Ecosystem Services 46 (2020) 101205

Contents lists available at ScienceDirect

Ecosystem Services

journal homepage: www.elsevier.com/locate/ecoser

# The value of coastal wetlands for storm protection in Australia

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ARTICLE INFO

*Keywords:*
Coastal wetlands
Storm protection
Ecosystem services
Service valuation
Bayesian analysis

ABSTRACT

Cyclones cause significant damage, particularly to coastal areas. In the 50 years between 1967 and 2016, 54 cyclones struck Australia with total damages of approximately AUD 3 billion. Wetlands diminish cyclone impacts by absorbing storm surges and slowing winds. We examine the effects of wetlands on cyclone damage by creating a Bayesian regression model for storm damage as a function of wind speed, economic development in the storm swath, and the area of wetlands in the coastal plain in the storm swath using data from all 54 storms. Our results show that wind speed has a strong positive effect on cyclone damage and that wetland area has a strong negative effect. We estimate a total of AUD 29.6 billion of damage was averted during the 54 storms because of the presence of wetlands with a median of AUD 236 million per storm. This equates to an average of AUD 4203 per year per hectare of wetland, consistent with previous studies. Our results suggest that preserving wetlands is a cost-effective way to minimize cyclone damage while providing numerous other valuable ecosystem services. We estimate that maintaining at least 1.5% of coastal area as wetlands maximizes the averted damage.

## 1. Introduction

### 1.1. Cyclone damage and wetlands

Currently, more than 40% of the global population lives within 100 km of the coast (United Nations, 2007). This percentage is even greater in Australia, where over 80% of the population (19 million people) lives within this coastal zone (Cechet et al., 2011). Cyclones, also known as typhoons or hurricanes (depending on the location of the storm), have a significant impact on this portion of the population. This is especially true as Australia is among the top 10 countries globally in terms of the number of natural disasters (Guha-Sapir et al., 2016).

Between1967 and 2013, the total economic losses from all disasters in Australia was estimated to be around $171.5 billion, or approximately $3.7 billion per year (including the costs of deaths and injuries) (Gentle et al., 2001; Handmer et al., 2018). Cyclones made up 21–28% of those losses (Ladds et al., 2017). Other estimates show that between 2007 and 2016, total economic costs from natural disasters might be as high as $18.2 billion per year, or 1.2% of gross domestic product (GDP) (Deloitte Access Economics, 2017).

This type of impact will continue to increase as coastal population and built infrastructure continue to grow within the coastal zone. Model projections of climate change impacts also show an increase in cyclone intensity over the coming decades (Webster et al., 2005; Knutson et al., 2010). Estimates show that by 2050, natural disaster economic costs could reach $39 billion per year, and this does not include the impact of climate change (Deloitte Access Economics, 2017).

However, some of this impact can be reduced through natural barriers, such as coral reefs, wetlands, seagrasses, mangroves, and marshes (Gedan et al., 2011). These ecosystems absorb some of the energy of the storm, acting as 'horizontal levees' or 'bioshields' for storm protection (Barbier et al., 2008; Costanza et al., 2008; Koch et al., 2009; Liu et al., 2019). This is done both directly and indirectly. Above- and below-water plants or reef structures reduce wave velocity and turbulence as well as soil erosion by stabilizing the soil substrate (Gedan et al., 2011). Previous studies have shown that wetlands can mitigate up to USD 52.88 billion of economic costs from cyclones (Ouyang et al., 2018).

Unlike vertical, human-made levees, storm protection is only one of the critical services that these ecosystems provide to local and global populations (Costanza et al., 1997, 2014). Coral reefs, wetlands,

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https://doi.org/10.1016/j.ecoser.2020.101205
Received 16 April 2020; Received in revised form 26 September 2020; Accepted 7 October 2020

seagrasses, mangroves, and marshes also provide other ecosystem services, which include recreation, soil formation, habitats and safe breeding areas, gas regulation, waste treatment, and nutrient cycling, among many others. The value of these services was estimated to be USD 9.9 trillion for coral reefs, USD 6.8 trillion for seagrass/algae beds, USD 5.2 trillion for estuaries, and USD 26.4 trillion for wetlands (de Groot et al., 2012; Costanza et al., 2014; Kubiszewski et al., 2017).

There is also evidence that these ecosystems, especially mangroves, can protect populations from tsunamis. After the 2004 Indian Ocean tsunami, it was found that communities located behind mangroves had significantly less damage than those that were completely exposed (Danielsen et al., 2005; Kathiresan and Rajendran, 2005; Vermaat and Thampanya, 2006; Olwig et al., 2007). Although much research is still being done around the storm protection properties of various ecosystems, there is a growing body of literature showing the significant value of storm damage reduction by natural systems (Gedan et al., 2011).

### 1.2. Modeling approach

Assessing the relationship between wetlands and storm damage is very challenging with many potential sources of error. Cyclones are not frequent, they vary widely in their characteristics, total damages are difficult to estimate, and damages are correlated with the amount of built infrastructure within the swath of the storm at the time of its occurrence, a variable that is difficult to estimate in the current time, and even more challenging when needing to account for changes over decades. Here, we used a Bayesian analysis to assess the role of wetlands in the prevention of cyclone damage. A Bayesian modeling approach is theoretically founded on Bayes' theorem and is well-suited to incorporating the kinds of uncertainty found in an analysis of this type. The goal of a Bayesian analysis is to estimate the joint probability distribution for model parameters given the available data and to be able to use the resulting probability model to predict likely distributions for other unobserved variables such as future storm damages.

Bayes' theorem, given in Eq. (1), describes the relationship between the probabilities of two interdependent events, A and B. If we let A be the parameterized model we are estimating and B be the observed data, then we have a description of the relationship between the probability density for a set of parameters and the probability of the data which is assumed to be an observation drawn from a random variable.

