



Climate Impact Assessment

December 2022



International Towers 3 Sydney
300 Barangaroo Ave
Sydney NSW 2000

PO Box H67
Australia Square NSW 1215
Australia

ABN: 51 194 660 183
Telephone: +61 2 9335 7000
Facsimile: +61 2 9335 7001
DX: 1056 Sydney
www.kpmg.com.au

Victoria Hogg
Essential Energy
8 Buller St
Port Macquarie
NSW 2444

16 December 2022

Climate Impact Assessment

We are pleased to present this report on the climate impact assessment that Essential Energy and KPMG collaborated on during the period between 14 April 2022 and 16 December 2022. Importantly, this assessment incorporated the catastrophe risk models developed by Risk Frontiers for bushfire and flood risk.

This report has been prepared for Essential Energy to evidence the extensive collaboration with KPMG and Risk Frontiers which demonstrates the robustness of the modelling framework employed to deliver Essential Energy's climate impact assessment.

Some key sections of the report include:

- > Background and Scope (page 11)
- > Methodology (pages 12-15)
- > Reliances and Limitations (pages 16-17)

This report should be read in conjunction with the methodology playbook "Essential Energy Climate Impact Assessment Playbook – 16 December 2022.pdf" and the data and assumptions memo "Essential Energy Climate Impact Assessment Data and Assumptions – 16 December 2022.pdf".

Yours sincerely

Richard Yee
Executive

Tammy Falconer
Executive

Introduction - Climate Change

Climate change is having a significant impact on economies and societies across the globe. Seven of the world's hottest years have occurred in the last decade and there is growing evidence to link an increase in frequency and intensity of extreme weather events, including heatwaves and cyclones, to anthropogenic climate change¹.

The most recent report from the Intergovernmental Panel on Climate Change ("**IPCC**") stated that it was unequivocal that human influence has warmed the atmosphere, ocean and land, with global mean surface temperature ("**GMST**") having increased by 1.09°C between the pre-industrial baseline period (1850-1900) and the most recent decade of 2011-20.

It further states that climate change has impacted many weather and climate extremes in every region across the globe with evidence of observed changes in extremes such as heatwaves, heavy precipitation, droughts, and tropical cyclones. Without immediate and severe reductions in emissions, global warming of 1.5°C and 2°C will be exceeded during the 21st century. On current projections, the IPCC estimate 3°C of warming by the end of the century, increasing the risks of more uncertainty and extreme events.

Australia is recognised as having a higher level of susceptibility to climate impacts compared to other countries². Land areas have warmed by around 1.4°C between ~1910 and 2020, influencing heat extremes, rainfall (more time in drought, but more intense heavy rainfall events), number of dangerous fire weather days and a longer fire season. This assessment has quantified the impacts of RCP4.5 and RCP8.5, the associated projected temperatures of those scenarios are summarised in the table below:

Table 1: Details of Representative Concentration Pathways

Climate Scenario	Radiative Force in 2100	GHG Emissions	Change in Global Mean Surface Temperature ³
Climate Scenario RCP 2.6	2.6 W/m ²	GHG emissions decline after 2020 and zero by 2100.	1.6°C (0.9°C - 2.3°C)
Climate Scenario RCP 4.5	4.5 W/m ²	GHG emissions continue to rise to 2040, then decline.	2.4°C (1.7°C – 3.2°C)
Climate Scenario RCP 6.0	6.0 W/m ²	GHG emissions continue to rise to 2080, then decline.	2.8°C (2.0°C – 3.7°C)
Climate Scenario RCP 8.5	8.5 W/m ²	Emissions continue to increase in line with current business-as-usual pathway. GHG emissions continue to rise to 2100, which is the year that climate models are generally projected out to.	4.3°C (3.2°C - 5.4°C)

Greenhouse gases are those gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths within the spectrum of terrestrial radiation emitted by the Earth's surface, the atmosphere itself and by clouds. This property causes the greenhouse effect. Water vapour ("**H2O**"), carbon dioxide ("**CO2**"), nitrous oxide ("**N2O**"), methane ("**CH4**") and ozone ("**O3**") are the primary GHGs in the Earth's atmosphere.

The change in global mean surface temperature for 2081 – 2100 is in reference to the global mean surface temperature at pre-industrial times 1850 – 1900. The possible range represents the 5th to 95th percentile of the model simulations.

Introduction - Essential Energy Response

Across 7 months in 2022, Essential Energy (“**EE**”) has performed an extensive climate impact assessment on three acute hazards (bushfire, flood, and windstorm) to quantify the range of potential impacts that these hazards may have on EE’s assets and the customers they serve. EE commissioned KPMG’s climate impact assessment methodology and Risk Frontier’s catastrophe models for bushfire and flood risk.

Risk Frontiers is a specialist in catastrophe loss modelling, climate risk and resilience based in Sydney, NSW. It provides development and maintenance of natural catastrophe models focussed on the Asia Pacific Region and provides innovative science-driven research, analysis and solutions. Within this engagement, in addition to analysis of publicly available climate data, Risk Frontiers utilised FireAUS and FloodAUS proprietary software.

Two climate projections were considered within the assessment. The two scenarios were selected as a plausible projection of future global mean temperatures (RCP4.5) and a worst case projection (RCP8.5), although the actions of Governments and Organisations around the globe to date would indicate that the worse case scenario selected is unlikely to be realised.

Multiple time horizons were considered within the assessment, as different time horizons are relevant depending on the business decision. For example 2070 provides a time horizon where the average age of poles would be 87 years, which exceeds an assumed 75 year lifecycle for poles, while 2050 provides a time horizon where changes in climate begins to accelerate.

The outputs of the assessment provide EE decision makers with a wide range of metrics to allow them to make informed decisions based on a defensible and scientific approach. The assessment was performed on Essential Energy’s current portfolio of assets with no new interventions. The only exception is the model assumed that poles were to be replaced by a new pole of the same material once they reach 75 years of age.

This report summarises the approach and findings of the assessment at a depot level. Further details on the approach can be found in an accompanying playbook titled “Essential Energy - Physical Vulnerability Playbook - 16 December 2022”.

Executive Summary

Key Findings – Climate Projection

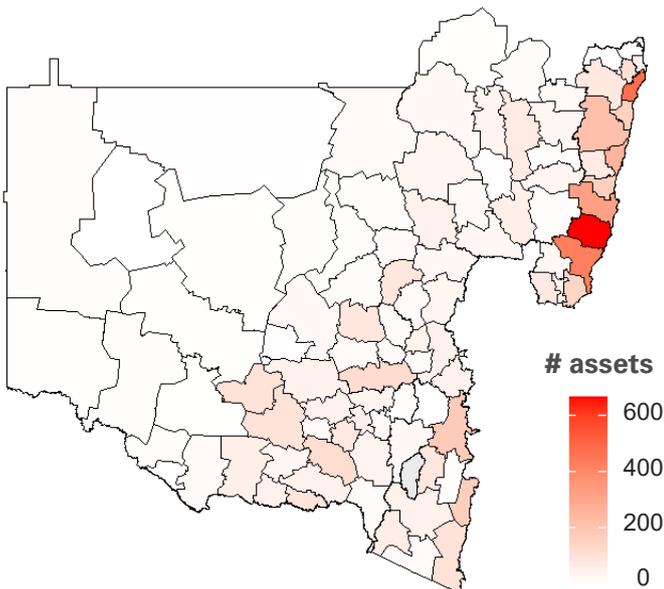
Climate projections capture the frequency, severity and location of the climatic events of concern, before allowing for their impact on Essential Energy’s asset portfolio. In the table below, the current total expected exposure to a bushfire footprint, a “>0m” flood, and a 90km/h windstorm is presented along with a description of how it will change over time in Representative Concentration Pathway (“RCP”) 4.5.

Average Number of Assets Exposed RCP 4.5 ('000')				
Year	Baseline	2050	2070	2090
Bushfire (in footprint)	6.2	6.9	7.6	8.5
Flood (>0m)	3.1			
Windstorm (90km/h)	118.4	189.5	155.4	172.3

RCP 4.5 is projected to lead to increases in occurrences of bushfire and windstorm. The trend for windstorm showcases volatility due to natural variability such as the El Niño–Southern Oscillation (“ENSO”).

The number of assets exposed to a “>0m” flood does not change within this assessment, as the flood model used incorporates the impact of climate change on flood depths, but not the size of a flood footprint. The results may therefore under-represent the impact of climate change on flood, all else being equal.

The chart below is a heatmap of the average count of assets in a bushfire footprint for Baseline conditions.

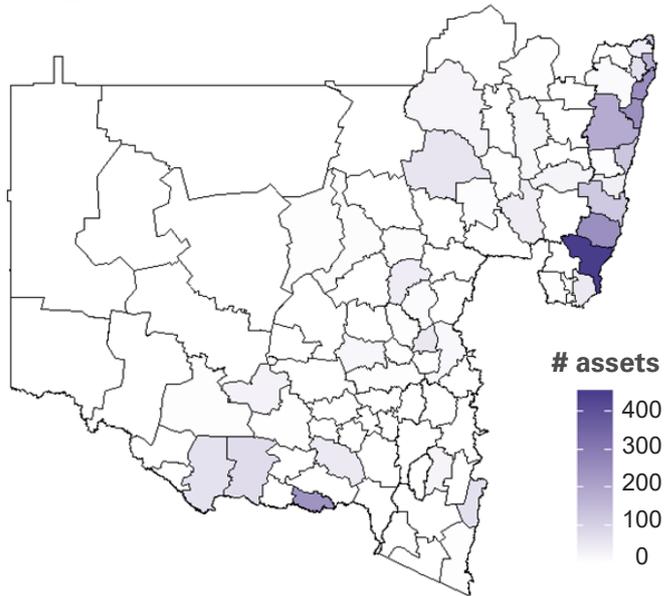


The Baseline simulation of bushfire events shows a concentration of number of assets at risk on the Mid North Coast. The service depot with the highest average number of assets exposed to a bushfire is Port Macquarie, followed by Ballina, Taree, and Kempsey.

In addition to projected burnt areas for bushfire, the forest fire danger index (“FFDI”) has been modelled to inform asset burn rates. In the table below, the likelihood of an FFDI category, given an asset is within a bushfire footprint has been summarised for RCP4.5.

Likelihood of FFDI for exposed assets RCP 4.5				
Year	Baseline	2050	2070	2090
High	58.8%	50.6%	43.0%	37.7%
Extreme	41.2%	49.4%	56.9%	62.2%
Catastrophic	0.01%	0.01%	0.06%	0.12%

The chart below is a heatmap of average count of assets within a simulated “>0m” flood footprint for Baseline conditions.

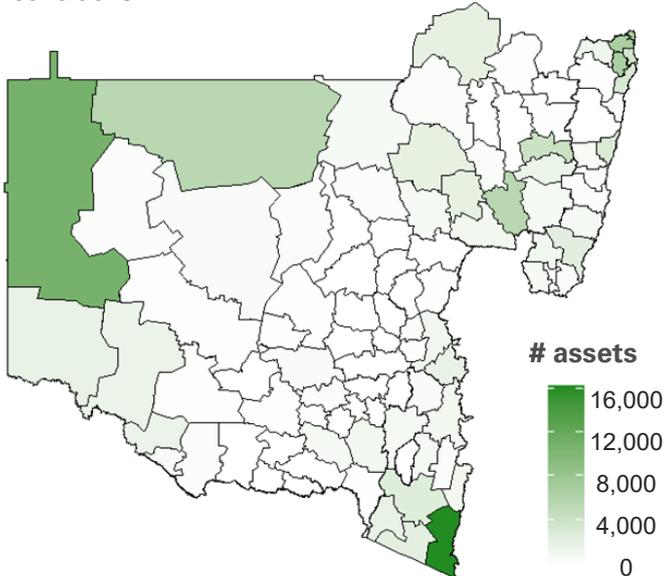


The Baseline simulation of flood events shows a concentration of number of assets at risk on the Mid North Coast. The service depot with the highest average number of assets exposed to a Flood is Taree, followed by Albury, Port Macquarie, Ballina, and Maclean.

In addition to the projected number of assets within a “>0m” flood footprint, the number of assets within more extreme flood depths was modelled to increase at a materially higher rate.

Executive Summary

The chart below is a heatmap of average count of assets within a simulated 90km/h windstorm for Baseline conditions.



The Baseline simulation of 90km/h windstorm events shows a wider spread of risk across the network relative to the other hazards. The highest exposure was in Bega, followed by Broken Hill, Lismore, and Murwillumbah.

Key Findings – Climate Impacts

The impact analysis modelled the effect of the climate projections on Essential Energy’s asset portfolio and subsequent network impacts, assuming no new interventions. The results have been broken into the key modelled metrics: number of asset failures, total financial costs (direct financial costs plus value of customer reliability), customers interrupted, and customer downtime.

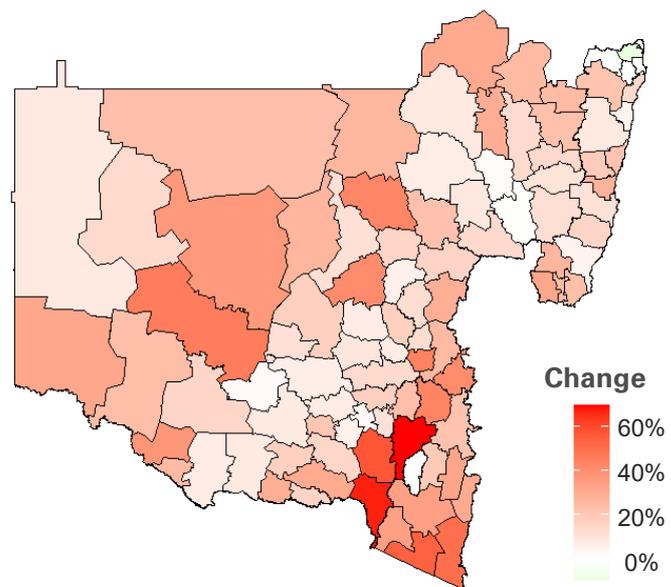
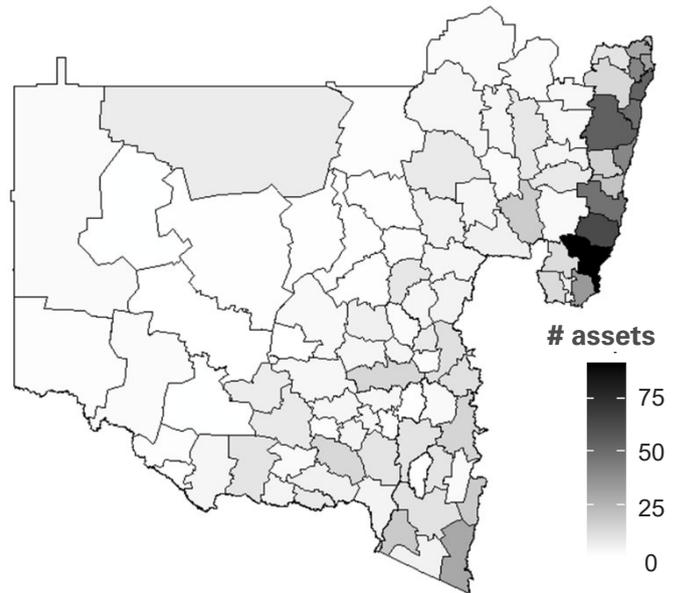
Key Findings – Number of Asset Failures

In the table below, the current total modelled number of asset failures (poles, conductors, substations etc) due to bushfire, flood, and windstorm is presented, along with a projection of how it will change over time in RCP 4.5.

Average Number of Asset Failures RCP 4.5				
Year	Baseline	2050	2070	2090
Bushfire	491	545	610	685
Flood	248	255	257	259
Windstorm	318	550	400	426
Combined	1,057	1,351	1,267	1,370

RCP 4.5 is projected to lead to changes in asset failures requiring replacement consistent with the exposure to each hazard. Similar to the hazard exposure, windstorm was modelled to increase to 2050 and decrease in 2070 before increasing again.

The chart below is a heatmap of combined impact on asset failures due to bushfire, flood, and windstorm for Baseline conditions (1st chart) and the % change by 2070 under RCP4.5 (2nd chart).



The Mid North Coast had the highest concentration of asset failures across the three hazards in Baseline, while the highest rate of increase was associated with Yass, Tumbarumba, and Tumut.

Executive Summary

Key Findings – Total Financial Costs

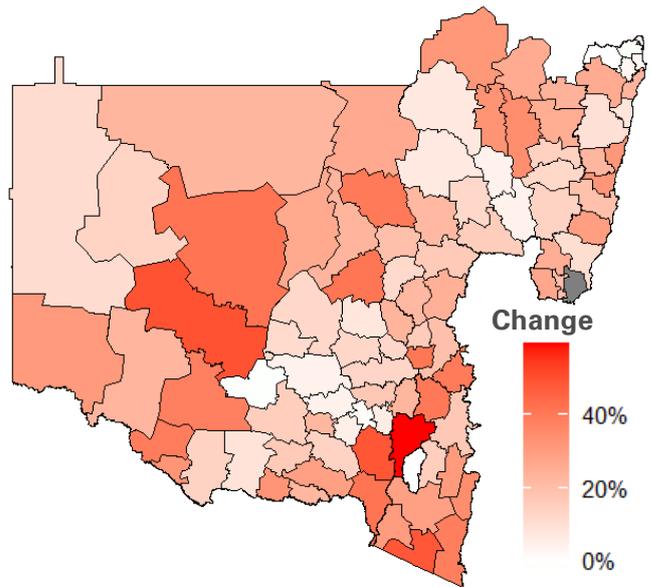
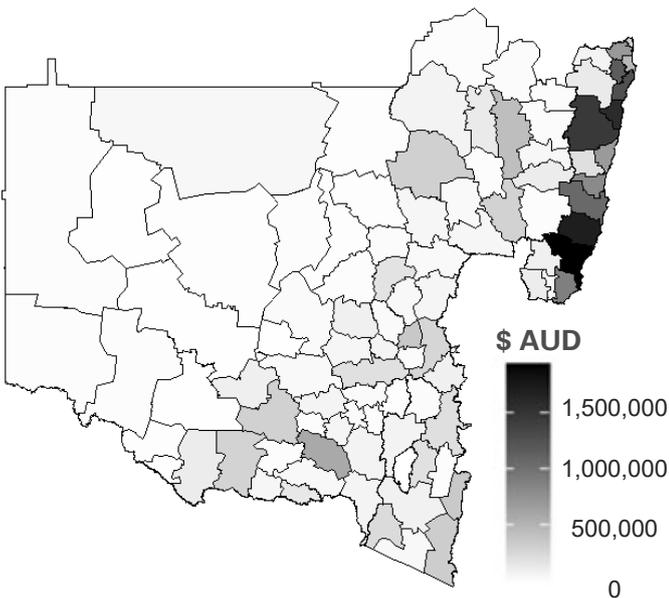
To summarise the total financial costs to Essential Energy due to the modelled impacts of bushfire, flood, and windstorm, direct financial costs (asset replacement and labour) are added to the value of customer reliability.

In the table below, the current total modelled financial costs due to bushfire, flood, and windstorm are presented, along with a projection of how it will change over time in RCP 4.5.

Total Financial Costs RCP4.5 (\$m)				
Year	Baseline	2050	2070	2090
Bushfire	11.2	12.6	14.1	15.9
Flood	10.2	10.5	10.6	10.7
Windstorm	3.4	5.8	4.3	4.6
Combined	24.7	29.0	29.1	31.2

This results in a 26% increase in total financial costs related to bushfire by 2070 under RCP4.5, a 5% increase due to flood and a 26% increase due to windstorm. At a combined hazard level, there is a modelled 17% increase in the total financial costs by 2070 under RCP4.5 compared to Baseline.

