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The physical impact of strong winds and heavy rain on residential housing: a pilot study

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ABSTRACT

Research in the social science area have pointed out that "traditional" hazard-based forecasts and warnings may not be well understood so that mitigating actions for the protection of life and property are not taken (Demuth et al. 2012). The extension of a hazard forecast towards the description of impacts on the forecast recipient might effect a more suitable mitigating response and has led to an emerging and growing desire among National Hydrological and Meteorological Services for impact-based forecasts and warnings (Harrowsmith 2015; World Meteorological Organization 2015).

A number of major weather services (e.g. UK Met Office, Bureau of Meteorology) have therefore introduced impact-based services in recognition of the above findings. Since 2011 the UK Met Office has issued impact-based warnings where the warning level is derived from a risk matrix in a partly subjective procedure (Met Office 2018). In a related manner, the Extreme Weather Desk at the Australian Bureau of Meteorology has recently developed the Community Hazard Risk Outlook. Forecasters subjectively rate the expected impact level of a model-predicted hazard on a range of assets from which an aggregated impact level is calculated. Combined with a subjective likelihood assessment the UK Met Office risk matrix concept is again utilised to derive an overall hazard risk.

In addition to subjective or partly subjective impact specifications, the factors influential in the final likelihood, location or magnitude of an impact can be delivered as layers, which leaves their integration to the user. An example of such a system is the Global Hazard Map, also produced by the UK Met Office (Robbins and Titley 2018).

Introduction

There are comparatively few attempts to quantitatively and objectively integrate the various hazard, exposure and vulnerability components to calculate a final impact output. One such hazard impact model is the Vehicle Overturning Model which combines probabilistic hazard information with exposure and vulnerability data to produce a forecast of vehicle overturning risk (Hemingway and Gunawan, 2018; Hemingway and Robbins, 2019). A second example is the Surface Water Flooding hazard impact model (Aldridge et al. 2016).

In this paper we outline early steps towards a potential future Australian wind and rain hazard impact model through a combined effort of Geoscience Australia's capability for impact simulation, and the Bureau of Meteorology's provision of detailed spatial hazard grids.

The impact forecasting workflow

In the project, we use a paradigm of Hazard – Exposure – Vulnerability – Impact ("HEVI") for evaluating the physical impact of an extreme weather event. This paradigm reflects the integrated nature of impacts, and the dependence of the final outcome on the interaction of the three components (Figure 1). If any of the three components is reduced, then the overall impact is reduced. For this project, we formulated a specific definition of each of the components (reference?). Due to the cross-cutting themes involved in impact modelling, it is important that all stakeholders understand the terms used in communicating "impact"provides the definitions of the terms used for the project. While these definitions for hazard and exposure can cover a wide range of phenomena and assets, we restrict ourselves to wind speed and rainfall for the hazard, and to residential houses for exposure. More details on each of these components are provided in the hazards, exposure and vulnerability sections below.

Table 1: Definitions of the core terms used in impact forecasting.

Hazard	Exposure	Vulnerability	Impact
A severe weather event that has the potential to cause impacts to people, buildings, infrastructure, agriculture, environmental assets and communities. For this project, we are exploring the wind and rainfall elements of east coast lows.	The elements that may (or may not) be impacted by a hazard event. Elements at risk includes dwellings or households, buildings and structures, public facilities and infrastructure assets.	The degree to which a building, structure, or other exposure element, is damaged by a given intensity of hazard.	The consequences of a hazard event on an asset - the physical damage to an exposure element due to a hazard event. Commonly uses qualitative descriptions such as "slight", "moderate", "major" or "complete"

The interaction of the three components can be non-linear. For example, the vulnerability, examined in the section on vulnerability below, is often a non-linear function of the hazard magnitude, with a twofold increase in the hazard commonly leading to much more than a twofold increase in impact. An example is the pressure force exerted by the wind - a doubling of the wind speed leads to a four-fold increase in the wind pressure. Further, the calculation of impact, discussed in the impact section below, is performed on the building scale but must be aggregated to larger geographic areas in order to reduce the influence of uncertainties. Despite this, the uncertainty in each of the workflow components combines to result in substantial levels of uncertainty in the impact, making verification challenging. There are additional challenges to verification, which will be explored in the verification section.

Each of the impact components vary in space, with the hazard also varying in time as the weather forecast evolves. Thus, the impact forecast can be expected to vary spatially and temporally. The challenge for a forecaster or emergency manager is to combine the individual components in a meaningful way, with sufficient time to guide decision making within the context of their operations for communicating threats to the public – in the form of suitably worded and targeted warnings – or making preparations to reduce or respond to the impacts of an impending extreme weather event.

There are challenges in bringing together the components of hazard, exposure and vulnerability for a nationally consistent view of the potential impacts of extreme weather. In the hazard space, the choice of weather forecast variables can greatly influence the predicted impact. In utilising numerical weather prediction model data (or, equivalently, reanalysis data), model grid spacing, choice of model physics parameterisations and available diagnostic variables can influence the resulting impact products.

Knowledge of the exposed assets, in a consistent manner across the country, means there are challenges in defining key attributes where available data may be limited or only available as aggregate statistics. Similarly, it is not feasible to understand the vulnerability of individual buildings across the country, so the assets need to be categorised on the basis of a small number of attributes such as building age or roof type, so we can assign the most appropriate vulnerability model (from a limited number of such models) to each asset.

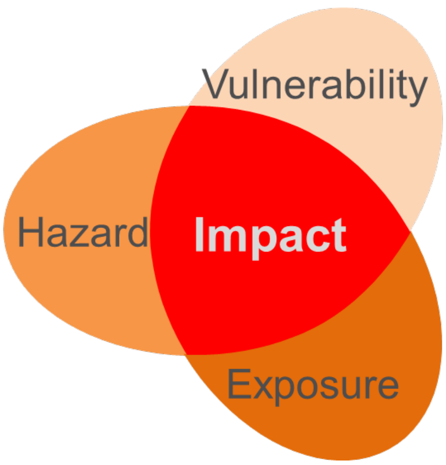


Figure 1: Integration of the three components – hazard, exposure and vulnerability – to arrive at an estimate of impact (after Zscheischler et al. 2018).