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)} \tag{1}$$

Since it is generally not feasible to calculate P(B)—the probability of observing the data over all possible model parameterizations—in practice Bayesian modeling uses the proportional form given in Eq. (2) in conjunction with an approximating algorithm such as a Markov Chain Monte Carlo algorithm. In Eq. (2), P(A|B) is termed the posterior distribution for the model given the data. It is proportional to P(B|A), the likelihood function for the data given the model, multiplied by P(A), the prior probability distribution for the model.

$$P(A|B) \propto P(B|A) \cdot P(A) \tag{2}$$

The role of priors is to effectively allow the analysis to incorporate previous data and analyses, allowing science to build knowledge sequentially. But this also means that the results of an analysis are influenced by previous findings. Inference from a Bayesian analysis is not only based on the data available in the current analyses but is also able to draw on the knowledge about a system that is the result of previous research. To help understand the role of priors in the results, sensitivity analyses are generally conducted (Hobbs and Hooten, 2015).

Bayesian analyses have been used in similar contexts in many other studies. Chu and Zhao (2007) used a Bayesian regression to predict cyclone activity over the Northern Central Pacific. Poelhekke et al. (2016) used Bayesian networks to estimate storm damage over time to coastal areas. Similarly, Jagger and Elsner (2006) used Bayesian methods to make use of old and unreliable data in climatology models of cyclones. For comparable reasons, we feel justified in using the more complex methods of Bayesian analysis to handle the intricacies of modeling cyclone effects, especially when we must account for multiple sources of error including missing data on historical trends.

### 1.3. Hypothesis and purpose of the study

The goal of this study is to determine whether or not wetlands have an effect on cyclone damage, the extent of that effect, and the nature of the relationship between wetlands and damage prevention. A better understanding of this relationship will be useful both for conservationists and governments seeking to prevent cyclone damage. Demonstrating the value of wetlands, particularly the marginal value in locations with sparse wetlands, gives a powerful argument for protecting current wetland areas. Ideally, we might also be able to identify a critical density of wetlands below which predicted cyclone damages increase significantly with further wetland loss.

## 2. Methods

### 2.1. Data collection

There are a number of sources for the data used in this analysis (Appendix A). We selected government and NGO datasets that are freely available online. These data have been vetted by both government and scientific agencies. The preprocessing to get the data into a format for this analysis used ArcGIS, Python scripts, and Excel. All spatial information about GDP, built-up area, wetlands, swamp and mangrove landcovers, and cyclones was converted to tabular format for use in the statistical analysis.

The independent variables needed to develop this model are as follows: the wind speed of the hurricane at landfall, the areal extent of wetlands within the hurricane swath, and proxy measures of GDP density within the swath of the storm (modeled using nighttime lights, time-series data of the state-level GDP data, and time-series data from the global human settlement layer). The dependent variable, the damage caused by the hurricanes, was sourced from the Insurance Council of Australia (ICA), which collects disaster data produced by governments and agencies and synthesizes that data into comprehensible datasets.

The workflow proceeded along these lines. First, we projected all data to a common projected coordinate system for Australia (EPSG 3112). The spatial datasets included: boundaries of the states and territories of Australia, paths of the hurricanes from 1967 to 2016, nighttime satellite image data derived from the DMSP OLS archive, built-up area within the swath from the Global Human Settlement layer (for the years 1975, 1990, 2000 and 2014), and several land cover datasets that were used to develop a unified wetlands dataset. Wind speed for each hurricane was determined by intersecting the tracks of the hurricanes with the coastline data. If wind speed data did not exist at the location of the hurricane track, a modeled speed was used based on a regression of barometric pressure ($R^2 = 0.92$). GDP in the swath at the time of the hurricane was estimated as follows: first, we developed a prior estimate of temporal trajectory of economic growth within the swath of the hurricane using changes to the built-up area as measured by the four Global Human Settlement layers. The sum of lights from the DMSP OLD nighttime image data product (2013) was used as a proxy measure of GDP in 2013. GDP at the time of the storm was treated as a latent variable that was compared to the 2013 GDP based on the estimated growth trajectory. Wetlands were derived by combining several datasets using mangroves, wetlands, and swamps (Appendix A) to produce a binary dataset (1 – wetland or mangrove or swamp, 0 – not a wetland). This binary layer was intersected with hurricane swaths to calculate area of wetlands in the swath.

### 2.2. Model development

Using Bayesian estimation techniques and following Costanza et al. (2008), we modeled the total damage caused by 48 storms in 2015 dollars (*dam*) as a random variable where $\ln\left(\frac{dam}{GDP}\right)$ is normally distributed with standard deviation σ and mean μ given by:

$$\mu = \alpha + \beta_1 \cdot \ln(wind) + \beta_2 \cdot \ln(wetlands) \quad (3)$$

*GDP* is a random variable measuring gross domestic product in the swath of the storm at the time of the storm (measured in 2015 AUD). *Wind* measures the maximum 10-minute average wind speed of the storm in knots, and *wet* measures the total wetlands comprised of mangroves, swamps, and other terrestrial wetlands in the swath of the storm in $m^2$. These were generally treated as observations without error with the following exception. Observations for *wind* were not available for the storms prior to 1974. For the earliest nine storms, *wind* was treated as a random variable with a prior distribution given by a linear regression of wind speed on barometric pressure from the other 39 storms ($R^2 = 0.916$).

To account for economic growth in estimating GDP within the swath at the time of the storm, we used our estimate of GDP within the swath in 2015 (described earlier) combined with an estimate of the *rate* of GDP growth in the swath since the time of the storm. Thus, $GDP = GDP_{2015} \cdot rate^{-t}$ where *t* is the number of years between the time of the storm and 2015. Posterior distributions for the annual GDP growth rate in each cyclone swath (*rate*) were estimated as part of the Bayesian model. Normal prior distributions for *rate* were developed using estimates for built infrastructure in each swath for the years 1975, 1990, 2000, and 2014 (Corbane et al., 2018) under the assumption that changes in GDP and built infrastructure are strongly correlated. Standard deviations for the priors ranged from 0.007 to 0.013 based on how close the occurrence of the storm was to when data was available on built infrastructure.

Other variables were assessed for potential effects on storm damage. These included storm duration, presence and extent of coral reefs, and differentiation by wetland type. None of these factors improved model goodness of fit using multiple regression adjusted $R^2$ as a measure.

T-distributions with 32 degrees of freedom were used as prior distributions for $\beta_1$ and $\beta_2$ based on the results from Costanza et al. (2008) using the estimated means and standard errors derived in that work. Standard errors were doubled to account for the difference in context between the US and Australia. Non-informative priors were used for $\alpha$and $\sigma$.

