

Assessing the Impact of Typhoons on Rice Production in the Philippines

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ABSTRACT

This study quantifies the impact of typhoons on rice production in the Philippines. To this end, satellite-derived reflectance data are used to detect the location of rice fields at 500-m resolution. Utilizing typhoon-track data within a wind field model and satellite-derived precipitation measures, fragility curves are then employed to proxy the damage of storms on rice production within each rice field. The results from a panel spatial regression model show that typhoons substantially reduced local provincial production in the quarter of the strike, having caused losses of up to 12.5 million tons since 2001. Using extreme value theory to predict future losses, the results suggest that a typhoon like the recent Haiyan, which is estimated to have caused losses of around 260 000 tons, has a return period of 13 years. This methodology can provide a relatively timely tool for rice damage assessments after tropical cyclones in the region.

1. Introduction

Tropical storms cause considerable amount of damage globally, estimated to be about \$26 billion per year (Mendelsohn et al. 2012). In this regard, the Philippines is one of the most cyclone-prone countries in the world. With ~6–9 landfalling storms per year since 1970, it currently ranks second only to China (Hurricane Research Division 2015). One sector of the Philippine economy that is particularly susceptible to these extreme events is rice cultivation. More specifically, typhoons can cause considerable damage to rice production by exposing it to strong winds and excessive rainfall. As a matter of fact, in a study of climate-induced damage to the rice industry since 2007, Israel (2012) estimated that typhoon damage constituted at least 70% of the \$276 million (U.S. dollars) of annual damage caused by extreme weather events, including floods and droughts. For a nation like the Philippines, for which rice is the staple food for nearly 90% of the population—providing half their calories and constituting 20% of food expenditures—but which consumes more rice than

it produces and where rice accounts for nearly 25% of national agricultural value added, these storms can thus be of particular significance.

The Philippines government has, of course, been aware of the vulnerability of its rice industry to typhoons for a long time and has tried to address the issue through explicit policymaking. More specifically, the National Food Authority¹ (NFA)—the agency in charge of ensuring the stability of the supply and price of rice—imports rice to counteract production shortfalls predicted using seasonal climate forecasts and agricultural production surveys. These import decisions are typically adjusted on a quarterly basis, procurement occurring twice a year, so that imports after a final decision made in January arrive between February and April, just before the rainy season. However, import orders are often readjusted when major events, like a typhoon, cause unexpected production shortfalls. For example, after Typhoon Haiyan

¹ The NFA is the Philippine agency responsible for ensuring the food security of the Philippines and the stability of the supply and price of rice; it has existed since 1981. In 1985 it was granted exclusive authority to import rice. As of May 1999 some importing by the private sector is possible, although these imports, unlike the public ones, carry a large in-quota tariff and thus generally are only a small percentage of total rice imports.

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in November 2013, the NFA approved the import of a further 355 000 tons of rice in addition to the 350 000 originally procured (Dela Cruz and Thukral 2013). An important difficulty for the NFA in adjusting imports to address shortages due to tropical cyclones is that orders must be made fairly quickly since filling them takes time. However, immediate initial estimates of the actual damage to rice production due to these storms tend to be imprecise, and more accurate assessments have to rely on time-consuming local surveys. In this paper, we provide an approach that will allow more accurate and immediate estimate of the impact of typhoons on rice in the Philippines, which can help policymakers be more effective in their response to these storms.

There is already a small but growing academic literature that has attempted to statistically quantify the impact of tropical cyclones on the agricultural sector. For instance, Chen and McCarl (2009) examine the case of the United States using county-level data of crop production and hurricane intensity measured using the Saffir–Simpson intensity categorization and find different effects across crop types. Spencer and Polachek (2015), in contrast, employ a hurricane incidence measure for Jamaica parishes and similarly find different impacts for different crops. Examining the Philippines, Israel and Briones (2012) alternatively use the number of typhoons and the incidence of a typhoon of different intensity levels but only find very weak effects on rice production at the province level. Similarly for the Philippines, Koide et al. (2013) note a significant negative correlation between accumulated cyclone energy and provincial rice production. Strobl (2012) finds a negative effect of hurricanes on agriculture in the Caribbean.

In contrast to the previous literature, our study melds multiple methodological approaches to obtain a more accurate estimate of the impact of cyclones on rice production that will reduce measurement error. First, we construct provincial-level estimates of rice damage from localized rice fragility curves, which encompass damage due to both wind and rainfall, rather than using storm incidence or intensity measures. To this end, we take into consideration the location-specific nature of tropical storm destruction, in terms of both wind and precipitation exposure and the rice fields they are likely to affect.² More specifically, we first detect the location and growing period of rice paddies at the 500-m level across the Philippines by using satellite-derived information on

spectral reflectance and the detection algorithm developed by Xiao et al. (2002a). This approach allows for the spatial and temporal variations in rice paddies at a spatially detailed level. With the location of rice fields at hand, we then measure local wind exposure using a wind field model and local precipitation exposure during the storm. Damage is then proxied using the fragility curves estimated by Masutomi et al. (2012). Aggregating these for each quarter at the provincial level and combining them with provincial-level rice data allows us to then statistically estimate the impact on rice production. Also in contrast to the previous literature, we do so within a spatial panel regression framework, which takes account of both potential spatial correlation and spatial spillovers across regions. Finally, we use extreme value theory to predict future losses.

The remainder of the paper is organized as follows. In the next section we describe the number of methodologies employed in our analysis. Section 3 outlines our datasets. Section 4 provides the details and discussion of results. Some final remarks are provided in the last section.