The resulting impact information is intended to assist forecasters and emergency managers in formulating warnings or preparing for an event. Two key questions that need to be addressed is what type of impact information is of use to these end users, and what decisions are being made? Is the indicative damage state of residential buildings suitable to guide decisions, or are other metrics of more value? These questions should be addressed in developing a future plan for utilising impact-based forecast products, but are not explored in detail here.

Hazards: how do we represent severe weather?

In choosing forecast weather elements as hazard representation, it is important to understand how these elements are observed, forecast and affect impact. The language we use to describe weather typically deconstructs the atmosphere into discrete components. However, atmospheric variables are complex and vary continuously in space and time. An example of this is in the description of wind which can fluctuate rapidly between extremes. Standard conventions describe this distribution as some mean component and a fluctuating "gust" which characterises the extreme values. But the duration over which this mean value and gust are calculated must be specified. The World Meteorological Organization (WMO) recommends a definition based on a running 3-second mean wind, with the 10-minute mean and 3-second maximum within a 10-minute interval the mean and gust for that interval (World Meteorological Organization 2008). Correspondingly, efforts have been made within model development to mirror these observations as output diagnostics (Sheridan 2018).

Within the Unified Model, which underpins the suite of numerical weather prediction models at the Bureau of Meteorology, a parameterisation of the surface gust, based on the work of Beljaars (1987), the 3-second definition above is used. This is readily converted to a 0.2-second duration gust which is commonly used as the hazard measure for wind vulnerability relations (Harper et al. 2010).

There are similar issues with the description and measurement of rainfall. While the total amount of rain will clearly modulate the effects of flooding and impact soil moisture (which has implications for tree fall and landslides), intense rainfall over short durations can lead to flash flooding and, when combined with strong winds, rain ingress (Blocken and Carmeliet, 2004). As with wind, structures and assets respond differently: a particular drainage system may cope well with a large amount of steady, accumulated rainfall spread over 24 hours, but may struggle to dissipate high intensity rainfall over a period of 15 minutes.

The key question then, is how to broadly characterise the hazards in order to capture the spread of impact over these varying scales. In this regard, the project is somewhat limited by the output of the chosen numerical weather model, BARRA: the Bureau of Meteorology Atmospheric high-resolution Regional Reanalysis for Australia (Su et. al. 2019). There are two key drivers behind the choice of this model. Firstly, atmospheric reanalyses such as BARRA provide a model estimate of the atmosphere constrained by observations to form a spatially continuous record over long periods. Reanalysis output can therefore be used to estimate a suite of weather variables at a particular time and location, not necessarily near an observation station. This is advantageous when considering historical severe weather events as the reanalysis output is generally more accurate than forecasts produced by operational models and provides a good estimate of hazardous weather during the period of interest. Secondly, the BARRA dataset comprises a 12 km horizontal grid spacing suite over the Australian region (BARRA-R) and a number of nested, 1.5 km horizontal grid spacing suites over some of the major Australian cities (BARRA-XX). These suites are akin to the operational ACCESS-R and ACCESS-C forecast models (Bureau of Meteorology 2010; Bureau of Meteorology 2013; Puri et al. 2013), respectively, used by Bureau of Meteorology forecasters and on which future impact forecasting will be based. For the chosen case study in this paper, the 20-22 April 2015 Dungog East Coast Low (ECL; Pepler and Coutts-Smith 2013; Speer et al. 2009), the spatial extent of damage lies within the domain of the BARRA-SY reanalysis dataset incorporating the region around Sydney. Model output referenced henceforth is extracted from this dataset.

In order to represent the hazards that most closely produce the observed impact on residential housing through our workflow, we consider a range of wind and rain metrics which best characterise the inherent variation to each model output weather element of interest. For wind, these are the event maximum surface (10-m) mean windspeed (designated PSMW), 10-m wind gust (PSWG) and a "neighbourhood" wind gust (NSWG) calculated as the maximum within 40 km of a point over the course of the event. Event maxima are calculated from 10-minute reanalysis fields during the 72-hour period from 03 UTC 19 April 2015 to 03 UTC 22 April 2015. The neighbourhood wind gust provides some allowance for model placement errors in the spatial location of strong winds. In addition to these three surface fields, the event maximum "gradient-level" windspeed at 900 hPa (roughly 900 m AMSL) is calculated at each point in order to provide a supplementary characterisation of the wind energy in the lower atmosphere (PGWS). Combined, these four metrics (Figure 2), provide a reasonable characterisation of the maximum near-surface wind strength variability over the course of the event.

Likewise, the rain hazard is represented at a point by the event maximum rainfall accumulated over periods of 10 minutes (PIRR), 1 hour (P1RR) and 6 hours (P6RR), calculated from model data output at rolling 10-minute intervals. The total event rainfall accumulation at a point (PTEA) is also considered. These intervals are chosen in order to represent rain impact from the closest reanalysis field to the instantaneous scale (10 minutes), through medium-duration rain events (1 and 6 hours) up to the full event rainfall. As with wind, a neighbourhood metric is calculated for the event maximum 1-hour rainfall (N1RR). A matrix showing all wind and rain metrics calculated is shown in Table 2.

