Verification of a prototype wind impact forecast using building damage reports

BNHCRC Impact-based forecasting for the coastal zone: East Coast Lows

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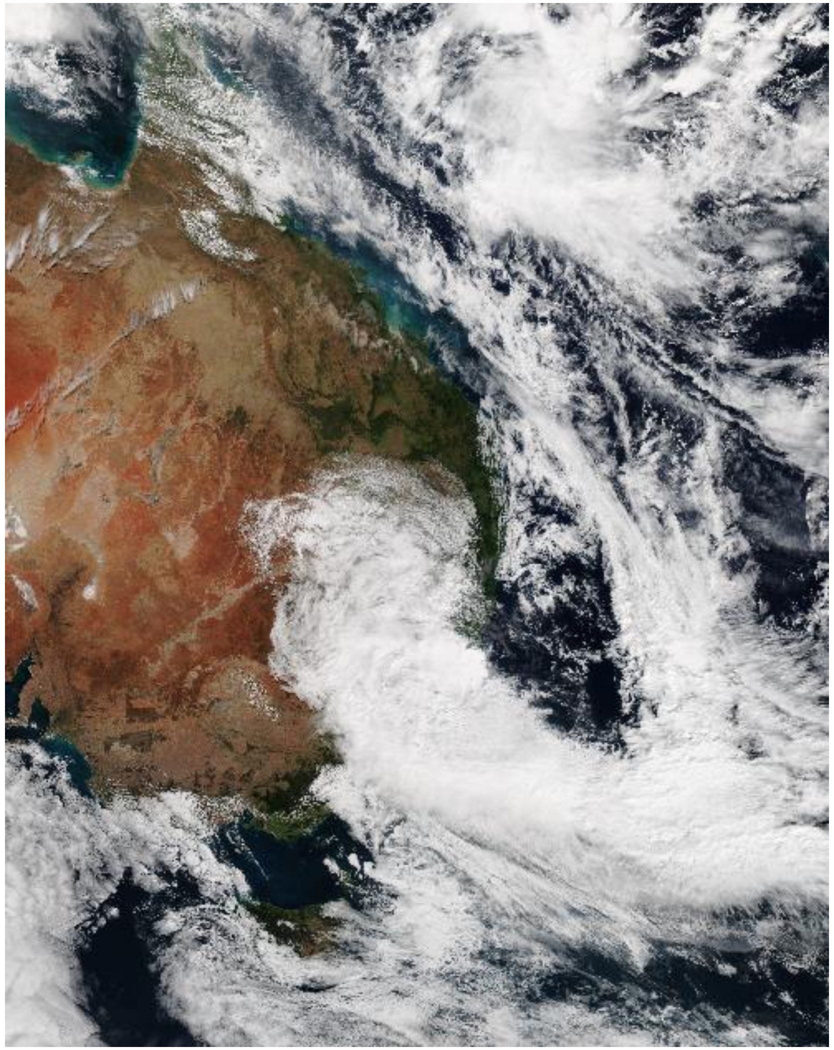