2. Methods

a. Typhoon damage area index (DA)

As noted by Masutomi et al. (2012), typhoons can result in two types of damage to rice. First, the strong winds can cause the lodging, striping, and injury of plant organs, as well as induce water stress due to enforced transpiration. Second, continuous inundation due to excessive rainfall can result in a decrease in photosynthesis and respiration. In considering the impact of these features, it is also important to recognize that the timing of a typhoon relative to the growth stage of rice will play a role in the extent of damage, where the resistance of paddy rice to environmental change is typically lowest during the heading stage. Masutomi et al. (2012) incorporate all of these aspects in constructing a rice fragility curve for Japan. We follow the same methodology to construct an index for the Philippines. More specifically, the probability of damage to an area i is assumed to follow a Weibull distribution, as follows:³

$$\text{Pr}_{ij}(I_{ij}) = 1 - e^{-(I_{ij}/\lambda_{ij})^k}, \quad (1)$$

where Pr_{ij} is the probability that damage is caused by intensity I_{ij} of typhoon j in area i of intensity I , and k and λ are the shape and scale parameters of the Weibull

² The only other study to do so is Strobl (2012), which uses gridded 1-km cropland data from the Global Land Cover 2000 database to determine cropland location for the Caribbean, although it does not distinguish between crop types.

³ Masutomi et al. (2012) also explore alternative distributions.

distribution, respectively. To take into account the fact that damage is likely to be highest near the heading stage, Masutomi et al. (2012) assume that the scale parameter λ is a quadratic function of the number of days between the day when the maximum wind speed is observed W_{ij} and the heading day HD_{ij} :

$$\lambda_{ij} = b(W_{ij} - HD_{ij})^2 + c(W_{ij} - HD_{ij}) + d, \quad (2)$$

where b , c , and d are functional form parameters. The typhoon intensity is defined as follows:

$$I_{ij} = W_{ij} + mP_{ij}, \quad (3)$$

where W is the maximum wind speed of the storm, P is the accumulated rainfall during the storm, and m is a translation parameter. Finally, the damage to area i attributed to typhoon j DA_{ij} is equal to the product of the probability of damage and the area planted at the time of the storm PA_i :

$$DA_{ij} = Pr_{ij}PA_i. \quad (4)$$

From (1)–(4), the parameters m , b , c , d , and k are to be determined. To estimate these parameters, Masutomi et al. (2012) use official estimates of rice areas damaged by 42 typhoons in Japan and a downhill simplex method to minimize the error between DA and reported damaged areas. Unfortunately, as there is no similar damage data available for the Philippines, we thus use their estimated optimum parameters. More specifically, we assume that $m = 0.001283$, $b = -0.0007692$, $c = 2.007$, $d = 0.0001757$, and $k = 6.725$. Thus with these parameters at hand and measurements for observed maximum wind speed W_{ij} and accumulated rainfall P_{ij} , one can calculate the damage area DA_{ij} using (1)–(4) for every planted rice area i due to storm j . To obtain normalized measures of DA due to typhoon j at the province level p we simply sum DA within provinces relative to the total area planted in a province:

$$DA_{pj} = \frac{\sum_i Pr_{ij}PA_i}{\sum_i PA_i}. \quad (5)$$

This measure ranges between 0 and 1 and can also be calculated on a temporal scale rather than just on a storm by storm basis.

b. Rice field detection

The intensity of wind and rain experienced during a typhoon is fairly heterogeneous even within a relatively

small area. Moreover, rice planting can change considerably over space and time. It is thus important to detect rice fields and measure subsequent potential damage due to a storm at the most spatially disaggregated scale as possible. Unfortunately, there is no consistent time series of rice field location for the Philippines at a very spatially disaggregated level available from statistical sources.⁴ However, rice paddies possess unique physical features that allow one to use satellite-derived images to proxy field locations. More specifically, rice is first transplanted on a field covered by between 2 and 15 cm of water. The paddy surface is subsequently composed of a combination of water and green growth until about between 50 and 60 days after transplanting when the canopy is totally covered by rice plants. Finally, the leaf moisture and density decreases during the ripening phase until harvest (Le Toan et al. 1997). Importantly, these surface changes allow one to use satellite-derived spectral reflectance data to detect the presence of rice fields based on the temporal combination of the extent of surface water and green vegetation.

To detect rice fields, we follow the methodology detailed in Xiao et al. (2005) using imagery from the Moderate Resolution Imaging Spectroradiometer (MODIS) Surface Reflectance product (MOD09A1) on board the *Terra* and *Aqua* satellites, which provides 500-m resolution land surface reflectance from seven spectral bands every 8 days, available since 2000. More specifically, one can use the near-infrared (NIR; 841–876 nm) and red (620–670 nm) spectral bands reflectance ρ to calculate the normalized difference vegetation index (NDVI), which is highly correlated with the leaf area index:⁵

$$NDVI = \frac{\rho_{NIR_1} - \rho_{red}}{\rho_{NIR_1} + \rho_{red}}. \quad (6)$$

The enhanced vegetation index (EVI) reduces residual atmospheric contamination and variable soil background reflectance by adjusting the reflectance in the red band as a function of the reflectance in the blue band (459–479 nm) and is defined as

$$EVI = 2.5 \left(\frac{\rho_{NIR_1} - \rho_{red}}{\rho_{NIR_1} + 6\rho_{red} - 7.5\rho_{blue} + 1} \right). \quad (7)$$

⁴ Time-varying spatial data on rice field location for the Philippines are only available at the aggregate provincial level, with no indication of how rice fields are dispersed within provinces.

⁵ In essence, the leaf area index is a quantitative measure of the greenness of plant canopies.