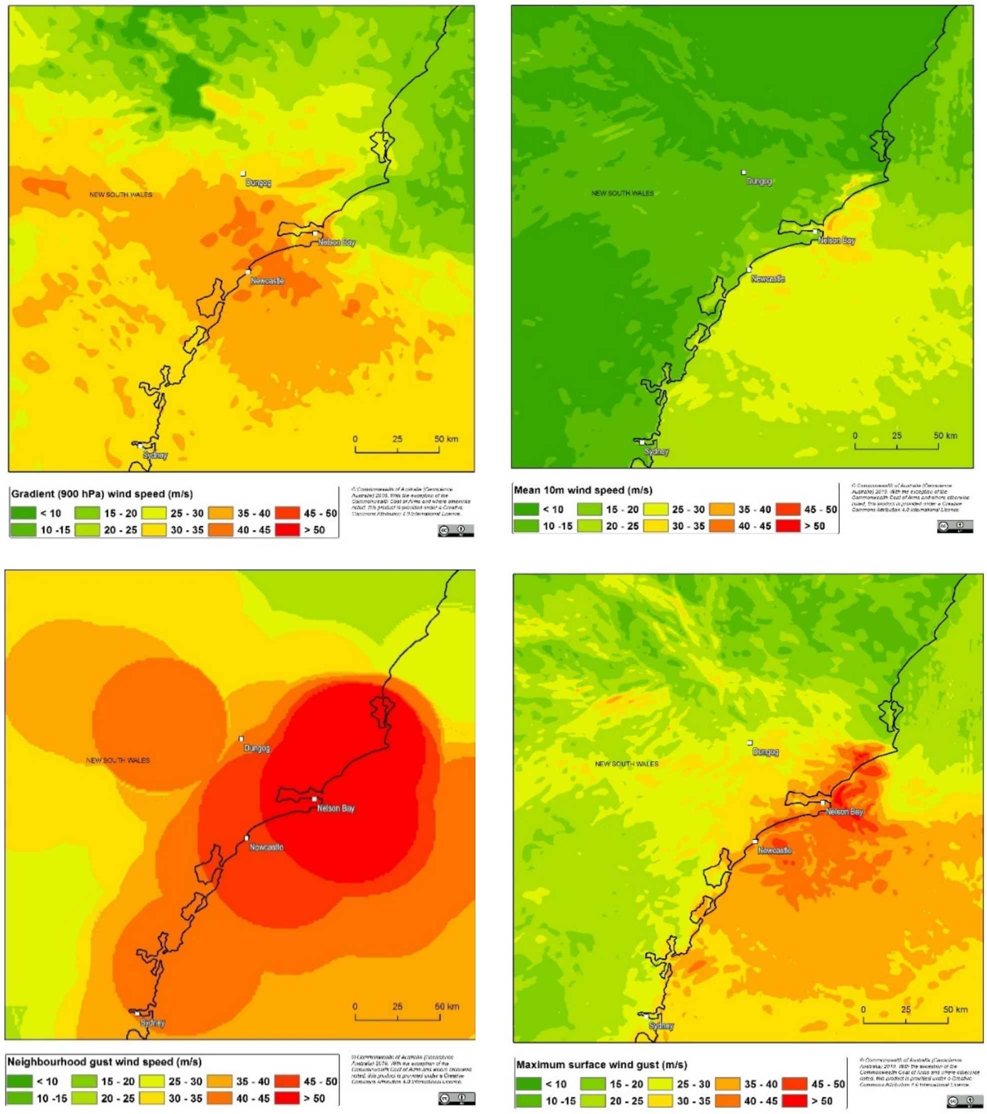


Figure 2: Four characterisations of wind hazard for the 2015 East Coast Low event, as simulated in the BARRA-SY reanalysis (clockwise from top left): point gradient wind speed, point mean wind speed, point gust wind speed and neighbourhood gust wind speed. All values are in units of metres per second.

Table 2: Nine hazard types (5 for rainfall impact, 4 for wind impact) are extracted from the high-resolution reanalysis dataset BARRA-SY. A Quadratic Discriminant Analysis (QDA) will utilise each of the wind and rain fields below to determine which combination of wind and rain hazard proxies possesses the optimum predictive capability for residential housing damage for the 2015 East Coast Low event.

Metric	Description	Use
PSWG	Event maximum point surface wind gust (estimated 3-second duration)	Impact forecast, QDA
PSMW	Event maximum point surface mean wind (estimated 10-minute mean)	Impact forecast, QDA
NSWG	Event maximum neighbourhood surface wind gust	Impact forecast, QDA
PGWS	Event maximum point gradient-level (900 hPa) wind speed	Impact forecast, QDA
PIRR	Event maximum point 10-minute accumulated rainfall	QDA
P1RR	Event maximum point 1-hour accumulated rainfall	QDA
P6RR	Event maximum point 6-hour accumulated rainfall	QDA
N1RR	Event maximum neighbourhood 1-hour accumulated rainfall	QDA
PTEA	Point total event accumulated rainfall	QDA

Exposure: what will be impacted?

The list of elements exposed to an extreme weather event can be extensive, with different stakeholders having different assets of interest. For example, State Emergency Services may prioritise the impacts to buildings, while electricity transmission line operators would prioritise impacts on their transmission lines and substation assets. Businesses and lifeline utilities, including energy, water, communication, and transport will also be impacted. Although they play a significant role and are of interest to emergency services and the owners and operators of those assets, due to the interdependencies and complexity of these networks they are not addressed in this project.

To constrain the scope of this pilot study, residential buildings, comprising semi-detached and separate houses, are initially selected as the asset class for the demonstration of the project workflow. Geoscience Australia's National Exposure Information System (NEXIS; Power et al. 2017) contains nationally-consistent construction type information for these house types.

NEXIS contains publicly available exposure information. Where building-specific information is not publicly available, NEXIS derives attribute information based on transparent statistical methods and rules. There are challenges arising from the available source information used to define the various methods, and the derived NEXIS attributes may not reflect the actual constructional information at a local scale (individual buildings). Statistically derived building attributes are one of the many sources of uncertainty in the quantitative calculation of physical impacts on residential buildings.

Vulnerability: how much damage will be caused?

The last step in the workflow to forecast impact is to estimate how much damage is caused by the forecast hazard to the inventory of exposed assets. To make this estimate, relationships between some measure of damage and hazard magnitude are used. Such relationships can be either vulnerability functions or fragility functions.