Suomi NPP satellite image of east coast low 21 April 2015

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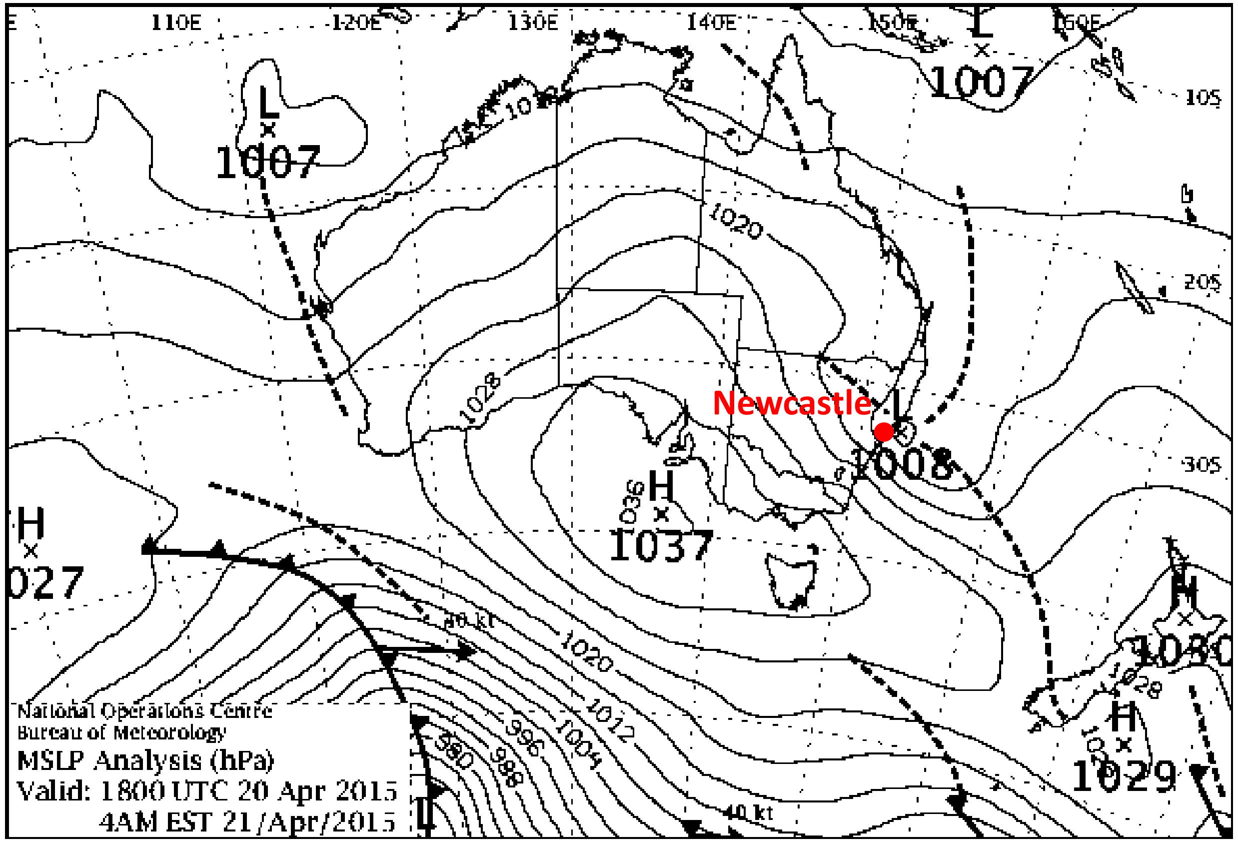
Australian Government Department of Industry, Innovation and Science

Business Cooperative Research Centres Programme

Background:

- Pilot project to develop a basic wind impact forecast for residential buildings.
- Need a case-study to assess performance
  - April 2015 East Coast Low impacted north of Sydney, near Newcastle, NSW.
  - Max. wind gusts of 135km/h along the coastal fringe.
  - Significant flood/rain damage, esp. inland… not ideal for our purposes.
  - But… there was a large amount of damage data collected by emergency services to (hopefully) verify against.



Mean Sea Level Pressure (MSLP) at 4am (local time), 21 April 2015.

The forecast:

Bureau of Meteorology

Wind hazard:
72-hour event maxima wind gust from BARRA-SY reanalysis

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Geoscience Australia

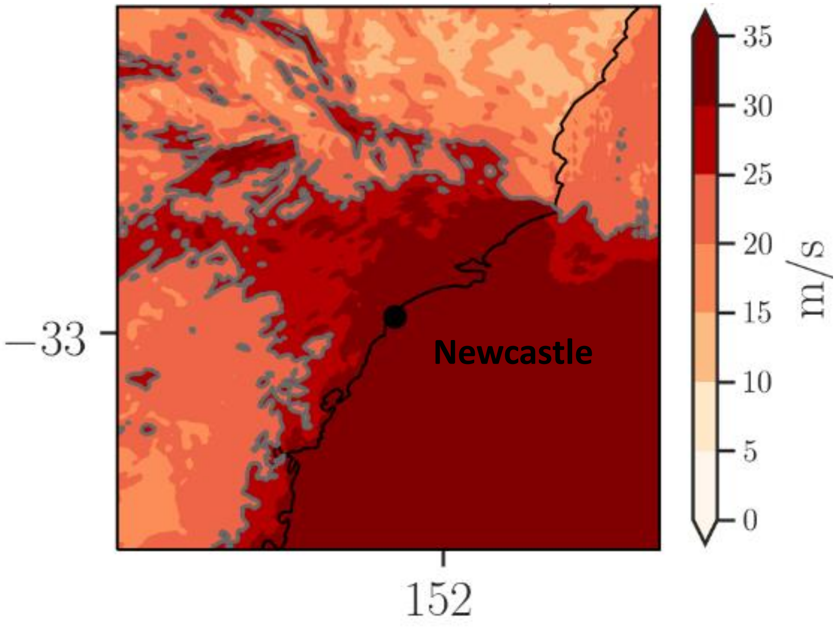
Exposure and Vulnerability data:
Using NEXIS and heuristic curves

