The Short-Term Economic Impact of Tropical Cyclone Pam:

An Analysis using VIIRS Nightlight Satellite Imagery

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Abstract

Cyclones are relatively instantaneous shocks where arguably most of the important consequences take place in the first few weeks or months. In this paper we construct destruction proxies of wind exposure and storm surge damages and use satellite measures of nightlight intensity to investigate the short-term impact of tropical cyclones using the case study of Cyclone Pam, which struck the South Pacific Islands in March 2015. Using the unaffected islands as a control group our regression analysis reveals that initially the storm reduced economic activity in the affected islands by as much as 111%, but by the 7th month there were positive boosts to nightlight intensity. By the 9th month this resulted in cumulative net increases in activities related to nighttime electricity usage. More generally, our results suggest that there is likely considerable temporal heterogeneity in the response of areas affected by tropical cyclones and demonstrates the potential of using nightlight imagery to assess the short-term economic impact of tropical storms, and possibly other extreme event phenomena, in a relatively timely manner.

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1. Introduction

Over the last few years there has been an increasing concern over the economic impact of tropical cyclones on countries, in part because of the possibility that the frequency or strength of storms may increase in certain regions due to climate change, see Walsh et al. (2015). Unsurprisingly there are now a number of papers that have investigated the macroeconomic consequences of these storms. While, the evidence thus far has been mixed, most published studies suggest, if anything, a small negative effect. For instance, Rasmussen (2004) in a study of tropical storms in the Caribbean for the period 1970-2002 found a negative effect of 0.05% on GDP growth. Similarly, Strobl (2011) estimated a negative impact of 0.83% on United States county income growth rates. Importantly all of the existing studies have examined the impact of tropical storms at a relatively low temporal frequency, that is, annually or more long term. However, arguably, given that tropical storms are almost instantaneous shocks, much of the fundamental reaction to these storms occurs in the first few weeks or months. These short-term consequences are likely to be muddled in lower frequency data, particularly if they are heterogeneous over time. For example, while one might expect an immediate negative impact on economic activity due to the destruction and indirect losses caused by cyclones, as time goes by recovery through international aid, re-construction, and investment may dominate any still existing negative effects and eventually boost economic activity (Horwich 2000).

The main obstacle in trying to explore the short-term impact of cyclones has arguably been the lack of availability of appropriate temporally high frequency economic activity data. However, researchers have over the last few years increasingly resorted to nightlight intensity imagery to measure local economic activity on a consistent basis when data collected by statistical agencies has not been sufficient; see, for instance, Chen and Nordhaus (2011), Henderson et al. (2012), and Rybnikova and Portnov (2014). These earlier studies generally used the Defense Meteorological Satellite Program (DMSP) images, which are publicly available annual composites of nightlight intensity at a local scale (30 arc-seconds) globally since 1992. However, more recently, the National Aeronautics and Space Administration (NASA) has also started providing satellite imagery data at higher frequency (monthly) and a higher resolution (15 arc-seconds). Specifically, a consistent series of monthly nightlight intensity images, known as the Visible Infrared Imaging Radiometer Suite (VIIRS) light data, that is available since January 2014 and updated with only a few months delay. Recent studies, such as Li et al. (2013), Ma et al. (2014), and Kyba et al. (2015), have confirmed their potential for measuring economic activity even at a very local scale.

The objective of this paper is to investigate the impact of tropical cyclones measured by wind exposure and storm surge destruction indices on economic activity, proxied by VIIRS monthly nightlight data, using the case study of Cyclone Pam, which struck the South Pacific islands in May 2015. Cyclone Pam first formed in the Southern Pacific Basin in early March of 2015, but by 12 March mutated into the most powerful tropical cyclone recorded in the southern hemisphere in history, with estimated wind speeds of 250 km h^{-1} and wind gusts that peaked at around 320 km h^{-1} (Esler 2015 and OCHA 2015a). It wrecked havoc mainly in the islands of Vanuatu, and to a lesser degree Solomon Islands and Tuvalu. The case study here provides an example of how monthly nightlight data can reveal the extent to which economic activity can be affected in the very short-term by tropical cyclones.

2. Data

2.1. Study Region

The country sample studied in this paper consists of the South Pacific islands, which include American Samoa, Cook Islands, Fiji, Federated States of Micronesia, Guam, Kiribati, Marshall Islands, Northern Mariana Islands, New Caledonia, Norfolk Island, Niue, Nauru, Pitcairn, Palau, French Polynesia, Solomon Islands, Tokelau, Tonga, Tuvalu, Vanuatu, Wallis and Futuna and Samoa. These are all small developing countries in terms of land area, population density, and Gross Domestic Product (GDP), and rely mostly on tourism for income generation.

