Technical appendix: Detailed Sectoral Models

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1. Introduction

Most of the climate impacts quantified in the American Climate Prospectus rely on econometrically-derived impact functions. To assess the impact of changes in temperature on energy demand and expenditures, and changes in sea level and storm activity on coastal property and infrastructure, we employ more detailed sectoral models. For energy sector impacts, we employ RHG-NEMS, a version of the EIA's National Energy Modeling System (EIA, 2013). For coastal impacts, we employ Risk Management Solutions' (RMS) North Atlantic Hurricane Model.

2. Energy Impact Modeling

As discussed in Chapter 10, we limited our analysis of climate-related energy sector impacts to changes in electricity demand, energy expenditures, and electricity generation capacity due to changes in heating and cooling requirements. While a handful of studies have attempted to quantify these relationships, Deschênes and Greenstone (2011) provides the only nationally applicable, recent, empirical estimate of changes in energy demand resulting from changes in heating and cooling requirements. However, this paper provides information on changes in residential demand only.

To supplement the findings in Deschênes and Greenstone, we use RHG-NEMS, a version of the Energy Information Administration's (EIA) National Energy Modeling System (NEMS) (EIA, 2013), maintained by the Rhodium Group. RHG-NEMS is a detailed multi-sector bottom-up model of US energy supply and demand with detailed residential, commercial, and industrial demand modules, electricity and primary energy supply modules, and energy market and macroeconomic modules, among others. Consumer demand curves are derived from detailed consumer choice algorithms that allow consumers to substitute, subject to limited foresight, from a wide array of available end-use technologies in order to satisfy their energy service demands (see section 2.2).

2.1. Physical Data

We model changes in energy demand by varying the number of heating degree days (HDDs) and cooling degree days (CDDs), which in turn drive heating and cooling service requirements in NEMS. HDDs and CDDs are a measure of the approximate number of degrees that a living space must be heated or cooled for each day summed over all the days in the year. Daily minimum and maximum temperature projections were drawn from the outputs of the climate modeling process (see Technical Appendix I), meaning that the projections are both consistent with the other impact categories in this study, and that they covary in the macroeconomic modeling process described in Technical Appendix IV. The method for calculating HDDs and CDDs is described in tables C1 and C2 (see for example UK Met Office, 2012).

2.2. RHG-NEMS

Our analysis of the impact on residential and commercial heating and cooling demand due to climate change relies heavily on RHG-NEMS, a version of the Energy Information Administration's (EIA) National Energy Modeling System (NEMS) maintained by the Rhodium Group. EIA uses NEMS to produce their Annual Energy Outlook (AEO), which projects the production, conversion, consumption, trade, and price

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Table C1: Formula for calculating daily HDD-65

Condition	Formula Used
$T_{min} > 65F$	$D_h = 0$
$\frac{(T_{max}+T_{min})}{2} > 65F$	$D_h = \frac{(65F-T_{min})}{4}$
$T_{max} >= 65F$	$D_h = \frac{(65F-T_{min})}{2} - \frac{(T_{max}-65F)}{4}$
$T_{max} < 65F$	$D_h = 65F - \frac{(T_{max}+T_{min})}{2}$

Table C2: Formula for calculating daily CDD-65

Condition	Formula Used
$T_{max} < 65F$	$D_c = 0$
$\frac{(T_{max}+T_{min})}{2} < 65F$	$D_c = \frac{(T_{max}-65F)}{4}$
$T_{min} <= 65F$	$D_c = \frac{(T_{max}-65F)}{2} - \frac{(65F-T_{min})}{4}$
$T_{min} > 65F$	$D_c = \frac{(T_{max}+T_{min})}{2} - 65F$

of energy in United States through 2040. NEMS is an energy-economic model that combines a detailed representation of the US energy sector with a macroeconomic model provided by IHS Global Insight. The version of RHG-NEMS used for this analysis is keyed to the 2013 version of the AEO. The NEMS model is documented in full in US Energy Information Administration (2009). Documentation of the macroeconomic and energy sector assumptions used in the AEO 2013 version of NEMS is available in US Energy Information Administration (2013a).

RHG-NEMS is designed as a modular system with a module for each major source of energy supply, conversion activity and demand sector, as well as the international energy market and the US economy (figure C1). The integrating module acts as a control panel, executing other RHG-NEMS modules to ensure energy market equilibrium in each projection year. The solution methodology of the modeling system is based on the Gauss-Seidel algorithm. Under this approach, the model starts with an initial solution, energy quantities and prices, and then iteratively goes through each of the activated modules to arrive at a new solution. That solution becomes the new starting point and the above process repeats itself. The cycle repeats until the new solution is within the user-defined tolerance of the previous solution. Then the model has ‘converged’, producing the final output.