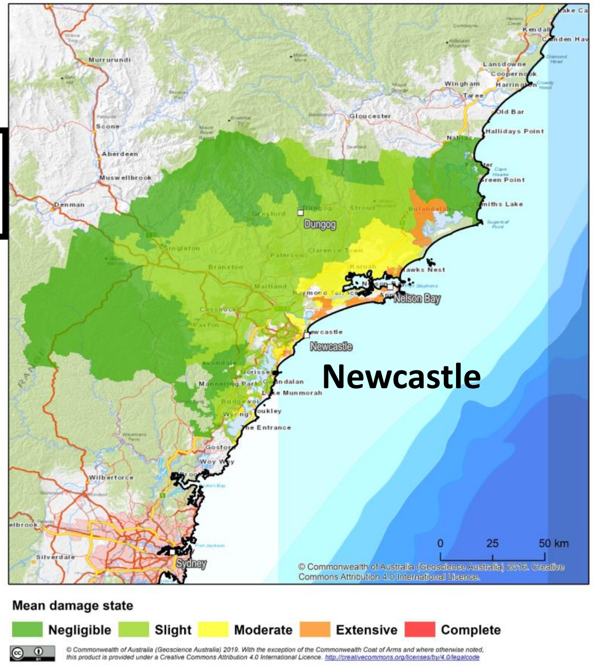
Mean structural loss ratio (SA1 areas)