The chart below is a heatmap of combined impact on total financial costs due to bushfire, flood, and windstorm for Baseline conditions (1st chart) and the % change by 2070 under RCP4.5 (2nd chart).



The Mid North Coast has the highest concentration of total financial costs across the three hazards in Baseline, while the depot with the highest increase was Yass.

Key Findings – Direct Financial Costs

Direct financial costs include the cost to replace assets and the labour cost required to restore failed assets. In the table below, the current total modelled direct financial costs due to bushfire, flood, and windstorm is presented, along with a projection of how it will change over time in RCP 4.5.

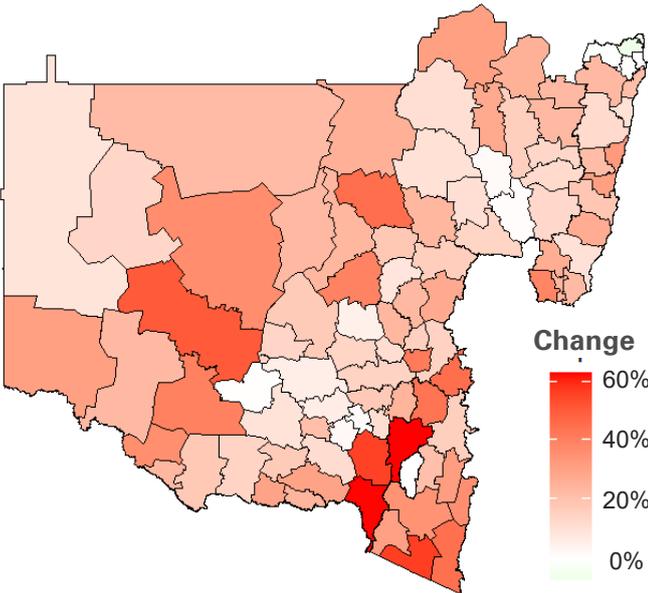
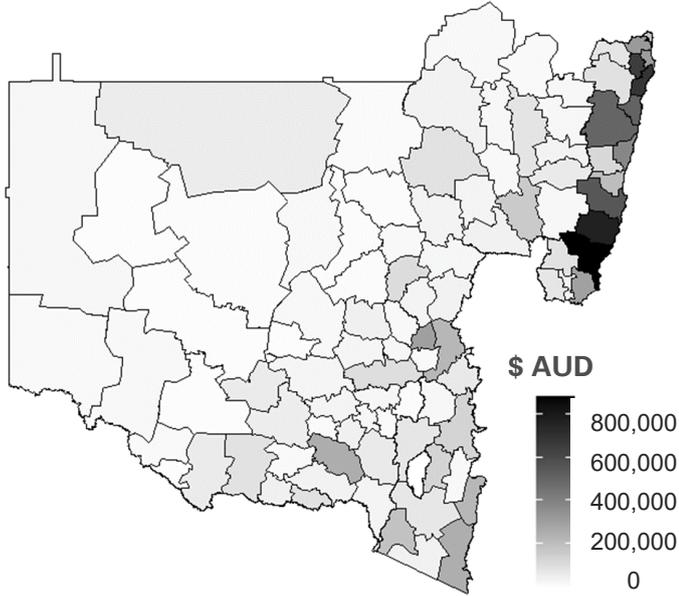
Average Direct Financial Costs RCP 4.5 (\$m)				
Year	Baseline	2050	2070	2090
Bushfire	5.7	6.3	7.0	7.9
Flood	4.6	4.8	4.8	4.8
Windstorm	3.0	5.1	3.7	4.0

RCP 4.5 is projected to lead to increases in direct financial costs for bushfire that are proportionately larger than the changes in number of assets exposed to bushfire. This outcome is driven by modelling for the FFDI to have an impact on an asset's burn rate.

This results in a 25% increase in direct financial costs related to bushfire by 2070 under RCP4.5. The corresponding impact for flood and windstorm is a 4% and 26% increase respectively.

Executive Summary

The chart below is a heatmap of combined impact on direct financial costs due to bushfire, flood, and windstorm for Baseline conditions (1st chart) and the % change by 2070 under RCP4.5 (2nd chart).



The Mid North Coast has the highest concentration of direct financial costs across the three hazards in Baseline, while the highest rate of increase was associated with Yass, Tumbarumba, and Tumut.

Key Findings – Value of Customer Reliability

Where a customer was without energy, a value of customer reliability (“VCR”) was calculated as:

$$\sum_{Service\ Depot=1}^N \alpha * \beta * \gamma$$

- α = customer downtime
- β = energy at risk assumption
- γ = value of customer reliability rate assumption

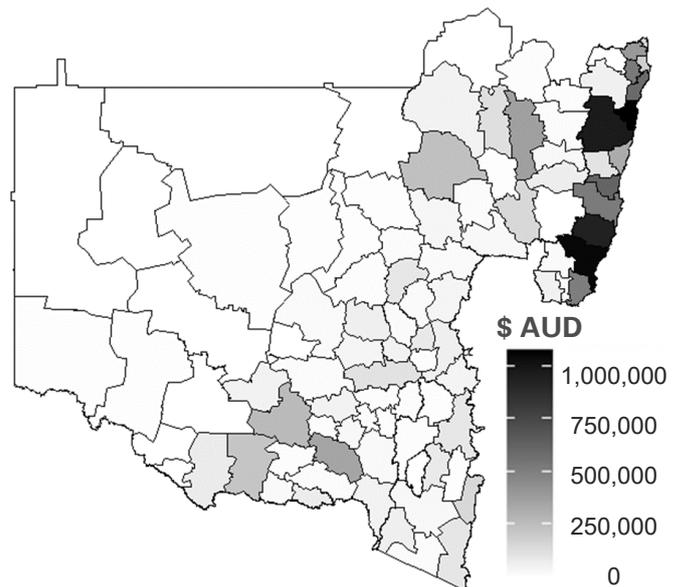
In the table below, the current total modelled VCR due to bushfire, flood, and windstorm is presented, along with a projection of how it will change over time in RCP4.5.

Value of Customer Reliability RCP4.5 (\$m)				
Year	Baseline	2050	2070	2090
Bushfire	5.5	6.3	7.1	8.0
Flood	5.5	5.8	5.8	5.9
Windstorm	0.5	0.7	0.6	0.6

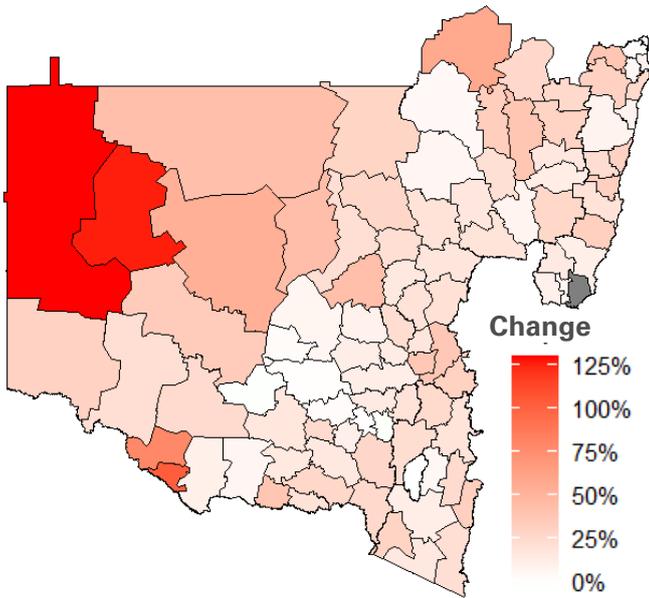
RCP 4.5 is projected to lead to changes in the VCR. The assumptions for energy at risk and value of customer reliability rate were constant, therefore the VCR was proportional to the total customer downtime.

This results in a 28% increase in direct financial costs related to bushfire by 2070 under RCP4.5. The corresponding impact for flood and windstorm is a 5% and 27% increase respectively.

The chart below is a heatmap of combined impact on value of customer reliability due to bushfire, flood, and windstorm for Baseline conditions (1st chart) and the % change by 2070 under RCP4.5 (2nd chart).



Executive Summary



The Mid North Coast has the highest concentration of VCR impact across the three hazards in Baseline, while the highest rate of increase was associated with Broken Hill and Wilcannia, although the quantum is \$1.3k for Broken Hill in 2070 under RCP4.5, while it is \$1.7m for Port Macquarie.

One limitation of the data was related to private conductors where reclosers and sectionalisers of very long private conductors could not be identified. This resulted in long single assets that were susceptible to vegetation impacts due to their length and having widespread customer impacts. As such, Bulahdelah has been greyed out to omit results caused by this data limitation. This limitation primarily impacted the windstorm hazard due to the increase in exposure to vegetation impacts for a long single asset.

The VCR can be assessed by the number of customer interruptions and the duration of customer downtime. These metrics are explored below.

Key Findings – Customer Interruptions

The climate impact assessment quantifies network and customer impacts, which are downstream outcomes following a modelled asset failure.

Customers will have their energy services disrupted where an asset failure results in the de-energisation of a feeder-segment. The identification of de-energised feeder-segments is informed by a NEO4J connectivity model. Switching was not considered within the analysis.

In the table below, the current total modelled number of customers interrupted due to bushfire, flood, and windstorm is presented, along with a projection of how it will change over time in RCP4.5.

Customers Interrupted RCP4.5 ('000')				
Year	Baseline	2050	2070	2090
Bushfire	1.1	1.2	1.4	1.5
Flood	0.9	0.9	0.9	0.9
Windstorm	0.4	0.7	0.5	0.6

RCP4.5 is projected to lead to changes in customer interruptions. Similar to the hazard exposure, windstorm was modelled to increase to 2050 and decrease in 2070 before increasing again. While, Flood was modelled to have a minor impact to customer interruptions.

Key Findings – Customer Downtime

Following the de-energisation of feeder-segments, EE would restore assets according to a priority score. Once all failed assets on a feeder-segment have been restored, then the feeder-segment is re-energised, as long as all upstream feeder-segment are energised.

In the table below, the current total modelled customer downtime due to bushfire, flood, and windstorm is presented, along with a projection of how it will change over time in RCP4.5.

Customers Downtime RCP4.5 ('000' hours)				
Year	Baseline	2050	2070	2090
Bushfire	100.7	116.1	129.2	145.8
Flood	101.2	105.7	106.6	107.5
Windstorm	1.9	3.4	2.6	2.8

RCP 4.5 is projected to lead to changes in customer downtime. Customer downtime was modelled, such that it would not necessarily be proportional to modelled asset failures.

The number of service crews deployed within a service depot was capped at 20 per service depot. Where asset damage was significant within a depot, there would be waiting time before some assets within that depot could be tended to. This resulted in significant customer downtime.

Contents

Section	Sub-section	Page Number
	Background, scope and key terms	11
	Overview of Approach – Climate Projections	12
	Overview of Approach – Direct Impacts	13-14
	Overview of Approach – Indirect Impacts	15
	Reliances and Limitations	16-17
Climate Projections	Climate Projections – Climate Data	18
	Climate Projections – Bushfire	19-20
	Climate Projections – Flood	21
	Climate Projections – Windstorm	22
Climate Impacts	Impact Analysis – Introduction	23
	Impact Analysis – Asset Failure Count	24-26
	Impact Analysis – Total Financial Costs	27-29
	Impact Analysis – Direct Financial Costs	30-32
	Impact Analysis – Value of Customer Reliability	33-35
	Impact Analysis – Customer Interruptions	36-38
	Impact Analysis – Customer Downtime	39-41
	Next Steps	42
Appendices	Sensitivity Tests	43-44
	Convergence Tests	45-46
	References	47

Background, Scope and Key Terms

Essential Energy's climate impact assessment uses a stochastic Monte Carlo Simulation Model ("MCSM"). The results of this modelling will be used to support EE's business case for resilience expenditure to the Australian Energy Regulator ("AER") for physical climate risk.

A business case to the AER needs to be supported by:

- scientifically accurate climate models
- asset and network impact logic that is representative of the assets and network
- appropriately granular asset impact modelling
- robust model assumption setting process

Each of these requirements are addressed within this report, along with the results and conclusions of the assessment.

In the table below, some of the key terminology used within this analysis have been described in lay terms.

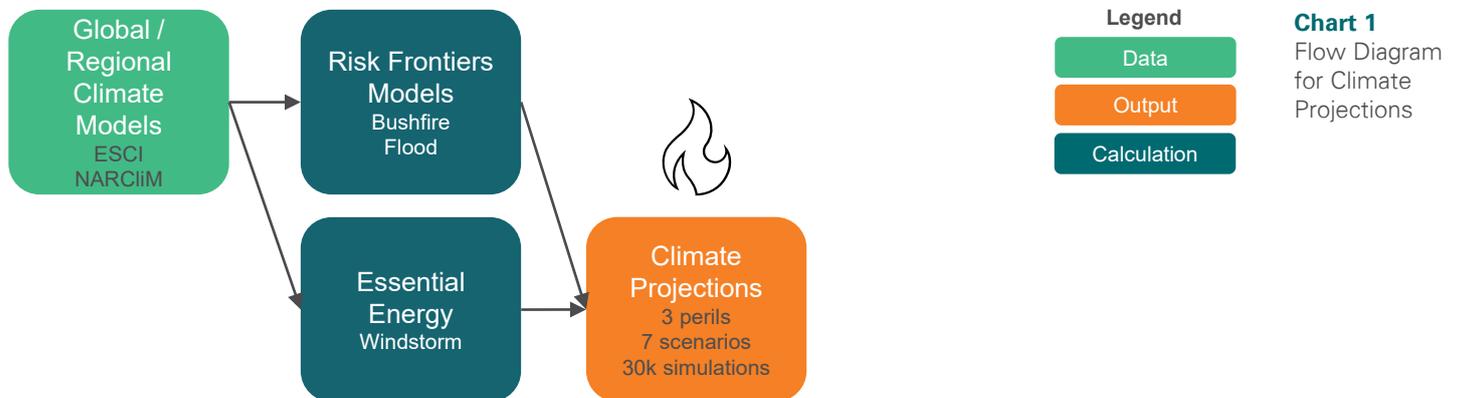
Description of Key Terms	
Baseline	The present-day baseline climate equivalent to average conditions over the past 10-20 years.
Percentile	A percentile is a statistical term used to describe how an outcome compares to the full range of possible outcomes. For example a 99 th percentile will be greater than 99% of all the possible outcomes.
Stochastic	A stochastic process within the Climate Impact Assessment model is an algorithm used to replicate a real world phenomena that occurs with an assumed likelihood. One example is a burn rate, which describes how likely an asset will burn if it is within a bushfire footprint. Across the 30,000 simulations, an algorithm will determine if an asset burns based on a random number generator, where the average result should broadly match the assumed rate.
Representative Concentration Pathway	Representative Concentration Pathways ("RCP") describe a wide range of possible changes in future anthropogenic Greenhouse Gas ("GHG") emissions. The numerals associated with the naming of the RCPs correspond to the radiative forces reached by 2100. For example, RCP4.5 corresponds to 4.5 W/m ² of radiative forces in 2100, which assumed GHG emissions continue to rise to 2040, then decline.
Bushfire	A bushfire within this assessment is defined as an ignition of vegetation due to all possible sources, which then propagates as damaging fires. The area covered by the propagation of fires is called the bushfire footprint. These damaging fires may come into close proximity to EE assets and an asset is susceptible to burning if it is located within close proximity (1km) of a bushfire. A bushfire footprint has been simulated to 1km granularity.
Forest Fire Danger Index	In Australia, the McArthur Forest Fire Danger Index ("FFDI") (McArthur 1967) is widely used to forecast the influence of weather on fire behaviour, and the Australian Bureau of Meteorology ("BoM") routinely issues forecasts of Grassland and Forest Fire Danger Index ("GFDI" and "FFDI") for use by fire authorities. This assessment focussed on FFDI as a risk measure, as the most severe fires are generally related to forest fires.
Flood	A flood within this assessment is defined as a build up of water due to extreme rainfall and it covers riverine flood, but not flash flood ⁴ . The area under water is called the flood footprint. The flood footprint has been simulated to a 100 metre granularity.
Windstorm	A windstorm within this assessment is defined as the occurrence of windspeeds in excess of 90km/h, which is the level identified by the Bureau of Meteorology for damaging winds.

Table 2
Description of
Key Terms

Overview of Approach – Climate Projections

The approach adopted by EE to project climate uses a selection of global and regional climate models to inform climatic conditions. Specialist catastrophe models developed by Risk Frontiers for bushfire and flood, and a bespoke model developed by Essential Energy and reviewed by KPMG for windstorm was used in this analysis.

The chart below depicts the data flow climate projections.



The Coupled Model Intercomparison Project Phase 5 (“**CMIP5**”) is a collaborative framework designed to improve knowledge of climate change. Coupled models are computer-based models of the earth’s climate, in which different parts (such as atmosphere, oceans, land, ice) are “coupled” together, and interact in simulations.

The IPCC simulated the earth’s climate for given RCPs through CMIP5. There are 40 global climate models (“**GCM**”) contained in CMIP5. Each of these models would describe GHG emissions, temperature metrics, along with a comprehensive range of other weather metrics.

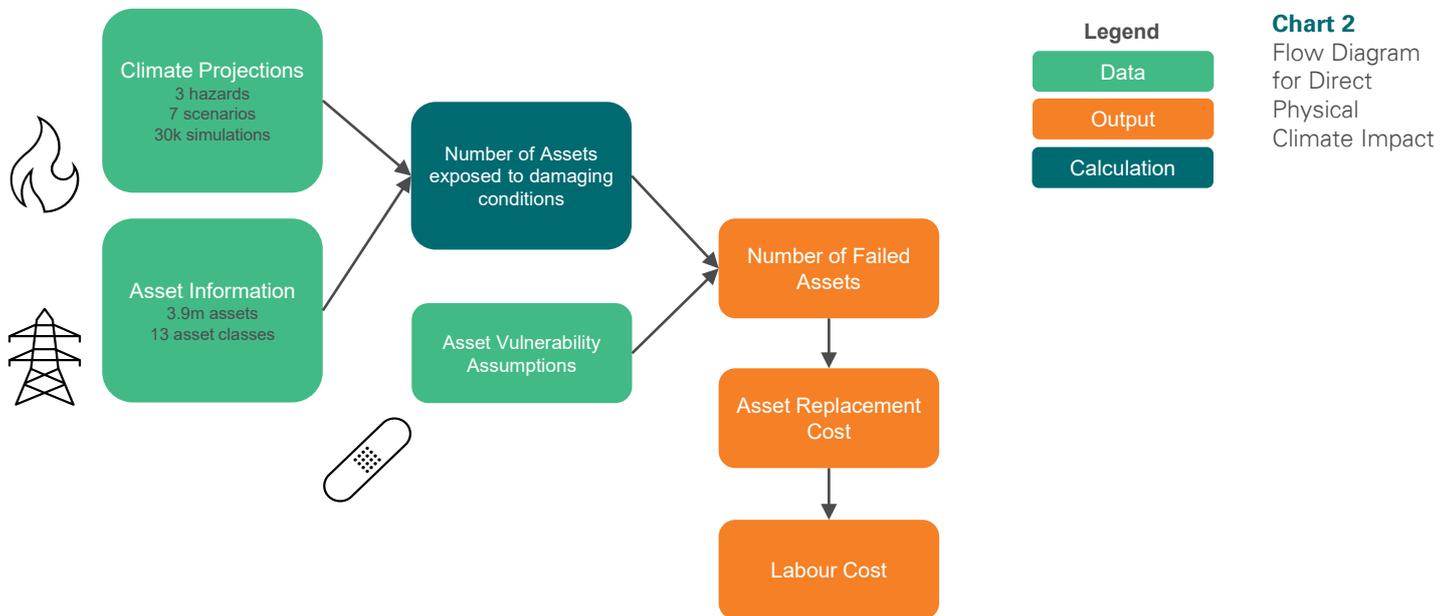
The best practice approach to design climate scenarios for a given RCP is to select an ensemble of models from the 40 GCMs and other available models for the following reasons:

- CMIP5 models have been thoroughly investigated by organisations such as CSIRO and Energy Sector Climate Information (“**ESCI**”) project.
- CMIP5 models have been employed by other DNSPs across Australia
- Ensembling models alleviates biases inherent within individual models. Individual climate models such as those within CMIP5 would exhibit biases as a result of:
 - The methodologies employed within the climate models
 - Confounding model biases to create assumptions

Further information on each of the bushfire, flood, and wind models is described in the Climate Projections section of this report.