To account for water content, we calculate the land surface water index (LSWI), which utilizes the short-wave infrared (SWIR) spectral band (1628–1652 nm) and is sensitive to leaf water and soil moisture (Maki et al. 2004; Xiao et al. 2002a):

$$\text{LSWI} = \frac{\rho_{\text{NIR}_1} - \rho_{\text{SWIR}_1}}{\rho_{\text{NIR}_1} + \rho_{\text{SWIR}_1}}. \quad (8)$$

One should note that these four indices all capture different aspects important of rice production. More specifically, NDVI is closely correlated to the leaf area index of paddy rice fields. In contrast, the EVI accounts for residual atmospheric contamination and variable and canopy background reflectance. Finally, LSWI allows one to capture water thickness.

Using the LSWI, NDVI, and EVI vegetation indices, we follow the algorithm employed by (Xiao et al. 2002b, 2005, 2006), which focuses on detecting the flooding/transplanting period and the first part of the crop growth period leading to full canopy expansion. Rice paddy flooding and transplanting is identified using a threshold of either $\text{LSWI} + 0.05 \geq \text{EVI}$ or $\text{LSWI} + 0.05 \geq \text{NDVI}$. For each flooded pixel, the identification of rice growing is based on the assumption that rice canopy reaches its maximum within 2 months (Xiao et al. 2002c). Therefore, a flooded pixel is considered as a “true rice pixel” if EVI reached half of the maximum EVI value of the current crop cycle within 40 days following the flooding/transplanting date.

Pixels having a high blue band reflectance (≥ 0.2) but not identified as clouds, which could lead to a false identification of rice paddies, are also removed. Permanent water bodies are distinguished from seasonal water bodies, such as paddy rice, by analyzing the temporal profile of NDVI and LSWI of each cell. More precisely, a pixel is assumed to be covered by water if $\text{NDVI} < 0.10$ and $\text{NDVI} < \text{LSWI}$, and it is considered to be a persistent water body if it was covered by water in 10 or more 8-day composite periods within the year. Natural evergreen vegetation areas are also omitted from the analysis to avoid confusing moist tropical regions and mangrove forests, which tend to have similar temporal flooding characteristics as paddy rice fields. In contrast to rice paddies, evergreen forests exhibit consistently high NDVI values throughout the year. Therefore, a pixel for which $\text{NDVI} \geq 0.7$ over at least twenty 8-day composites during the year was considered an evergreen forest. Since the NDVI forest restriction is a cumulative count, we used a gap-filled product that corrects NDVI values in the time series where clouds were present. In terms of evergreen shrublands and woodlands, one should note that these do not typically have exposed soils, contrary to

cropland during postharvest land preparation. Pixels with no $\text{LSWI} < 0.10$ throughout the year were thus considered to be natural evergreen vegetation and therefore not included. Cloudy pixels are removed by using the cloud quality pixel from MOD09A1, where pixels affected by clouds were replaced with a temporary fill interpolated from previous and next composites to obtain a complete time series. Finally, to detect the heading date of each field, we used the day of the maximum NDVI, following Wang et al. (2012).

c. Typhoon maximum wind speed (W_{ij})

The level of wind a field will experience during a passing typhoon depends crucially on that field's position relative to the storm and the storm's movement and features. It thus requires explicit wind field modeling. To calculate the wind speed experienced because of typhoons within each pixel, we use Boose et al.'s (2004) version of the well-known Holland (1980) wind field model. More specifically, the wind experienced at time t because of typhoon j at any point $P = i$, that is, W_{ij} , is given by

$$W_{ij} = GF \left\{ V_{m,jt} - S[1 - \sin(T_{ajt})] \frac{V_{h,jt}}{2} \right\} \left\{ \left(\frac{R_{m,jt}}{R_{it}} \right)^{B_{jt}} \times \exp \left[1 - \left(\frac{R_{m,jt}}{R_{it}} \right)^{B_{jt}} \right] \right\}^{1/2}, \quad (9)$$

where V_m is the maximum sustained wind velocity anywhere in the typhoon, T is the clockwise angle between the forward path of the typhoon and a radial line from the typhoon center to the pixel of interest, $P=i$, V_h is the forward velocity of the hurricane, R_m is the radius of maximum winds, and R is the radial distance from the center of the hurricane to point P . The remaining ingredients in (9) 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 storm, and the shape of the wind profile curve, respectively.

In terms of implementing (9), one should note that V_m is given by the storm-track data described below, V_h can be directly calculated by following the storm's movements between locations, and R and T are calculated relative to the pixel of interest $P = i$. All other parameters have to be estimated or assumed. For instance, we have no information on the gust wind factor G . However, a number of studies (e.g., Paulsen and Schroeder 2005) have measured G to be around 1.5, so we also use this value. For S , we follow Boose et al. (2004) and assume it to be 1. We also do not know the surface friction to directly determine F . However, Vickery et al. (2009) note that in open water the

reduction factor is about 0.7 and reduces by 14% on the coast and by 28% 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, whereas we use the parametric model estimated by Xiao et al. (2009) to derive R_{\max} .

d. Regression model

Given their relatively small size, provincial rice markets and production in the Philippines are unlikely to be independent, thus potentially inducing some spatial correlation in rice production and area harvested.⁶ Importantly, neglecting such spatial correlation in the dependent variable in a regression analysis can lead to biased and inconsistent estimates (see LeSage 2008). As is common, we employ a Moran's test as a first indication whether spatial correlation may be a feature of our data.

Another important aspect of our dataset is that it consists of what is commonly known as "panel data," that is, we have information about provinces over time. Importantly, this allows one to take account of unobserved factors that may be correlated with both the outcome variable—in our case, rice production—and the explanatory variable of interest, that is, the DA index, which could bias our estimated coefficient. More specifically, with panel data, this can be taken into account by either demeaning all variables or by including a set of unit-level (in our case, province-level) indicator variables. One should note that controlling for province-specific time-invariant unobservable effects means that the estimated coefficients are to be interpreted in terms of within provinces across time impacts rather than across provinces.