The full posterior distribution is given by:

$$[\alpha, \beta_1, \beta_2, \sigma, rate, wind_{pre1973} | dam, GDP_{2015}, wind, wet] \propto \left[ ln\left(\frac{dam}{GDP_{2015} \cdot rate^{-t}}\right) | \alpha, \beta_1, \beta_2, wind, wet, t, rate, \sigma \right] \cdot [rate] \cdot [wind_{pre1973}] \cdot [\sigma] \cdot [\beta_1] \cdot [\beta_2] \cdot [\sigma] \quad (4)$$

Following Hobbs and Hooten (2015), a full model diagram is given in Fig. 1.

The posterior distribution was estimated using a Markov Chain Monte Carlo algorithm with Gibbs sampling (Gelfand and Smith, 1990; King et al., 2009). 8 chains were run and the Gelman-Rubin R statistic (Gelman and Rubin, 1992) was used to determine whether the model had achieved convergence for each parameter. 2,200,000 iterations were conducted with the first 200,000 discarded for burn-in. The remaining 2,000,000 were thinned by a factor of 500 yielding final chains of 4000 values drawn from the joint posterior distribution. Tuning parameters for proposals were adjusted so that acceptance rates were generally between 20 and 40%. Model specification was tested by comparing the predicted median for simulated damages using the Markov chain parameters to the observed median, and no significant departure was detected ($p = 0.36$).

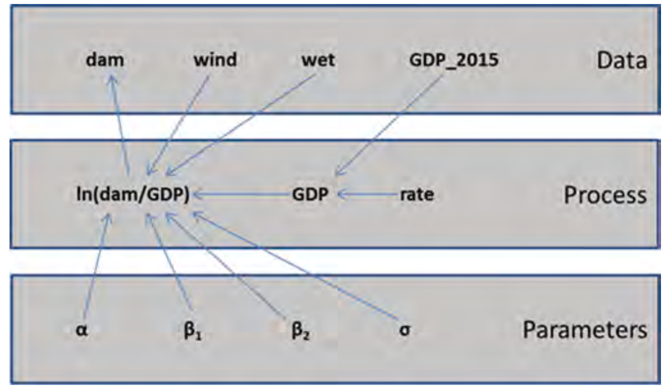


**Fig. 1.** Bayesian network for cyclone damage prediction.

Four cyclones were removed from the analysis as outliers. Cyclone Elsie (1967) had the lowest number of total wetlands in the storm swath (9.2 ha), 1–4 orders of magnitude below other storms. Since the model has a log–log structure, predicted damage goes to infinity as wetlands decrease to zero. This is clearly not realistic, causing the model to break down at low levels of wetlands. This is apparent in the extremely high damage predicted for Elsie by model parameters.

Tasha, Yasi, and Tracy were removed because of their relatively high levels of damage attributable to other factors besides wind and the initial storm surge. Tasha had one of the highest levels of recorded damage but a maximum wind speed of only 40 knots and a relatively low level of GDP. Tracy and Yasi had levels of recorded damage that were 1 – 3 orders of magnitude higher than all other storms despite low to very low levels of GDP. While the model does assume lognormally distributed variability in damage, in all of these cases actual damages were still well outside the distribution of the other 45 storms suggesting the processes behind the damage were significantly different from those we are seeking to model.

The resultant joint posterior distribution was then used to generate a probability distribution for the predicted damage for each observed storm. To do this, each set of values for the parameters and state variables in the Markov chain was used to produce a probability distribution for $\ln\left(\frac{dam}{GDP}\right)$. A random draw from this distribution was then used to produce a predicted damage for that set of values. The resulting chain of values for each storm is then representative of the probability distribution for damages from that storm.

The percentage of damage averted as a result of wetlands was calculated using Eq. (5a). Because the model breaks down at low levels of wetlands, Eq. (5a) must separately calculate the damage above and below a specific cutoff value ($c = 4000$ ha), and thus can be divided into two components: Eq. (5b) and Eq. (5c). Eq. (5b) is the additional damage that would have occurred if there had only been 4000 hectares of wetlands in the hurricane swath. Eq. (5c) produces an estimate for the difference in damage between 4000 ha wetlands and no wetlands. It simply calculates the marginal value for the 4000th hectare of wetland and multiplies that by 4000. This produces an underestimate, but is a

**Table 1**
Median and 95% confidence intervals for parameter estimates from the joint posterior distribution. The Bayesian p-value reports the percent of values that overlapped 0.

| | α | β1 | β 2 | σ |
|---|---|---|---|---|
| Median | 8.948 | 3.287 | −0.651 | 2.927 |
| 2.5% | −3.921 | 1.195 | −1.102 | 1.799 |
| 97.5% | 22.740 | 5.381 | −0.203 | 5.967 |
| p-value | 0.083 | <0.001 | <0.005 | NA |

good method for generating an approximate value.

$$\Delta TD = \frac{(MV_c \cdot \mathrm{c} + \Delta TD_{>c})}{TD} \tag{5a}$$

$$\Delta TD_{>4000} = e^{\alpha} \cdot wind^{\beta_1} \cdot (c^{\beta_2} - wet^{\beta_2}) \cdot \left(GDP_{2015} \cdot rate^{-(2015-year)}\right) \tag{5b}$$

$$MV_{4000} \cdot 4000 = e^{\alpha} \cdot wind^{\beta_1} \cdot (3999^{\beta_2} - 4000^{\beta_2}) \cdot \left(GDP_{2015} \cdot rate^{-(2015-year)}\right) \cdot 4000 \tag{5c}$$

### 2.3. Model validation

Several steps were taken to validate the model. Three sets of simulated data were produced by random draws from a joint distribution with known parameter values, and the model was then used to estimate the joint posterior distribution for parameter values given the simulated data. In all three cases, the model performed well in estimating the parameters (estimates well within an equidistant 95% confidence interval). The Gelman-Rubin statistic to test for chain convergence was less than 1.003 for all parameters in the logistic model. Scatterplots were produced for each random variable in the posterior distribution and showed little or no autocorrelation. The model was run multiple times, and marginal distributions were stable between runs. We assessed the impact of the priors for $\beta_1$ and $\beta_2$ by doubling and tripling the standard errors, and these did not have a significant impact upon the estimation