Overview of Approach – Direct Impacts

The approach adopted by EE to quantify the physical climate impact uses a MCSM. A series of calculations were performed 30,000 times per climate hazard and scenario. This emulated the variability within the climate impact, which allowed EE to assess the potential range of severity and likelihoods, providing a comprehensive assessment of risk needed to produce a defensible business case for resilience expenditure to the AER. The chart below depicts the data flow for direct physical climate impacts.



Direct physical climate impacts are the immediate financial and non-financial consequences to EE directly due to the occurrence of physical climate hazards such as bushfire, windstorm, and flood.

Data within the direct physical climate impact

There are three key data components required to determine the direct physical climate impacts.

- **Climate Projections:** this dataset describes the frequency, severity, and location of the physical climate hazards. This covers three acute hazards (bushfire, windstorm, and flood), across 7 scenarios (current, Representative Concentration Pathway (“RCP”) 4.5 and 8.5 for 2050, 2070, and 2090). Each combination of hazard, RCP, and time horizon required 30,000 simulated annual datapoints per unique asset location.
- **Asset Information:** this data describes the location and asset class for 3.9 million assets scoped within the analysis. The asset class was crucial to identify the asset vulnerability assumptions related to the asset. Extensive discussion and data reconciliation was held with different EE data owners. EE signed off the data as appropriate for this assessment.
- **Asset Vulnerability Assumptions:** this dataset describes how each asset class would respond to the acute hazards. At a high level, the assumptions can be summarised as a probability of failure measure (burn rates, wind failure rate, flood failure rate) and a severity measure (unit rate).

Overview of Approach – Direct Impacts

Calculating the direct physical climate impact

The calculation of physical climate impact begins with matching the climate projections with the asset information and asset vulnerability assumptions across the 30,000 simulations per scenario. Calculations are performed stochastically and these are described in the table below.

The table below describes the calculation performed to determine the outputs of the direct physical climate impact:

Description of Calculation	
Number of Failed Assets	<ul style="list-style-type: none"> A primary acute hazard metric was sourced from climate/catastrophe modelling specialists for each of the acute hazards at the associated asset locations. For example, a bushfire burnt flag was mapped to each modelled asset across the 30,000 simulations. The approach then mapped the hazard metric to a likelihood of failure assumption. The likelihood of failure for each of the hazards varied according to the asset class and hazard combination. The model stochastically determined if the asset failed, based on the likelihood of failure. This calculation was performed for all assets, and all hazards, across all simulations.
Asset Replacement Cost	<ul style="list-style-type: none"> The replacement cost assumption per failed asset was based on the asset class and grossed up for unplanned resource constraints. For each simulation, the cost of asset replacement was either \$0 if the asset had not failed, or the replacement value if the asset failed.
Labour Cost	<ul style="list-style-type: none"> The labour cost was calculated as the total restoration time (travel and repair) for all failed assets at an assumed wage rate per service crew. This did not account for overheads. This grossed up for unplanned resource constraints.

Table 3
Direct Physical Climate Output Calculations

A comprehensive methodology can be found in a separate document titled 'Essential Energy - Physical Vulnerability Playbook – 16 December 2022'.

Indirect physical climate impacts are the downstream impacts to EE and its customers as a result of asset failures due to the occurrence of physical climate hazards such as bushfire, windstorm, and flood. The chart below depicts the data flow for indirect physical climate impacts.

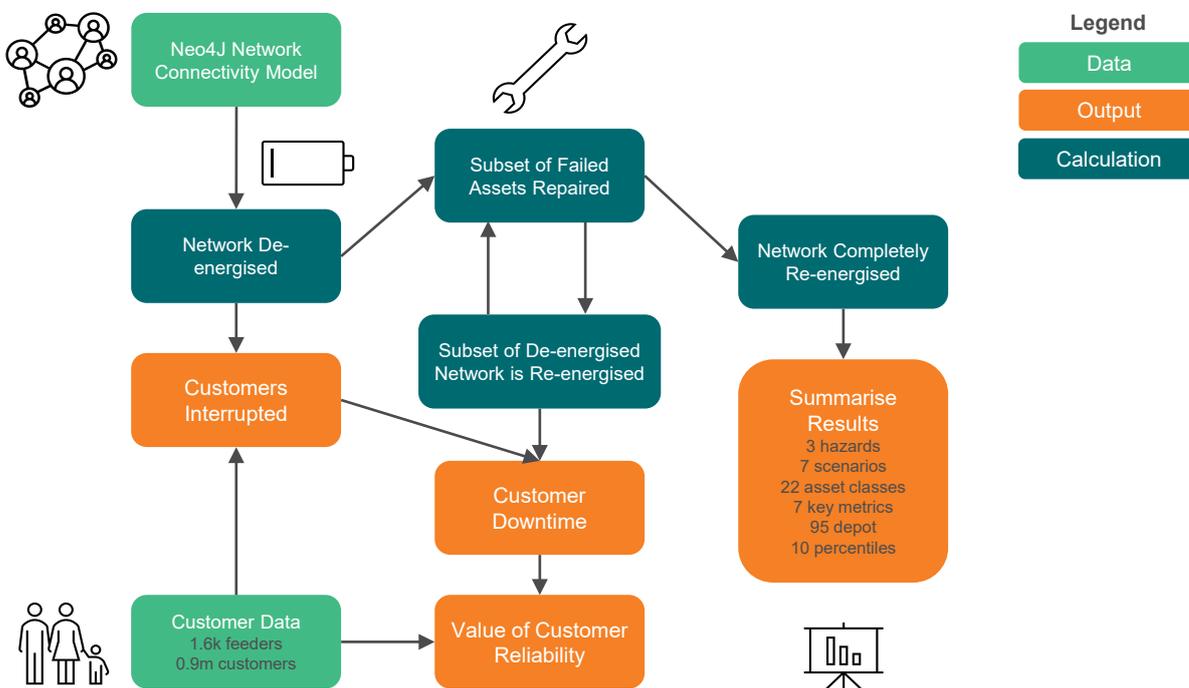


Chart 3
Flow Diagram for Indirect Physical Climate Impact

Overview of Approach – Indirect Impacts

Data within the indirect physical climate impact

There are two key data components required to determine the indirect physical climate impacts.

- **NEO4J Network Connectivity Model:** this dataset describes the relationships between assets with respect to the transmission of electricity. This data was created based on a network connectivity model developed in NEO4J by EE. The data identifies all of the de-energised downstream assets, given a specified asset has failed or is de-energised.
- **Customer Data:** this dataset describes the number of customers within each segment of the NEO4J model. This information is required to determine the number of customers interrupted and hence the total customer downtime and value of customer reliability.

Calculating the indirect physical climate impact

The table below describes the calculation performed to determine the outputs of the indirect physical climate impact:

Description of Calculation	
Customers Interrupted	<ul style="list-style-type: none"> • De-energised feeders were identified based on where there were failed assets. • All downstream de-energised feeders were determined by an energy dependency algorithm. • The customers supported by each de-energised feeder were identified.
Customer Downtime	<ul style="list-style-type: none"> • A prioritisation score was assigned to each feeder that was de-energised, based on EE's asset restoration priorities. • The total number of service crews deployed to restore failed assets was based on the number of total failed assets. • Each service crew was deployed to the highest priority asset to restore, with travel time, restoration time, and working hours within a day considered. • A feeder was restored when all the failed assets associated with it were restored. This calculation assumed that one service crew can restore one asset at a time and the time taken to restore the asset was dependent on the asset class and hazard combination. • The customer downtime was equal to the time since the simulated occurrence of the hazard when the feeder was re-energised. • Electrical switching, as a quick response to restore customers was not modelled.
Value of Customer Reliability	<ul style="list-style-type: none"> • The energy at risk and value of customer reliability rate were fixed assumptions. • The customer downtime for each feeder was multiplied by the total energy at risk and the value of customer reliability rate to determine the value of customer reliability.

Table 4
Indirect
Physical
Climate Output
Calculations

A comprehensive methodology can be found in a separate document titled 'Essential Energy - Physical Vulnerability Playbook – 16 December 2022'.

Reliances and Limitations

The modelling has inherent uncertainty and there are limitations in the approach and assumptions in building and utilising the model. In any modelling, types of uncertainty include, but are not limited to:

1. Not having the ability to capture every scenario or possible outcomes for many years into the future.
2. Calibration of the model, while as accurate as possible for each assumption, there is a limitation of historical data availability and applicability.
3. Asset classes that span large areas / distances such as conductors have been modelled as a point asset, based on the mid-point of the area.
4. The model results were a point in time estimate based on today's current portfolio of assets. The only exception is the model assumed that poles were to be replaced by a new pole of the same material once they reach 75 years of age.

Description of Calculation

Table 5
Physical
Climate Impact
Inclusions and
Exclusions

Description of Calculation	
Bushfire	<p>Inclusions:</p> <ul style="list-style-type: none"> The bushfire / grassfire hazard model simulated fire footprints, where bushfire ignitions / starts captured all possible sources. <p>Exclusions / Approach Assumptions:</p> <ul style="list-style-type: none"> The model assumed that service crews would be able to access the failed asset after a time to allow for the bushfire to subside. The time was assumed to be proportional to the total burn area within a location, up to a maximum of 3 days. The model does not account for different characteristics of a bushfire / grassfire such as intensity or height. These measures have been broadly captured with a Forest Fire Danger Index ("FFDI") to impact the asset burn rates. The model does not account for costs associated with bushfire liability. This is the liability to EE for starting a bushfire, which would result in additional costs such as residential, commercial, and industrial property damage, business interruption, personal injury, and loss of life.
Flood	<p>Inclusions:</p> <ul style="list-style-type: none"> The flood hazard model simulated damage to assets exposed to flood depths from water levels rising within a river system. <p>Exclusions / Approach Assumptions:</p> <ul style="list-style-type: none"> The model does not account for moving debris within flood waters. The model does not account for flash flooding. The model does not account for coastal inundation. The model does not account for impacts to asset life due to exposure to flood waters. The model assumed that service crews would be able to access failed assets after a time for the flood to recede. The time was assumed to be proportional to the flood depth within a location, up to a maximum of 3 days. The model applied a simplified approach to incorporating future climate into the simulation of flood. Flood depths are modelled to change, but the locations and frequency of flood does not. <p>This simplified approach will result in an under-estimation of the flood impacts, all else being equal.</p>

Reliances and Limitations

Description of Calculation

Windstorm

Inclusions:

- The windstorm hazard model simulated unique 3s windgusts at each asset location across a 10 year historical period. The simulations were re-sampled with additional climate escalation factors applied.
- The 3s windgust is modelled to cause certain assets to fail.
- The 3s windgust is modelled to damage vegetation, causing vegetation impact to certain assets.

Exclusions / Approach Assumptions:

- The model does not account for soil conditions such as wet / dry soil or soil type.
- The model does not account for vegetation type or height.
- The model does not account for specific vegetation clearance activity.
- The model does not account for the impact of heavy precipitation.
- The model does not account for the impact of thunderstorms / 'Microcells'.
- The model does not account for lightning.

Uncertainty

There was uncertainty within the projection of climate metrics and the resulting climate impacts and financial results.

There was uncertainty related to the damage / failure of each asset class as it was placed under the damaging forces of either bushfires, floods, or windstorms. The failure curves, burn rates, and flood depth thresholds were informed by literature review, historical EE events and discussions with EE asset managers. The windstorm assumptions were informed by external parties and EE experts who relied on literature review, historical EE data, and historical data sourced from energy distribution organisations in other countries.

While the analysis performed assessment at an individual asset level, there were uncertainties within these asset level assessments which, when analysed in aggregate overcome the individual asset level uncertainty to present a more robust result when assessing the whole portfolio.

Validation Testing

Validation testing provided EE with confidence that the climate impact assessment was producing results in line with expectations and a quantified understanding of the uncertainty inherent within modelling real world phenomena such as physical climate risk.

Sensitivity Testing

Sensitivity testing involved changing individual model assumptions to assess the impact on the overall results. This allowed EE to identify the assumptions that the analysis was most sensitive to. This analysis informed where the most scrutiny should be applied on the assumption selections and hence improve the robustness of the assumption setting process.

Convergence Testing

Convergence testing determined the impact of simulation variability on the results informing the conclusions of the analysis. Convergence testing for EE's analysis was performed by re-running the stochastic simulation for each hazard an additional 5 times, to essentially produce 180,000 simulations per hazard. The simulations that informed conclusions needed to be representative of the 180,000 simulations.

Climate Projections – Climate Data

Climate projections were based on the climate datasets recommended in the Electricity Sector Climate Information (“**ESCI**”) report. The ESCI report evaluated a range of climate model simulations for their representation of temperature and rainfall under RCP 4.5 and RCP 8.5 scenarios and recommended a 3-model ensemble. The data produced in the ESCI project was limited to bias corrected daily maximum and minimum temperature, daily rainfall, and FFDI. For variables and scenarios outside the ESCI data, alternative simulations were sourced, and bias corrected.

The datasets used in Climate Impact Assessment were:

- Historical weather data from the European Centre for Medium Range Weather Forecasting (“**ECMWF**”) ERA5 and ERA5-Land reanalysis. ERA5-Land provided a comprehensive range of hourly weather variables on a 0.1x0.1 degree grid, approximately 9km spatial resolution.
- The Australian Bureau of Meteorology (“**BOM**”) Australian Water Availability Project (“**AWAP**”) provided gridded hydrological and temperature data on a 0.05-degree grid (approximately 5km) for all of Australia.
- ESCI Project evaluated a wide range of simulations from different Regional Climate Models and Global Climate Models (“**RCM-GCM**”) combinations. Simulations were bias corrected using Quantile Mapping for Extremes (“**QME**”) and evaluated for suitability at representing rainfall and temperature for two scenarios: RCP 4.5 and RCP 8.5.
- The NSW and ACT Regional Climate Model (“**NARClIM**”) climate model simulations version 1.5 data were produced as part of a NSW government-led project, providing high resolution climate change projections across NSW for two scenarios: RCP 4.5 and RCP 8.5. NARClIM1.5 outputs have been bias corrected using Quantile Mapping.

For RCP 4.5 and RCP 8.5 scenarios, variables which are not part of ESCI climate projections have been sourced from the NARClIM1.5 ensemble; this includes east coast lows, winds, extreme heat, and a suite of variables required for Bushfire modelling. NARClIM1.5 winds have been bias corrected to ERA5 Land.

Climate model data interpretation should only be carried out with full consideration of data limitations, for example as outlined in the CMSI (2020) [report](#). Three important considerations are: bias correction; the use of ensembles; and time averaging to account for natural climate variability. Bias correction accounts for systematic differences between model simulations and observations and has been applied to all climate model data used in this study. To account for possible errors in model accuracy the mean output from a minimum of 3 models is used, with the standard deviation providing an estimate of uncertainty. Projections are also based on a minimum 20-year average to account for natural (stochastic) variability inherent in the climate system and as simulated by climate models. Actual future climate experience would exhibit greater variability, i.e. some years would be worse than the 20 year-average, and some less.

Additional data transformations and models were required to produce the acute climate risk data. A brief description of the models is in the following sections.

Climate Projections – Bushfire

For bushfire data, Risk Frontiers' model "FireAUS" was used.

FireAUS is Risk Frontiers' probabilistic model for bushfire and grassfire losses in Australia. A key component of the model is to predict fire ignitions for stochastic events using machine learning models. These models are trained on historical fire ignitions derived from the Moderate Resolution Imaging Spectroradiometer ("MODIS") Burned Area product, MCD64A1 Version 6 (2001-2018) using fire tracking algorithms. Firstly, these fire ignitions are classified into five categories based on the quantiles of burned area sizes in each state. Two-step supervised machine learning models are then defined on 1° by 1° grid cells. The first model is used to predict if fires occur in a grid for each calendar month and, if so, the second model is used to predict the number of fire ignitions for each burnt area category within that grid. The predictor variables used in these models include grid locations and climate classifications as well as population-based, environmental and climate variables. The climate variables for the training data are derived from the National Centers for Environmental Prediction ("NCEP") Climate Forecast System Reanalysis ("CFSR") (1979-2010) and Climate Forecast System Version 2 ("CFSv2") (2011-2018) data.

To project changes in fire hazard, fire prediction models from FireAUS were used to estimate the ignition parameter changes for different future climate scenarios. All predictors used in the models, except the climate variables, remain unchanged across historical baseline and future scenarios. Therefore, the changes in fire ignitions are exclusively caused by changes in climate variables for each climate change scenario. NARClIM projects were used to derive climate variables for the ignition projection pertaining to the emission scenarios RCP4.5 and RCP8.5, as outlined previously.

NARClIM climate data are resampled to 1° resolution and bias corrected against the reanalysis data used for the training dataset. Using these derived climate variables as new input predictors, the trained fire prediction models are used to estimate the number of fire ignitions for each 1° by 1° grid for each month. Since the NARClIM dataset are multi-member outputs, the predicted fire ignition counts are averaged from the models in the RCMs' ensemble per 1° grid, then averaged again per future time horizon definition (i.e., 2041-2060 for 2050s and 2081-2099 for 2090s). Ignition changes for each 20-year period are then calculated as the ratio of the number of fire ignitions for the reference (1979-2018) to the ignition number for the future periods. These ratios are then used to sample the events for future climate scenarios from the event catalogue of the current FireAUS model.

FireAUS comprised 50,000 years of fire footprints, aggregated into individual events based on the ignition dates and a 7-day time window, under the current climate. The baseline event set for this project was a 10,000-year sample of the full FireAUS catalogue of events.

Climate Projections – Bushfire

The FireAUS simulations created 30,000 years of bushfire footprints across the EE service area. The average number of bushfires across the 30,000 simulation years with Baseline conditions, and the average count of assets within these bushfire footprints, are illustrated in the charts below.