In some parts of our analysis, we distinguish between irrigated and rainfed rice production. One should emphasize in this regard that the satellite detection technique described in section 2 does not allow one to explicitly distinguish spatially between irrigated and rainfed rice fields. Thus in those regression models where we examine the impact of typhoons on these different agrisystem types, we assume that their distribution across space is similar to that of all rice fields within provinces. Under this assumption we can use the provincial-level destruction index as representative of the impact of typhoons on both rainfed and irrigated rice fields.

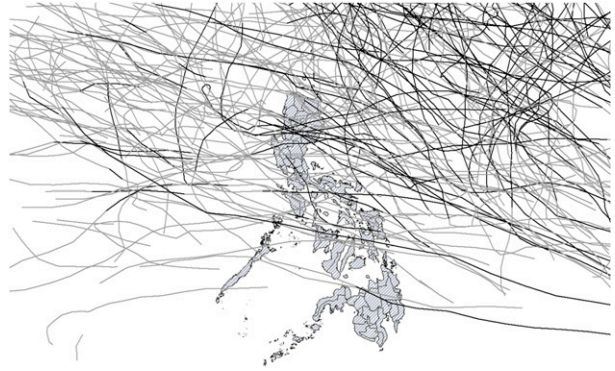


FIG. 1. Typhoon tracks during 2001–13.

In the context of potentially spatially correlated panel data, we employ a spatial panel data estimation model. In this regard, we employ a spatial Durbin model (SDM), which allows for spatially lagged dependent as well as independent variables:⁷

$$y_{it} = \alpha + \varphi \sum_{j=1}^n w_{ij} y_{jt} + \sum_{k=1}^K x_{itk} \beta_k + \sum_{k=1}^K \sum_{j=1}^n w_{ij} x_{jtk} \theta_k + \mu_i + \gamma_t + v_{it}, \quad (10)$$

and w_{ij} are the elements of an exogenously chosen spatial weight matrix of dimension $n \times n$, of which the diagonal elements are zero and the off-diagonal elements are the spatial weights. The quantity \mathbf{x} is a vector of K explanatory variables, μ are the province-specific unobserved time-invariant factors, γ are the time-specific effects, and v is an independent and identically distributed (iid) error term. An important component of the spatial model is of course the spatial weighting matrix. One popular option is a first-order contiguous neighbor matrix, where weights are equal to 1 if neighbors are contiguous of the first order and 0 otherwise. For the case of the Philippines, restricting the definition of neighbors to those that share common borders seems, however, overly restrictive, since there are a lot of provinces that are essentially neighbors but are separated by small bodies of waters (see Fig. 1). We thus opt for an inverse distance weighting matrix, where weights are defined as the inverse distance between the centroids of regions. One should note that significance of the estimated parameter φ indicates the presence of spatial correlation in the equation.

⁶ Allen (2014) shows that there is considerable trade in rice between provinces in the Philippines.

⁷ We also tested whether a spatial error model might be preferable to an SDM but found no evidence of this.

e. Risk analysis

One of the goals of our analysis is to use our estimates to provide an insight as to the probability of typhoon destruction on rice. In considering the probabilities of these losses, one should note that tropical cyclones are events that can take on extreme values, and thus their distribution function is by definition characterized by heavy tails. Tropical storms as extreme events have generally been studied using the peak over thresholds model (see, e.g., [Jagger and Elsner 2006](#)), and we here follow suit. The traditional approach in this regard, has been to fit a generalized Pareto distribution (GPD) to the data above a chosen threshold. However, as noted by [Scarrott and MacDonald \(2010\)](#), the weakness of the GPD threshold approach is that it does not take account of the uncertainty associated with the choice of threshold. As a consequence, a number of extreme value mixture models have been proposed, which encapsulate the usual threshold model in combination with a component capturing the nonextreme distribution, also known as the “bulk distribution.”⁸ Here we employ the parametric bulk model proposed by [Behrens et al. \(2004\)](#), which involves fitting a gamma model for the bulk distribution below the threshold and a GPD above it, where the components of the two distributions are spliced together at the threshold, which is treated as a parameter to be estimated.

3. Data

a. Typhoon tracks

Our source for typhoon data is the Regional Specialized Meteorological Centre (RSMC) Best Track Data, which has provided 6-hourly data on all tropical cyclones in the west Pacific since 1951. We linearly interpolate these to 3-hourly positions to be in congruence with our rainfall data described below. We also restrict the set of storms to those that came within 500 km of the Philippines and achieved typhoon strength (at least 119 km h^{-1}) at some stage within this distance.⁹ In all, a total of 116 typhoon-strength storms traversed the 500-km radius of the Philippines during our sample period of 2001–13. These storm tracks are shown in [Fig. 1](#), where the darker portion of the tracks indicates where the storms reached typhoon strength.

⁸ Despite their obvious advantages, a major drawback with regard to these newer models nevertheless persists, namely, that their asymptotic properties are still little understood.

⁹ Tropical cyclones generally do not exceed a diameter of 1000 km.

TABLE 1. Summary statistics for the top 10 most powerful storms.