2.2. VIIRS Nightlight Satellite Imagery and Economic Activity

There have been a number of studies that have used nightlight imagery to examine the economic impact of tropical cyclones, such as Elliott et al. (2015) and Bertinelli and Strobl (2013). These papers have all resorted to measures of nighttime brightness generated from the DMSP satellites. However, these nightlight composites suffer from a number of disadvantages, including saturation at upper levels, and the inability to discriminate combustion sources from lights; see Elvidge et al. (2013). In contrast, the recently available VIIRS nightlight imagery collected and processed from the Suomi National Polar-Orbiting Partnership satellite, offers a number of improvements, with particular relevance to the current context.

Firstly, the VIIRS publicly available product provides monthly nightlight intensity data, while the published DMSP data is available only on an annual basis. While the National Oceanic and Atmospheric Administration (NOAA) will sell monthly DMSP data available upon request, many observations are not usable due to the fact that the overpass of the source satellite is around 19h30 and thus when parts of the globe at certain times of the year are not dark yet. The VIIRS overpass, in contrast, is at 1h30 and hence captures nightlight all year round for most of the globe. Additionally, the VIIRS data does not have a saturation point, an aspect that can be important for urban cores. Moreover, VIIRS-DNB images have a relatively low light detection limit of near 2×10^{-11} W cm^{-2} sr^{-1}, compared to the around 5×10^{-10} W cm^{-2} sr^{-1} light detection limit of the DMSP composites (Elvidge et al. 2013). Finally, the

VIIRS provides intensity measures at a higher resolution (15 arc-seconds, around 750 m at the equator) than the DMSP product (30 arc-seconds, around 1 km at the equator).

To conduct our study we have accessed the monthly composites from January 2014 until April 2016, i.e., we have 27 months of data of which 13 are post Cyclone Pam. One should note that while, normally light intensity is measured in radiance units, in the calibration of the data from the VIIRS the effect of clear-sky is taken into account by subtracting estimates of this effect from the observed radiance values. Since this procedure does not take account of the contribution of airglow, the clear-sky offset tends to be too large. Thus near the noise floor of the data, in which values tend to be very small, there will be both small negative and positive values, resulting in what has been termed albedo radiance values; see Chen and Nordhaus (2015). One should note that the unit of the data as used throughout our analysis is in W cm^{-2} sr^{-1}. We show in Figure 1, as an example of nightlight intensity at the island levels, the distribution for parts of the Vanuatu island group in March, 2014, where the level of lights ranges from low (yellow) to high (red). Figure 1 shows considerable differences across the islands as well as within islands, where the red areas correspond to the more populated areas, and hence economic activity, intense areas.

Some discussion is warranted as to what extent nightlight images are capturing economic activity, or at least what sort of economic activity they are likely to capture. There is certainly growing evidence that, in the face of a lack of alternative proxies, nightlight can serve as a reasonable proxy of countries' GDP; see, for instance, Chen and Nordhaus (2011) and Henderson et al. (2012). In terms of the VIIRS data Li et al. (2013) also show that the derived nightlight images are highly correlated with regional GDP, capturing nearly 90% of their variation. However, at the same time it is likely that brightness at night may not be a good proxy for some types of economic activities. For instance, it is unlikely to capture agricultural cropland production, although this may be less of an issue in our South Pacific island example where the services sector, in particular tourism, rather than agricultural production is generally important in overall production. To further investigate this we plot the nightlight intensity as measured by VIIRS and GDP km^{-2} for the islands in our sample in Figure 2. The variables show a clear positive relationship, with a significant correlation coefficient of 0.97 (p-value of 0.02).