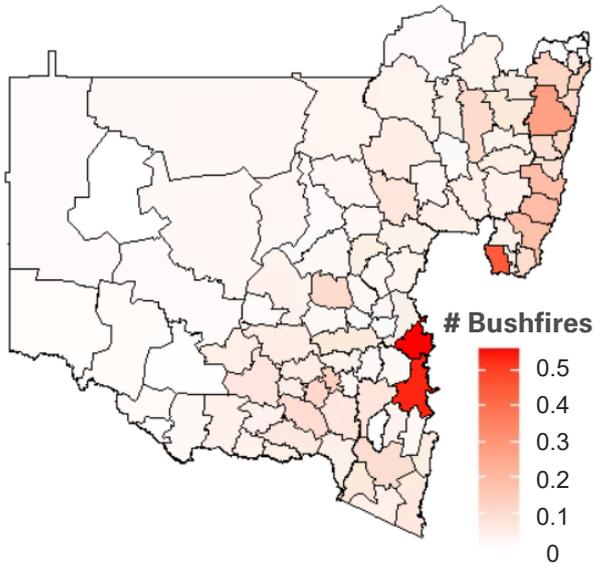


Chart 4 (Left)

Heatmap of average count of annual simulated bushfires for Baseline conditions

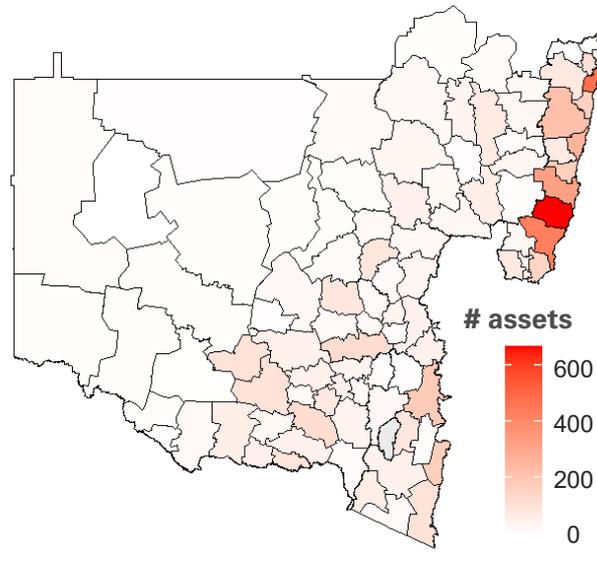


Chart 5 (Right)

Heatmap of average count of assets within a simulated bushfire footprint for Baseline conditions

The Baseline simulation of bushfire events shows a concentration of number of assets at risk on the Mid North Coast. The service depot with the highest average number of assets exposed to a bushfire is Port Macquarie, followed by Ballina, Taree, and Kempsey. The total average number of assets exposed to bushfire across scenarios are summarised in the table below:

Year	Average Number of Assets in a Bushfire Footprint				% Change from Baseline		
	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	6,226	6,871	7,627	8,516	10%	23%	37%
RCP8.5	6,226	8,131	8,921	9,770	31%	43%	57%

Table 6

Average number of assets exposed to bushfire per year under Baseline conditions and future scenarios

The number of EE assets exposed to a bushfire is forecast to increase over time for both RCP4.5 and RCP 8.5. Furthermore the associated FFDIs are projected to be more severe, which is modelled to increase the likelihood of an asset failing due to Bushfire. The table below illustrates the change in proportion of simulated assets exposed to bushfire footprints by FFDI.

Year	Proportion of simulated assets in a bushfire footprint by FFDI				% Change from Baseline		
	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5 (Low-High)	62.1%	55.2%	47.4%	41.3%	-11.1%	-23.6%	-33.4%
RCP4.5 (V High-Severe)	37.6%	43.9%	51.1%	56.6%	16.9%	35.9%	50.6%
RCP4.5 (Extreme-Catastrophic)	0.4%	0.9%	1.5%	2.1%	138.8%	297.2%	450.6%
RCP8.5 (Low-High)	62.1%	44.2%	39.0%	33.4%	-28.7%	-37.1%	-46.1%
RCP8.5 (V High-Severe)	37.6%	53.7%	57.6%	59.6%	43.0%	53.4%	58.7%
RCP8.5 (Extreme-Catastrophic)	0.4%	2.0%	3.3%	6.9%	434.2%	>500%	>500%

Table 7

Proportion of assets within a bushfire with FFDI classifications per year under Baseline conditions and future scenarios

The number of EE assets exposed to a bushfire is forecast to increase over time for both RCP4.5

Climate Projections – Flood

For flood data, Risk Frontiers’ “FloodAUS” was used.

FloodAUS is based on the National Flood Information Database (“NFID”) and generates residential, commercial, and industrial loss estimates for regions covered by these data sources. The scope of the model is further extended by using Risk Frontiers Flood Exclusion Zone (“FEZ”) methodology to filter out address which do not generate losses. FloodAUS covers a majority of the most flood-prone addresses in Australia.

In this analysis, a synthetic event set in FloodAUS was used to assess the flood risk for current and future climate. This event set has 50,000 simulation years and synthetic events are defined for basins and depths are derived from NFID. Since depth information from NFID are attached to the Geocoded National Address File (“G-NAF”) dataset, the flood depths were estimated at an asset based on the G-NAF points within 100m of that asset.

The FloodAUS simulations created 30,000 years of flood footprints across the EE service area. The average count of flood events across the 30,000 simulation years with Baseline conditions, and the average number of assets within these flood footprints are illustrated in the charts below.

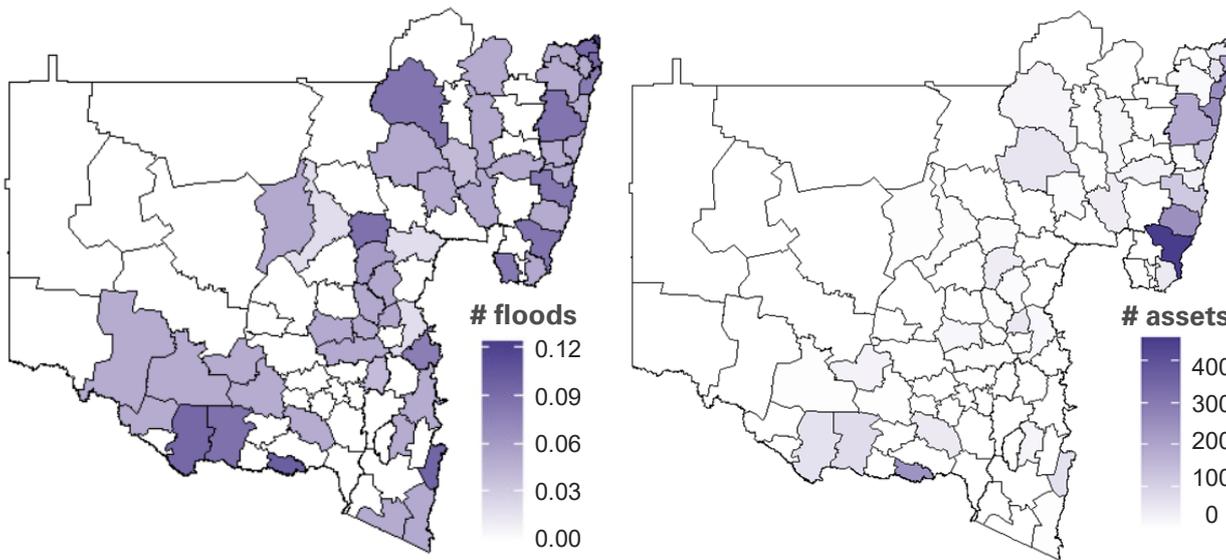


Chart 6 (left)

Heatmap of average number of annual flood events for Baseline conditions.

Chart 7 (right)

Heatmap of average count of assets within a simulated “>0m” flood footprint for Baseline conditions

The Baseline simulation of flood events shows a concentration of number of assets at risk on the Mid North Coast. The service depot with the highest average number of assets at risk to a Flood is Taree, followed by Albury, Port Macquarie, Ballina, and Maclean. The total average number of assets exposed to flood above 1m and 4m across scenarios are summarised in the table below:

Year	Average # of Assets Exposed				% Change from Baseline		
	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5 (1m)	594	613	619	623	3%	4%	5%
RCP4.5 (4m)	72	78	80	81	8%	11%	13%
RCP8.5 (1m)	594	622	646	666	5%	9%	12%
RCP8.5 (4m)	72	82	90	97	14%	25%	35%

Table 8

Average number of assets exposed to a 1m and 4m flood per year under Baseline conditions and future scenarios

The number of EE assets exposed to a 1m flood are forecast to increase over time for both RCP4.5 and RCP 8.5. The percentage increase is more significant for higher flood depths.

Climate Projections – Windstorm

For windstorm data, a Generalised Additive Model (“**GAM**”) was used to simulate maximum 3s windgusts at each pole location based on the following independent variables: Distance to coast, Altitude, Slope and Aspect

The residuals (model vs historical difference) of the GAM were modelled using a Kriging model, which is a regression based on the residuals at each pole location. Kriging assumes that the distance or direction between sample points reflects a spatial correlation that can be used to explain variation in the surface. Literature review has shown the Kriging to be an accurate interpolation method to predicting climatic variables⁵.

The windstorm simulations created 30,000 years of windgusts across the EE service area. The average count of high wind days (with maximum wind gusts above 90km/h⁶ across the 30,000 simulation years with Baseline conditions, and the average number of assets exposed to 90km/h wind gusts in these same conditions are illustrated in the chart below.

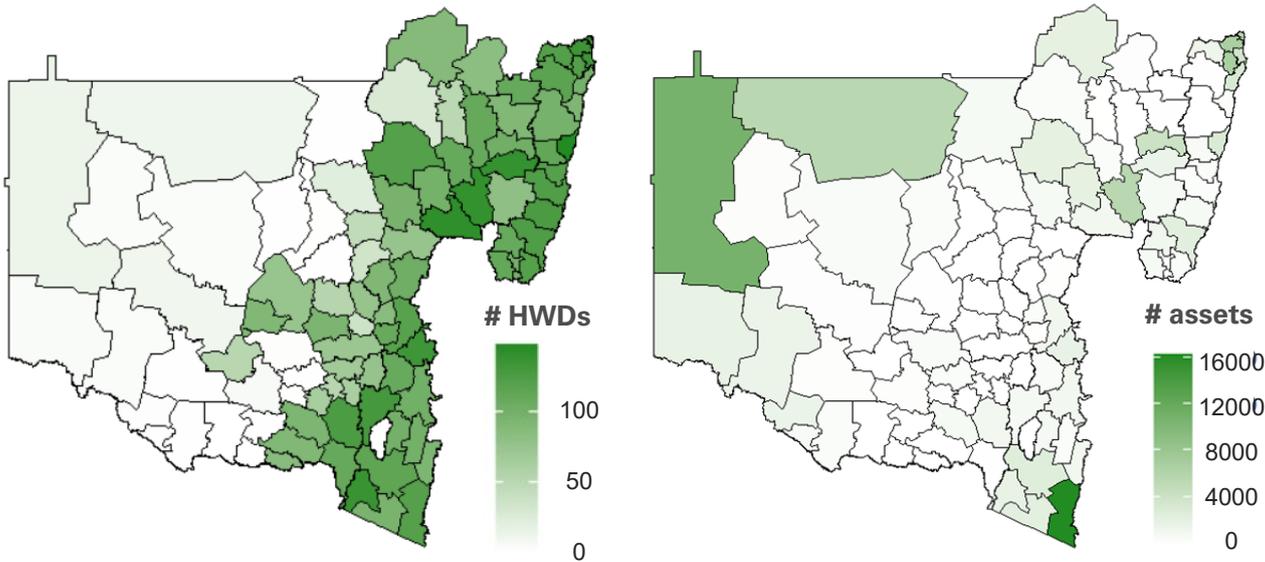


Chart 8 (left)
Heatmap of average count of High Wind Days (HWDs) with at least one 90km/h windgust for Baseline conditions

Chart 9 (right)
Heatmap of average count of assets exposed to a 90km/h windgust for Baseline conditions

The Baseline simulation of 90km/h windstorm events shows a wider spread of risk across the network relative to the other hazards. The service depot with the highest average number of assets exposed to a 90km/h windstorm is Bega, followed by Broken Hill, Lismore, and Murwillumbah. The total average number of assets exposed to 90km/h wind across scenarios are summarised below:

Average Number of Assets Exposed to 90km/h Windgusts				% Change from Base			
Year	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	118,390	189,520	155,370	172,267	60%	31%	46%
RCP8.5	118,390	208,951	157,083	166,540	76%	33%	41%

Table 9
Average number of assets exposed to 90km/h windgust per year under Baseline conditions and future scenarios

The number of assets increases to 2050, then reduce in 2070 etc. This is driven by natural variability modelled such as the El Niño–Southern Oscillation (“**ENSO**”).

Reference 5: M. Keskin, K. Ozdogu, ‘Comparison of Interpolation Methods for Meteorological Data’, 2011, Accessed 8 November 2022

Reference 6: Australian Bureau of Meteorology, ‘Other Types of Severe Weather’, [No Date], Accessed 8 November 2022

Impact Analysis - Introduction



The Impact analysis modelled the effect of the climate forecasts on EE's asset portfolio and the provision of electricity to its customers. The impact can be summarised into a few key components, such as:

- Number of EE assets that fail directly due to bushfire, flood, or windstorm
- Financial cost to EE to restore the failed assets. The financial cost is comprised of:
 - Asset replacement costs
 - Labour cost
- The total number of customers interrupted and the duration of interruption. This informed the value of customer reliability.

The impact analysis section is presented in accordance with each of these components with the addition of combining all hazards. Any key observations regarding specific hazards are highlighted within the relevant sections of the analysis.

Impact Analysis – Asset Failure Count

The chart below shows the number of asset failures across percentiles for the Baseline scenario split by hazard. A black dot is used to represent asset failures in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

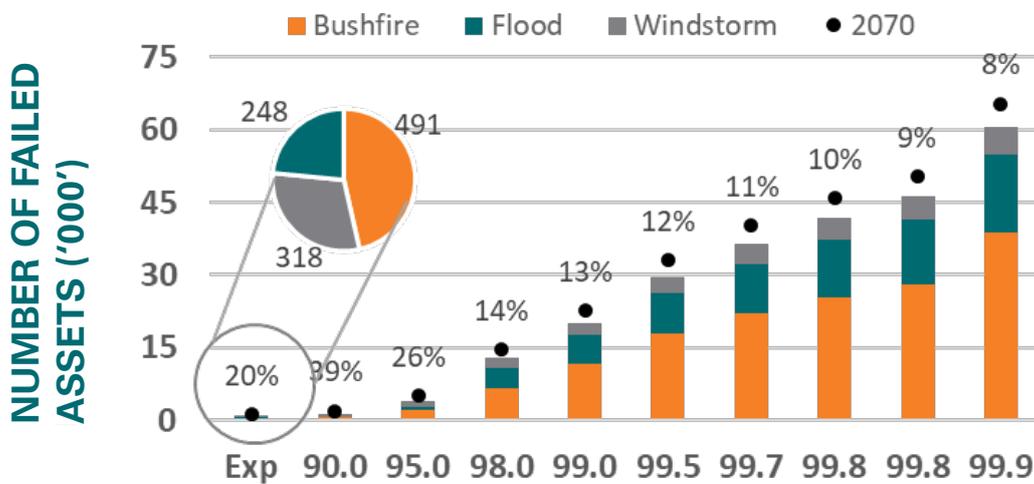


Chart 10
Expected number of failed assets by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

EE asset failures (requiring replacement) were forecast to be highest for Bushfire risk (491). The driver of the most severe events for asset failures is Bushfire, followed by Flood. The black dots show the total increase of asset failures for all hazards 2070 under RCP4.5. On average, there is a 20% increase in the number of asset failures:

- Bushfire and Windstorm asset failure count were modelled to increase by 24% and 26%
- Flood asset failure was modelled to moderately increase by 4%

The rate of change for asset failure count by hazard varied across RCP and time horizon. The table below shows the number of expected asset failures by hazard over time for the two RCPs.

Average Number of Asset Failures						% Change from Baseline		
Scenario	Hazard	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	491	545	610	685	11%	24%	40%
	Flood	248	255	257	259	3%	4%	4%
	Windstorm	318	550	400	426	73%	26%	34%
RCP8.5	Bushfire	491	654	730	861	33%	49%	75%
	Flood	248	258	267	274	4%	8%	10%
	Windstorm	318	573	393	406	80%	24%	28%

Table 10
Expected number of failed assets by hazard by RCP and time horizon.

The rate of change for asset failures is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths are modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

Impact Analysis – Asset Failure Count

The chart to the right shows the expected number of asset failures for the Baseline scenario due to bushfire. There is a concentration of asset failures on the Mid North Coast and a moderate spread of asset failures on the east of NSW.

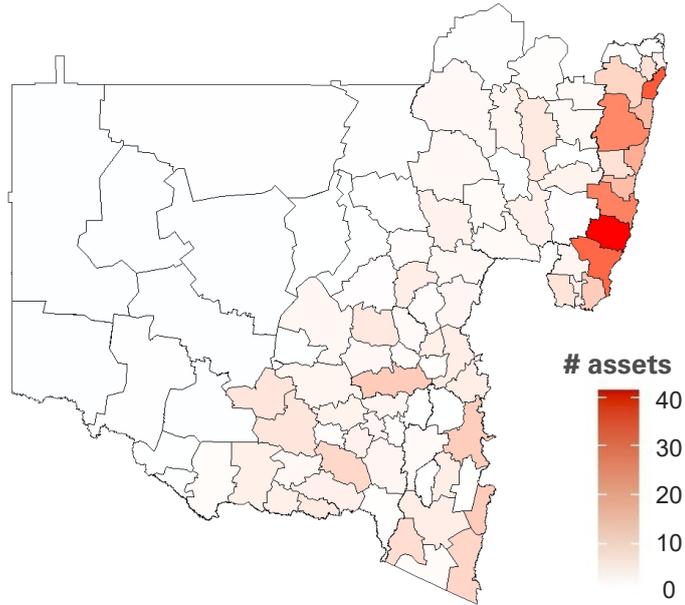
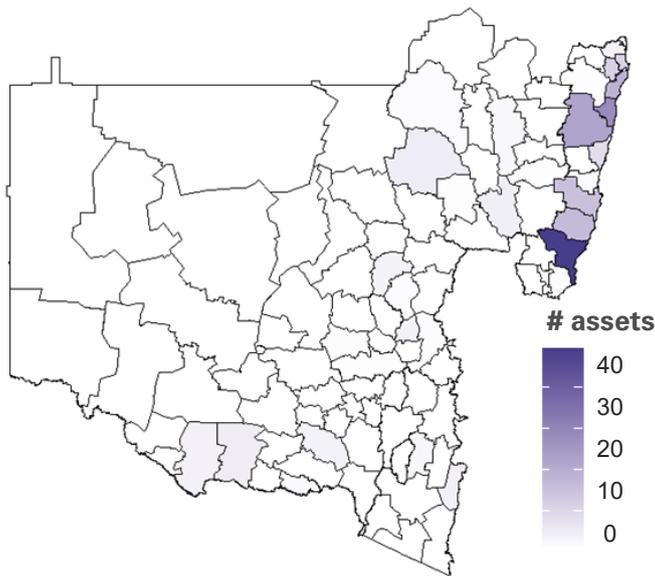


Chart 11
Expected number of failed assets due to Bushfire under Baseline



The chart to the left shows the expected number of asset failures for the Baseline scenario due to flood. There is a concentration of asset failures on the Mid North Coast.

Chart 12
Expected number of failed assets due to Flood under Baseline

The chart to the right shows the expected number of asset failures for the Baseline scenario due to windstorm. There is some concentration of asset failures on the East coast of NSW, which is driven by higher wind gusts and a heavier density of vegetation compared to the West. There is also some concentration of asset failures to the West of NSW, which is driven by longer conductor lengths, which are more exposed to vegetation.

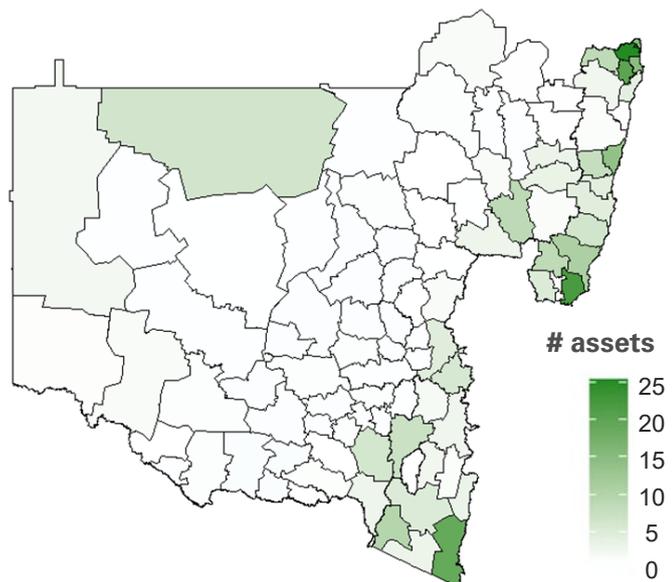


Chart 13
Expected number of failed assets due to Windstorm under Baseline

Impact Analysis – Asset Failure Count

The chart to the right shows the expected number of asset failures for the Baseline scenario for all hazards combined. The heatmap is driven by the modelled Bushfire asset failures.