Vulnerability functions relate average damage suffered by a population of similar assets to hazard magnitude. Fragility functions relate proportions of a population of similar assets in different damage states to hazard magnitude. Often, both types of functions are presented as S-shaped curves although there is no requirement to do so. This is particularly the case for flood hazard where the required repair increases in a series of steps as water depth increases.

Vulnerability and fragility functions can be developed by three methods: heuristic estimation, analytical computation and, finally, empirical data. In terms of measuring damage, or the vertical axis of a vulnerability

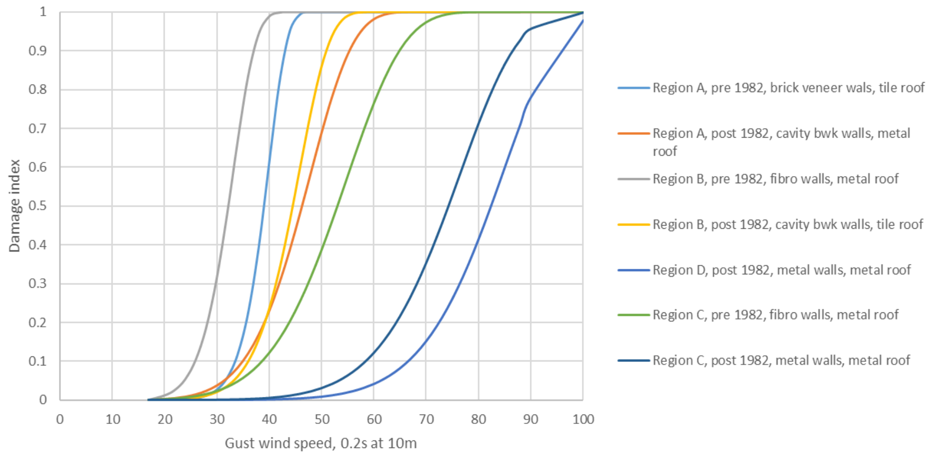


Figure 3: Heuristic vulnerability functions for a range of WA house types exposed to severe wind hazard (Boughton, 2018).

curve, damage index is often used as this is a non-dimensional measure of damage which is defined as repair cost divided by replacement cost. Since it is non-dimensional it can be applied to any building of the relevant type irrespective of building size.

Heuristic vulnerability and fragility functions are developed by people experienced in observing or estimating loss from natural hazard qualitatively estimating a vulnerability function informed by their experience and any available empirical data. Figure 3 shows an example set of heuristic vulnerability curves for a selection of Western Australian house types exposed to severe wind hazard (Boughton 2018).

Analytical vulnerability and fragility functions are developed using an engineering model to estimate damage caused by a hazard of a certain magnitude and then costing the repair of the modelled damage. Figure 4 shows an example of an analytical vulnerability function for a modern house type exposed to riverine (low velocity) inundation. In this instance, the repair work at a range of inundations depths (hazard magnitudes) was documented and the repair work costed. The repair work at each depth was divided by the house's replacement cost to produce a damage index and the points plotted.

Empirical vulnerability and fragility curves are produced by fitting functions to scatters of points of damage against hazard magnitude. The empirical data can be sourced from a variety of sources such as:

- Postal surveys,
- Insurance loss data,
- Post-disaster surveys,
- Rapid damage assessments, or
- Emergency service call-out records.

Figure 5 shows example empirical damage data for a single storey brick-veneer slab-on-grade house exposed to riverine flooding.

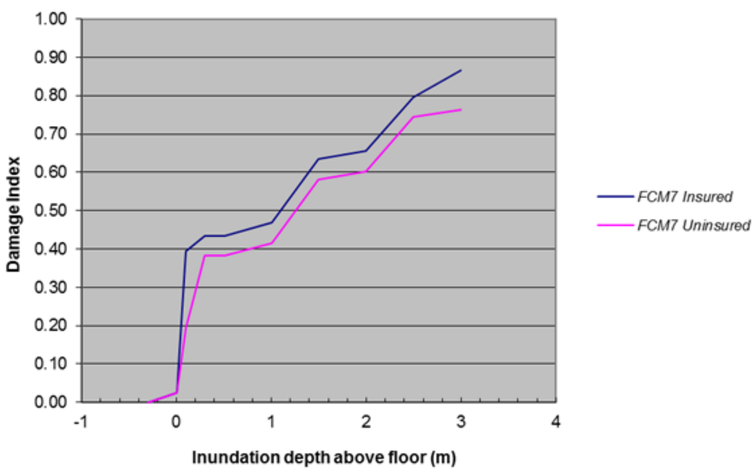
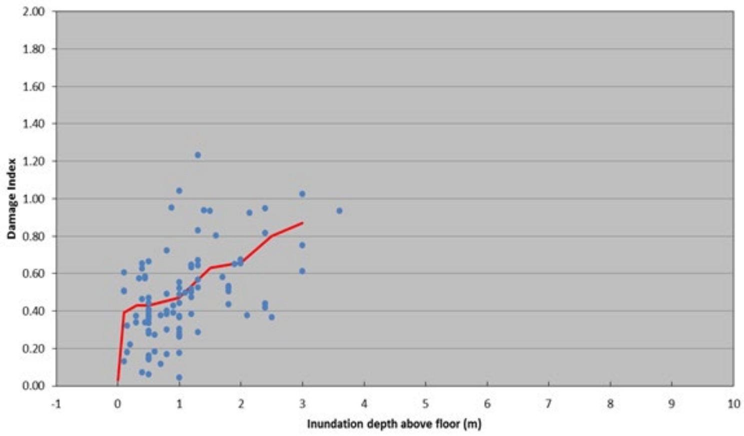
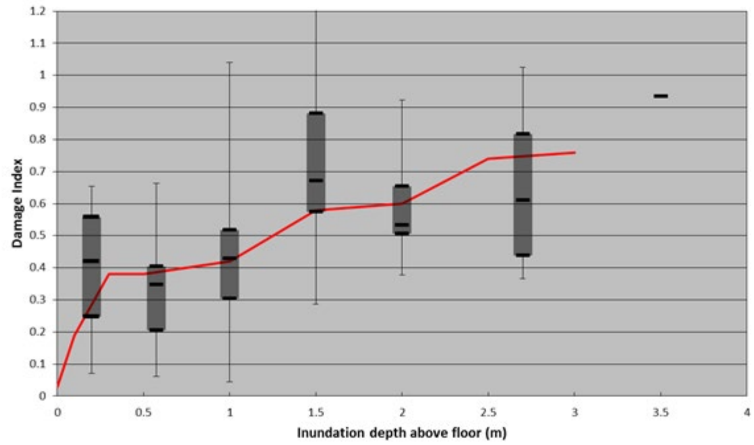