2.2. Typhoon Destruction Indices

Destruction caused by tropical storms typically is due to damages due to strong winds, storm surge and heavy rainfall. To capture the potential destruction due to strong wind exposure we use an index in the spirit of Strobl (2012), which measures the wind speed experienced at a very localized level, taking account of the spatial heterogeneity of winds during a cyclone, and then use exposure weights to arrive at an island (group) specific proxy. More specifically, for a set of locations, $i=1, \dots I$, in our case the centroids of the nightlight cells, in island j we define the destruction as:

$$D_j = \sum_{i=1}^{I} w_{i,j} \left(W_{j,i}^{\max}\right)^3 \qquad W^{\max} \geq W^* \qquad (1)$$

where D is the wind damage index, $W^{\max}$ is the maximum measured wind speed at point i during the storm, W^* is a threshold above which wind is damaging, and w is exposure weights in the month prior to the cyclone of locations, $i=1, \dots I$, which aggregate to 1 at the island j level. We set W^* equal to 119 km h^{-1}, which is the threshold which corresponds to Saffir-Simpson Scale Level 1, i.e., the lowest wind speed at which a tropical storm is considered the equivalent of a tropical cyclone in the North-Atlantic basin. One may want to note that we allow local destruction to vary with wind speed in a cubic manner, since, as noted by Emanuel (2011), kinetic energy from a storm dissipates roughly to the cubic power with respect to wind speed and this energy release scales with the pressure acting on a structure; see Kantha (2008) and ASCE (2006). From (1), our index D requires local wind speed, W, and exposure weights, w, as inputs in order to be operational.

In order to calculate the local wind speed we use Boose et al.'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced due to the storm at any point $P = i$, i.e., W_i is given by:

$$W_i = GF\left[M - S(1-\sin(T_i))\frac{H}{2}\right]\left[\left(\frac{X}{R_i}\right)^B \exp\left(1-\left[\frac{X}{R_i}\right]^B\right)\right]^{\frac{1}{2}} \qquad (2)$$

where M is the maximum sustained wind velocity anywhere in the storm, T is the clockwise angle between the forward path of the storm and a radial line from the storm center to the pixel of interest, $P=i$, H is the forward velocity of the hurricane, X is the radius of maximum winds, and R is the radial distance from the center of the storm to point $P=i$. The remaining variables in (2) consist of the gust factor G and the scaling parameters F, S, and B, for surface friction, asymmetry due to the forward motion of the cyclone, and the shape of the wind profile curve, respectively.

In terms of implementing (2) one should note that M can be obtained from storm track data, H can be directly calculated by following the storm's movements between locations along its track, and R and T are calculated relative to the point of interest $P=i$. All other parameters have to be estimated or assumed. We have no information on the gust wind factor G, but a number of studies, for instance Paulsen and Schroeder (2005) have measured G to be around 1.5, and we also use this value. For S we follow Boose et al. (2004) and assume it to be 1. While we also do not know the surface friction to directly determine F, Vickery et al. (2009) note that in open water the reduction factor is about 0.7 and reduces by 14% on the coast and 28% further 50 km inland. We thus adopt a reduction factor that linearly decreases within this range as we consider points i further inland from the coast. Finally, to determine B we employ Holland's (2008) approximation method, and we use the parametric model estimated by Xiao et al. (2009) to estimate X. In terms of the implementation of (2) we use the best track data for Cyclone Pam as taken from the Joint Typhoon Warning Center, which provides information, amongst other things, on the maximum wind speed and the location of the storm eye at 6 hourly intervals. We interpolate these data to obtain hourly observations. For each hourly observation of the storm we can then calculate the W for each nightlight cell centroid contained within our South Pacific islands and retain this value of at least 119 km h^{-1}.

In order to derive island specific aggregate time varying measures of destruction we also want to take exposure into account using w. Ideally we would like to have time varying information on the degree of dispersion of economic activity within islands at the most spatially disaggregated level as possible, given that wind speeds due to tropical storms can differ substantially across space. Since this is not available we instead use the above described nightlight imagery values at the cell level in the month (February 2015) before Cyclone Pam struck. As the calibration of the nightlight imagery induced negative values for some cells, we add a constant to all values equal to the absolute value of the largest negative value plus a small positive constant (0.00001). This enabled us to have positive weights for all nightlight cells and ensured that any weight, calculated as a percentage of an island's total, varied between 0 and 1.