Name	Max wind speed (km h^{-1})	Year	Month
Megi	230	2010	October
Haiyan	230	2013	November
Jangmi	215	2008	September
Jelawat	205	2012	September
Usagi	205	2013	September
Sepat	205	2007	August
Sanba	205	2012	September
Shanshan	205	2006	September
Songda	195	2011	September
Durian	195	2006	December

We also list the top 10 most powerful storms in terms of maximum sustained wind speed in [Table 1](#). As can be seen, the maximum wind speed varied from storms like Haiyan and Megi at 230 km h^{-1} to slightly weaker ones standing at 205 km h^{-1} such as Songda and Durian. One may want to note that most of these storms struck in the latter half of our sample period, with a mean year of 2009.

b. Provincial rice data

Rice data are taken from the Philippine Bureau of Agricultural Statistics Database (Philippine Statistics Authority; available online at <http://countrystat.psa.gov.ph/>). Production is available in total and disaggregated by agrisystem (i.e., rainfed or irrigated) on a quarterly basis at the province level. There are also data on area harvested, from which one can then calculate yields. Although these data series are complete, there were occasions where provinces and subregions of provinces were redefined over our sample period. To have a complete and consistent series, we grouped these together where appropriate. We therefore obtained a balanced panel of 78 provinces over our sample period. Summary statistics of our provincial quarterly production and area harvested data are given in [Table 2](#). As can be seen, the average quarterly rice production is around 50 000 tons, but with considerable variation. We also decompose the quarterly figures by agrisystem. Accordingly, on average, about 75% of production is from irrigated fields. The spatial distribution of rice production and rice yields presented in [Figs. 2](#) and [3](#)¹⁰ show that the rice production is not evenly distributed across provinces. Similarly, there are considerable differences in rice yields across the Philippines.

¹⁰ Since the spatial distribution of area harvested was not significantly different from production, we do not depict this graphically.

TABLE 2. Summary statistics of provincial quarterly data.

Variable	Unit	Mean	Std dev	Max	Min
Production—All	ton	49 501	79 829	783 939	0
Production—Irrigated	ton	37 141	63 099	677 885	0
Production—Rainfed	ton	12 359	26 447	370 683	0
Area harvested	ha	13 739	20 170	177 172	0
Yield	ton ha ⁻¹	3.4	0.8	6.2	1.1
WB	mm h ⁻¹	2.52	4.89	44.14	−6.04
RAD	W m ⁻²	407.0	34.93	292.5	455.9
TMIN	°C	20.2	1.13	15.7	22.6
TMAX	°C	32.5	1.36	27.5	36.3
RAIN	mm	7.0	4.5	0	49.8
DA	—	0.055	0.126	0.921	0
DA ≠ 0	—	0.098	0.155	0.921	3.11 × 10 ⁹

c. Weather

To control for climatic influences, we consider data on rainfall, water balance, temperature, and radiation. Since rainfall estimates from weather stations are not consistently available on a temporal scale or a spatial scale for the Philippines, we instead use the satellite-derived Tropical Rainfall Measuring Mission (TRMM) adjusted merged-infrared precipitation product 3B42, version 7 (Goddard Earth Sciences Data and Information Services Center 2015). These provide 3-hourly precipitation estimates at a $0.25^\circ \times 0.25^\circ$ spatial resolution. To derive the daily water balance for each rice pixel in our dataset, we use daily reference evapotranspiration (ET_o) data at $1^\circ \times 1^\circ$ resolution from the Famine Early Warning Systems Network (FEWS NET) global data portal (USGS 2015) and daily rainfall from the TRMM data to calculate the daily water balance during a rice field season WB, which is calculated as the difference between the two. We also extract minimum and maximum surface temperatures in degrees Celsius at $1^\circ \times 1^\circ$ resolution using data from the Berkeley Earth Surface Temperature (BEST) project (Rohde et al. 2013; NCAR 2015). Monthly solar radiation measured in watts per meter squared at $1^\circ \times 1^\circ$ resolution is obtained from the Clouds and Earth's Radiant Energy Systems (CERES) Energy Balanced and Filled (EBAF) project (Loeb et al. 2009; Loeb and NCAR 2014).

4. Results and discussion

a. Rice field detection

Given that one needs at least one year of previous observations to study the temporal variation of the indices outlined above, our period of rice field detection was limited to 2001–13. To this end, we found 1 539 881 different 500-m pixels that were occupied by rice paddy fields at some point in time over our sample period. The mean number of seasons was about 7, but

with considerable variability. As an example, we depict the rice fields identified in 2013 and the start of their growing season (in terms of quarter) in Fig. 4. There is considerable spatial variation of rice fields both across and within provinces, although all provinces have a nonnegligible portion of area dedicated to rice planting for at least some part of the year. Examining the

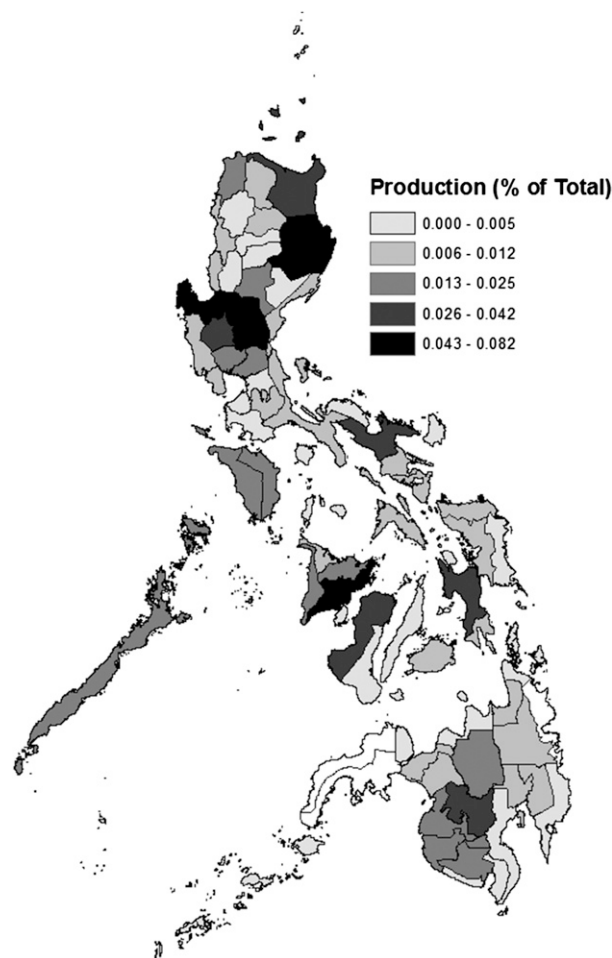


FIG. 2. Rice production by province for 2013.