Figure 4: Analytical vulnerability function for a single storey brick veneer, slab-on-grade house exposed to riverine flood hazard (Wehner et al. 2017).



(a)



(b)

Figure 5: Empirical data sourced from a postal survey of damage incurred due to flooding to the same house type as Figure 4. Figure (a) shows the scatter of data and Figure (b) shows a box plot for the same data. In each figure the red line is the analytical vulnerability curve shown in Figure 4 (Wehner *et al.*, 2017).

The choice of using either vulnerability functions or fragility functions to estimate damage depends on the required output from the impact forecasting. For example, impact expressed as estimated numbers of houses in different states may be of more use to an emergency manager than an estimate of the aggregate repair bill across an event footprint, whereas the insurance industry would be more interested in the latter.

The above examples of vulnerability and fragility functions relate damage to a single hazard: wind or flood. The BNHCRC Impact Forecasting project is examining a workflow to forecast impacts to residential houses from storms. Storms (such as ECLs) can cause damage via several mechanisms:

- Direct structural damage caused by wind loads exceeding the strength of building components,
- Wind-borne debris,
- Tree-fall caused by wind actions on trees close to buildings,
- Water ingress resulting from rainfall (wind-driven or not).

Whilst some heuristic vulnerability curves for houses exposed to wind exist, these could be improved using empirical data for calibration. No existing vulnerability or fragility functions use rainfall amount or rainfall rate as a hazard measure. Furthermore, the hazard measure used for the wind vulnerability curves is often the 0.2s gust wind speed at 10m at the building of interest. This is a quantity that is not presently forecast by the numerical weather prediction models used by weather services around the world.

The project attempted to generate project-specific fragility functions for residential houses exposed to storm hazard from empirical data sourced from the NSW Emergency Information Coordination Unit (EICU). Figure 6 shows a plot of damage state plotted against model forecast surface gust wind speed. Each black dot represents a data point. There is no relationship of increasing numbers of houses in higher damage states with increasing hazard magnitude. Figure 7 shows damage state plotted against forecast maximum 6-hour rainfall rate. Again, there is no relationship of increasing numbers of houses in higher damage states with increasing hazard magnitude.

The figures illustrate that there is a complex relationship between multiple perils and resulting damage.
To explore the potential use of a combined damage predictor (wind and rainfall measures) the project investigated combinations of four different measures of wind hazard and five different measures of rainfall hazard.

Figure 8 shows the results of the investigation. The combination of hazard measures that yielded the best results (highest probabilities) is the point 10-minute accumulated rainfall (PIRR) and the point maximum gradient wind speed (PGWS) shown in the top right-hand panel of Figure 8.

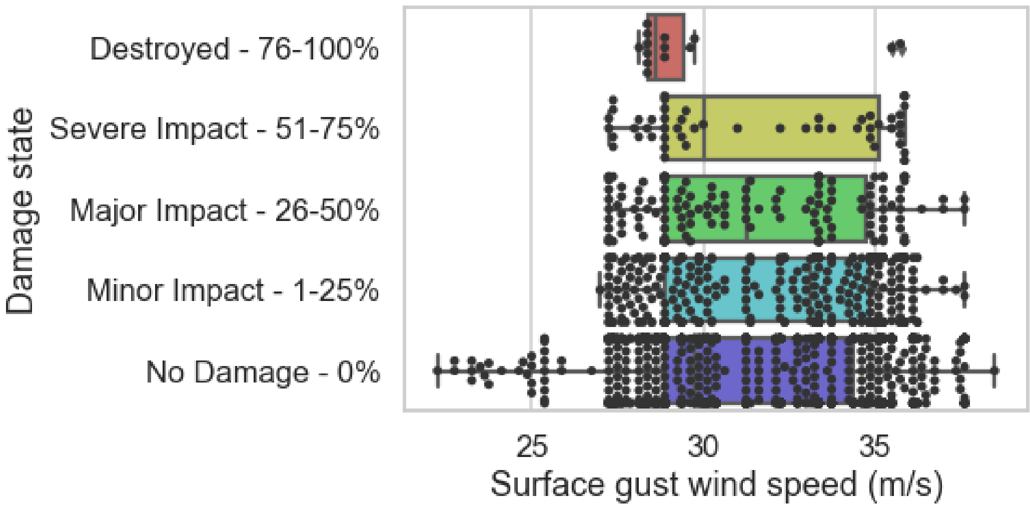


Figure 6: Fragility data from 2072 EICU damage assessments for the 20-22 April 2015 ECL storm plotted against the event maximum surface gust wind speed (PSWG) simulated by the BARRA-SY Reanalysis.