~200-800 persons

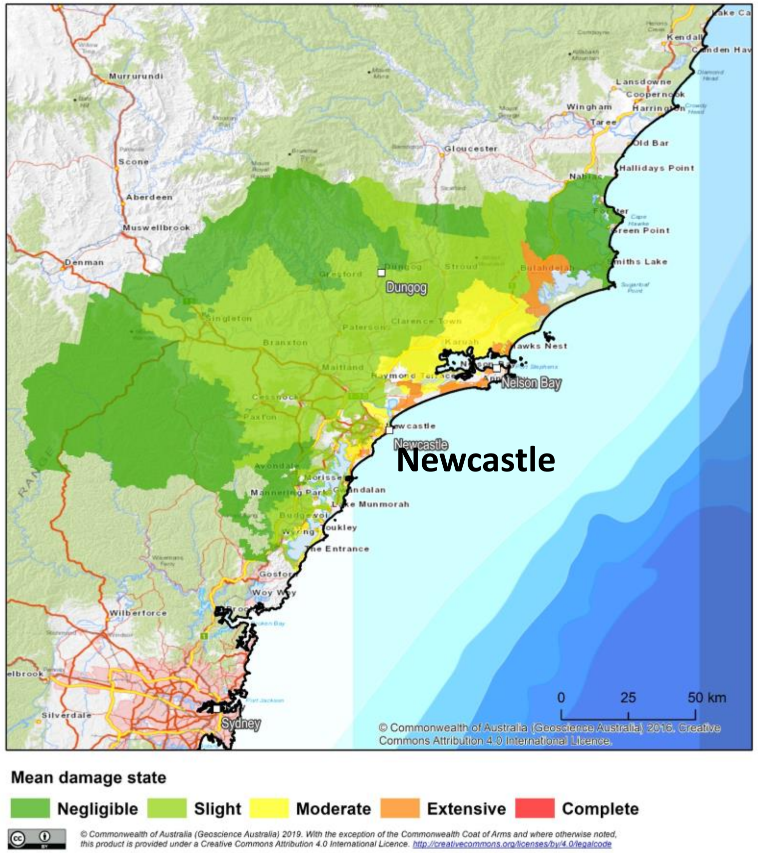
Categorical conversion

Damage state forecast
wind impact on residential structures





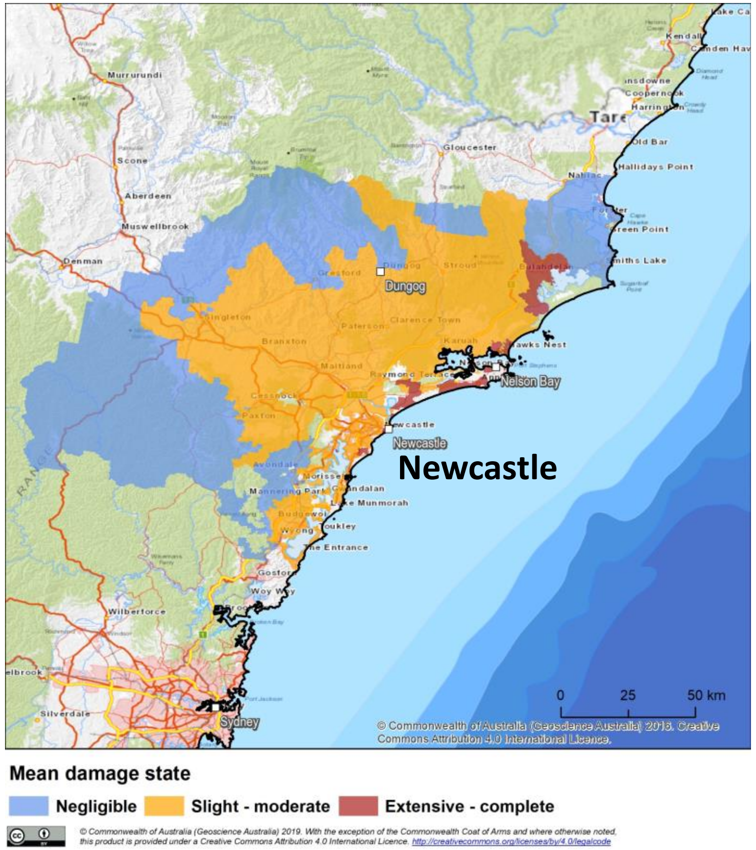
Wind gust impact forecast:



5-category

Combining

categories



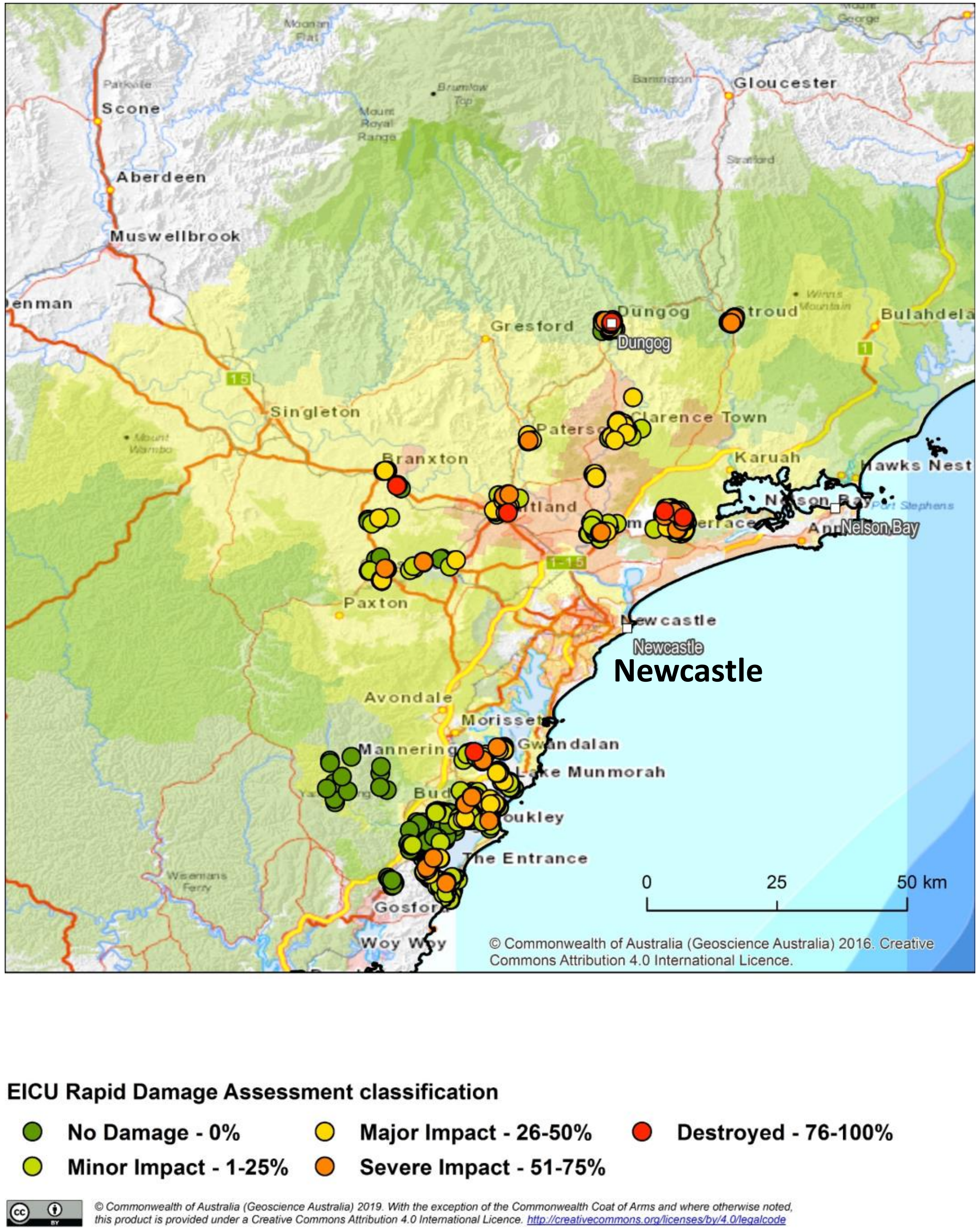
3-category

How can we verify?

- 'Observations' available from two sources:

- State Emergency Service (SES) request for assistance (**RFA**) data:
  - Good spatial coverage
  - Records response to a wide-range of issues…
  - … but can't disaggregate.
  - No damage state information.

- Rapid Damage Assessment (**RDA**) data from the NSW Emergency Information Coordination Unit (EICU)
  - Asset damage state recorded in 5-categories.
  - Additional info such as 'water level', presence of water inundation, building type etc.
  - Limited spatial coverage.



Filtering the RDA data:

- Can filter damage data to remove:
  - Damage not due to wind (i.e. implicitly related to rain/flood)
  - Damage not inflicted on residential buildings.

- Can also use BARRA-SY data to identify regions where rainfall was significant (defined using AEP).

- Not ideal! The process could be made easier if hazard-damage linkages were *explicit*.

Aggregating the RDA data:

- To compare to the forecasts, we need to find some representative damage state for each SA1 area.
- For simplicity, we take the ceiling of the mean damage state of the N_O filtered observations (E_i) recorded within the SA1 area.
- Issue: Unlikely all damaged/undamaged houses in the SA1 are surveyed.

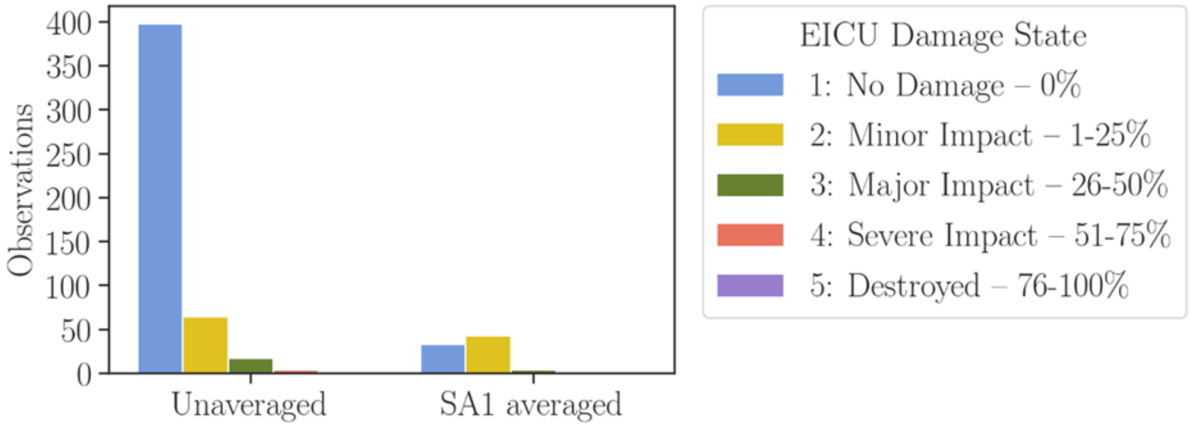
$$E_{SA1} = ceil\left(\frac{1}{N_O}\sum_{i=1}^{N_O} E_i\right)$$

Aggregating the RDA data:

What does the data look like?