2.2.1. Residential and commercial demand modules

In RHG-NEMS, energy consumption estimates of residential and commercial sectors are modeled using the Residential and Commercial Demand modules. The Residential Demand Module projects energy demand by end-use service, fuel type, and Census division (table C3). Similarly, the Commercial Demand Module projects energy demand by end-use service and fuel type for eleven different categories of buildings in each Census division (table C4). Both modules use energy prices and macroeconomic projections from the RHG-NEMS system to estimate energy demand based on extensive exogenous inputs including consumer behavior, appliance efficiency and choices, and government policies.

One of the factors affecting energy demand in RHG-NEMS is climate. Future climate is represented as annual HDDs and CDDs by census region in both the residential and commercial demand modules. The modules incorporate the future change in heating demand (due to change in HDDs) and cooling demand (due to change in CDDs) to inform decisions about appliance purchases as well as total energy consumption. For further details see Residential Demand module (US Energy Information Administration, 2013c) and Commercial Demand module documentations (US Energy Information Administration, 2013b).

2.3. Impact Estimation

Due to the complexity and run time of RHG-NEMS, running the model for each of our weather draws was infeasible. Instead, we constructed representative scenarios that varied the HDDs and CDDs from our

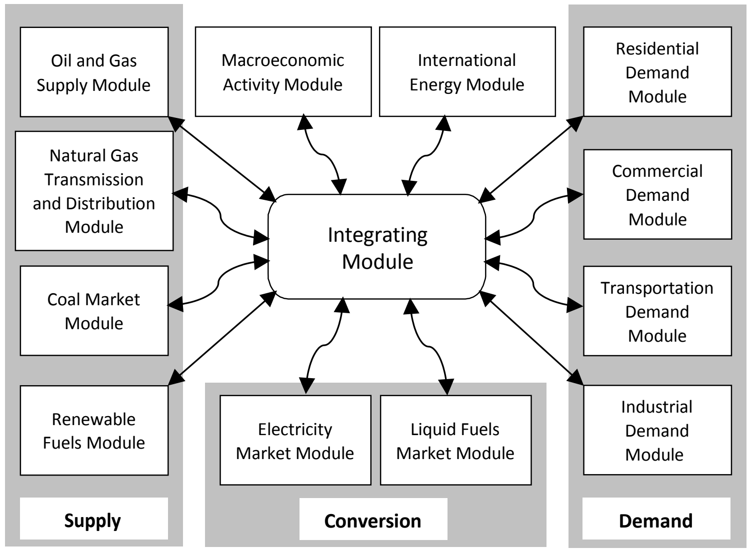


Figure C1: Basic NEMS structure and Information Flow

Index Value	**Census Division**	**Housing Type**	**Fuel**	**Technology Choice**
1	New England	Single Family	Distillate	Space Heating
2	Middle Atlantic	Multifamily	LPG	Space Cooling
3	East North Central	Mobile Home	Natural Gas	Clothes Washing
4	West North Central		Electricity	Dishwashing
5	South Atlantic		Kerosene	Water Heating
6	East South Central		Wood	Cooking
7	West South Central		Geothermal	Clothes Drying
8	Mountain		Coal	Refrigeration
9	Pacific		Solar	Freezing

Table C3: Residential Module: Key Variables

baseline and recorded the response of the model in the variables of interest: changes in energy and electricity demand, energy and electricity expenditures and electricity generation capacity. Using the results of these runs, we built the response functions to estimate, for each census region, the percent change in a particular variable due to absolute changes in the number of HDDs and CDDs. Table C5, for example, presents the response functions for electricity demand from an increase in 1 HDD or CDD.

The final distributions were estimated using a Monte Carlo simulation of the changes in county, state, regional, and national energy expenditures, electricity demand, and changes in national electricity generation capacity given the set of all modeled changes in county daily temperature extremes. The HDD-CDD response functions given above are applied to all counties within each census region. This process yields a set of covarying distributions for percent changes in electricity and energy demand at the county level for each year in the analysis. Changes in state, regional, and national quantities use population-weighted average changes in HDDs and CDDs at the state level. Base values are EIA estimates of state-level electricity sales (2014a) and energy expenditures (2014b). For maps displaying county-level absolute changes in electricity and energy demand, we multiply each county's share of the state population by the state's base energy or electricity demand to find a base county-level value. In some cases where the statewide energy or electricity demand distribution departs significantly from the population distribution this will misrepresent the magnitude of changes at the county level. However, the data portrayed in these maps are intended for illustrative purposes and do not factor into any state or national calculations.