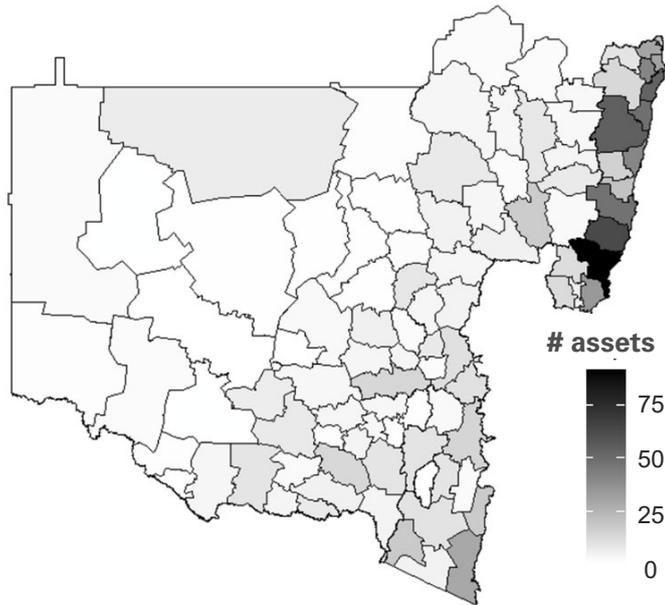
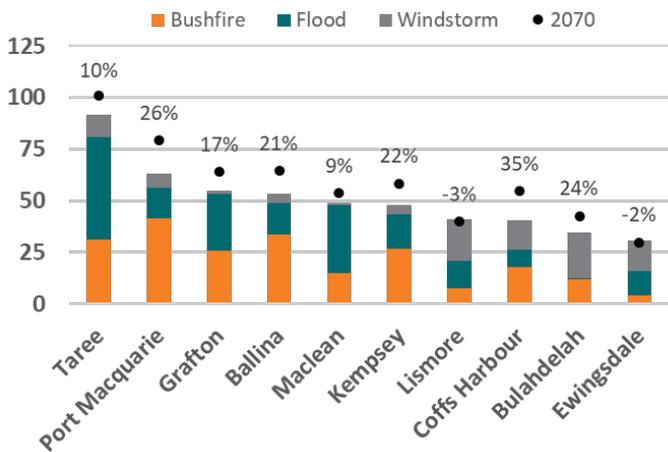


Chart 14
Expected number of failed assets due to all hazards combined under Baseline

NUMBER OF FAILED ASSETS



The exhibit to the left shows the expected asset failures by hazard for the top 10 depots. Taree was modelled to have the highest number of failed assets. Port Macquarie, Ballina and Coffs Harbour were modelled to have the highest percentage increase of the top 10 service depots, which was driven by Bushfire.

Chart 15
Expected number of failed assets by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Bulahdelah was modelled to have the highest number of asset failures per customer which was driven by Windstorm. This was due to the proportion of private conductors within Bulahdelah relative to other depots.

The modelled increases to number of asset failures by 2070 under RCP4.5 were varied across regions, between -3% and 35% for the top 10 depots. The large increases were driven by Bushfire risk for Coffs Harbour and Port Macquarie.

Lismore shows a decrease due to a forecast decrease in wind escalations factors for Lismore derived from global climate models.

ASSET FAILURES PER CUSTOMER

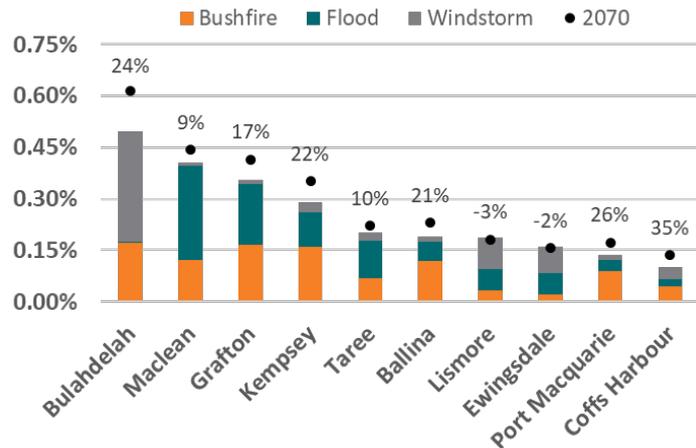


Chart 16
Expected number of failed assets per customer by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Impact Analysis – Total Financial Costs

To summarise the total financial costs to Essential Energy due to the modelled impacts of bushfire, flood, and windstorm, direct financial costs are added to the VCR impact.

The exhibit below shows the modelled total financial costs across different percentiles by hazard. A black dot is used to represent direct financial costs in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

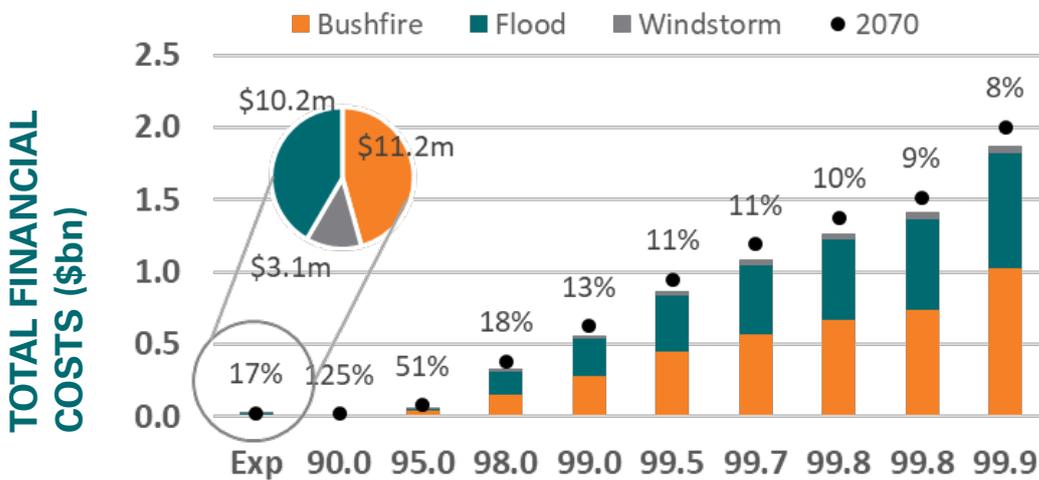


Chart 17
Total financial costs by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Bushfire and Flood were modelled to be broadly equally responsible for the VCR on the expected case. Bushfire tail events resulted in a large number of asset failures, while Flood tail events resulted in the failure of expensive zone substations. There is a 17% increase in the expected total financial costs:

- Bushfire and Windstorm total financial costs were both modelled to increase materially by 26%
- Flood total financial costs was modelled to increase by 5%

The rate of change for total financial cost by hazard varied across RCP and time horizon. The table below shows the total financial cost by hazard over time for the two RCPs.

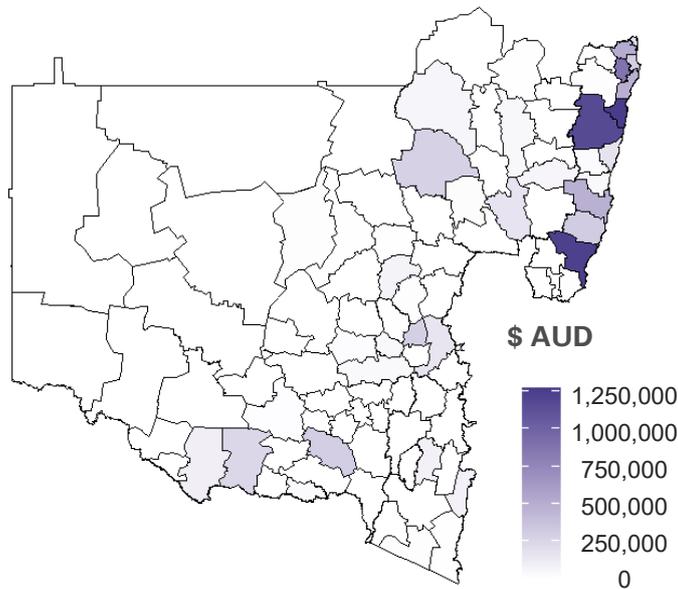
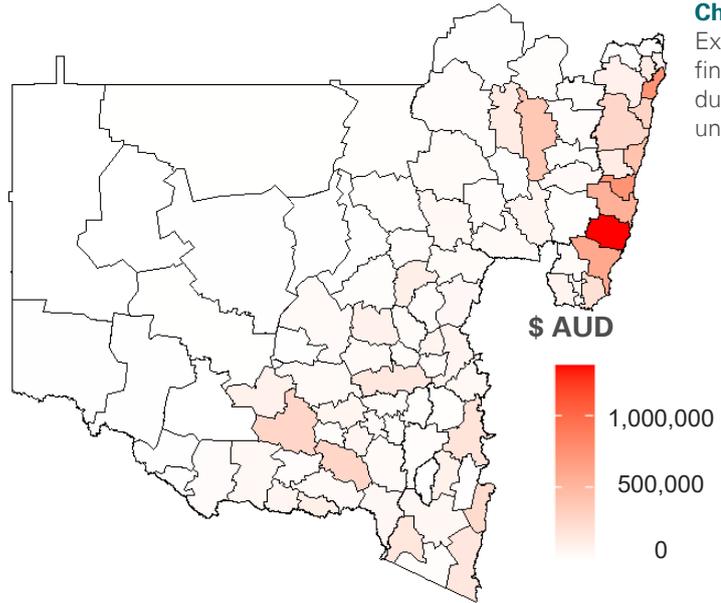
Scenario	Hazard	Average Total Financial Costs (\$m)				% Change from Baseline		
		Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	11.2	12.6	14.1	15.9	13%	26%	42%
	Flood	10.2	10.5	10.6	10.7	4%	5%	5%
	Windstorm	3.4	5.8	4.3	4.6	69%	26%	33%
RCP8.5	Bushfire	11.2	15.2	17.0	19.5	37%	52%	75%
	Flood	10.2	10.7	11.1	11.4	5%	9%	12%
	Windstorm	3.4	6.0	4.3	4.3	74%	25%	27%

Table 11
Expected total financial costs by hazard by RCP and time horizon.

The rate of change for total financial cost is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths were modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

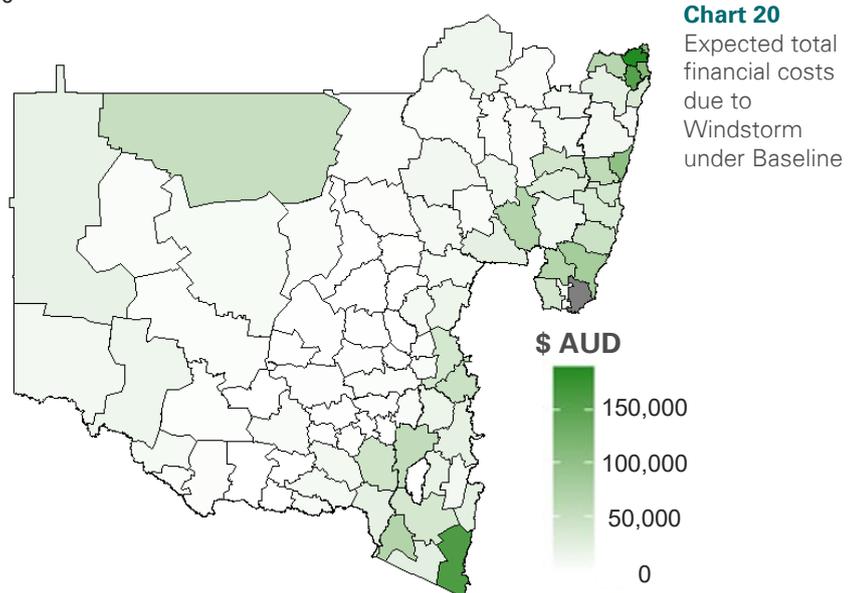
Impact Analysis – Total Financial Costs

The chart to the right shows the expected total financial costs for the Baseline scenario due to bushfire. There is a concentration of total financial cost on the Mid North Coast and some moderate concentration in Leeton and Wagga Wagga. This metric is aligned with the modelled asset failures.



The chart to the left shows the expected total financial costs for the Baseline scenario due to flood. There is a concentration of total financial cost on the Mid North Coast and North Coast. This metric is aligned with the modelled asset failures.

The chart to the right shows the expected total financial costs for the Baseline scenario due to windstorm. There is a concentration of total financial cost in Bega,



Impact Analysis – Total Financial Costs

The chart to the right shows the expected total financial costs for the Baseline scenario for all hazards combined. The heatmap is driven by the modelled Bushfire and Flood asset failures.

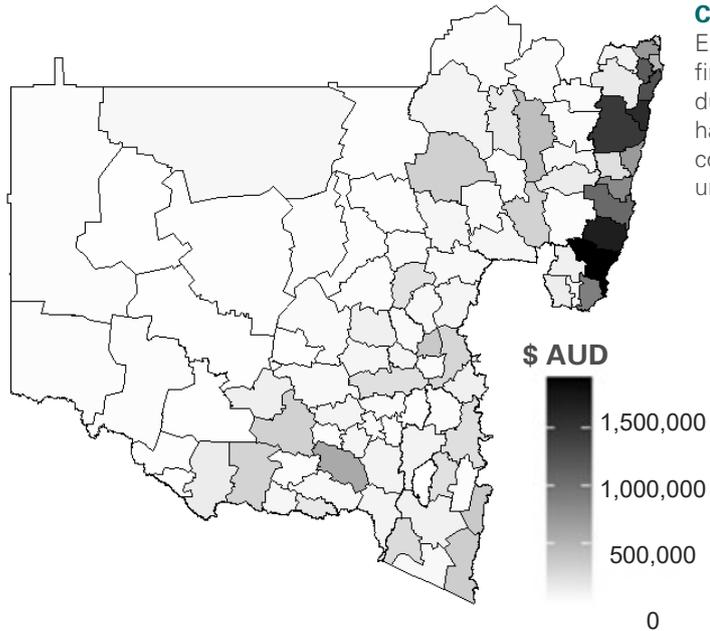
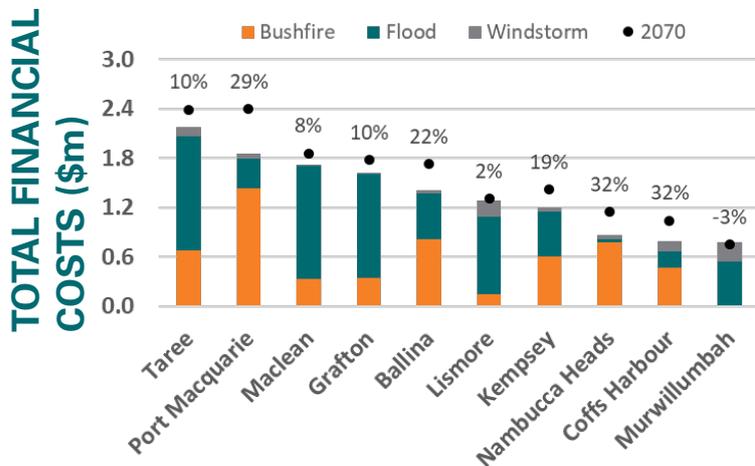


Chart 21
Expected total financial costs due to all hazards combined under Baseline



The exhibit to the left shows the expected total financial costs by hazard for the top 10 depots. Taree was modelled to have the highest total financial cost. Nambucca Heads, Port Macquarie, and Coffs Harbour were modelled to have the highest percentage increase of the top 10 service depots, driven by Bushfire.

Chart 22
Total financial costs by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Maclean was modelled to have the highest total financial cost per customer which was driven by Flood.

The modelled increases to total financial cost by 2070 under RCP4.5 were varied across regions, between -3% and 32% for the top 10 regions. The large increases were driven by Bushfire risk for Nambucca Heads and Port Macquarie.

Murwillumbah shows a decrease due to a forecast decrease in wind escalations factors for Murwillumbah derived from global climate models.

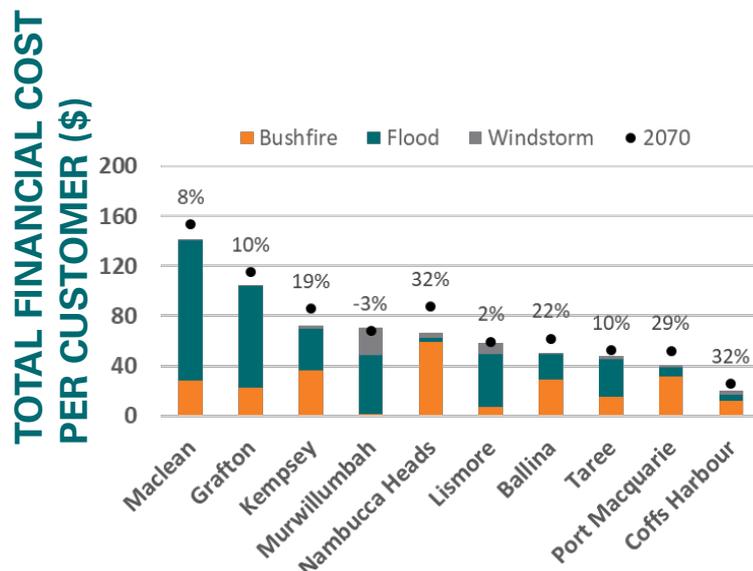


Chart 23
Total financial costs per customer by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Impact Analysis – Direct Financial Costs

Direct financial costs were modelled to take effect following asset failures. These costs corresponded to asset replacement and labour cost. The graph below shows the total direct financial costs across percentiles for the Baseline scenario by hazard. A black dot is used to represent direct financial costs in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

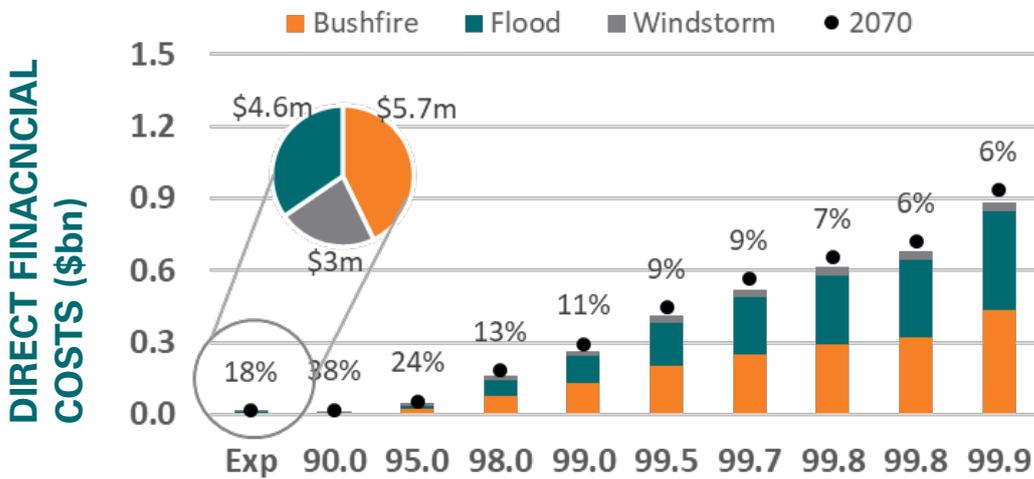


Chart 24
Direct financial costs by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

EE direct financial costs were forecast to be highest for Bushfire risk. The driver of the most severe events for asset failures is Bushfire, but followed by Flood due to the potential costs related to zone substations. There is a 18% increase in the expected direct financial costs:

- Bushfire and Windstorm direct costs were modelled to increase materially by 25% and 26%
- Flood direct costs was modelled to increase by 4%

The rate of change for direct financial cost by hazard varied across RCP and time horizon. The table below shows the direct financial cost by hazard over time for the two RCPs.