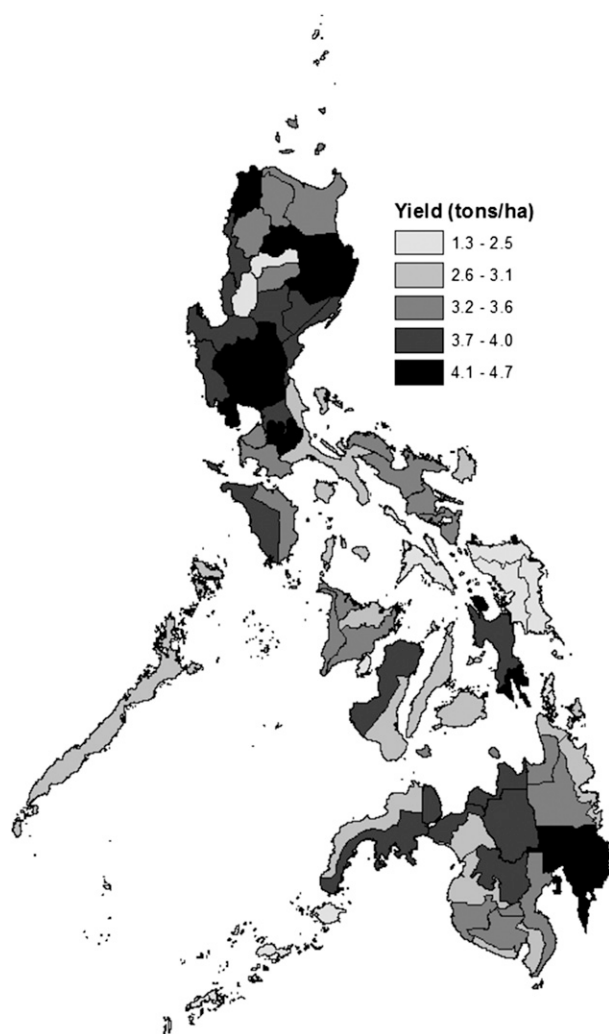


FIG. 3. Rice yields by province for 2013.

distribution of growing season onset, one can note that this also differs widely across as well as within provinces. This further justifies our use of local field detection methods to try to accurately capture potential damage when a typhoon strikes.

Of course, the reliability of our analysis will depend on the success of the outlined method in detecting rice fields. In this regard one should note that the algorithm is mainly designed for the identification of lowland rice rather than upland rice. In the Philippines, over 95% of rice is of the lowland variety, so that the lack of detection of upland rice paddies is unlikely to play a significant role (Xiao et al. 2006). However, Xiao et al. (2005) developed and verified their algorithm using field data from China, so that one may still wonder about its appropriateness for the Philippines. Reassuringly, a comparison between the satellite-detected fields with extensive local field data from 24 provinces in 2770

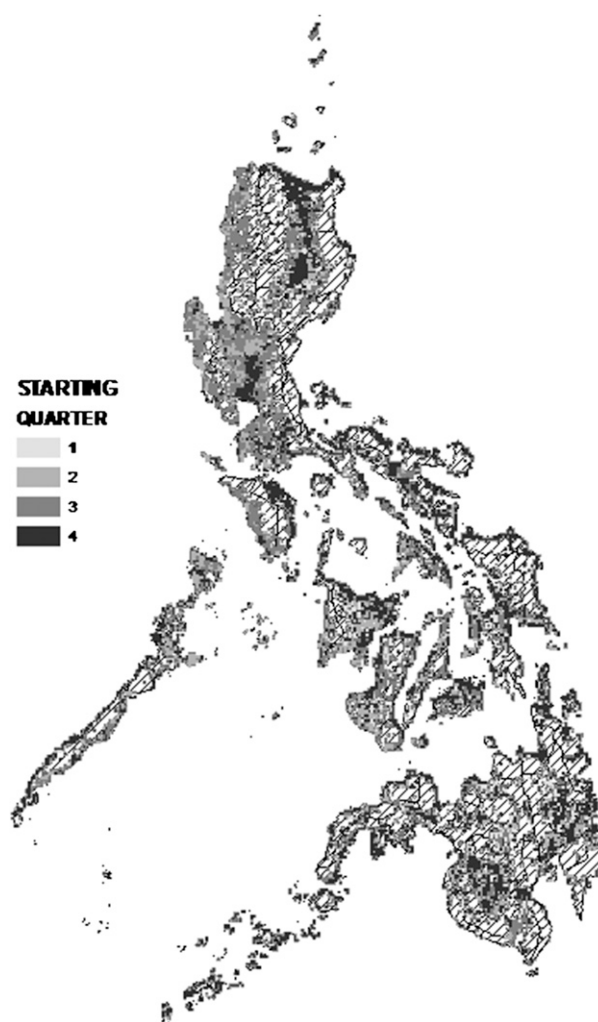


FIG. 4. Rice fields growth onset by quarter for 2013. Data are from rice field detection methods (see section 2), and hatching indicates no rice fields.

locations undertaken by the International Rice Research Institute (IRRI 2015) showed a nearly 80% accuracy rate for the Philippines. As an auxiliary check, we aggregated the area of rice fields across provinces and quarters over our sample period and compared these to quarterly provincial data on area harvested (see Fig. 5). Accordingly, there is a clear positive correlation between the two data series. As a matter of fact, regressing the area harvested on the satellite-detected rice field area produced an R^2 of 0.74. Considering all this evidence together, we are fairly confident that our satellite field detection procedure does not involve any excessive amount of measurement error.

b. DA index

We used data from sections 3a through 3c to construct our DA index for all typhoons since 2001. In doing so,