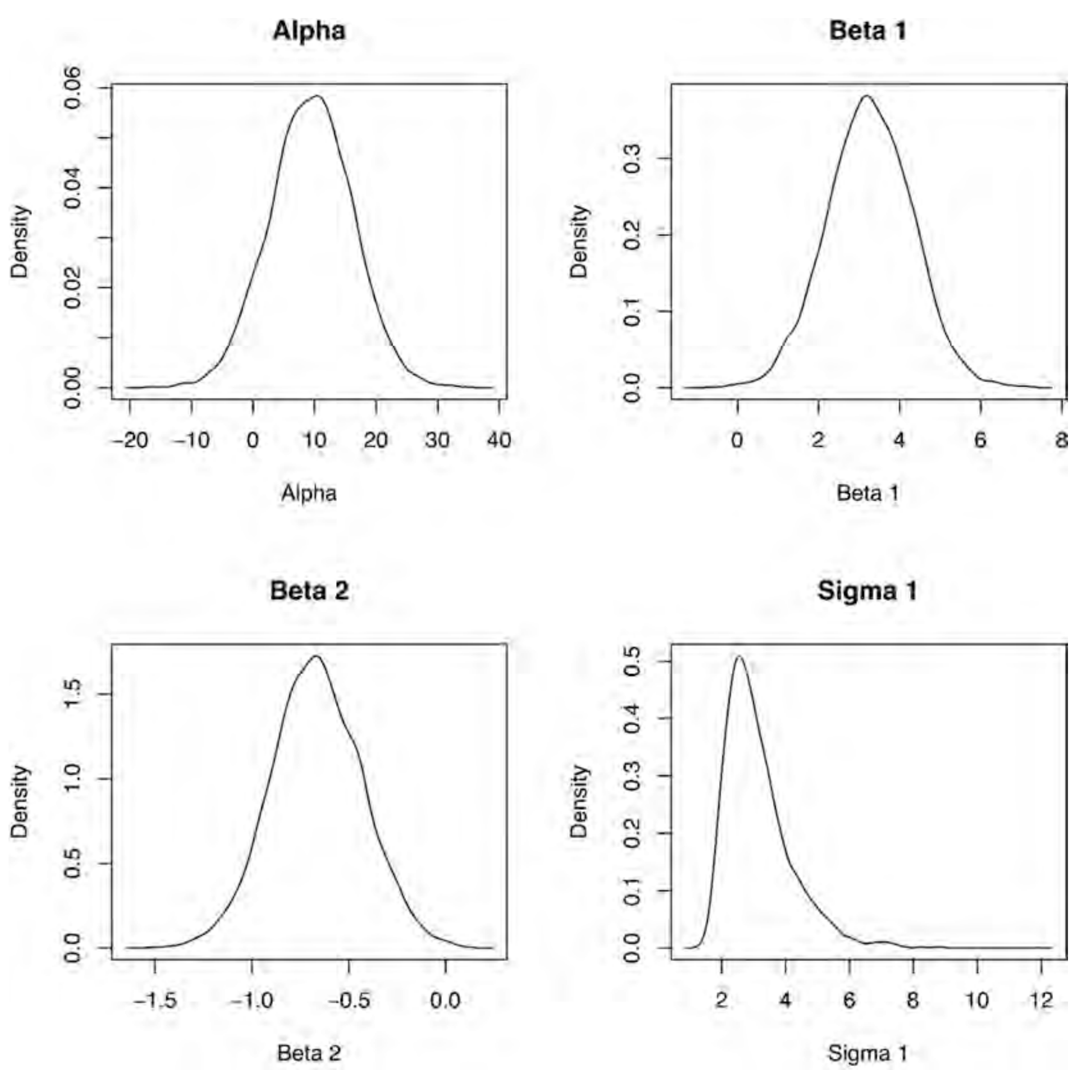


**Fig. 2.** Density plots for the posterior marginal distributions for model parameters.

**Table 2**
Characteristics and estimated values for each storm. Note that all dollar values are in 2015 AUD. CI stands for the confidence interval of the estimate for marginal value (MV) and both confidence intervals and marginal values are in 2015 AUD.