		Average Direct Financial Costs (\$m)				% Change from Baseline		
Scenario	Hazard	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	5.7	6.3	7.0	7.9	11%	25%	40%
	Flood	4.6	4.8	4.8	4.8	3%	4%	4%
	Windstorm	3.0	5.1	3.7	4.0	72%	26%	34%
RCP8.5	Bushfire	5.7	7.6	8.4	9.8	34%	49%	73%
	Flood	4.6	4.8	5.0	5.1	4%	8%	10%
	Windstorm	3.0	5.3	3.7	3.8	79%	24%	27%

Table 12
Expected direct financial costs by hazard by RCP and time horizon.

The rate of change for direct financial cost is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths are modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

Impact Analysis – Direct Financial Costs

The chart to the right shows the expected direct financial costs for the Baseline scenario due to bushfire. There is a concentration of asset failures on the Mid North Coast and a moderate spread of asset failures across the east of NSW. This metric is aligned with the modelled asset failures.

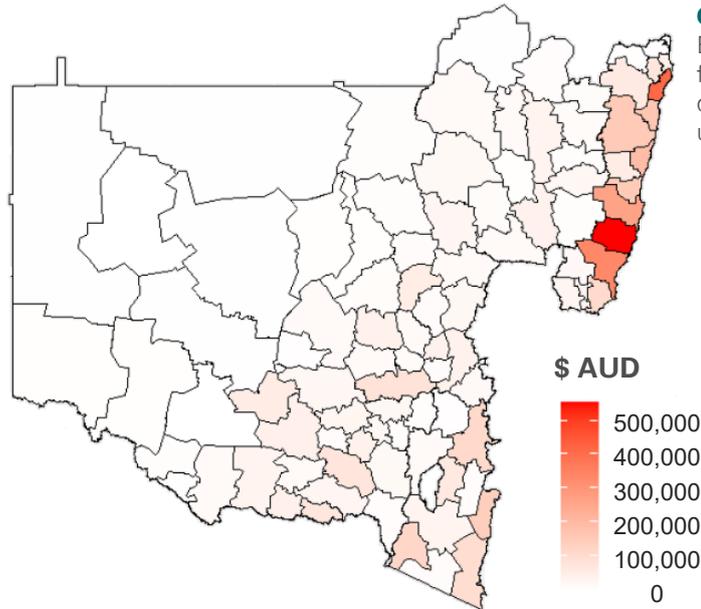
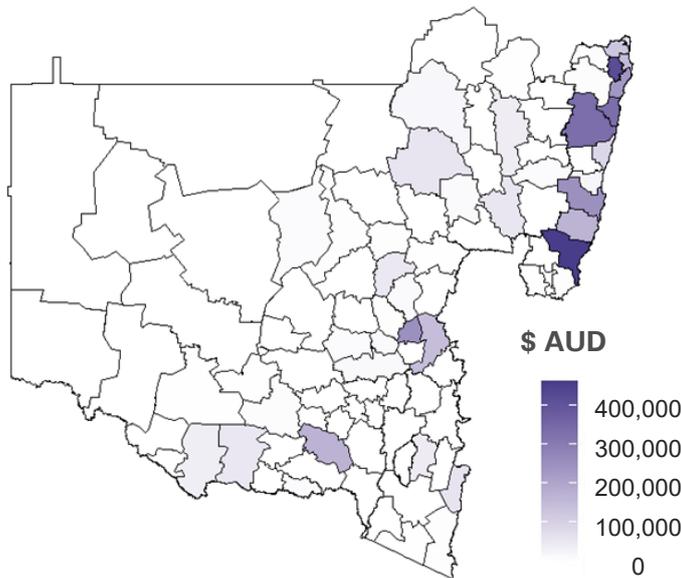


Chart 25
Expected direct financial costs due to Bushfire under Baseline



The chart to the left shows the expected direct financial costs for the Baseline scenario due to flood. There is a concentration of asset failures on the Mid North Coast. This metric is aligned with the modelled asset failures.

Chart 26
Expected direct financial costs due to Flood under Baseline

The chart to the right shows the expected direct financial costs for the Baseline scenario due to windstorm. There is some concentration of asset failures on the East coast of NSW, which is driven by higher wind gusts and a heavier density of vegetation compared to the West. There is also some concentration of asset failures to the West of NSW, which is driven by longer conductor lengths, which are more exposed to vegetation. This metric is aligned with the modelled asset failures.

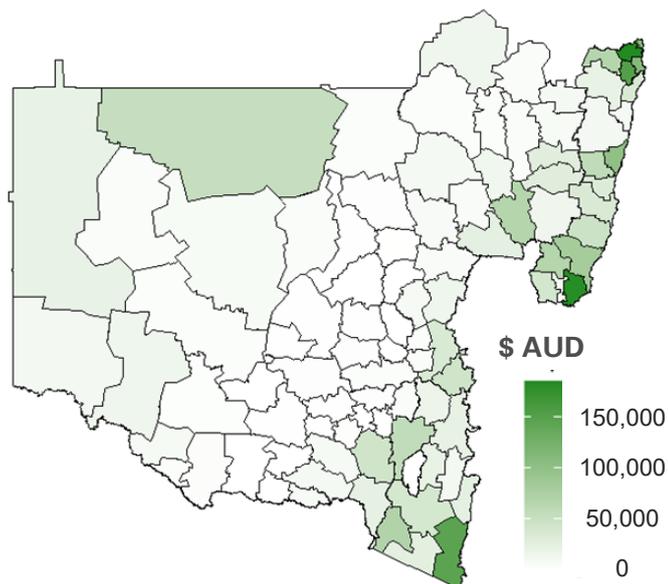
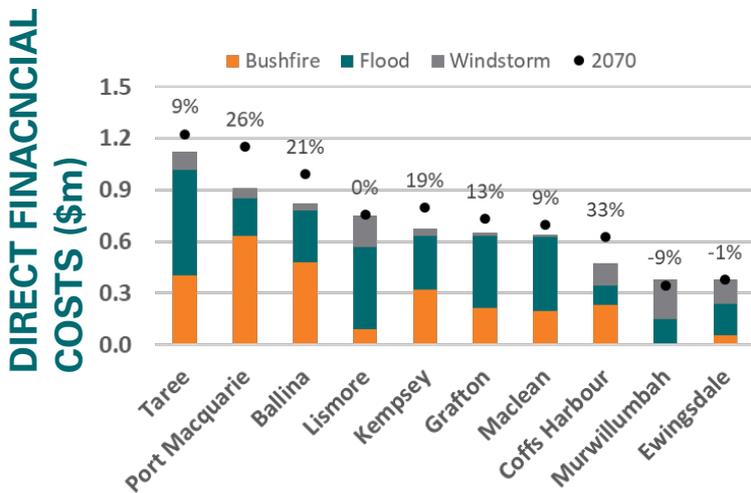
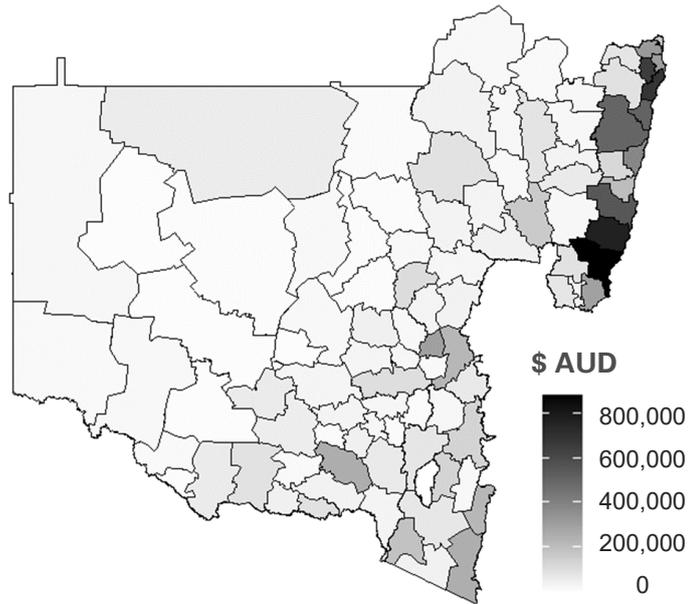


Chart 27
Expected direct financial costs due to Windstorm under Baseline

Impact Analysis – Direct Financial Costs

The chart to the right shows the expected direct financial costs for the Baseline scenario for all hazards combined. The heatmap is driven by the Bushfire and Flood asset failures.



The exhibit to the left shows the direct financial costs by hazard for the top 10 depots. Taree was modelled to have the highest direct costs. Port Macquarie and Ballina were modelled to have the highest percentage increase of the top 10 service depots, driven by Bushfire.

Chart 29
Expected direct financial costs by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Maclean was modelled to have the highest total financial cost per customer which was driven by Flood.

The modelled increases to direct financial costs by 2070 under RCP4.5 were varied across regions, between -9% and 33% for the top 10 regions. The large increases were driven by Bushfire risk for Port Macquarie and Ballina.

Murwillumbah shows a decrease due to a forecast decrease in wind escalations factors for Murwillumbah derived from global climate models.

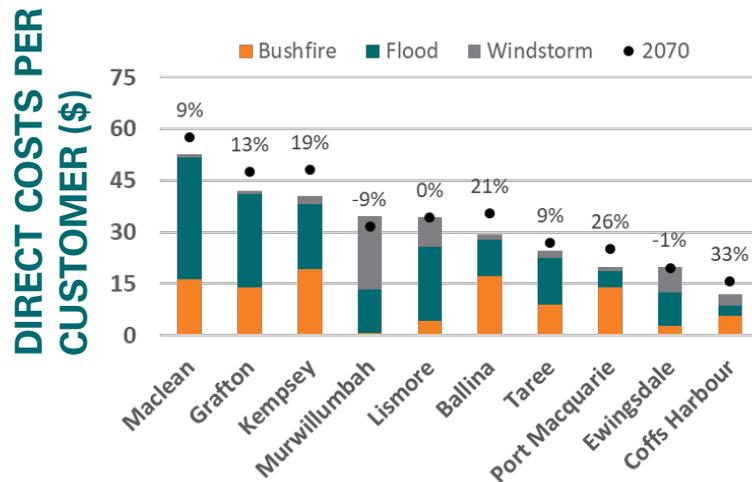


Chart 30
Direct financial costs per customer by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Impact Analysis – Value of Customer Reliability

The value of customer reliability was estimated using a fixed estimate for energy at risk and value of customer reliability (“VCR”) rate. The result is proportional to the total customer downtime.

The exhibit below shows the modelled VCR across different percentiles by hazard. A black dot is used to represent VCR in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

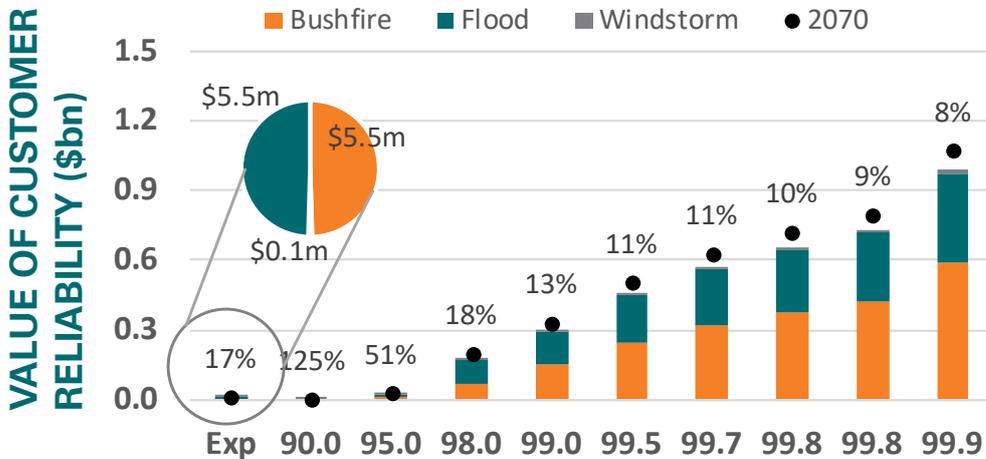


Chart 31
Value of Customer Reliability by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Bushfire and Flood were modelled to be broadly equally responsible for the VCR on the expected case, but Bushfire drove the tail events. VCR is driven by waiting time for service crews to complete the restoration of an asset before tending to another. Windstorm asset failure rates are very low and hence failures were not modelled to occur as localised concentrations, hence windstorm VCR is relatively low compared to Bushfire and Flood. There is a 18% increase in the expected VCR:

- Bushfire and Windstorm VCR were modelled to increase materially by 28% and 34%
- Flood VCR was modelled to increase by 5%

The rate of change for VCR impact by hazard varied across RCP and time horizon. The table below shows the VCR impact by hazard over time for the two RCPs.

Scenario	Hazard	Average VCR (\$m)				% Change from Baseline		
		Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	5.5	6.3	7.1	8.0	15%	28%	45%
	Flood	5.5	5.8	5.8	5.9	4%	5%	6%
	Windstorm	0.1	0.2	0.1	0.2	80%	34%	45%
RCP8.5	Bushfire	5.5	7.7	8.5	9.8	39%	55%	78%
	Flood	5.5	5.9	6.1	6.3	6%	10%	14%
	Windstorm	0.1	0.2	0.1	0.1	89%	32%	43%

Table 13
Expected VCR impact by hazard by RCP and time horizon.

The rate of change for VCR is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths are modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

Impact Analysis – Value of Customer Reliability

The chart to the right shows the expected VCR impact for the Baseline scenario due to bushfire. There is a concentration of asset failures on the Mid North Coast and generally a moderate spread of VCR impact across the east of NSW. This metric is aligned with the modelled asset failures.

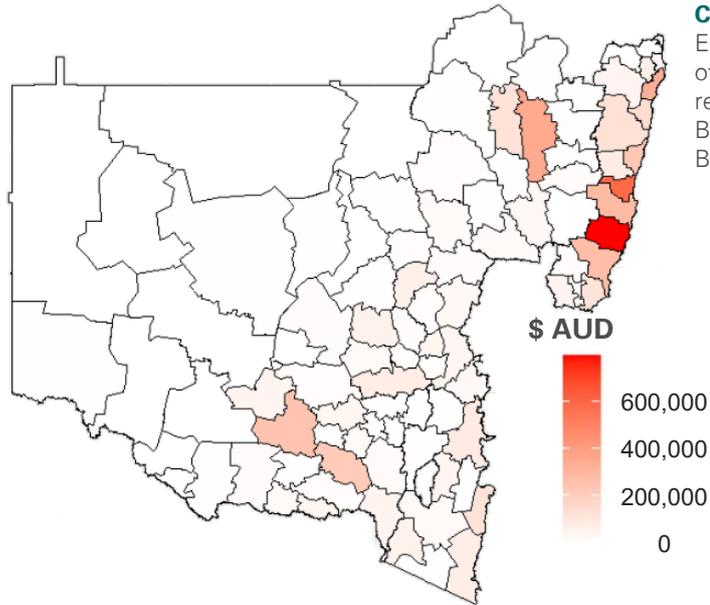
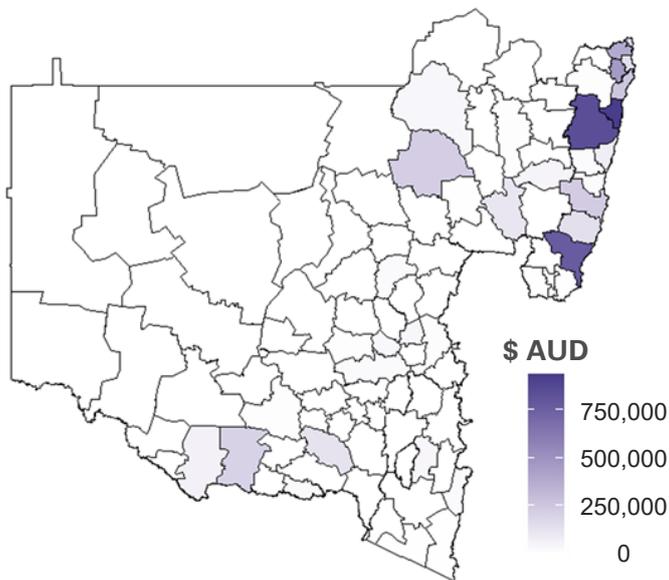


Chart 32
Expected value of customer reliability due to Bushfire under Baseline



The chart to the left shows the expected VCR impact for the Baseline scenario due to flood. There is a concentration of VCR impact on the Mid North Coast and North Coast. This metric is aligned with the modelled asset failures.

Chart 33
Expected value of customer reliability due to Flood under Baseline

The chart to the right shows the expected VCR impact for the Baseline scenario due to windstorm. There are high risk depots such as Bega, Leeton, and Nambucca heads, which are location in different regions. This demonstrates how windstorm risk has a wider spread of risk than bushfire or flood.

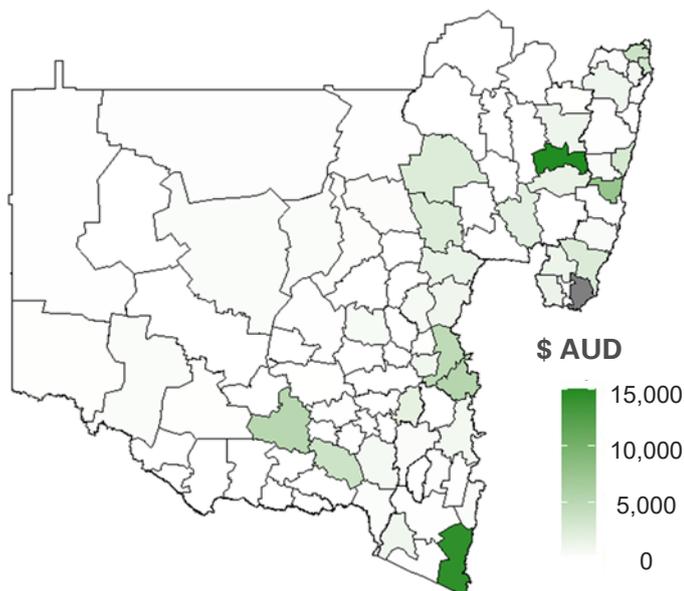


Chart 34
Expected value of customer reliability due to Windstorm under Baseline

Impact Analysis – Value of Customer Reliability

The chart to the right shows the expected VCR impact for the Baseline scenario for all hazards combined. The heatmap is driven by the modelled Bushfire and Flood asset failures.