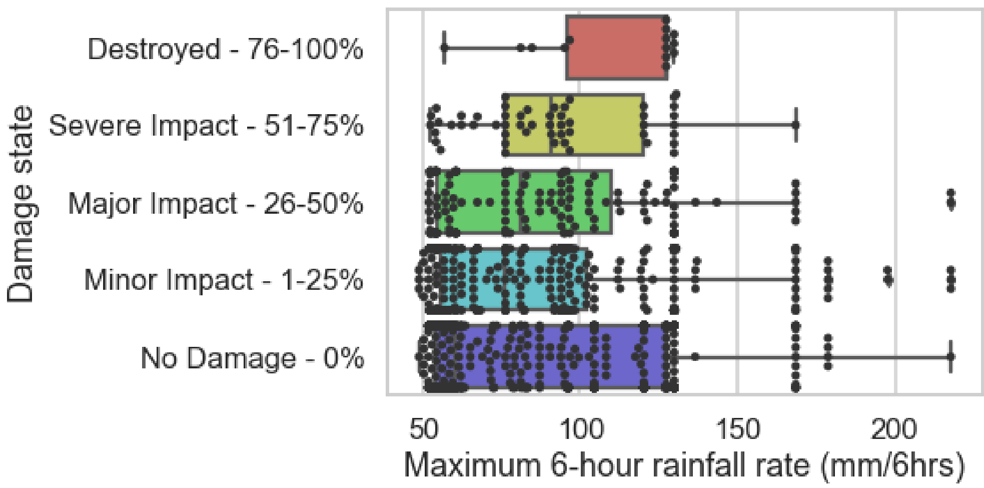


Figure 7: Fragility data from 2072 EICU damage assessments for the 20-22 April 2015 ECL storm plotted against maximum 6-hour rainfall rate (P6RR) modelled by the BARRA-SY Reanalysis.

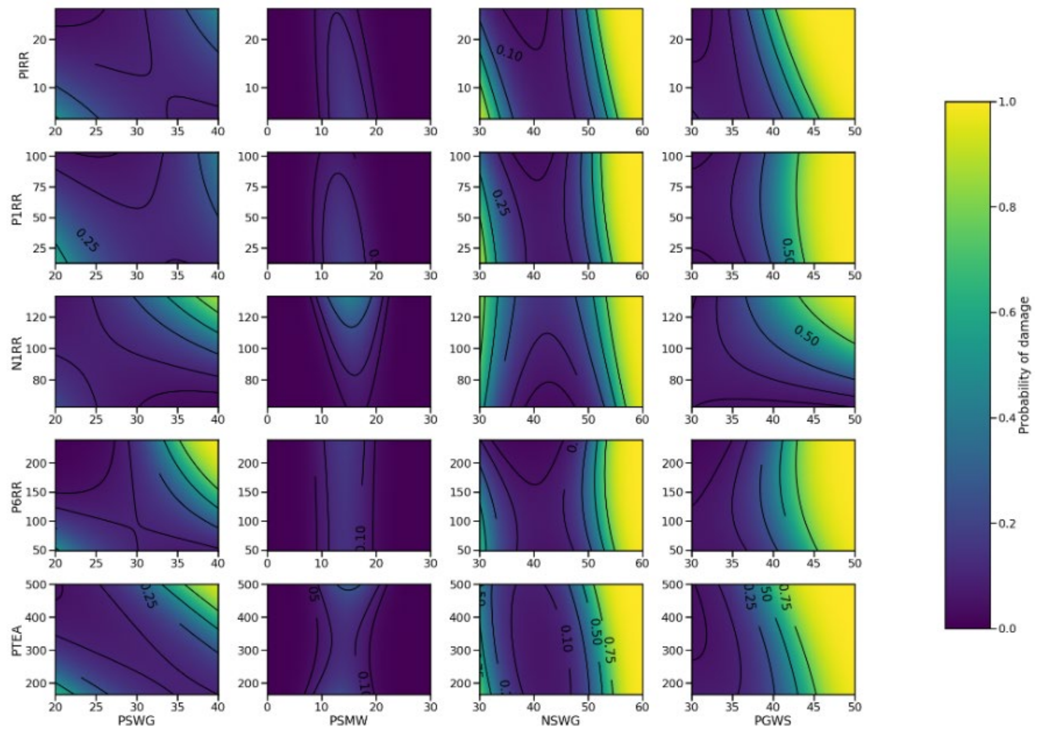


Figure 8: Quadratic discriminant analysis (QDA) of damage arising due to combination of rainfall and wind hazards. The colours represent the probability of a building being damaged in an event with the prescribed wind and rainfall hazard levels. See Table 2 for definitions of hazard parameters. "Damaged" is defined as EICU damage ratings in the categories moderate, extensive or complete. Contour intervals are 0.25.

The project's work has highlighted the benefit that empirical damage data gathered during rapid damage surveys and emergency services call-outs can bring to improving the understanding of the relationship between damage and causative hazards. However, to be of use for quantitative impact prediction some basic attributes have to be collected:

- Location of the observation,
- The nature of the building where the observation is made,
- The causative hazard or hazards, e.g. direct wind damage, water ingress, tree fall, etc., and
- The severity or degree of damage.

The above data needs to be collected in a consistent manner across events and jurisdictions.

Impacts: what does the forecast look like?

Impacts are calculated at individual building level, so that each asset is assigned a specific hazard magnitude and resulting damage index. To reduce the influence of uncertainties, largely associated with the definition of exposure, the results of the impact calculations are aggregated to larger geographical areas by attributing the mean damage index to this area, in line with the statistical definition of exposure attributes (see SA1 area definition below). The mean damage index is then expressed in terms of five damage state categories, as mapped out in Table 3. The aggregation from the individual building scale to the areal scale reduces the likelihood of users attributing a high level of spatial precision to the results (akin to our earlier discussion on the "neighbourhood" hazard definition).