Important points:

- Majority of unaggregated filtered obs are of no damage (398/484, 82%), and only one obs in the 'Destroyed' state (0.2%).
- Aggregation (82 obs) skews distribution toward 'Minor impact'.
- **No observations** in the highest damage category in the aggregated data.
- Significant damage (three highest categories), comprises **below 8%** of the aggregated dataset.



Damage state	Observations	Percentage
1: No Damage	33	40%
2: Minor Impact	43	52%
3: Major Impact	4	4.9%
4: Severe Impact	2	2.4%
5: Destroyed	0	0%

SA1 aggregated

Categorical comparison:

- Use contingency tables to compare obs/forecast pairs.
- Allows us to compute a number of scores:
  - Proportion Correct (PC)
  - Gerrity Score (GS)
  - Heidke Skill Score (HSS)

- HSS and GS provide a measure of **how well the forecast performed relative to random chance**.

- GS will reward relatively rare, correct forecasts and will **punish small errors less than large errors**.

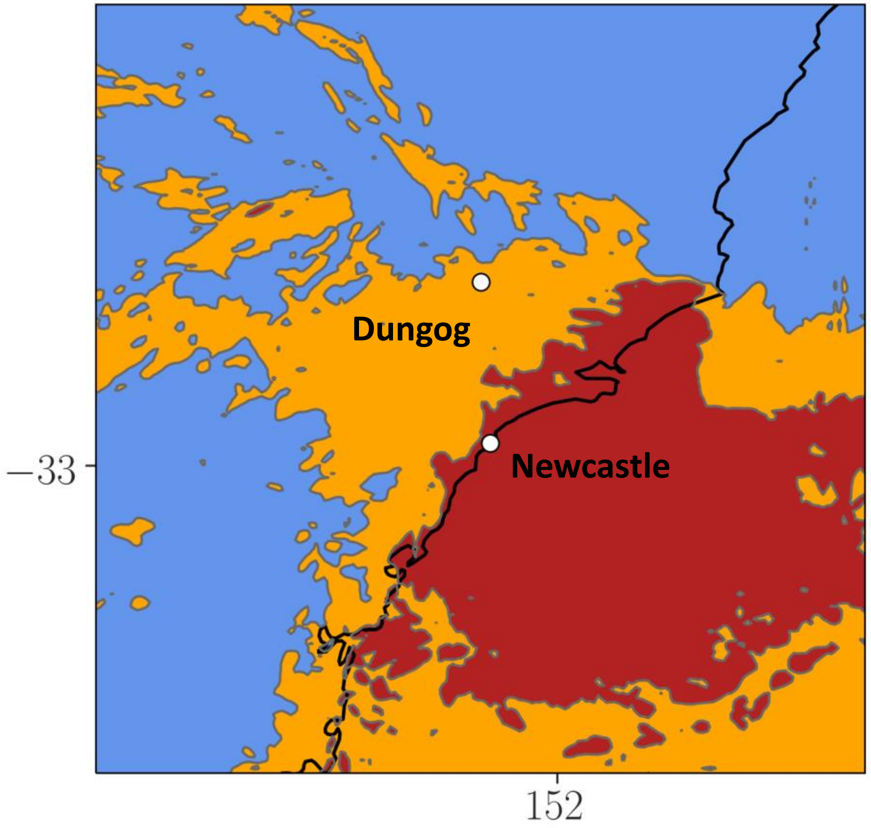
- Can determine 95% confidence intervals using bootstrapping.

		Observed			Total
	i, j	**nil**	**minor**	**major**	
Forecast	**nil**	$n(F_1, O_1)$	$n(F_1, O_2)$	$n(F_1, O_3)$	$N(F_1)$
	minor	$n(F_2, O_1)$	$n(F_2, O_2)$	$n(F_2, O_3)$	$N(F_2)$
	major	$n(F_3, O_1)$	$n(F_3, O_2)$	$n(F_3, O_3)$	$N(F_3)$
Total		$N(O_1)$	$N(O_2)$	$N(O_3)$	N

Can we do better than this?