| Cyclone | Year | Wind (knts) | Wetlands (ha) | 2015 GDP (Mil.) | Rate | Reported Damage (Mil.) | Estimated MV/ha | 25% CI | 75% CI | Averted damage (Mil.) |
|---|---|---|---|---|---|---|---|---|---|---|
| Dinah | 1967 | 92 | 1324 | $171 | 1.039 | $435 | $8295 | $3258 | $20,612 | $2 |
| Barbara | 1967 | 50 | 2086 | $15,549 | 1.030 | $26 | $59,357 | $21,663 | $151766 | $42 |
| Ada | 1970 | 75 | 18,731 | $3235 | 1.021 | $139 | $2272 | $1240 | $4,05 | $244 |
| Sheila | 1971 | 112 | 35,746 | $1860 | 1.056 | $33 | $375 | $214 | $666 | $129 |
| Fiona | 1971 | 77 | 165,207 | $17,147 | 1.015 | $33 | $427 | $265 | $666 | $2067 |
| Sally | 1971 | 87 | 4432 | $2726 | 1.115 | $33 | $727 | $346 | $1521 | $4 |
| Althea | 1971 | 85 | 79,837 | $11,702 | 1.020 | $275 | $1198 | $747 | $1909 | $1685 |
| Daisy | 1972 | 78 | 96,119 | $24,056 | 1.036 | $21 | $656 | $416 | $1063 | $1288 |
| Zoe | 1974 | 75 | 68,434 | $16,333 | 1.049 | $18 | $441 | $266 | $718 | $477 |
| Joan | 1975 | 115 | 31,619 | $2143 | 1.143 | $155 | $35 | $19 | $65 | $10 |
| Beth | 1976 | 70 | 3796 | $2778 | 1.008 | $20 | $39,691 | $19,138 | $84967 | $144 |
| Otto | 1977 | 45 | 81,773 | $14,658 | 1.012 | $53 | $268 | $148 | $485 | $399 |
| Leo | 1977 | 90 | 41,592 | $2987 | 1.124 | $18 | $30 | $19 | $46 | $14 |
| Peter | 1978 | 80 | 43,014 | $3855 | 1.041 | $24 | $469 | $295 | $733 | $228 |
| Hazel | 1979 | 105 | 4983 | $5629 | 1.047 | $121 | $51310 | $24,861 | $107,678 | $368 |
| Amy | 1980 | 115 | 20,483 | $973 | 1.062 | $12 | $714 | $387 | $1,287 | $89 |
| Dean | 1980 | 110 | 15,283 | $615 | 1.114 | $11 | $124 | $67 | $223 | $9 |
| Winifred | 1986 | 85 | 20,017 | $3081 | 1.014 | $107 | $4964 | $2855 | $8138 | $597 |
| Aivu | 1989 | 110 | 52,658 | $1885 | 1.029 | $57 | $976 | $609 | $1544 | $676 |
| Joy | 1990 | 90 | 44,552 | $2747 | 1.008 | $64 | $1706 | $1099 | $2626 | $884 |
| Bobby | 1995 | 105 | 359,290 | $4769 | 1.116 | $19 | $20 | $13 | $29 | $377 |
| Justin | 1997 | 80 | 113,527 | $7995 | 1.004 | $283 | $797 | $559 | $1132 | $2115 |
| Sid | 1997 | 45 | 403,932 | $1140 | 1.069 | $118 | < $1 | < $1 | $1 | $15 |
| Vance | 1999 | 120 | 567,190 | $1192 | 1.021 | $58 | $23 | $15 | $37 | $939 |
| Steve | 2000 | 60 | 1,116,422 | $21865 | 1.048 | $18 | $10 | $6 | $16 | $1241 |
| Chris | 2002 | 110 | 16,706 | $605 | 1.207 | $4 | $391 | $221 | $692 | $34 |
| Monica | 2006 | 135 | 1,230,095 | $4613 | 1.050 | $7 | $33 | $19 | $56 | $4771 |
| Laurence | 2009 | 110 | 514,579 | $2,219 | 1.026 | $3 | $46 | $30 | $69 | $1580 |
| Ului | 2010 | 105 | 16,450 | $273 | 1.027 | $14 | $1564 | $894 | $2,17 | $135 |
| Heidi | 2012 | 80 | 19,494 | $4408 | 1.025 | $3 | $8379 | $4965 | $13,877 | $973 |
| Jasmine | 2012 | 60 | 47,702 | $163 | 1.025 | $4 | $27 | $17 | $43 | $16 |
| Lua | 2012 | 85 | 15,819 | $149 | 1.025 | $8 | $492 | $285 | $830 | $39 |
| Peta | 2013 | 45 | 124,783 | $378 | 1.025 | $5 | $5 | $3 | $9 | $15 |
| Rusty | 2013 | 90 | 19,627 | $1185 | 1.025 | $8 | $3385 | $2008 | $5569 | $398 |
| Tim | 2013 | 50 | 27,916 | $3045 | 1.025 | $3 | $712 | $388 | $1262 | $155 |
| Alessia | 2013 | 40 | 442,092 | $1626 | 1.025 | $5 | $2 | $1 | $3 | $46 |
| Dylan | 2014 | 60 | 18,590 | $3805 | 1.024 | $12 | $3263 | $1837 | $5650 | $339 |
| Fletcher | 2014 | 35 | 499,197 | $2389 | 1.025 | $4 | $1 | < $1 | $3 | $45 |
| Ita | 2014 | 120 | 185,224 | $20 | 1.024 | $23 | $3 | $2 | $5 | $21 |
| Lam | 2015 | 100 | 227,889 | $6244 | 1.027 | $45 | $432 | $302 | $610 | $3749 |
| Marcia | 2015 | 110 | 102,374 | $3463 | 1.027 | $544 | $1258 | $826 | $1877 | $2748 |
| Olwyn | 2015 | 75 | 23,537 | $1011 | 1.028 | $67 | $1228 | $753 | $1992 | $200 |
| Quang | 2015 | 100 | 102,379 | $573 | 1.028 | $5 | $152 | $103 | $221 | $333 |
| Stan | 2016 | 55 | 16,696 | $82 | 1.028 | $9 | $67 | $36 | $120 | $6 |

of significance and parameter medians were only marginally moved.

## 3. Results

Median values and 95% confidence intervals are reported for each of the main model parameters in Table 1. Posterior distributions are shown in Fig. 2. Bayesian p-values were calculated for $\alpha$, $\beta_1$, and $\beta_2$. $\beta_1$ was strongly positive (median = 3.274, p = 0.002) showing the clear impact of wind upon damage. $\beta_2$ was strongly negative (median = −0.651, p = 0.003) providing evidence that wetlands reduce damages from cyclones.

Median estimates for the rates of GDP growth in the storm swaths, median damages from the posterior distribution, reported damages, marginal values for wetlands (with 25% and 75% confidence intervals), and an estimate of the total damage averted for each storm are shown in Table 2. GDP growth varied between 0.4% and 20.7% while damage ranged from AUD 3 million to AUD 544 million. The marginal value of a hectare of wetlands varied between less than a dollar and approximately AUD 60,000 by storm, with a median value of AUD 469. A total of AUD 29.6 billion of damage was averted, with the damage averted from individual storms ranging from AUD 2 million to AUD 4.7 billion with a median of AUD 236 million. Additionally, the marginal distributions for storm damage for six representative storms are shown in Fig. 3. For each distribution, the reported damage lies well within the distribution.

Model fit can be seen in Fig. 4, which plots the log-ratio of damage to GDP for the predicted and reported damages. Predicted damages are taken from the median for each posterior distribution. While model fit is not as good as that reported in Costanza et al. (2008) ($R^2 = 0.31$ vs. $R^2 = 0.60$), it was still highly significant ($p < 0.001$ based on OLS regression).

Finally, Fig. 5 shows the joint distribution for $\beta_1$ and $\beta_2$. As is apparent, the two parameters are not correlated with an estimated correlation coefficient of less than 0.001.