Figure 9 shows the mean damage state for SA1 geographical areas (Australian Bureau of Statistics, 2019), derived using the point maximum surface wind gust (PSWG) hazard variable. The values are determined as a damage ratio for each building point in the region, then averaged across the geographical area. The values are then mapped to indicative damage states (Table 3) for dissemination. In general, the areas of highest damage are close to the coast, where gust wind speeds are highest

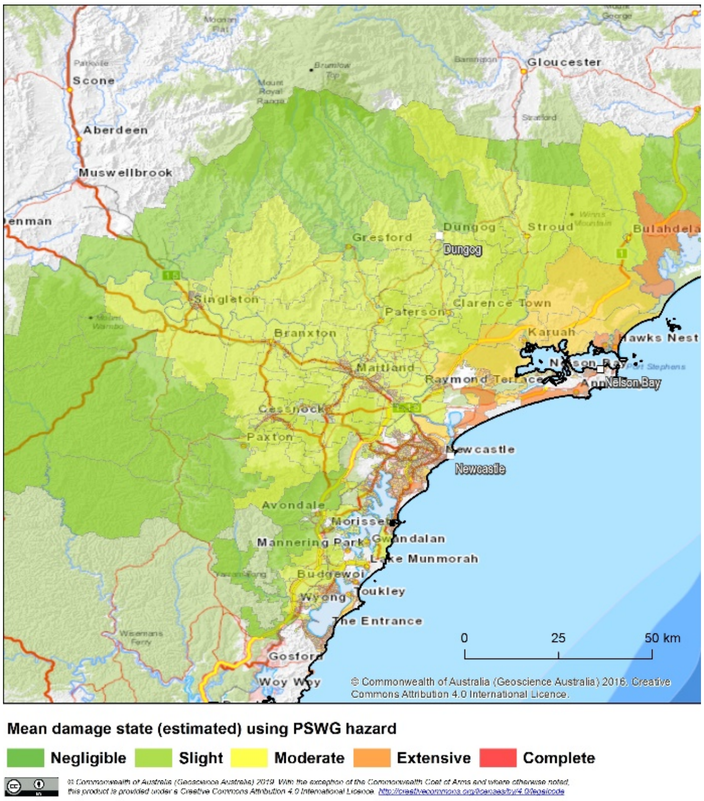


Figure 9: Forecast mean damage state due to point maximum surface wind gust (PSWG) on residential buildings, aggregated to SA1 geographical regions for the 20-22 April 2015 Dungog ECL.

Accuracy: how do we verify this?

It is important to verify forecasts to measure their accuracy and facilitate continual model improvement. Impact forecast verification requires observed impact data, ideally in the same format as the forecast. For example, a temperature forecast for a particular time can be compared with the observed thermometer reading in an unambiguous way. Verifying an impact forecast, however, is complicated as the observations are not routinely conducted and there is no standardised format. For the Dungog ECL, impact observations are available from two sources. Rapid damage assessment (RDA) data compiled by Fire and Rescue NSW for the Emergency Information Coordination Unit (EICU), or by analysing State Emergency Service (SES) callout data. EICU data (**Error! Reference source not found.**) provide a measure of the level of damage inflicted upon a structure within five qualitative categories: Negligible, Slight, Moderate, Extensive, Complete. Unfortunately, this data has limited spatial coverage, and is typically concentrated around urban centres. Conversely, SES callout data provides better spatial coverage, but records emergency response due to a range of issues (tree fall, power lines down etc.) and there is no clear way to disaggregate the damage reports by hazard within the dataset. The callout data also doesn't capture any detail of the damage level. Instead, a “service demand” parameter can be calculated to determine the comparative impact across SA1 areas (for a definition, see Australian Bureau of Statistics, 2019) where relatively high service demand is assumed to correspond to relatively higher impact:

$$Service\ demand = \frac{number\ of\ callouts\ per\ SA1}{number\ of\ houses\ per\ SA1}$$

Because the service demand is spatially complete and applies to SA1 areas, this measure is more readily compared with the output of an impact forecast than the EICU data which are collected in limited areas only. An example is shown for wind gust impact on residential buildings (Figure 11). While not strictly like-for-like, comparison of the spatial impact forecast with the relative service demand can be used to answer a number of questions regarding the skill and utility of the wind impact forecast. For example:

- How well does the prediction discriminate between different observed outcomes?
- Does the forecast rank SA1 area impact in the same order as the service demand is observed?
- Does the location of maximum forecast impact match the location of highest service demand?
- Is the area of total damage well predicted?

The relative importance of these questions is determined by the end-user of the forecast. For example, the ability to predict where the maximum impact will occur can help target the warning message and assist in planning where to deploy responders. Having confidence in the total damage area would help agencies to plan for a response of an appropriate size.

Table 3: Definition of damage states for residential separate houses.

Damage state	Damage index range	Description for residential houses
Negligible	0.0 – 0.02	Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof cover, with no or very limited water penetration.
Slight	0.02 – 0.1	Moderate roof damage that can be covered to prevent additional water ingress. One window, door or garage door broken.
Moderate	0.1 – 0.2	Major roof damage, moderate window breakage. Minor roof sheathing failure. Some water damage to interior.
Extensive	0.2 – 0.5	Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water.
Complete	> 0.5	Complete roof failure and/or failure of wall frame. Loss of more than 50% of roof sheathing.