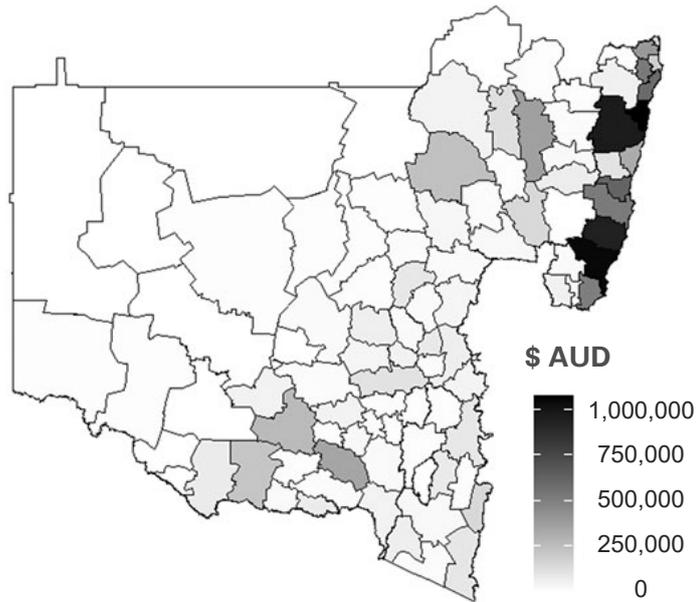
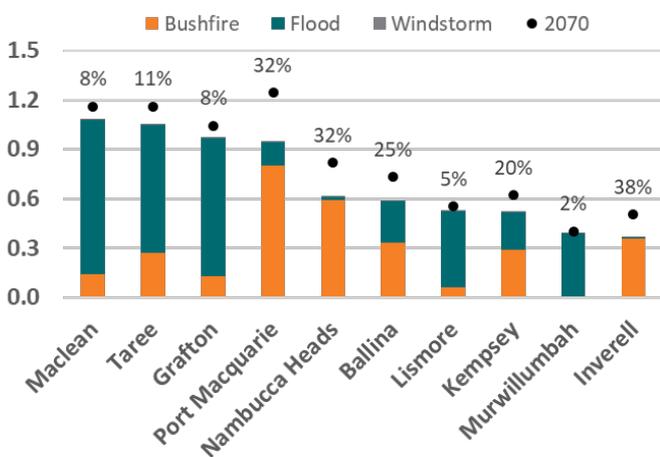


Chart 35
Expected value of customer reliability due to all hazards combined under Baseline

VALUE OF CUSTOMER RELIABILITY (\$m)



The exhibit to the left shows the expected VCR impact by hazard for the top 10 depots. Maclean was modelled to have the highest VCR, driven by Flood. Inverell, Port Macquarie and Nambucca Heads have the highest percentage increase of the top 10 depots, driven by Bushfire.

Chart 36
Value of Customer Reliability by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Maclean was modelled to have the highest VCR per customer, driven by Flood. When a flood event occurred in Maclean, a very large number of cubicles were at risk of failure. This resulted in long wait times. For example, a 98th percentile event was modelled to cause an expected 409 cubicle failures in Baseline.

The modelled increases to value of customer reliability by 2070 under RCP4.5 were varied across regions, between 2% and 38% for the top 10 depots. The large increases were driven by Bushfire risk for Inverell, Port Macquarie, and Nambucca Heads.

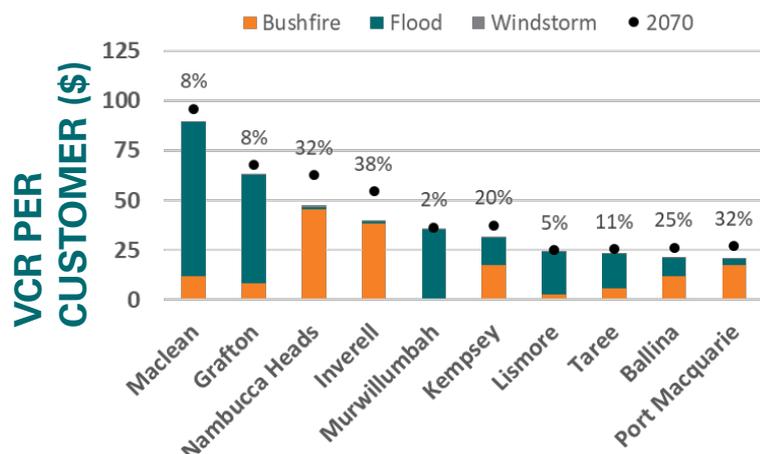


Chart 37
Value of Customer Reliability per customer by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Impact Analysis – Customer Interruptions

Customer interruptions were captured as non-financial impacts. A customer was modelled to experience an interruption where an asset failure occurred on or upstream of their feeder.

The exhibit below shows the modelled number of interruptions across different percentiles by hazard. A black dot is used to represent customer interruptions in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

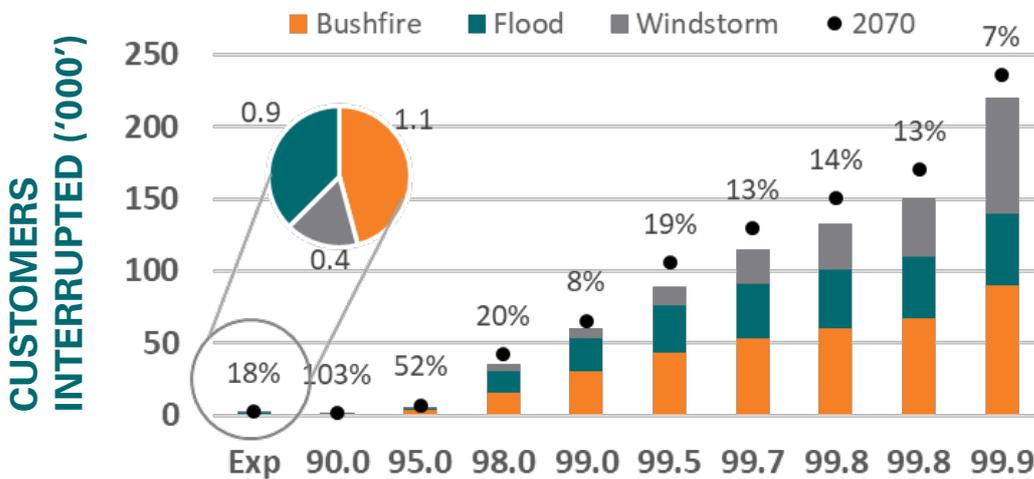


Chart 38
Customer interruptions by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Bushfire was modelled to be responsible for the most interruptions on average and this was also true for the most severe events, along with Windstorm. There is a 18% increase in the expected customers interrupted:

- Bushfire and Windstorm customers interrupted were modelled to increase materially by 28% and 27%
- Flood customers interrupted was modelled to increase by 2%

The rate of change for customers interrupted by hazard varied across RCP and time horizon. The table below shows the customers interrupted by hazard over time for the two RCPs.

		Average Customers Interrupted ('000')				% Change from Baseline		
Scenario	Hazard	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	1.1	1.2	1.4	1.5	15%	28%	43%
	Flood	0.9	0.9	0.9	0.9	2%	2%	3%
	Windstorm	0.4	0.7	0.5	0.6	62%	27%	38%
RCP8.5	Bushfire	1.1	1.5	1.6	1.8	37%	51%	69%
	Flood	0.9	0.9	0.9	0.9	3%	5%	7%
	Windstorm	0.4	0.7	0.5	0.6	68%	28%	37%

Table 14
Expected customers interrupted by hazard by RCP and time horizon.

The rate of change for customers interrupted is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths are modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

Impact Analysis – Customer Interruptions

The chart to the right shows the expected customer interruptions for the Baseline scenario due to bushfire. There is a concentration of customer interruptions on the Mid North Coast and a moderate spread of customer interruptions across the east of NSW. This metric reflects the asset failures, network energy dependency and where customers are located.

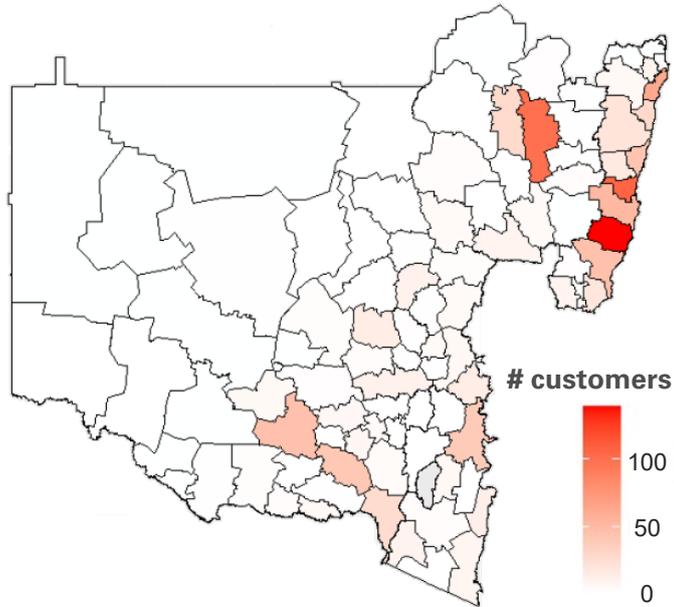
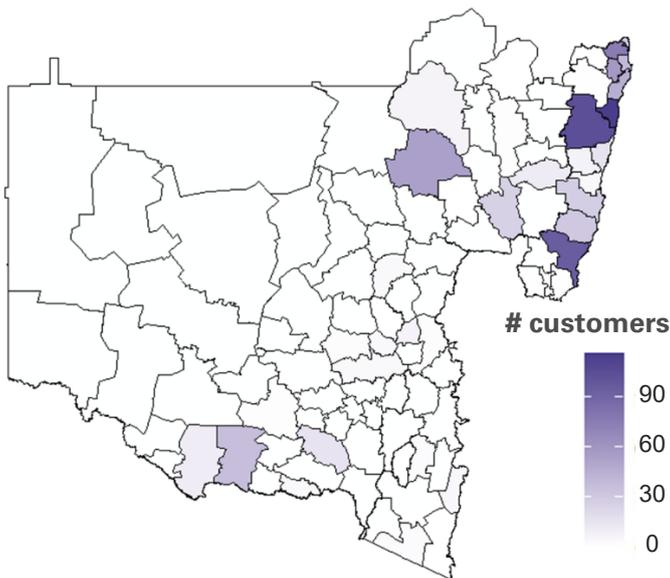


Chart 39
Expected customer interruptions due to Bushfire under Baseline



The chart to the left shows the expected customer interruptions for the Baseline scenario due to flood. There is a concentration of customer interruptions on the Mid North Coast and North Coast. This metric reflects the asset failures, network energy dependency and where customers are located.

Chart 40
Expected customer interruptions due to Flood under Baseline

The chart to the right shows the expected customer interruptions for the Baseline scenario due to windstorm. There are high risk depots such as Bega, Leeton, and Nambucca heads, which are location in different regions. This is aligned with the spread of risk for VCR. This metric reflects the asset failures, network energy dependency and where customers are located.

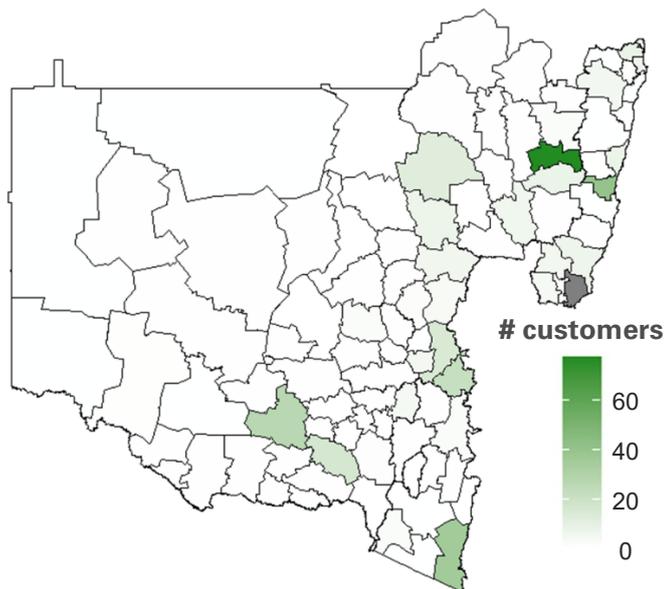


Chart 41
Expected customer interruptions due to Windstorm under Baseline

Impact Analysis – Customer Interruptions

The chart to the right shows the expected customer interruptions for the Baseline scenario for all hazards combined. The heatmap is driven by the modelled bushfire asset failures.

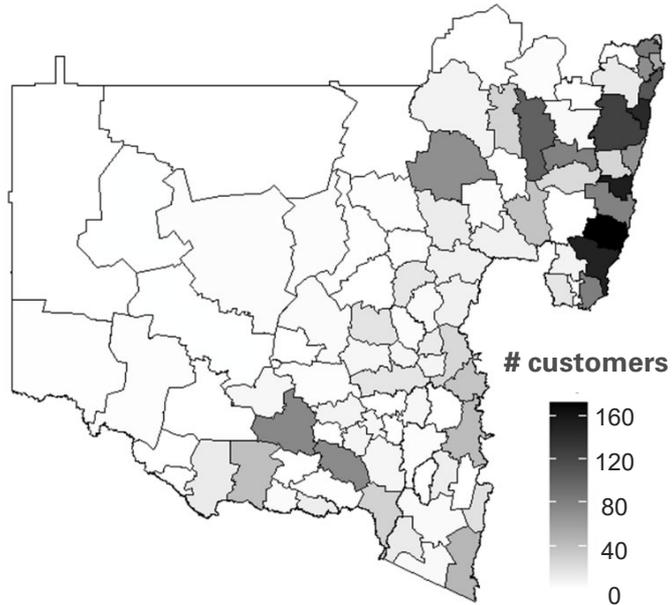
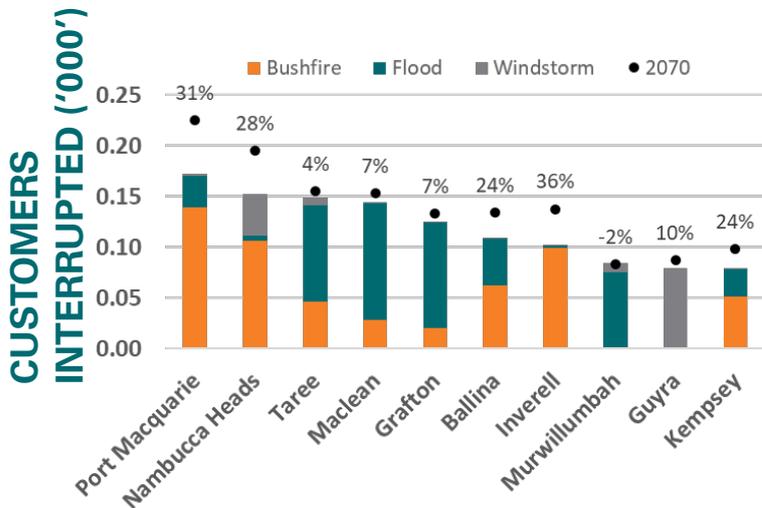


Chart 42
Expected customer interruptions due to all hazards combined under Baseline



The exhibit to the left shows the expected customer interruptions by hazard for the top 10 depots. Port Macquarie was modelled to have the highest number of customers interrupted, driven by Bushfire. Inverell and Port Macquarie were modelled to have the highest percentage increase of the top 10 service depots, driven by Bushfire.

Chart 43
Customer interruptions by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Guyra was modelled to have the highest interruptions per customer. However, further investigation showed this was caused by a data limitation on a long private conductor. No manual amendments were made for the data limitation, except for Bulahdelah. Maclean was modelled to have the second highest interruptions per customer which was driven by Flood.

The modelled increases to customer interruptions by 2070 under RCP4.5 were varied across regions, between -2% and 36% for the top 10 regions. The large increases were driven by Bushfire risk for Inverell and Port Macquarie.

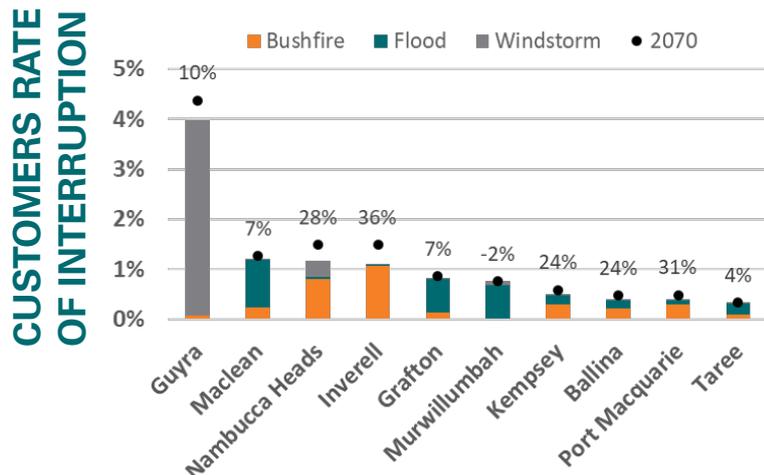


Chart 44
Customer interruptions per customer by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Impact Analysis – Customer Downtime

Customer downtime was captured as non-financial impact. A customer was modelled to experience downtime where an asset failure occurred on or upstream of their feeder.

The exhibit below shows the modelled duration of downtime across different percentiles by hazard. A black dot is used to represent aggregate customer downtime in 2070 under RCP 4.5 for all hazards combined, while the % is the movement between Baseline and 2070 for combined hazards.

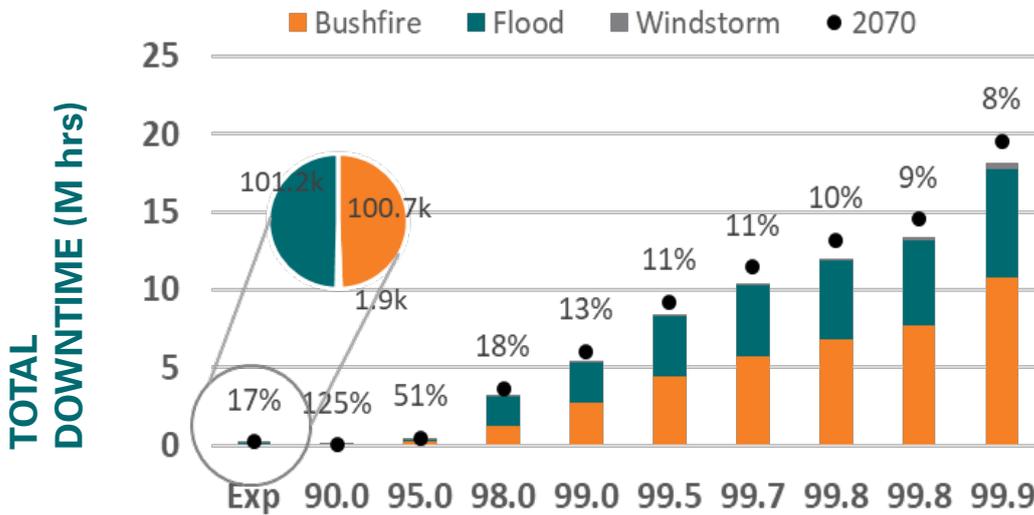


Chart 45
Customer downtime by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Bushfire was modelled to be responsible for the most customer downtime on average and this was also true for the most severe events. This was followed closely by Flood. There is a 17% increase in the expected customer downtime:

- Bushfire and Windstorm customer downtime were modelled to increase materially by 28% and 34%
- Flood VCR customer downtime modelled to increase by 5%

The rate of change for customer downtime by hazard varied across RCP and time horizon. The table below shows the customer downtime by hazard over time for the two RCPs.

Average Total Customers Downtime ('000' hrs)					% Change from Baseline			
Scenario	Hazard	Baseline	2050	2070	2090	2050	2070	2090
RCP4.5	Bushfire	100.7	116.1	129.2	145.8	15%	28%	45%
	Flood	101.2	105.7	106.6	107.5	4%	5%	6%
	Windstorm	1.9	3.4	2.6	2.8	80%	34%	45%
RCP8.5	Bushfire	100.7	140.1	156.2	178.8	39%	55%	78%
	Flood	101.2	107.4	111.8	115.2	6%	10%	14%
	Windstorm	1.9	3.6	2.5	2.7	89%	32%	43%

Table 15
Expected total financial costs by hazard by RCP and time horizon.