While the extent of wind damage due to cyclones is certainly correlated with the amount of storm surge, this is probably only very imperfectly so; see, for instance, Needham and Keim (2014). Storm surge should therefore ideally be modeled independently. Unfortunately, storm surge modeling requires detailed local data, such as bathymetry and surface roughness that is unavailable for the South Pacific. We thus construct a rather crude index of storm surge prone areas as the weighted share of the area of low elevation coastal zone (L), in a similar spirit to

Elliott et al. (2015). More specifically, in order to identify L in the affected islands we follow McGranahan et al. (2007) and Brecht et al. (2012) and define land areas contiguous with the coastline up to a 10 m rise elevation using the Shuttle Radar Topography Mission (SRTM) 30 m elevation data set. We then isolate the share of nightlight in these areas to arrive at an island share of nightlight intensity in storm surge prone areas. As before we add a constant to all values equal to the absolute value of the largest negative value plus a small positive constant (0.00001) to obtain positive weights. More precisely, we construct a measure of storm surge damages, S as:

$$S_j = \sum_{i=1}^{I} w_{i,j} \frac{L_{i,j}}{A_j} \qquad L_i\text{=1,0} \qquad (3)$$

where L is an indicator of whether cell i lies within an low elevation coastal zone (=1) or not (=0) and A is the area of island j. The estimated values of S of the three affected islands are shown in the last column of Table 1. Accordingly, the largest storm surge potential damages are in Tuvalu, followed by the Solomon Islands and then Vanuatu.

The final destructive aspect of tropical cyclones is that due to heavy rainfall. Unfortunately, we know of no data set that would give us a local enough measure of rainfall on a monthly basis since 2014, covering all islands within our sample. We hence must rely on the somewhat scarce evidence that suggests that local rainfall during a tropical storm is considerably correlated with local wind exposure. For instance, it has been found that both winds and precipitation are highest nearer to the eye of the storm (Riehl 1954). It must nevertheless be kept in mind that at best our wind damage proxy is capturing both damages due to wind exposure and rainfall, and at worst that our analysis can only be interpreted in terms of capturing damages due to wind exposure and, to a limited extent, storm surge.

3. Methodology

3.1. Graphical Analysis

We undertake two forms of graphical analysis. Firstly we take the island of Vanuatu as an example to show how pixel level nighttime intensity may have changed after the typhoon. To this end we extract all pixels within the islands' land surfaces for the composites March 2014, March 2015, and March 2015. We then subtracted the radiance values of March 2014 from March 2015 and the values of March 2015 from March 2016, in order to show possible changes in nighttime intensity values that may have coincided with the storm. Secondly, we calculate the average of pixel values for each set of islands affected by the typhoon according to our damage indices *D* and *S* outlined above for each month of the composites. For those unaffected we calculate out the average across all islands. The monthly series of the three affected islands are then compared to the unaffected group.

3.2. Regression Analysis

In order to statistically disentangle the effect of wind and storm surge destruction of Cyclone Pam on the South Pacific islands we estimate the following:

$$N_{jt} = \alpha + \sum_{k=0}^{12} \phi_{t-k} S_j + \sum_{k=0}^{12} \beta_{t-k} D_j + \lambda_t + \mu_j + \varepsilon_{j,t} \qquad (4)$$

where *N* is the average nightlight intensity in island *j* at time *t* and *D* and *S* are our wind and storm surge destruction proxies described above, with contemporaneous (k=0) and lagged (k>0) effects. One should note that prior to March 2015, i.e., prior to Typhoon Pam, *D* and *S* are zero. λ is a vector of time specific indicator variables and is included in order to control for time specific shocks common to all South Pacific islands. μ is a vector of island specific time invariant indicator variables. In order to account for these we employ a panel fixed effects estimator, which essentially transforms the variables into deviations from their means, and thus purges μ (as well as α) from (4). ε is an i.i.d. error term, while α is a standard intercept term. In order to allow for spatial- and autocorrelation we calculate Driscoll and Kraay (1998) standard errors. One may also want to note that after we control for island specific time invariant unobservables, μ, arguably D and S are exogenous since they can be viewed as random realisations of storm occurrence. Thus one can with reasonable confidence interpret the coefficients of interest to be estimated, i.e., the ϕ*'s* and β*'s*, as capturing the causal effect of wind and storm surge destruction on average nightlight intensity.

3.3. Quantitative Implications

One can use the estimated coefficients from (4) in order to gain insight into the quantitative significance of Cyclone Pam. More specifically, we can construct the following measure of cumulative impact, C, for each of our 12 months after the cyclone:

$$C_{j,s} = \alpha + \sum_{k=0}^{12} \frac{\phi_{t-k} S_j}{N_{j,t=-1}} 100 + \sum_{k=0}^{12} \frac{\beta_{t-k} D_j}{N_{j,t=-1}} 100 \qquad s=1,\ldots,12 \qquad (5)$$

where $N_{j,t=-1}$ is the average nightlight intensity in island j in the month (February 2015) before Cyclone Pam. Importantly, one should note that as we calculate C for each period after the cyclone we set β_{t-s} and ϕ equal to 0 when they are not significant. Moreover, for any k we set the additional C itself to 0 if an *F-test* of the coefficients, excluding the ones that are not significant, indicated that the null hypothesis that they are jointly equal to zero cannot be rejected at the 5% significance level. We are thus considering cumulative impacts as those where both the marginal and total cumulative impacts were significant.