In calculating total direct costs and benefits, including all impact categories, we used changes in residential and commercial energy expenditures, derived from the percent changes in this quantity provided by RHG-

Index Value	Census Division	Building Type	Fuel	End-use Service
1	New England	Assembly	Electricity	Space Heating
2	Middle Atlantic	Education	Natural Gas	Space Cooling
3	East North Central	Food Sales	Distillate Oil	Water Heating
4	West North Central	Food Service	Residual Oil	Ventilation
5	South Atlantic	Health Care	LPG	Cooking
6	East South Central	Lodging	Steam Coal	Lighting
7	West South Central	Office - Large	Motor Gasoline	Refrigeration
8	Mountain	Office - Small	Kerosene	Office Equip. - PCs
9	Pacific	Mercantile & service	Wood	Office Equip. - other
10		Warehouse	Municipal Solid Waste	Misc. End-Use Loads
11	U.S. Total	Other	Hydro	
12			Waste Hear	
13			Other Gaseous Fuels	

Table C4: Commercial Module: Key Variables

Table C5: Predicted change in residential and commercial electricity demand from a change in 1 HDD/CDD [percent]

Census Region	HDD	CDD
New England	0.00056%	0.00329%
Middle Atlantic	0.00150%	0.00895%
East North Central	0.00101%	0.00924%
West North Central	0.00023%	0.00755%
South Atlantic	0.00040%	0.00718%
East South Central	−0.00138%	0.00620%
West South Central	−0.00047%	0.00742%
Mountain	0.00061%	0.00881%
Pacific	0.00130%	0.00673%

NEMS and the base energy expenditures by state from EIA (US Energy Information Administration, 2014b).

Table C6: Predicted change in residential energy demand from a change in 1 HDD/CDD [percent]

Census Region	**HDD**	**CDD**
New England	0.00102%	0.00511%
Middle Atlantic	0.00116%	0.00012%
East North Central	0.00040%	0.00011%
West North Central	0.00010%	0.00012%
South Atlantic	0.00102%	0.00907%
East South Central	−0.00193%	0.00759%
West South Central	0.00494%	0.00010%
Mountain	−0.00010%	0.00014%
Pacific	0.00239%	0.00769%

Table C7: Predicted change in commercial energy demand from a change in 1 HDD/CDD [percent]

Census Region	**HDD**	**CDD**
New England	0.00013%	0.00160%
Middle Atlantic	0.00176%	0.00621%
East North Central	0.00157%	0.00776%
West North Central	0.00037%	0.00317%
South Atlantic	−0.00030%	0.00505%
East South Central	−0.00056%	0.00423%
West South Central	−0.00681%	0.00410%
Mountain	0.00138%	0.00322%
Pacific	0.00048%	0.00600%

Table C8: Predicted change in national electricity capacity required from a change in 1 HDD/CDD [GW]

	HDD	**CDD**
US Total	0.08184	0.2856

3. Coastal Impacts

3.1. Introduction to RMS

Risk Management Solutions, Inc. ("**RMS**") is a leading provider of products and services for the quantification, management and transfer of catastrophe risk. RMS offers risk assessment models for over 50 territories world-wide, encompassing major perils such as earthquakes, tropical cyclones, other windstorms, floods, terrorist attacks and infectious disease. Founded at Stanford University in 1988, RMS operates today from ten offices in the United States, Europe, India, China and Japan, with headquarters in Newark, California. RMS is a subsidiary of the U.K.-based Daily Mail and General Trust plc media enterprise.

RMS employs professionals with backgrounds in actuarial and statistical sciences, meteorology, physics, geology, seismology, structural and civil engineering, management consulting, economics and finance. RMS also utilizes a global network of academic contacts and consulting engineers who are retained for periodic review of RMS technology or for specific projects.

3.2. RMS Modeling Overview

This section describes in general terms the RMS modeling process for a number of catastrophe risk perils.