The rate of change for customers downtime is most severe for Bushfire, followed by Windstorm and Flood. However, a limitation of the Flood model was that flood depths are modelled to change, but the locations and frequency of flood was not. The impact of changes to location and frequency is expected to increase the rate of change.

Impact Analysis – Customer Downtime

The chart to the right shows the expected total customer downtime for the Baseline scenario due to bushfire. There is a concentration of aggregate customer downtime on the Mid North Coast and a moderate spread across the east of NSW. This metric reflects EE’s network energy dependency and the asset restoration priority.

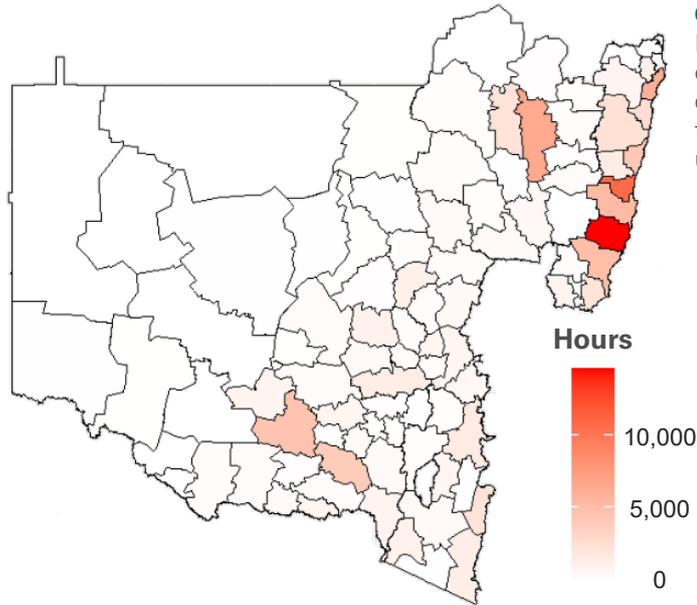
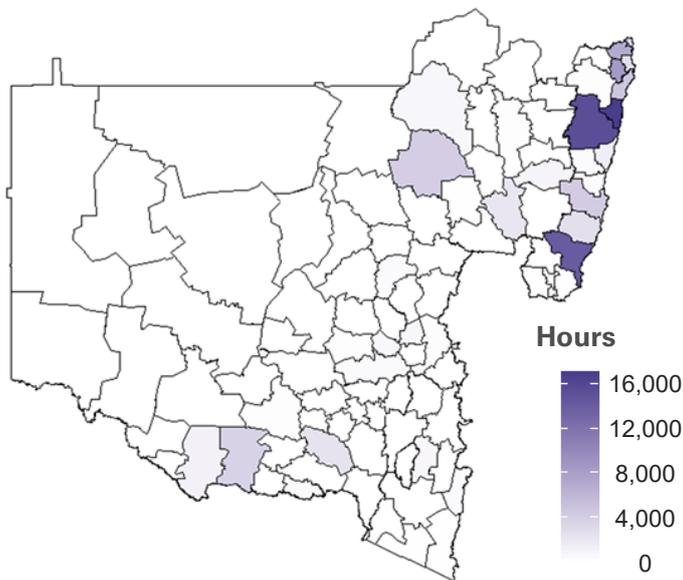


Chart 46
Expected customer downtime due to Bushfire under Baseline



The chart to the left shows the expected total customer downtime for the Baseline scenario due to flood. There is a concentration of aggregate customer downtime on the Mid North Coast and North Coast. This metric reflects EE’s network energy dependency and the asset restoration priority.

Chart 47
Expected customer downtime due to Flood under Baseline

The chart to the right shows the expected total customer downtime for the Baseline scenario due to windstorm. There are high risk depots such as Bega, Leeton, and Nambucca heads, which are location in different regions. This is aligned with the spread of risk for VCR. This metric reflects the asset failures, network energy dependency and asset restoration priority.

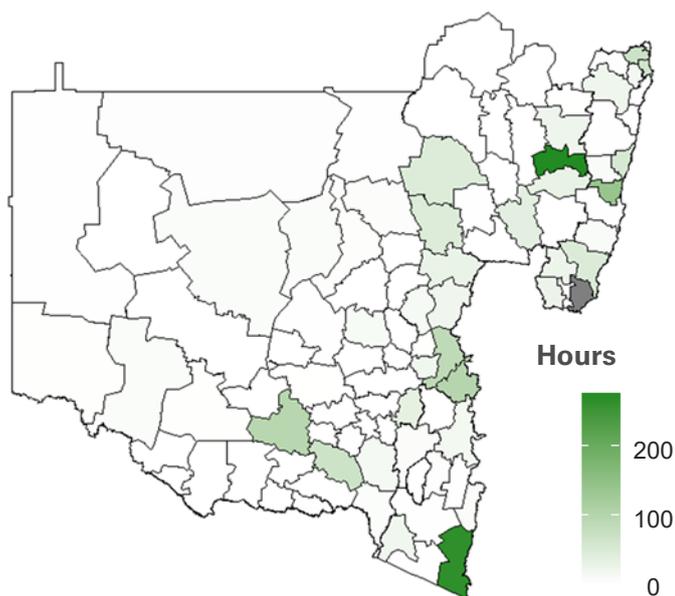


Chart 48
Expected customer downtime due to Windstorm under Baseline

Impact Analysis – Customer Downtime

The chart to the right shows the expected total customer downtime for the Baseline scenario for all hazards combined. The heatmap is driven by the modelled bushfire asset failures.

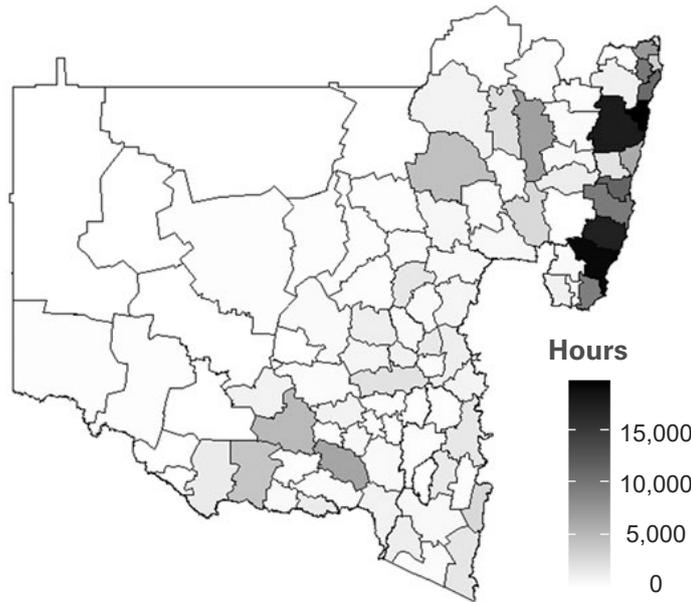
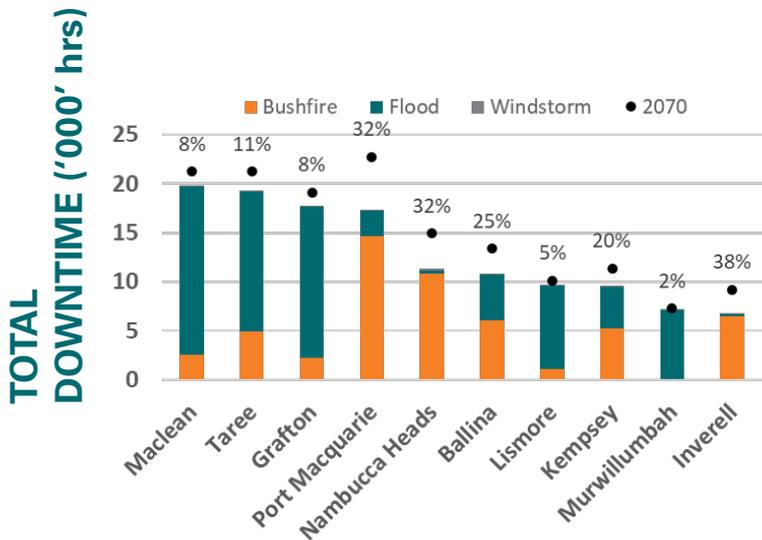


Chart 49
Expected customer downtime due to all hazards combined under Baseline



The exhibit to the left shows the expected customer downtime by hazard for the top 10 depots. Maclean was modelled to have the highest customer downtime, driven by Flood. Inverell, Port Macquarie and Nambucca Heads were modelled to have the highest percentage increase of the top 10 service depots, driven by Bushfire.

Chart 50
Customer downtime by hazard for the top 10 service depots under Baseline and 2070 under RCP4.5

Maclean was modelled to have the highest downtime per customer, driven by Flood. Inverell, Port Macquarie and Nambucca Heads were modelled to have the highest percentage increase of the top 10 service depots, driven by Bushfire.

The modelled increases to downtime per customer by 2070 under RCP4.5 were varied across regions, between 2% and 38% for the top 10 regions. The large increases were driven by Bushfire risk for Inverell, Port Macquarie, and Nambucca Heads.

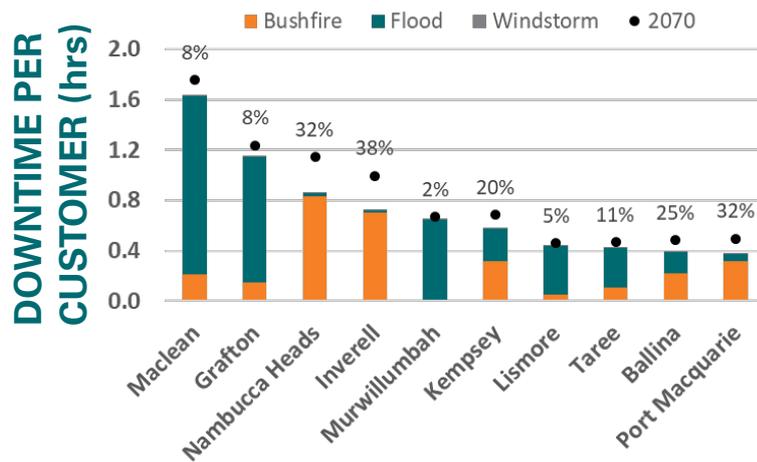


Chart 51
Downtime per customer by hazard and likelihood percentile under Baseline and 2070 under RCP4.5

Next Steps

Other ways to present outputs

The Impact analysis has been presented primarily as the aggregate result by depot area, which would support Essential Energy with a defensible business case for resilience expenditure.

There are many ways to present the results of the climate impact assessment, some examples include:

- Showing each metric on a per asset basis, specific to the asset class
- Showing each metric summarised at a maintenance area granularity
- Showing each metric at specific likelihood percentiles

Framework development

The climate impact assessment is EE's first attempt at modelling the direct and network impacts due to bushfire, flood, and windstorm hazards. There has been significant collaboration with KPMG, who have delivered similar engagements for other DNSPs across Australia, but the area of study for climate change is rapidly maturing. As such, there is the potential to refine and enhance the analysis, building up from a robust foundation. Some options have been listed in the table below, split between new data sources or modelling improvements.

Climate Impact Assessment Development Options		
Hazard	Potential New Data Sources	Potential Modelling Improvements
Bushfire	<ul style="list-style-type: none"> • Other bushfire intensity information, such as Fire Behaviour Index. • Industry asset failure data. 	<ul style="list-style-type: none"> • Incorporate bushfire ignition locations and the associated risk of EE assets causing said ignition. • Incorporate fire duration stochastically.
Flood	<ul style="list-style-type: none"> • Asset specific flood depth vulnerabilities. 	<ul style="list-style-type: none"> • Model changes to flood footprints in addition to changes in flood depths. • Model impacts of moving debris within flood waters. • Incorporate flood water subsiding stochastically,
Windstorm	<ul style="list-style-type: none"> • Asset condition reports. • Soil conditions. • Vegetation type and height. • Vegetation clearance activity. • Asset maintenance activity. 	<ul style="list-style-type: none"> • Model microburst wind events. • Model specific vegetation failure and fall range.

Table 16
Climate impact assessment development options

Sensitivity Tests

Sensitivity testing allows EE to understand which assumptions the assessment is most sensitive to and also sense check that the model is working as intended. The assumptions that are most sensitive should be given the most scrutiny and justification.

In the tables below, the results of the hazard sensitivity testing on all the output types is summarised. An arbitrary 10% flex on the burn rate assumptions, 10% flex on flood threshold depths, and a 1% flex on wind vulnerability curves was applied and commentary was provided on whether the result is as expected.

Bushfire Sensitivity Results

Assumption	Original	Burn Probability (+/- 10%)	
Failed Assets	491	10%	-10%
Total Financial Cost	11,202,428	10%	-10%
Direct Financial Cost	5,682,598	10%	-10%
Asset Replacement Cost	4,577,549	10%	-10%
Labour Cost	1,105,049	10%	-10%
Value of Customer Reliability	5,519,830	10%	-10%
Customer Interruptions	1,066	6%	-6%
Customer Downtime	100,963	10%	-10%

Table 17
Bushfire sensitivity test results

The sensitivity analysis results for burn probabilities are consistent with expectations. The number of customer interruptions is less sensitive to the burn probabilities, where a 10% increase to burn rates results in a 6% increase to the number of customers interrupted. This occurs because there may be multiple asset failures related to a customer interruption.

Flood Sensitivity Results

Assumption	Original	Flood Thresholds (+/- 10%)	
Failed Assets	248	-11%	9%
Total Financial Cost	10,159,316	-9%	8%
Direct Financial Cost	4,630,369	-8%	7%
Asset Replacement Cost	3,791,269	-8%	7%
Labour Cost	839,100	-8%	8%
Value of Customer Reliability	5,528,947	-10%	10%
Customer Interruptions	872	-6%	6%
Customer Downtime	101,129	-10%	10%

Table 18
Flood sensitivity test results

The sensitivity analysis results for flood failure threshold depths are consistent with expectations. The number of customer interruptions is less sensitive to the burn probabilities, where a 10% increase to flood failure rates results in a 6% increase to the number of customers interrupted. This occurs because there may be multiple asset failures related to a customer interruption.

Sensitivity Tests

Windstorm Sensitivity Results

Assumption	Original	Wind Curve (+/- 1%)	
Failed Assets	317	1%	-1%
Total Financial Cost	3,415,905	0%	1%
Direct Financial Cost	2,966,578	1%	-1%
Asset Replacement Cost	2,412,972	1%	-1%
Labour Cost	553,605	1%	-1%
Value of Customer Reliability	449,328	1%	-1%
Customer Interruptions	2,201	1%	-1%
Customer Downtime	8,219	1%	-1%

Table 19
Windstorm
sensitivity test
results

The sensitivity analysis results for windstorm failure probabilities are consistent with expectations. Most metrics changed by 1% as the wind curves were adjusted by 1%.

Convergence Tests

Convergence testing provides EE with the confidence that the number of simulations were high enough to reduce the impact of simulation error on the output metrics.

The tables below summarises each hazard model run compared against the average of 5 additional unique simulation re-runs. The outputs were compared across different results percentiles to identify if the results have converged over 30,000 simulations.

Each number in the table represents the ratio of the simulated result against the average of a further 150,000 simulations. A 100% metric indicates that there was no difference in the simulation compared to the average of a further 150,000 simulations. A variation against the 150,000 simulations of +/- 5% is acceptable

Bushfire Convergence Results

Percentile	90	95	98	99	99.5	99.7	99.8	99.8	99.9
Failed Assets	100%	100%	100%	100%	100%	100%	100%	100%	100%
Total Financial Cost	98%	101%	99%	103%	100%	99%	100%	99%	99%
Direct Financial Cost	96%	103%	100%	108%	101%	98%	100%	99%	99%
Asset Replacement Cost	95%	103%	100%	109%	102%	97%	100%	99%	99%
Labour Cost	100%	100%	100%	100%	100%	100%	100%	100%	100%
Value of Customer Reliability	100%	99%	98%	100%	100%	100%	100%	99%	98%
Customer Interruptions	100%	100%	100%	100%	99%	100%	100%	100%	99%
Customer Downtime	100%	99%	98%	100%	100%	100%	100%	99%	98%

Table 20
Bushfire
Convergence
test results

The convergence test results for bushfire show that the simulation run presented within the results is within -5% and +3% of the average

For the asset replacement metric, the simulation result was 5% lower than the average of a further 150,000 simulations for bushfire at the 90th percentile. This is within an acceptable range of stochastic volatility. Asset replacement exhibited the most volatility, which was driven by cable joints.

Flood Convergence Results

Percentile	90	95	98	99	99.5	99.7	99.8	99.8	99.9
Failed Assets	100%	100%	100%	100%	100%	100%	100%	100%	100%
Total Financial Cost	101%	99%	100%	100%	100%	100%	100%	100%	100%
Direct Financial Cost	103%	98%	100%	100%	100%	99%	100%	100%	100%
Asset Replacement Cost	104%	97%	100%	100%	100%	99%	100%	100%	100%
Labour Cost	100%	100%	100%	100%	100%	100%	100%	100%	100%
Value of Customer Reliability	100%	100%	100%	100%	100%	100%	100%	100%	100%
Customer Interruptions	100%	100%	100%	100%	100%	100%	100%	100%	100%
Customer Downtime	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 21
Flood
Convergence
test results

The convergence test results for flood show that the simulation run presented within the results is within -3% and +4% of the average of the 5 additional model runs. This indicates that the results converged across the presented percentiles.

Convergence Tests

The table below summarises the windstorm model run compared against the average of 5 additional unique simulation re-runs. The outputs were compared across different results percentiles to identify if the results have converged over 30,000 simulations. A higher level of convergence is expected at the lower percentiles.

Windstorm Convergence Results									
Percentile	90	95	98	99	99.5	99.7	99.8	99.8	99.9
Failed Assets	100%	100%	100%	101%	101%	100%	100%	100%	98%
Total Financial Cost	98%	104%	98%	101%	99%	100%	100%	100%	99%
Direct Financial Cost	98%	104%	97%	100%	98%	98%	100%	100%	97%
Asset Replacement Cost	98%	105%	96%	100%	98%	98%	100%	100%	96%
Labour Cost	100%	100%	100%	101%	101%	100%	100%	100%	99%
Value of Customer Reliability	100%	103%	101%	102%	102%	102%	100%	100%	102%
Customer Interruptions	100%	101%	100%	102%	102%	101%	101%	101%	98%
Customer Downtime	100%	103%	101%	102%	102%	102%	100%	100%	102%

Table 22
Windstorm
Convergence
test results

The convergence test results for windstorm show that the simulation run presented within the results is within -4% and +5% of the 5 additional model runs. This indicates that the results converged across the presented percentiles.

References

Reference	Details	Page Number
1	CarbonBrief, 'Mapped: How climate change affects extreme weather around the world', 2022, Accessed 8 November 2022	3
2	HSBC, 'Fragile Planet 2022', 2022, Accessed 8 November 2022	3
3	IPCC, 'Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change', 2013, Accessed 8 November 2022	3
4	Australian Bureau of Meteorology, 'Understanding floods', 2020, Accessed 8 November 2022	11
5	M. Keskin, K. Ozdogu, 'Comparison of Interpolation Methods for Meteorological Data', 2011, Accessed 8 November 2022	22
6	Australian Bureau of Meteorology, 'Other Types of Severe Weather', [No Date], Accessed 8 November 2022	22

Table 23
Report
References

Essential Energy

Contact us:

General enquiries 13 23 91
Power outages 13 20 80
essentialenergy.com.au
info@essentialenergy.com.au



EssentialEnergyAU



essentialenergy



essentialenergytv



engage.essentialenergy.com.au