4. Results

Calculation of D and S from equations (1) through (3) reveals that the Solomon Islands and Vanuatu were potentially affected by typhoon winds, with values of 0.00340 and 1.2389, respectively, while the Solomon Islands, Tuvalu, and Vanuatu were potentially affected by storm surge damage, with values of 1.309×10^{-6}, 0.0005, and 5.739×10^{-7}, respectively.

Our graphical pixel level analysis in Figures 3 and 4, using Vanuatu as an example, shows that in Vanuatu compared to one year prior to the typhoon there were some visual decreases in nighttime intensity, particularly where much of the intensity is concentrated, as suggested by Figure 1, whereas one year after storm intensity increased in this area again.

Figure 5 depicts the trends in average nightlight intensity for the three affected countries, i.e., parts (b), (c), and (d), as well as the average of all unaffected countries in part (a). For the three affected islands there is a drop in intensity just after the storm. However, this fall in intensity seems to also have occurred on average for unaffected groups. Moreover, it seems to coincide with the general seasonal patterns during this period of the year. This underlines the importance of trying to disentangle the potential effect of Typhoon Pam with regression analysis.

We estimate the regression equation in (4) using all islands, affected and unaffected, the results of which are given as Model 1 in Table 1. As can be seen, after purging island specific effects, μ, from (4) using a fixed effects estimator, the control variables manage to explain 14 per cent of the variation in nightlights. Looking at the individual coefficients, one can see that wind exposure has a negative and significant impact in the month of the strike and the 5 months thereafter, except for the 3rd month. From the 7th month onward the trend is reversed when a positive significant impact sets in which continues until the end of our sample period, i.e., 12 months after Typhoon Pam first produced damage.

In contrast to wind exposure, the effect of storm surge is shown to be insignificant at the time of the cyclone strike as well as in the months thereafter. This may be because storm surge does not have a significant enough- or long enough, if the impact lasts less than a month, effect to show up in our nightlight measure of local economic activity. Alternatively, our 'modeling' of storm surge may be too simplistic to accurately capture its nature, hence inducing attenuation bias. Since the latter reason is likely to play at least some role, one must view our finding with regard to storm surge with at least some caution. Another reason may be that the wind destruction proxy is already capturing storm surge and hence there is a problem of multi-collinearity. We thus in Model 2 in Table 1 excluded *D* and its lags from (4), but, as can be seen, this similarly produced insignificant coefficients on *S* and its lags and reduced the explanatory power of the model to an R^2 of 0.08.

Damage assessment reports suggest that Tuvalu experienced the most severe destruction from storm surge compared to Vanuatu and Solomon Islands in that there was inundation from storm surge and sea swells of 3-5 m in 7 of its 9 islands and the government had to declare a state of emergency (OCHA 2015c). We thus experimented with setting *S* equal to zero for Vanuatu and the Solomon Islands but kept the value for Tuvalu unchanged. As depicted in Model 3 in Table 1, this did not produce any significant effect of *S* on island average nightlight intensity.

We next calculate the implied cumulative impact in (5) over time for wind exposure using the significant β's for the Solomon Islands and Vanuatu, but setting the ϕ's, in accordance with our regression results, to zero. The resultant values are shown in Figures 6 and 7, respectively. As can be seen, given that we are using the same β for both islands, the pattern of the cumulative impact is identical. In this regard, one finds that the cumulative negative effect of Cyclone Pam increases slowly until the 5^{th} month after the event, until it begins to fall as the marginal impact turns positive. By the 8^{th} month the overall cumulative impact is

0. Thereafter, as the positive effects in response to the storm accumulate, there is a starkly rising beneficial impact of the storm on nightlight intensity. While the pattern of the impact is by construction the same across the two islands, the quantitative nature of this effect differs substantially. For the Solomon Islands the total negative impact is never greater than two percentage points of the pre-storm level of intensity, while one year after the event the net cumulative positive effect has risen to a little over 5 percentage points. Hence one can conclude that the overall net impact of Pam was relatively small for the Solomon Islands, at least measured in terms of nightlight intensity.