Analytical and statistical models for quantifying catastrophe risk have become a key component in how insurance and reinsurance companies manage the risk of natural disasters. These models are founded on a range of analytical, engineering and empirical techniques. Given the scientific understanding of natural catastrophes, the methodology behind these models incorporates established principles of meteorology, seismology, wind and earthquake engineering, and other related fields to model the frequency, severity and physical characteristics of natural catastrophes. To estimate the losses resulting from such catastrophes, RMS has developed a computer program and certain related utilities that provide a mathematical representation of catastrophes and that simulate the ultimate damage and insured losses to property for each simulated even.

The figure below summarizes the data and processes used to model the financial loss from catastrophe events within RMS' commercially available models.

The RMS property loss models consist of three main elements:

1. **Pre-compiled databases** defining the events, site hazards (for example, distance to coast for hurricane, topography for surge) and details about the building stock vulnerability.

2. **Analytical modules** including stochastic, hazard, vulnerability and financial analysis components, as described below.

3. **Exposure data** describing the properties of the exposure analyzed (typically for insurance the property exposure) including its location, building information and details of insurance coverages including covered perils and financial terms.

Regardless of the peril, RMS Models follow a consistent structure comprising four principal modules.

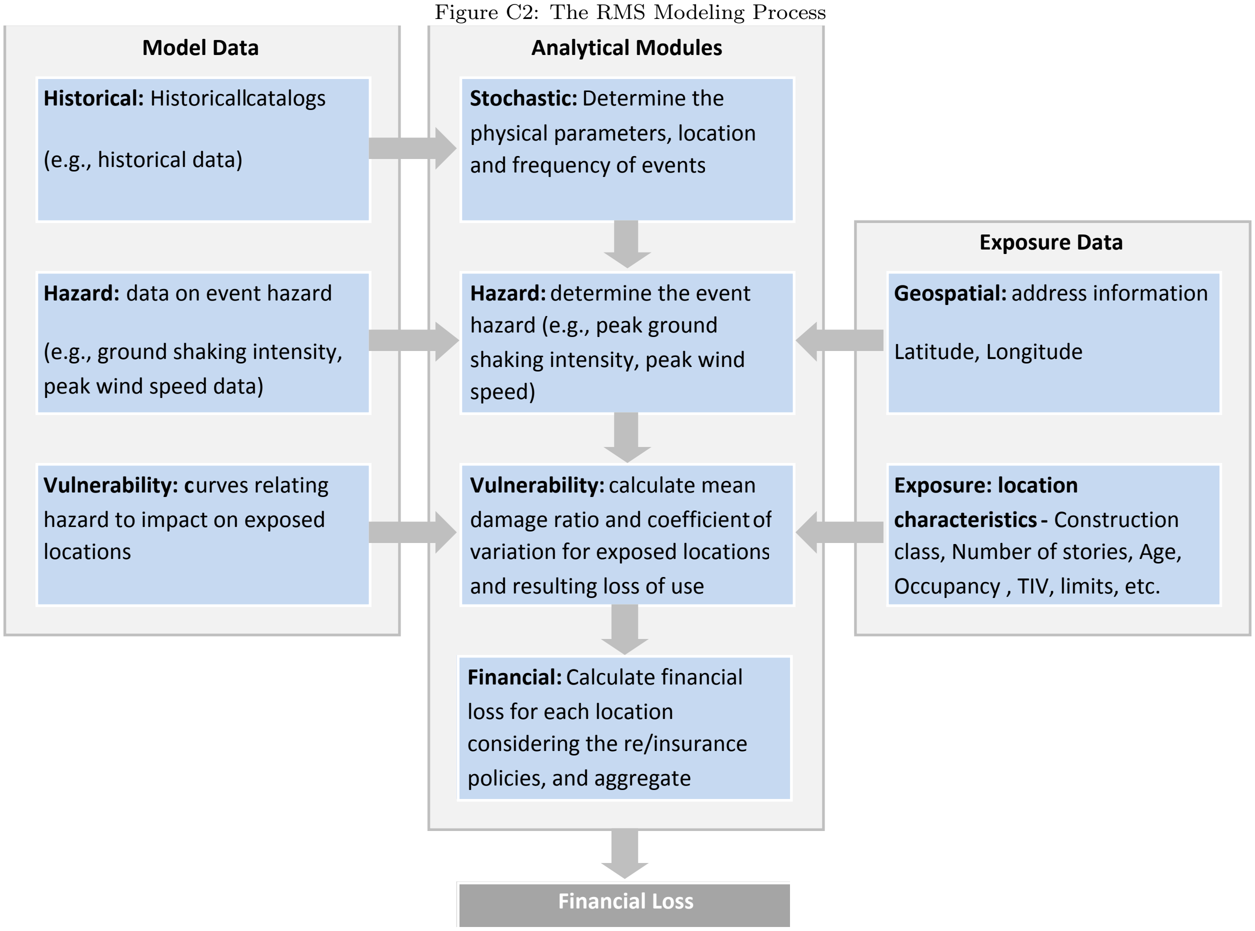
1. **Stochastic Module**: simulates tens of thousands of hypothetical events, each uniquely identified by its location, physical characteristics and rate of occurrence, to provide a representation of the universe of physically plausible combinations of key event parameters more comprehensive than could be obtained from the sparse catalog of historical events.