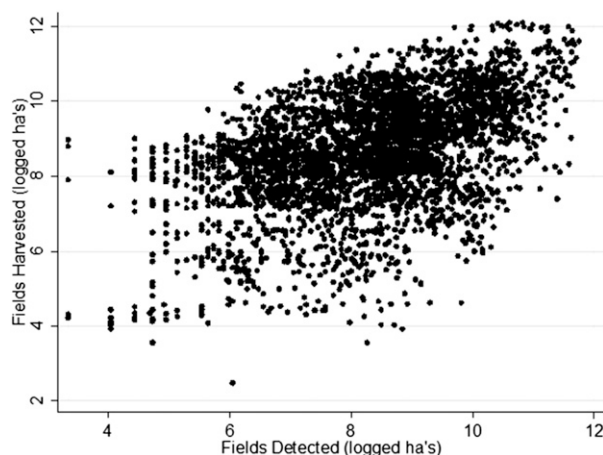


FIG. 5. Area harvested (hectares) vs rice field area detected (pixels).

we found that, out of the 116 typhoons that came within 500 km of the Philippines, 69 produced positive values of DA. According to the summary statistics in Table 2, the average quarterly value of DA was about 0.06; that is, potentially about 6% of rice fields were impacted by typhoons in every quarter since 2001. If we consider only those quarters where there was a nonzero potential damage, our index suggests that when a typhoon strikes it will affect about 10% of the rice fields on average per quarter. The largest potential destruction in any quarter was 92%: it occurred in the second quarter of 2013 in the province Siquijor and was due to Typhoon Utor.

One can also examine the value of DA for individual provinces and storms. For instance, the province that was on average most affected since 2001 was Kalinga (DA = 0.16), whereas the least impacted province was Tawi-Tawi. In terms of damage per storm, on average, the damaging storms over our sample period affected about 5% of rice fields per quarter. The most destructive cyclone for rice fields was Utor (total DA = 0.36),¹¹ whereas Typhoon Haiyan was the second most destructive typhoon in terms of rice fields (total DA = 0.26). One reason that Haiyan was less detrimental to rice than Utor despite being the stronger storm—a maximum wind speed of 230 km h^{-1} for the former versus 195 km h^{-1} for the latter—might be that Haiyan occurred at a time when most rice crops were already harvested.

¹¹ Utor struck the Philippines on 12 August 2013. It is estimated to have affected a total of 398 813 people and resulted in about \$24.8 million (U.S. dollars) in damages, primarily to the agricultural sector.

c. Regression results

As a first step, we conducted a Moran's test of spatial correlation for both rice production in each time period and found strong evidence of spatial dependence for all but two quarters. This supported our choice of using spatial panel methods to conduct our regression analysis. Our main regression results are given in Table 3. As can be seen, the spatial term is significant in all specifications,¹² thus confirming spatial dependence for provincial rice production. In terms of the actual estimated coefficients on the explanatory variables, however, one should note that when $\phi \neq 0$, the estimated parameters cannot be interpreted as marginal effects as in conventional linear models. Instead, the direct effect of a shock in an explanatory variable in a regional unit will not only affect that region's outcome variable directly, but may also have an indirect impact through feedback effects from its impact on other regions. The magnitude of this spillover effect will depend upon the position of the region in space, the degree of connectivity among region (as determined by the spatial weight matrix), the spatial parameter ρ measuring the strength of spatial dependence, and the magnitude of the estimated coefficient estimates θ and β . Given the difficulty in interpreting the estimated coefficients, we instead follow LeSage and Pace (2014) and calculate the marginal direct and indirect effects of our explanatory variables for all estimations undertaken.

In terms of specifications, we first estimated (10) with only the water balance variable WB, while also controlling for time-invariant province-level fixed effects as well as year and quarter indicator variables. The results in the first numbered column of Table 3, with only WB, indicate that there is a significant effect of water balance on rice production. In other words, greater net water availability in a region will increase rice production in the region itself. In contrast, there are no indirect impacts of water availability; that is, the water balance of other regions does not induce a change in a region's own rice production. In the second column, we next introduced our damage index DA. As can be seen, the coefficient on this variable is negative and strongly significant, suggesting that typhoons, by exposing rice fields to strong winds and excessive rain, reduce the production of paddy rice in the Philippines. As with water balance, however, we find no evidence of spillover effects from other regions. We further experimented with

¹² Throughout the text, we refer to significant coefficients as those for which the null hypothesis that the coefficient is zero can be rejected at least at the 5% level.

TABLE 3. Main regression results. The symbols ** and * depict 1% and 5% significance levels, respectively; standard errors are in parentheses. Dep. = dependent; Prod. = production.