Reports that assessed damage following Typhoon Pam similarly found that destruction was relatively lower for Solomon Islands. In Solomon Islands the islands affected by strong winds and rainfall were among the least populated territories thereby minimizing any negative impact. For instance, in Malaita and Temotu Province, just 30,000 people (5% of the total population) were affected by flooding caused by heavy rains (OCHA 2015c), while the islands of Anuta and Temotu were most affected by strong winds and rainfall and are among the least populated territories (OCHA 2015d). The Solomon Islands also received some international support for relief and reconstruction immediately following the cyclone, perhaps accounting for the subsequent positive impact after the cyclone struck.

In contrast to the Solomon Islands, both within the first few months when effects were negative, as well as after 9 months when the cumulative effect turned positive, the impact in Vanuatu was fairly large. More precisely, our results suggest that the total net negative impact on local economic activity reached a loss of as much as 111% by the 5th month. Damage reports also found losses to be high and were estimated to be approximately US$ 449.4 million (64.1% of GDP), which is most likely an underestimation because the figure was based on the best available information at the time (Esler 2015). The vast destruction is likely because Typhoon Pam directly struck Vanuatu at category 5 strength and all 6 provinces were affected with the larger and more populated islands being more negatively affected (OCHA 2015b). Moreover, the center of the storm passed east of the main island Efate, where the capital Port Vila was directly struck. The cyclone damaged or completely destroyed 17,000 buildings, including houses, schools, hospitals and clinics (Esler 2015). However, our results show that once the storm started enhancing economic activity there was a large positive effect. As a matter of fact, as of the final month of available data our regressions results suggest that local nighttime brightness has increased by over 300% relative to prior to the storm.

Our finding of an initial large negative impact within the first 5 months after Cyclone Pam struck followed by a large positive impact is supported by damage assessment reports. Esler (2015) stated that while Typhoon Pam was expected to reduce Vanuatu's GDP growth by 5.5 percentage points relative to the 2015 pre-cyclone forecast, the large scale of recovery and reconstruction activities along with international aid and funding received which started to take place almost immediately following the storm would allow for a large positive GDP growth of 1.4% in 2015, with further increases in 2016 and 2017. Furthermore, although tourism was one of the most negatively affected sectors, earnings in the industry were only negatively affected for 3-6 months while hotels remained closed for clean up and re-construction (Esler 2015). Additionally, government spending in quick response for recovery and reconstruction and international funds received, along with policies to increase tax exemptions and commercial bank lending, may have significantly increased economic activity within months after Typhoon Pam struck (Elser 2015).

Just days after Typhoon Pam struck the government of Vanuatu led response efforts with support from the Pacific Humanitarian Team and the Vanuatu Humanitarian Team and worked with various development partners for recovery and re-construction activities. The government spent US$ 2.21 million from its Emergency Relief Fund to support immediate humanitarian response and redeployed additional funds from their 2015 fiscal budgets (Esler 2015). Further, US$ 3.28 million was received from the European Union (EU), a US$ 1.84 million insurance payout was received from the World Bank for the 2015 recurrent fiscal budget to finance recovery-related expenditures, and grant funding of US$ 6.09 million was received from donors for recovery operations (Esler 2015). As of 26 March, just about 12 days after Thypoon Pam struck US$ 18 million was already received (OCHA 2015e). Overall, recovery and reconstruction were estimated at US$ 316 million, of which US$ 95 million was for short-term needs (Esler 2015).

5. Discussion

We investigate the short-term economic impact of Cyclone Pam using monthly composites of nightlight intensity and tropical cyclone destruction indices. Our regression analysis reveals that initially the storm reduced economic activity in the affected islands. However, by the 7^{th} month, positive boosts to nightlight intensity, possibly due to re-construction activities and government programs, began to counteract any negative effects and by the 9^{th} month resulted in cumulative net increases in activities related to nighttime electricity usage. More generally, our results suggest that there is likely considerable temporal heterogeneity in the response of areas affected by tropical cyclones. Moreover, the analysis demonstrates the potential of using nightlight imagery to assess the short-term economic impact of tropical storms, and possibly other extreme event phenomena, in a relatively timely manner.

There are of course a number of shortcomings of our study that future research could address. Most obviously, waiting for the availability of more monthly images would allow one to explore what the impact of tropical cyclones are beyond one year from their occurrence. From a methodological point of view, clearly a better storm surge destruction proxy, as well as one capturing the damages due to heavy rainfall destruction, would provide a more accurate picture of the economic consequences of these storms. Also, while very convenient in terms of spatial and temporal resolution, further investigation into what sort of economic activity nightlight images are capturing would be beneficial. Finally, since we find different patterns of impact as time passes since the event, a further understanding of what is driving these patterns would be insightful and aid policy makers in post event management strategies.