2. **Hazard Module**: determines an event's intensity of effect (such as windspeed, or flood depth) at a given location given the parameters of the event and their interaction with the site conditions.

3. **Vulnerability Module**: generates an estimate of the Mean Damage Ratio ("**MDR**") to a specific exposure as a function of the hazard, as well as a coefficient of variation ("**CV**") around the mean, reflecting uncertainty both in the estimation of the hazard and the resulting damage. The MDR is the repair cost to the exposure represented as a percentage of the value.

4. **Financial Analysis Module**: applies the MDR and the related CV generated by the Vulnerability Module for each event to estimate the distribution of losses for each event at each location and in the aggregate across all the events in the simulation.

Figure C2: The RMS Modeling Process



The RMS Models can be used to perform both "deterministic" and "probabilistic" analyses. For a deterministic analysis, the RMS Models produce a loss estimate for a single historical or scenario event. For a probabilistic analysis, the model generates a loss for each of the tens of thousands of stochastic events and the results are displayed from highest to lowest in the form of a cumulative probability distribution, also called an "occurrence exceedance probability (or EP) curve,". The EP curve provides the full spectrum of possible losses and their related annual probabilities of exceedance for a given set of insurance exposures or contracts. By selecting a particular annual probability — for example the 1% or '100 year average return period' - it becomes possible to identify the magnitude of the associated loss at this probability. The integral under the EP curve is the amount that would need to be set aside each year to fund all future losses — known as the average annualized loss. The EP curve loss distribution is not a prediction of future losses, but is solely intended to be illustrative of the range of possible losses and the likelihood of occurrence of these losses thereof. In each RMS Model, the first three modules comprise a peril- and region- specific implementation, discussed in further detail herein. The Financial Analysis Module consists of elements common to all models, as described below.

3.2.1. Financial Analysis Module

The Financial Analysis Module applies the MDR and the related CV generated by the Vulnerability Module for each event to estimate the distribution of losses both by location and in the aggregate for a given set of exposure data. To calculate the loss, the MDR for each coverage (i.e., building, contents and business interruption/alternative living expenses) at each location is applied to the insured values, resulting in an estimate of the ground-up economic loss to the value at risk at such location before applying the effects of insurance.

Secondary Uncertainty

Secondary uncertainty represents the uncertainty in the amount of loss, given that a specific event has occurred, and is represented in the model output by the event standard deviations. The Financial Analysis Module incorporates uncertainty from the following four sources: hazard uncertainty, vulnerability uncertainty, specification uncertainty and portfolio data uncertainty.

- Each peril has its own characteristic type of hazard uncertainty. Uncertainties related to windstorm perils include windfield and terrain effects.
- Vulnerability uncertainty refers to the uncertainty in the amount of damage a building may sustain given a specific local hazard condition.
- The uncertainty in the magnitude of loss can also be affected by the level of specificity of the relevant model parameters. Where it is possible to differentiate risk, a less detailed model produces a loss with a higher level of uncertainty. Specification uncertainty can arise from several sources: for example, the level of geographic resolution, construction characteristics, and local conditions can all be modeled at varying levels of detail. Refinements in a model's capacity to accurately reflect higher levels of detail in loss generation reduce the uncertainty in the model's loss estimates.
- Portfolio data uncertainty reflects the level of detail in the exposure data entered into the model, such as around the construction type, year of construction, and number of stories. More detailed data should mean reduced levels of uncertainty in the model. For example, using portfolio data with location information at the street address level instead of at the ZIP Code level generally decreases the secondary uncertainty.

Loss Amplification

Following a major catastrophic event, claims costs can exceed the normal cost of settlement due to a unique set of economic, social, and operational factors. Claims analysis studies from both the 2004 and 2005 hurricane season, as well as in research into other major catastrophes such as Hurricane Andrew in 1992 and the Northridge earthquake in 1994, show that loss amplification can be a significant source of loss.