## 4. Discussion

### 4.1. Comparison with previous research

Several previous studies have done analyses similar to this one. In particular, papers by Costanza et al. (2008) and Liu et al. (2019) both performed log–log regression analyses of hurricane damage in the United States and China respectively that incorporated coastal wetlands as a factor. Costanza et al. (2008) looked at 34 hurricanes that struck the east coast of the United States between 1980 and 2005. Their estimates

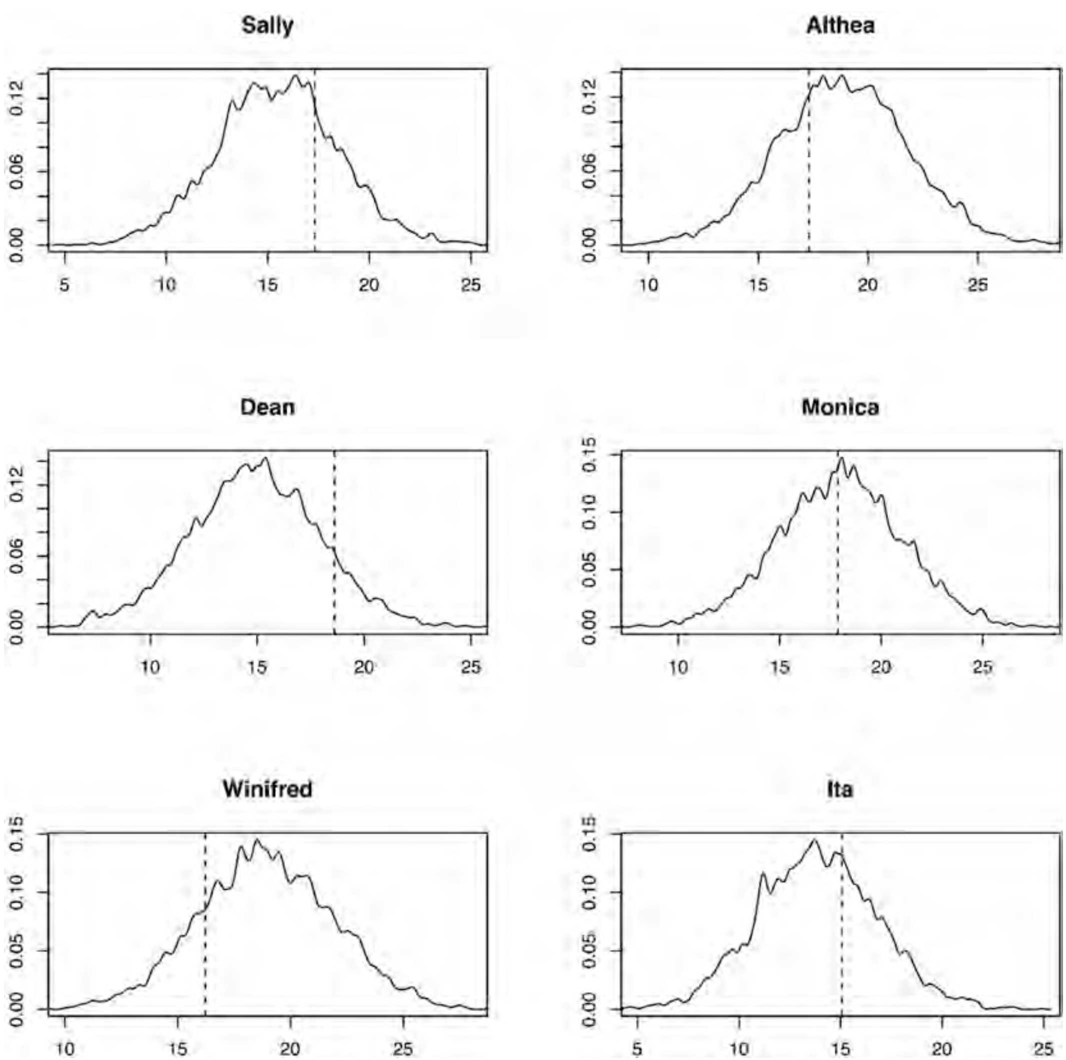


**Fig. 3.** Probability density plots for the natural log of damages (ln(Predicted Damage in 2015 AUD)) for specific storms. The dashed vertical line shows the observed damage for the storm. Storms with observed damages to the left of the mode had less than expected damages while those to the right had higher than expected damages.

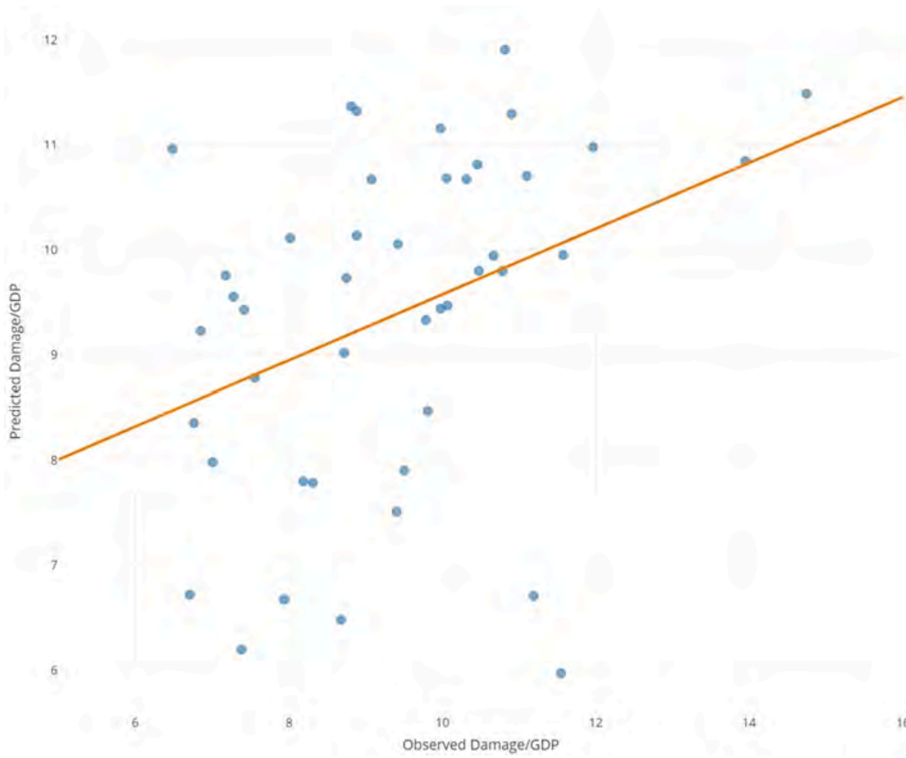


**Fig. 4.** Scatter plot of the natural log of the ratio of reported damages to estimated GDP at the time of the storm versus the natural log of the ratio of estimated damages to the estimated GDP at the time of the storm. The $R^2$ value is representative of the fit of the estimated model to the current data.

for the marginal value of a hectare of wetlands were far higher (a median value of AUD 8220 compared to AUD 469). This is attributable to the difference in development density modeled by GDP. The median GDP within a hurricane swath in the United States in that study was approximately 46 times that of the median hurricane swath in our analysis. When adjusted for GDP, the median marginal value of the Australian wetlands across storms included in this study was approximately 2.6 times as much per hectare, though this estimate depends on the assumed exchange rate. This highlights the relatively higher value of Australian wetlands and the spatial relationship between wetlands and development for storm damage prevention.