References

ASCE (2006). *Minimum Design Loads for Buildings and other Structures, ASCE/SEI 7-05, American Society of Engineers*, Reston, VA.

Bertinelli, L. and E. Strobl. 2013. "Quantifying the Local Economic Growth Impact of Hurricane Strikes: An Analysis from Outer Space for the Caribbean." *Journal of Applied Meteorology and Climatology* 52: 1688-1697.

Boose, E., I.S. Mayra, and R.F. David. 2004. "Landscape and Regional Impacts of Hurricanes in Puerto Rico." *Ecological Monograph* 74 (2): 335-352. doi:org/10.1890/02-4057.

Brecht, H., S. Dasgupta, B. Laplante, S. Murray, and D. Wheeler. 2012. "Sea-Level Rise and Storm Surges: High Stakes for a Small Number of Developing Countries." *The Journal of Environment and Development* 21(1): 120-138

Chen, X. and W. Nordhaus. 2015. "A Test of the New VIIRS Lights Data Set: Population and Economic Output in Africa." *Remote Sensing* 7: 4937-4947.

Chen, X and W. Nordhaus. 2011. "Using luminosity data as a proxy for economic statistics." Procedings of the national Academy of Sciences 108(21): 8589–94. www.pnas.org/cgi/doi/10.1073/pnas.1017031108

Crowards, Tom. 2000. "An Index of Inherent Economic Vulnerability for Developing Countries." Working Paper 6/00, Caribbean Development Bank, Barbados.

Driscoll, J.C., and A.C. Kraay. 1998. "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *Review of Economics and Statistics* 80 (4): 549-560.

Elliott, R., S. Puyang, and E. Strobl. 2015. "The Local Impact of Typhoons on Economic Activity in China: A View from Outer Space." *Journal of Urban Economics* 88: 50-66.

Elvidge, C., K. Baugh, M. Zhizhin, and F. Hsu. 2013. "Why VIIRS data are superior to DMSP for mapping nighttime lights." *Proceedings of the Asia-Pacific Advanced Network* 2013 35: 62-69.

Emanuel, K. 2011. "Global Warming Effects on U.S. Hurricane Damage." *Weather Climate and Society DOI: http://dx.doi.org/10.1175/WCAS-D-11-00007.1*

Esler, S. 2015. Vanuatu Post-Disaster Needs Assessment Tropical Cyclone Pam. Government of Vanuatu https://www.gfdrr.org/sites/default/files/publication/PDNA_Cyclone_Pam_Vanuatu_Report.pdf

Gassebner, M., A. Keck, and R. Teh. 2010. "Shaken, not Stirred: The Impact of Disasters on International Trade." *Review of International Economics* 18 (2): 351-368.

Henderson, V., A. Storeygard, and D. N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review 2012, 102(2): 994–1028*

Holder, R. and P. Raschky. 2014. "Regional Favouritism." *Quarterly Journal of Economics* 129: 995-1033.

Holland, G. 2008. "A revised hurricane pressure–wind model." *Monthly Weather Review* 136: 3432–3445.

Horwich, G. 2000. "Economic Lessons of the Kobe Earthquake." *Economic Development and Cultural Change* 48 (3): 521-542.

Kantha, L. 2008. "Tropical Cyclone Destructive Potential by Integrated Kinetic Energy." *American Meterological Society* DOI:10.1175/BAMS-89-2-219.

Kyba, C., Garz, S., Kuechly, H., de Miguel, A., Zamorano, J., Fischer, J., and Hoelker, F. (2015). "High-Resolution Imagery of Earth at Night: New Sources, Opportunities and Challenges*", Remote Sensing*, 7, pp. 1-23.

Li, X., H. Xu, X. Chen, and C.Li. 2013. "Potential of NPP-VIIRS Nighttime Light Imagery for Modeling the Regional Economy of China." *Remote Sensing* 5: 3057-3081.

Ma, T., Zhou, C., Pei, T., Haynie, S., Fan, J. 2014. Responses of Suomi-NPP VIIRS-Derived Nighttime Lights to Socioeconomic Activity in China's Cities", *Remote Sensing Letters*, 5: 165-174.