One component of loss amplification is economic demand surge, the increase in the cost of labor and materials needed to make repairs as a result of shortages after a large event. However, in the aftermath of

Hurricane Katrina, RMS launched a research initiative to evaluate and quantify factors beyond economic demand surge that could further amplify losses in severe catastrophes. As a result of this research, RMS has updated and expanded the demand surge module by quantifying three major factors under a broader loss amplification methodology: economic demand surge, claims inflation, and coverage expansion in super-catastrophe (Super-Cat) scenarios.

- **Economic Demand Surge**. Economic demand surge (EDS) is defined as the rapid increase in the cost of building materials and labor cost as demand for repair exceeds supply or capacity of the construction sector following a major hurricane. Demand surge factors have been developed independently for each coverage, with building and business interruption coverage contributing more than contents. EDS varies by region in the U.S. and in Canada.

- **Claims Inflation**. The claims inflation factor considers the increased cost associated with an insurer's inability to fully adjust claims when the number of claims is too high to work in accordance with standard claim adjustment procedures. Claims inflation can only be triggered if an event has activated economic demand surge. The impact of this factor varies with the estimated number of claims occurring for an event. Overall, claims inflation has a minor impact compared to the other two post-event Loss amplification (PLA) components.

- **Super-Cat**. This component of loss amplification encompasses expanding losses from a range of factors including containment failures (flooding from levee or dam failure, pipeline or tank rupture, release of toxic chemicals), long-term evacuation (due to breakdown of local infrastructure, such as water or sewage systems and resulting contamination), or systemic economic consequences of a severe catastrophe (absence of labor force to make repairs; hotels and retail facilities incapable of opening due to lack of tourism). Primary escalation for Super Cat events occurs with respect to time-element (such as business interruption ("BI") and adjusted living expenses) losses. This effect was modeled for several major urban areas in the U.S.

Claims inflation and Super-Cat loss amplification effects occur with more extreme events than those that would cause economic demand surge. The effects of these three components of loss amplification compound multiplicatively.

3.3. The RMS North Atlantic Hurricane Model

The RMS North Atlantic Hurricane Model explicitly includes direct damage from wind and storm surge to property, contents and interrupted businesses in the Gulf States, Florida and the east coast of the United States.

By virtue of using empirical claims calibration, the model implicitly includes related hurricane property damage from tree-fall, wind missiles, rain infiltration etc. The RMS North Atlantic Hurricane Model does not include the following potential sources of non-modeled loss:

- Inland flooding from hurricane-related rainfall, though some wind-driven rain losses are implicitly included through the empirical claims calibration

- Chaotic weather systems such as tornadoes and hailstorms that sometimes accompany hurricanes, though damage caused by such weather systems may be implicitly included through the empirical claims calibration to the extent of their prevalence in past events to which the claims data pertain

- Losses from any source occurring in areas that experience wind speeds below a modeling threshold of 50 mph

- Claims adjustment expenses

- Off-premises power losses

- Losses not covered in insurance policies

- Policy coverage expansion, for example due to legal mandates

- Contingent and other indirect time-element coverages (i.e., contingent business interruption)

Furthermore the RMS North Atlantic Hurricane Model does not include modeled storms that at no point over their life-cycles affect land as a hurricane (i.e., Category 1 or greater).

The RMS North Atlantic Hurricane Model's geographical coverage extends across 21 states of the continental United States and the District of Columbia, Hawaii, the Gulf of Mexico, the islands of the Caribbean and Canada. The 23 states/municipalities of the United States included within the RMS North Atlantic Hurricane Model are Alabama, Connecticut, Delaware, District of Columbia, Florida, Georgia, Hawaii, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas, Vermont, Virginia and West Virginia. The geographic extent of the model coverage is a reflection of the significant decay of wind hazard away from the coast. Tropical cyclones are fuelled by hot moisture-laden air from the ocean. Because hurricanes are dependent on ocean evaporation to sustain energy, the relatively lower moisture content over land contributes to the dissipation of winds after hurricane landfall.

While inland states may incur hurricane related losses from non-modeled sources such as inland flooding, their contribution to direct wind-related losses is very minor. During the period 1950 to 2013, approximately 98%[1] of insured losses from Atlantic hurricanes occurred within the RMS Modeled Hurricane States, and is principally related to inland flood.