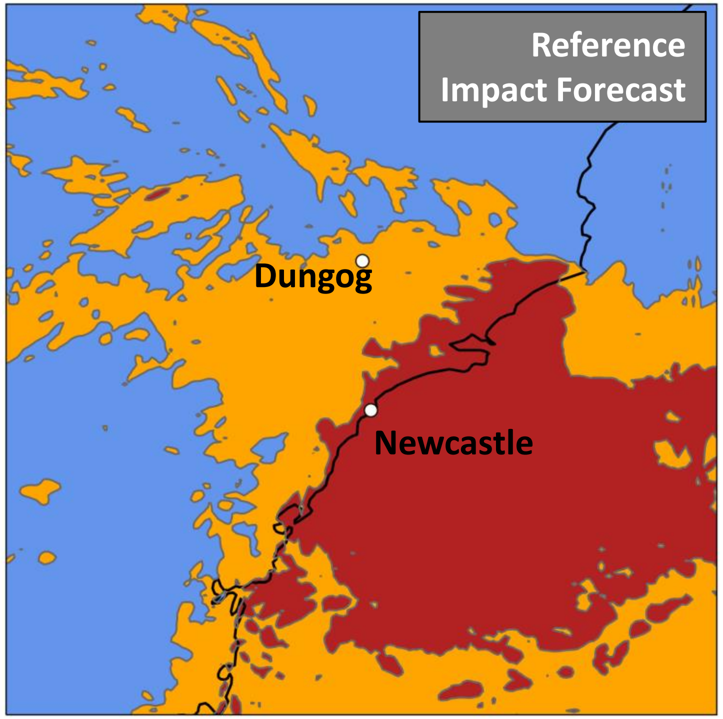
A reference forecast:

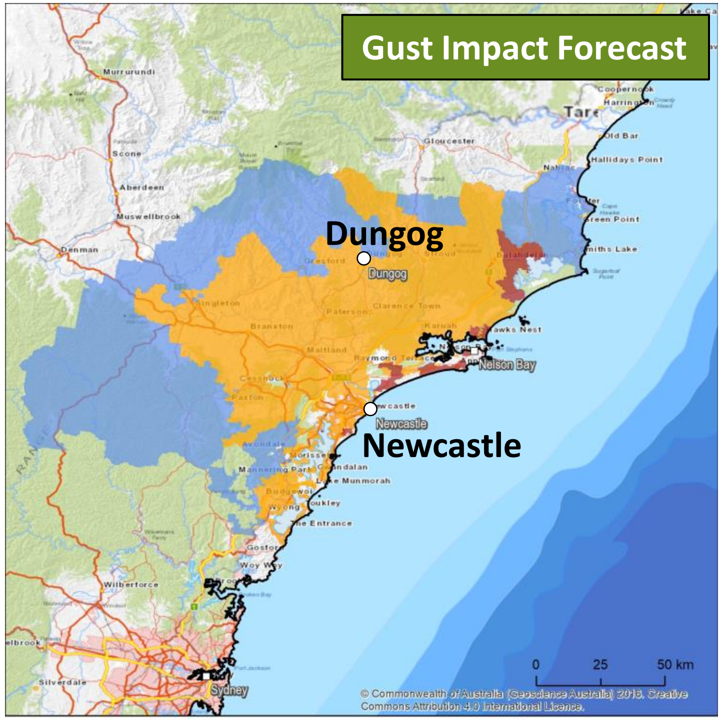
- One option: compare to a simple, 3-category forecast based on wind warning criteria from the Bureau of Meteorology:
    - Damaging wind gusts (> 90 km/h)
    - Destructive wind gusts (> 125 km/h)
- Not entirely unskilled as it includes in-built vulnerability and is derived from the same high-resolution model data.



Max surface wind gust	Damage state
$G < 25$ m/s (90 km/h)	1: Nil damage
$25 \leq G < 34$ m/s (90-125 km/h)	2: Minor damage
$G \geq 34$ m/s (125 km/h)	3: Major damage

Comparing forecasts:





Mean damage state

nil minor major

But… which performed better?

Results:

Observed

Forecast	nil	minor	major	
nil	2	0	0	2
minor	22	32	2	56
major	9	15	0	24
	33	47	2	82

Reference

	Reference
PC	**0.41** (0.3,0.52)
GS	**-0.12** (-0.18,-0.05)
HSS	**0.01** (-0.08,0.12)

Summary

- BoM and GA have developed a pilot project testing a basic wind impact forecast for residential buildings.
- Attempted to verify the forecast using a categorical comparison with area-aggregated building damage reports obtained from emergency services.
- Found that significant filtering of the reports is required to compare damage data to forecast.
    - Including information related to the weather/hazard within the reports, and estimates of the proportion of houses visited, could help dramatically.
- This approach could prove useful in future, but…
- There are lots of assumptions that need to be tested with more data/events.