McGranahan, G., D. Balk, and B. Anderson. 2007. "The Rising Tide: Assessing the Risks of Climate Change and Human Settlements in Low Elevation Coastal Zones." *Environment and Urbanization* 19 (1): 17-37.

Michalopoulos, S. and E. Papaioannou. 2014. “National Institutions and Subnational Development in Africa.” *Quarterly Journal of Economics* 129 (1): 151-213.

Needham, H. and B. Keim. 2014. “Correlating Storm Surge Heights with Tropical Cyclone Winds at and before Landfall.” *EARTH Interactions* 18: 1-26.

NOAA. 2014. “Visible Infrared Imaging Radiometer Suite (VIIRS) Imagery Environmental Data Record (EDR) User’s Guide”, NOAA Technical Reports, Washington, DC.

OCHA. 2015a. Vanuatu: Severe Tropical Cyclone Pam Situation Report No. 1 (as of 15 March 2015) http://reliefweb.int/report/vanuatu/vanuatu-severe-tropical-cyclone-pam-situation-report-no-1-15-march-2015

OCHA. 2015b. Vanuatu: Severe Tropical Cyclone Pam Situation Report No. 2 (as of 16 March 2015) http://reliefweb.int/report/vanuatu/vanuatu-severe-tropical-cyclone-pam-situation-report-no-2-16-march-2015

OCHA. 2015c. Vanuatu: Tropical Cyclone Pam Situation Report No. 4 (as of 18 March 2015) http://reliefweb.int/report/vanuatu/tropical-cyclone-pam-situation-report-no-4-16-march-2015

OCHA. 2015d. Vanuatu: Tropical Cyclone Pam Situation Report No. 7 (as of 21 March 2015) http://reliefweb.int/sites/reliefweb.int/files/resources/OCHA_VUT_TCPam_Sitrep7_20150321.pdf

OCHA. 2015e. Vanuatu: Tropical Cyclone Pam Situation Report No. 12 (as of 26 March 2015) http://reliefweb.int/sites/reliefweb.int/files/resources/OCHA_VUT_TCPam_Sitrep12_20150326.pdf

Paulsen, B.M., and J.L. Schroeder. 2005. “An Examination of Tropical and Extratropical Gust Factors and the Associated Wind Speed Histograms.” *Journal of Applied Meteorology and Climatology* 44 (2): 270-280.

Elliott, R., Strobl, E., and Sun, P. (2015). “The Local Impact of Typhoons on Economic Activity in China: A View from Outer Space”, *Journal of Urban Economics,* 88, pp. 50-66.

Rasmussen, T.N. 2004. “Macroeconomic Implications of Natural Disasters in the Caribbean.” Working Paper 04/224, The International Monetary Fund, Washington, USA.

Riehl, H. 1954. Tropical Meteorology, New York: McGraw-Hill Book Company.

Rybnikova, N. and Portnov, B. (2014). “Mapping Geographical Concentrations of Economic Activities in Europe using Light at Night (LAN) Satellite Data”, *International Journal of Remote Sensing*, 35, pp. 7706-7725.

Strobl, E. 2012. “The Macroeconomic Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in the Central American and Caribbean Region.” *Journal of Development Economics* 97 (1): 130-141.

Strobl, Eric. 2011. “The Growth Impact of Hurricane Activity: Evidence from US Coastal Counties.” *Review of Economics and Statistics* 93 (2): 575-589.

Vickery, P. J., D. Wadhera, M. D. Powell, and C. Yingzhao. 2009. “A Hurricane Boundary Layer and Wind Feld Model for use in Engineering Applications.” *Journal of Applied Meteorology* 48 (2): 381-405.

Walsh, K.J.E., J.L. McBride, P.J. Klotzbach, Balachandran, S.J. Camargo, G. Holland, T.R. Knutson, J. Kossin, T.-C. Lee, A. Sobel, and M. Sugi. 2015. Tropical cyclones and climate change. *WIRES Climate Change*, Nov 11.

World Bank. 2015. Vanuatu: Six Months after Cyclone Pam http://www.worldbank.org/en/news/feature/2015/09/29/vanuatu-six-months-after-cyclone-pam

Xiao, Q., X. Zhang, C. A. Davis, J. D. Tuttle, G. J. Holland, and P. J. Fitzpatrick. 2009. “Experiments of hurricane initialization with airborne Doppler radar data for the Advanced-research Hurricane WRF (AHW) model.” *Monthly Weather Review* 137: 2758-2777.