3.3.1. Hurricane Model

Stochastic Event Module

The stochastic module consists of a set of tens of thousands of stochastic events that represent more than 100,000 years of hurricane activity. RMS scientists have used state-of-the-art modeling technologies to develop a stochastic event set made of events that are physically realistic and span the range of all possible storms that could occur in the coming years.

At the heart of the stochastic module is a statistical track model that relies on advanced statistical techniques (Hall & Jewson 2007) to extrapolate the HURDAT catalog (Jarvinen et al., 1984) and generate a set of stochastic tracks having similar statistical characteristics to the HURDAT historical tracks. Stochastic tracks are simulated from genesis (starting point) to lysis (last point) using a semi-parametric statistical track model that is based on historical data. Simulated hurricane tracks provide the key drivers of risk, including landfall intensity, landfall frequency, and landfall correlation.

The stochastic event module is calibrated to ensure that simulated landfall frequencies are in agreement with the historical record. Target landfall rates are computed on a set of linear coastal segments (or RMS gates) by smoothing the historical landfall rates. The RMS smoothing technique uses long coastal segments, obtained by extending each RMS gate in both directions and keeping the orientation constant. Historical storms that cross an extended gate contribute to the landfall rate at the corresponding original segment.

Importance sampling of the simulated tracks is performed to create a computationally efficient event set of 30,000 events used for loss cost determinations. Each of these events has a frequency of occurrence given by its mean Poisson rate. Because event frequencies were calibrated against history (HURDAT 1900–2011), this set of Poisson rates represents the RMS baseline model and this rate set is called the "RMS historical rate set."

Windfield (or Wind Hazard) Module

The wind hazard module calculates windfields from both landfalling hurricanes and bypassing storms. Once tracks and intensities have been simulated by the stochastic module, the windfield module simulates 10 meter, three-second peak gusts on a variable resolution grid. Size and shape of the time stepping windfields are generated using an analytical wind profile derived from Willoughby (2006). Peak gusts are the driver of building damage and are used as the basis of many building codes world-wide, including the U.S.

Wind Vulnerability Module

[1] Derived from Property Claim Services Data, 1950-2013

The wind vulnerability module of the RMS U.S. Hurricane Model relates the expected proportion of physical damage for buildings and contents to the modelled peak three-second gust wind speed at that location. The severity of the damage is expressed in terms of a mean damage ratio (MDR), which is defined as the ratio of the expected cost to repair the damaged property relative to its replacement cost. The wind vulnerability module also estimates the variability in the expected damage ratio and models this with a beta distribution. Time-element losses due to business interruption and additional living expenses are estimated using occupancy-dependent facility restoration functions that relate the expected duration of the loss of use to the modeled building damage.

3.3.2. Storm Surge Model

The RMS North Atlantic Hurricane storm surge model utilizes the latest technology to quantify the risk of storm surge for the U.S. Atlantic and Gulf coastlines (from Texas to Maine). The model system uses wind and pressure fields, over the lifetime of the storm, from the stochastic event set of the RMS North Atlantic Hurricane Model as forcing (i.e., as input) for the state-of-the-art MIKE 21 hydrodynamic model system to estimate still-water (i.e. without wave effects) storm surges and wave impacts. The impact of rainfall accumulation during an event is not considered in the modeling of storm surge levels.

Storm Surge Hazard Module

Storm surge in the numerical model is driven by the wind-stress from the time-stepping windfield and the cyclones' low pressure field, together with the changes in sea level that accompany the tides. The storm surge is dependent on the storm's characteristics in the lead up to landfall, with a large storm surge resulting from the accumulated impact of low pressures and wind-stress acting for many days before the storm nears the coast. Storms may often weaken just at landfall but still retain much of the surge associated with their offshore intensity. For example, Hurricane Katrina, which reached Category 5 intensity in the Gulf of Mexico but weakened to Category 3 at landfall, produced a powerful 27-foot surge on the Mississippi coast.

In urban coastal areas, the resolution of the surge footprint is 100m. This resolution decreases to 500m and greater in non-urban areas. To calculate the surge hazard at a specified location the elevation of the terrain is subtracted from the surge height at the location to determine the depth of flooding. Once the elevation is subtracted from the surge height, the wave height is calculated based on the depth of flooding and the velocity of the flow. The velocity of the flow is dependent on the proximity to the open sea and the effects of local topography on the flow. For buildings that meet the construction class and year built criteria, and are within a FEMA zone, the Base Flood Elevation is applied to the lower floor of the property to calculate an effective flood depth. RMS has implemented improved elevation data based on the USGS National Elevation Dataset (NED), enhanced with airborne LIDAR data where available, and stored on an underlying 100m uniform resolution grid.