Liu et al. (2019) analyzed 127 storms that hit China between 1989 and 2016. They included storm duration and seawalls in their analysis in addition to wetland and windspeed. (While we considered storm duration, we did not find it to be a significant factor.) Liu et al. (2019) found a median marginal value per hectare of wetland to be AUD 26,267, far higher than both the United States study and our study. They do not report their estimates for economic density in the storm swaths, but a cursory analysis of GDP by province in China suggests far higher levels of GDP density.

### 4.2. Advantages of a Bayesian analysis

One of the main differences between this research and that of Costanza et al. (2008) is the use of a Bayesian analysis of the data. This gives several advantages over a standard parametric analysis, including more flexibility and higher confidence in the results. A Bayesian analysis estimates the joint probability distribution of all parameters involved. In addition to estimating the distributions of the parameters for the model, we can incorporate latent variables and missing data into the joint probability integral.

Our Bayesian estimation explicitly includes sources of error in the analysis instead of ignoring them. Two different predictor variables were used in this analysis which in a parametric analysis would have been treated as observations without error. The GDP within the swath of each storm was, in the previous paper, estimated using light levels from night imagery adjusted to the time of the storm using a national-level GDP deflator. This analysis incorporates the error introduced by the second part of this estimation by estimating the posterior probability distribution for each GDP deflator by year and swath. By estimating the GDP growth rate for each swath, error introduced by using nighttime light imagery as a correlate for GDP is also incorporated into the modeling process. Secondly, several cyclones had missing wind speed data which were estimated as latent variables using a regression model based on barometric pressure as a prior.

As a consequence of incorporating error within a sound theoretical framework, we also produce probability distributions for the observed data. Within a Bayesian framework, all variables are treated as random variables. Fig. 3 shows the probability distributions for the total damages for each storm, and there we can see where the observed damages lie within the distribution of possible outcomes based on the data. Thus, for example, Cyclone Dean had higher than expected damages while Cyclone Winifred had lower than expected damages.

A Bayesian analysis also allows for the incorporation of previous data in the form of priors. In this analysis, priors were generated from Costanza et al. (2008). This effectively means that our results are based on the data utilized in that analysis as well as data collected for this paper, something akin to a meta-analysis but with a more rigorous theoretical

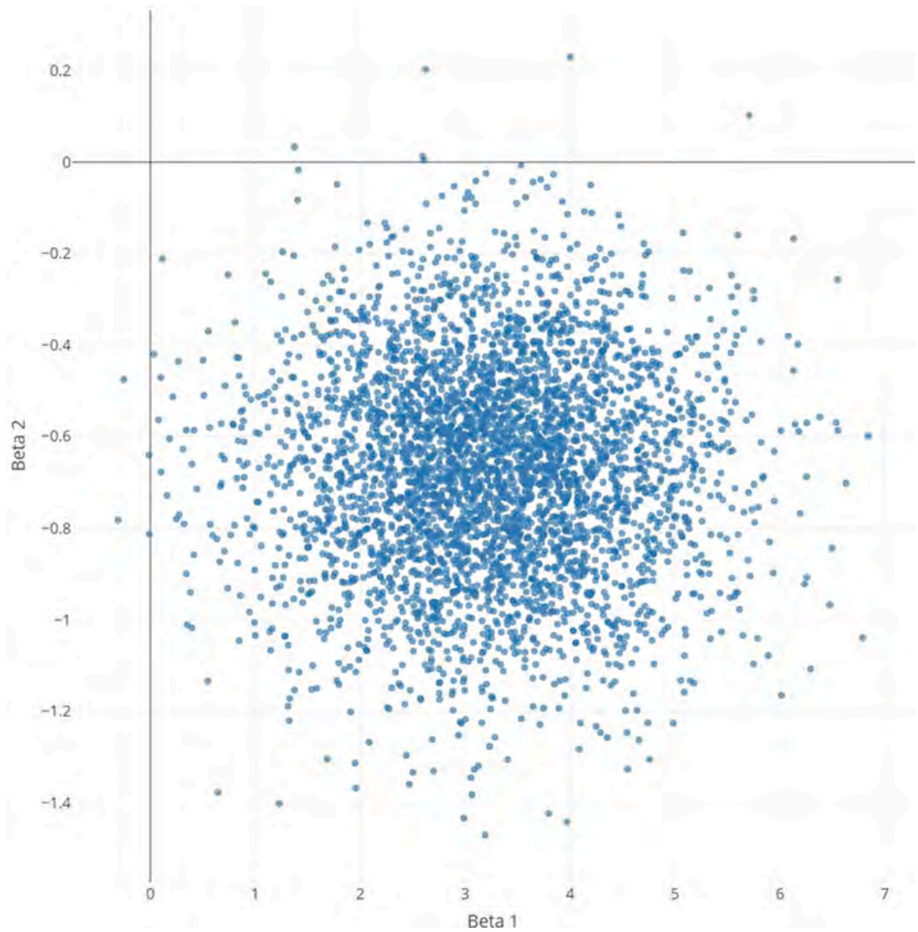


**Fig. 5.** Joint distribution for $\beta_1$ and $\beta_2$. The scatter plot shows no correlation between the values of the two parameters suggesting each factor is independent of the other.