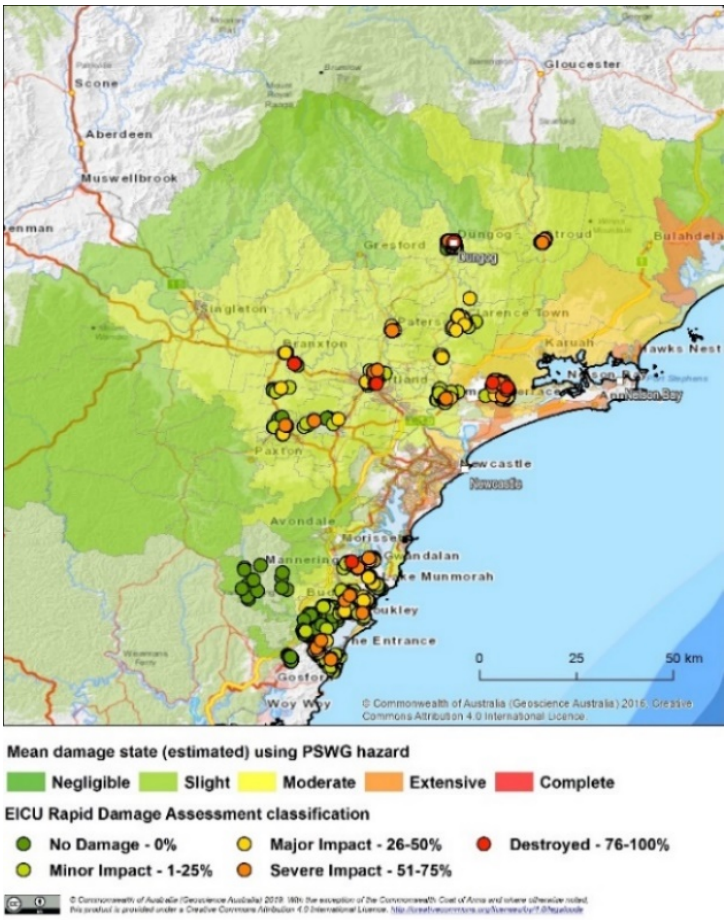


Figure 10: Rapid Damage Assessment (RDA) data from the Emergency Information Coordination Unit (EICU) overlaid on the predicted mean damage state based on BARRA-SY using the point maximum surface wind gust (PSWG) as the wind hazard for the 20-22 April 2015 Dungog ECL.

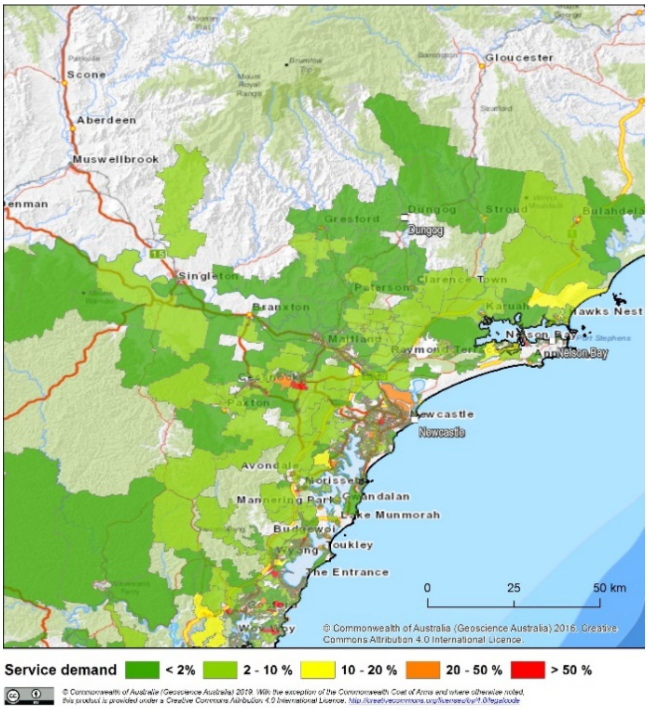


Figure 11: SES service demand averaged across SA1 areas, for the 20-22 April 2015 Dungog ECL.

The damage assessments by the EICU (**Error! Reference source not found.**) and the SES (Figure 11) show damage information that implicitly aggregates over all hazards and intermediary impacts including water ingress, flooding and tree fall. This mismatch between modelled and reported impacts is one of the primary drivers complicating the comparison of the impact modelling results with the ground truth damage data. In **Error! Reference source not found.**, the spatially selective damage survey approach inherent in the EICU data does not allow for a proper evaluation of predicted impacts in areas where no EICU reports are present. The predicted impact highlights an area north of Newcastle as a more severely affected region due to wind damage, and many of the EICU "destroyed" ratings can be found in broadly the same area. The spatial extent of the predicted impact area of negligible or more severe damage broadly captures the area in which the EICU carried out damage assessments, indicating that the model-predicted impact area is reasonably placed. In Figure 11, the predicted impact area highlights the coastal zone as the primary damage area, but the correspondence to the detailed service demand areas is rudimentary.

While the above approach is reasonable given the limitations of the observed data, improvements to the survey process are necessary to provide quantitative guidance on the accuracy of a spatial impact forecast. An ideal dataset combines the spatial coverage of the SES callout data with the damage state description of the EICU survey. Additionally, a report containing linkages between damage and the associated hazards could, for example, help to distinguish between wind and flood damage as well remove incidents related to tree fall and other events not considered within the workflow. In reality, impact is often a complex result of multiple hazards. Improved data and survey procedures will aid forecast verification as well as drive an enhanced understanding of structural response and vulnerability to a range of hazards.

Summary and the way forward

To date we combined wind hazards from a 1.5 km numerical weather prediction model with exposure data from NEXIS and heuristic vulnerability functions to calculate, without human input, spatial physical impacts on residential housing in Australia. The workflow that produced the calculated wind impact was tested on the 20-22 April 2015 East Coast Low event that was associated with three fatalities near Dungog, New South Wales. An attempt to derive case-specific empirical vulnerability functions revealed that the residential building damage (impact) in the Dungog event is not well explained by either the wind or the rain hazard as sourced from the high resolution (BARRA-SY) reanalysis data. A specific combination of the wind and the rain fields, determined by a quadratic discriminant analysis applied to 20 wind and rain hazard predictor combinations, appears to have a stronger linkage to the observed impact, underscoring yet again that physical impacts tend to be multi-hazard in origin.

The focus now, naturally, turns towards the usefulness and quality of the impact outputs that we can produce. Early verification attempts revealed that the required matching of predicted impact data with compatible damage assessment data on the ground is currently not fully achievable. On the modelling side, there is a need to capture how multiple and potentially interacting hazards lead to an integrated impact. On the damage data collection side there is a need to standardise and categorise the degree of damage and to link it to the underlying hazard or hazards that caused the damage. Moreover, an uplift in the availability of exposure data is essential for the future improvement of quantitative spatial physical impact prediction as it removes the large uncertainties associated with the need to infer building attributes from the currently available datasets.

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