Storm Surge Vulnerability Module

Storm Surge Vulnerability

The U.S. storm surge vulnerability module relates the expected amount of physical damage to buildings and contents to the modeled storm surge flood depth and the effects of wave action, if present. Like the wind vulnerability module, the severity of the damage is expressed in terms of a mean damage ratio (MDR) while the variability in the damage is characterized using a beta probability distribution. The U.S. storm surge vulnerability functions for buildings and contents are derived from a database of flood-related damage observations compiled by the U.S. Army Corps of Engineers (USACE) from major flood events in the U.S. This database consists of flood-depth-damage-ratio relationships that relate the incurred flood-related loss to the observed flood depth for different occupancy types. The storm surge vulnerability functions implemented in RiskLink also incorporate structural-engineering-based adjustments to account for the effects of the building height and construction class on the expected damage and are calibrated and validated using claims data from multiple storms.

Low Velocity Flooding and Wave Action

There are two sets of vulnerability functions in the storm surge model—one representing the damage caused by low-velocity flooding and a second for modeling the additional damage caused by wave action.

The low-velocity flooding curves, which are referred to as surge vulnerability functions, relate the MDR of a building or its contents to the estimated flood depth according to its occupancy type, construction class and number of stories. The wave vulnerability functions are used for loss calculations when a location has been characterized as unsheltered and the water depth exceeds seven feet. For a given building type and surge depth, the damage ratio predicted by the wave vulnerability function will be higher than that simply from low-velocity flow.

3.4. Modifying the RMS North Atlantic Hurricane Model to account for climate change

The RMS North Atlantic Hurricane Model can be adjusted to account for changed climate conditions by modifying various components of the above detailed model.

- Local sea level rise projections (Kopp et al., accepted, 2014) can be incorporated via adjusting the "*Storm Surge Hazard Module*"
- Changes in hurricane frequency and intensity (Emmanuel 2013 and Knutson et al. 2013) can be incorporated via adjustments to the "*Stochastic Event Module*" and specifically the frequency of occurrence of each event in the event set, i.e. by creation of alternative "rate sets"

Each adjustment can be applied independently or in combination to create multiple alternative versions of the RMS North Atlantic Hurricane Model conditioned on a specified future climate state. For the purposes of this report many hundred alternative versions of the model were created to span the range of time periods, RCPs, sea-level rise projections as well as alternative models / inputs for the changes in Hurricane Frequency and Intensity.

Local Sea Level Rise Projections

The "Storm Surge Hazard Model" calculates the local inundation of each stochastic event on 18 local grids nested within a lower resolution regional gird covering the domain of the model. The local sea level rise projections from Kopp et al. (accepted, 2014) were mapped to the individual local grids to assign a grid specific increase in sea level. The surge height of the footprint of each event was then adjusted at this local level before being recombined into a coherent 'event' footprint (which can cover multiple local grids).

Change in Hurricane Frequency and Intensity

The projections of future Hurricane activity in Knutson et al. (2013) provide the percentage change in activity in the Atlantic basin by category of storm for the multi-model ensemble mean from phase 5 of the Couple Model Inter-comparison Project using Representative Concentration Pathway 4.5. These changes were mapped directly to the "RMS historical rate set" according to the maximum lifetime intensity category of each storm in the event set. Knutson et al. provide the relevant changes by storm intensity Category for early- and late-twenty-first century time-slices, from which linear interpolation / extrapolation was used to infer the changes at the relevant time-periods required for this report.

The projections of future Hurricane activity in Emmanuel (2013) (supplemented through personal communications) were obtained as absolute values for basin activity and for activity at landfall (across the entire north Atlantic domain) by maximum storm intensity (as measured by the maximum 1-min sustained wind speed). Projections were provided for 6 individual General Circulation Models from phase 5 of the Couple Model Inter-comparison Project using Representative Concentration Pathway 8.5. Projections were provided for current, mid- and late-twenty-first century time-slices. The difference between the future and current activity is used to define a percentage change in activity and linear interpolation / extrapolation is used to infer the percentage changes at the relevant time-periods consistent with this report. The changes are mapped directly the "RMS historical rate set" according to maximum lifetime category or maximum landfall category of each storm in the event set to create multiple alternative rate sets.

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