**Table 3**
Multiple regression results for the model $\ln\left(\frac{\text{Damage}}{\text{GDP}}\right) = \alpha + \beta_1 \ln(\text{wind}) + \beta_2 \ln(\text{wetlands})$ where GDP in the swath of the storm is derived from 2015 estimates and a national GDP deflator. $R^2 = 0.155$, p = 0.032.

| Coefficient | Estimate | Standard Error | T-STAT H0: parameter = 0 | 2-tail p-value | 1-tail p-value |
|---|---|---|---|---|---|
| $\alpha$ | 8.81 | 4.96 | 1.78 | 0.083 | 0.041 |
| $\beta_1$ | 1.52 | 0.79 | 1.92 | 0.062 | 0.031 |
| $\beta_2$ | −0.304 | 0.17 | −1.84 | 0.073 | 0.037 |

foundation. This yields more precise and reliable parameter estimates.

### 4.3. Comparison with parametric results

To assess the impact of taking a Bayesian approach, we compared our results to the results derived by conducting a parametric multivariable regression. We used the same log–log model with the same independent and dependent variables, the only difference being that GDP in the swath was treated as observed without error and derived by taking the 2015 estimate and dividing by the appropriate national-level GDP deflator.

Regression results are presented in Table 3. $R^2$ for the analysis was 0.155 and the regression was significant at the $\alpha = 0.05$ level ($p = 0.032$). The signs of parameter estimates were consistent with our analysis, but they were quite different in magnitude. Our standard error estimates were larger because of the explicitly incorporated variability in GDP estimates. This is also true when compared to the results reported in Costanza et al. (2008) even though those results were used to determine the prior distributions for our coefficients. Overall, by explicitly incorporating GDP as a latent variable, we derived a more reliable estimate for the parameter values but with greater variability.

### 4.4. Wetlands and economically efficient development

An examination of Fig. 6 reveals an important trend that is naturally implicit in log–log models. As the number of wetlands increases, there is a turning point at around 30,000 hectares of wetlands at which the damage being averted by wetlands rises rapidly from 30% to 80%. Based on this figure it is possible to make explicit policy recommendations for the optimal percentage of coastal land that should be wetlands. Swaths with approximately 30,000 ha of wetlands avert 90% of potential cyclone damage. 3,000 ha avert only 30% of damage. Maintaining at least 30,000 ha of wetlands per swath (1.5% of coastal area) is advised in order to maximize the averted damage. Developing coastal wetlands when they comprise less than 30,000 ha within a radius of 100 km could lead to a significant increase in storm damage and the potential for economically inefficient development because of the unaccounted-for positive externalities of cyclone damage prevention.

## 5. Conclusion

As global warming intensifies and cyclones become more regular, large coastal urban areas will be more frequently affected by storms.

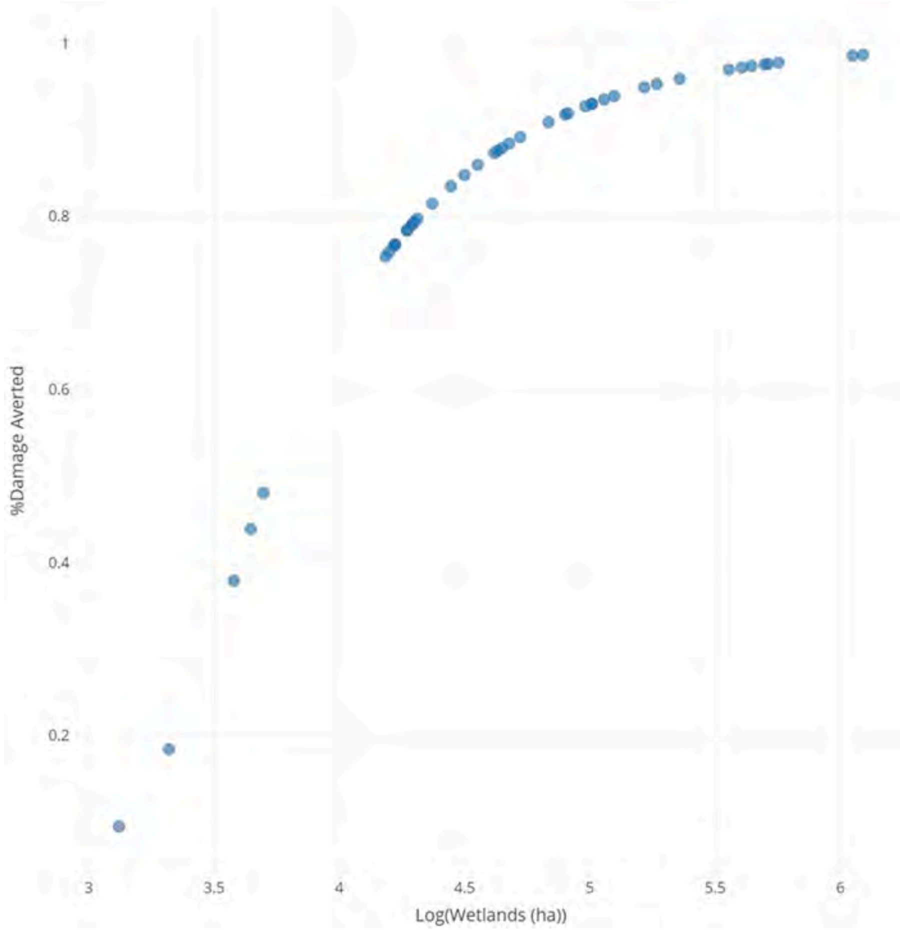


**Fig. 6.** This plot shows the natural log of wetlands by the percentage of damage averted from the total damage if no wetlands were present. Note that for the most part points lie on a smooth curve. The lowest datum is not in line because the model lacks accuracy at low values and must be approximated. Our approximation is an underestimate of avoided damage and therefore the point appears out of line.

Taking the storm damage prevention services of wetlands into account will allow for more efficient urban planning and reduced cyclone damage. Based on our assessment, wetlands have the ability to avert up to 90% of the damage from a hurricane while at the same time providing other positive externalities in the form of additional ecosystem services. Coastal areas with high levels of development and low levels of wetlands—where marginal values for damage prevention are high—should be a focus for wetland protection and restoration.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

We would like to thank our institutions for supporting us. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We would also like to thank the two anonymous reviewers for their helpful comments.

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