnings highlighted from prior mitigation credit approaches used for other perils.

Because of the hyper-local nature of the peril and the complex interaction between site-level mitigation and community-level mitigation, insurance companies are going to need site-specific attribute information to provide realistic Wildfire mitigation credits. Collection of detailed information from professionals trained to assess fire risk are critical to an effective mitigation program. And relativities cannot be developed from historical loss data. Too many conditions are changing invalidating experience rating as an effective tool in rate making.

Be careful not to have factors that a homeowner cannot really control be part of the mitigation credit scheme. For example, in the state of Florida in the recommended windstorm mitigation credit program (RMS 2010), roof shape was an attribute included in the credit scheme. While an important factor in overall wind risk determination, it provided an artificial 'credit' that basically de-emphasized other factors that were under the control of a homeowner, essentially discouraging those homes to undertake any further risk reduction. Instead factors that cannot be easily controlled should be part of the base rating approach rather than part of possible mitigation credit schemes.

Do not assume every building in the state is a ‘worst-case’ scenario. Note that 30-60% of structures even in the 2020 events survive the fire. There are already structures that are (or at least partially) wildfire resistant. The goal is to identify the key factors, based on building science, that increase the survivability and incentive investment in those factors.

While not fully described in this report, the catastrophe models for wildfire risk are as robust as those currently used in the market for hurricane and earthquake risk. The building science community has been studying wildfire risk for several decades, and the hazard assessment techniques in models like the RMS Wildfire model are an effective tool to overcome the limitations inherent in historical loss data. Insurance companies need the flexibility to create new insurance rating scheme that will provide the right incentives quantify and reduce the risk.

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