Sample Dep. variable	1 All ln(Prod.)	2 All ln(Prod.)	3 All ln(Prod.)	4 Irrigated ln(Prod.)	5 Rainfed ln(Prod.)	6 All ln(Area)	7 All Yield	8 All ln(Prod.)	9 All ln(Prod.)
Direct									
WB _t	0.020** (0.006)	0.0199* (0.008)	0.004 (0.013)	0.006 (0.012)	0.241** (0.029)	0.011 (0.012)	−0.021 (0.040)	0.007 (0.011)	0.007 (0.011)
WB _{t−1}			0.075** (0.015)	0.052** (0.012)	0.081** (0.025)	0.075** (0.014)	−0.018 (0.018)	0.078** (0.016)	0.078** (0.016)
DA _t		−1.1352** (0.281)	−0.832** (0.233)	−0.856** (0.234)	−1.284* (0.617)	−0.777** (0.222)	−0.877 (0.587)	−0.879** (0.335)	−0.849** (0.319)
DA _{t−1}			0.316 (0.408)	0.467 (0.364)	−1.317 (0.790)	0.357 (0.381)	−0.176 (0.312)	−0.032 (0.210)	0.041 (0.164)
Indirect									
WB _t	0.000 (0.005)	0.002 (0.007)	0.008 (0.011)	0.001 (0.010)	0.015 (0.012)	0.009 (0.010)	−0.011 (0.028)	0.008 (0.009)	0.009 (0.009)
WB _{t−1}			−0.013 (0.008)	−0.006 (0.008)	−0.004 (0.011)	−0.014 (0.008)	0.016 (0.015)	−0.011 (0.009)	−0.011 (0.009)
DA _t		0.242 (0.202)	0.215 (0.168)	0.366* (0.175)	−0.418 (0.262)	0.248 (0.158)	0.312 (0.545)	0.256 (0.207)	0.212 (0.191)
DA _{t−1}			0.527 (0.341)	0.103 (0.224)	−0.052 (0.288)	0.451 (0.315)	0.101 (0.350)	0.177 (0.199)	0.229 (0.183)
Spatial ϕ	0.268** (0.001)	0.270** (0.004)	0.273** (0.005)	0.272** (0.004)	0.263** (0.001)	0.271** (0.005)	0.302** (0.005)	0.272** (0.005)	0.272** (0.005)
Observations	2808	2808	2808	2808	2808	2808	2808	2808	2808
R ²	0.03	0.04	0.04	0.04	0.15	0.05	0.002	0.04	0.04

including lagged values of our explanatory climatic variables. One now discovers that the effect of water balance is actually lagged rather than contemporaneous. This may not be surprising given that water as an input is particularly important during the flooding period of the fields and may thus not show up until a quarter after a field is likely to be harvested. Regarding the damage index, in contrast, it is shown that the effect is only contemporaneous. Again, considering when rice is most sensitive to typhoons (that is, in the heading stage, which occurs relatively late in the growing period), this result may not be too surprising. One may also want to note that when we include the lagged variables, we now also find that there is an indirect effect of DA on rice production. More specifically, the more damage a typhoon induces in spatially close regions, the higher the production in a specific region will be. Nevertheless, given that this result is only significant at the 5% level and that it is dependent on including a lagged value of DA, this result is to be considered with some caution.

Data at the provincial level also separate rice production into irrigated and rainfed cropping categories. The results of rerunning our specification including up to $t-1$ lags for irrigated and rainfed rice are shown in columns 4 and 5. For irrigated rice, results are similar to the overall sample: water balance has a lagged effect, while DA continues to have a negative and significant

contemporaneous impact. We again find that there is now an indirect, although not completely robust, effect of DA on rice production. Our results also suggest, unsurprisingly, that rainfed rice is much more sensitive to water balance, where we find both a contemporaneous and lagged impact, and the coefficients are relatively large. Similarly, as for irrigated rice, typhoons have a significant negative contemporaneous effect on rainfed rice production. Interestingly, the coefficient on this variable is about 33% larger for rainfed rice. However, in contrast to irrigated rice, there appear to be no indirect effects of DA. This may suggest that irrigation technology is better able to deal with the potential damage due to typhoons. For example, irrigation systems may be able to counteract the excessive flooding during a storm. Nevertheless, it must be kept in mind that our assumption about a similar spatial distribution of rainfed and irrigated rice fields may be introducing some measurement error in how well DA captures damage across these two types and thus driving the differences across agrisystem types.

We also experimented with other dependent variables. More specifically, since production is a function of both area harvested and yields, it would be insightful to see how these subcomponents might be affected by the storms. The results for (logged) area harvested, shown in column 6 of Table 3, indicate that the impact of

typhoons is similar to that of production, namely a negative contemporaneous effect. In contrast, for yields, as depicted in the last column, there is no significant impact of typhoons. Thus, overall our results indicate that the fall in production resulting from a typhoon is due to decline in area harvested rather than in a drop in yield.

Our DA index depends in part on the parameters a , b , c , k , and m estimated by Masutomi et al. (2012) based on Japanese data, which may not be exactly the same for the Philippines. As noted earlier, we do not have access to sufficient damage data to estimate these directly for the Philippines. As an alternative, we investigated how changing these parameters might change our estimated effect. More specifically, we calculated the index first using the 5% confidence band values of the estimated parameters and then the 95% confidence band values, as provided by Masutomi et al. (2012). The subsequent regression results are shown, respectively, in columns 8 and 9 of Table 3. As can be seen, for both regressions, the direct effect of DA remains statistically significant. Moreover, there is only a marginal difference in their size when compared with the index we used so far, thus suggesting that our estimates are not too sensitive to the chosen parameters, at least for values within a reasonable range.

Finally, we also tried including alternative climatic explanatory factors. Following Welch et al. (2010) and Zhang et al. (2010), we considered the effect of minimum and maximum temperatures (TMIN and TMAX), precipitation (RAIN), and radiation (RAD). Additionally, as inspired by Peng et al. (2004), we accounted for the codependent effect of temperature and insolation by including the interaction term $\text{TMIN} \times \text{RAD}$. Since there was generally no evidence of indirect effects, we only report the direct effects in Table 4. Similarly to results in Table 3, results regarding the other explanatory variables are consistent to our earlier specifications, namely that our damage index significantly reduces production and area, but that there is no effect on rice yields. For the other independent variables, we find that TMIN and RAD and their interaction term have a significant effect on rice yields, whereas TMAX is insignificant. An increase in minimum temperature is beneficial to rice yield when radiation is low but detrimental when it exceeds 393 W m^{-2} . Precipitation changes, however, have a negative effect on rice yields only. When considering the impact on production and area harvested, the effects of $\text{TMIN} \times \text{RAD}$ are inverse from the impact on yields and the lag variables are significant, suggesting an adaptation by farmer to weather conditions detrimental to rice productivity.

TABLE 4. As in Table 3, but for auxiliary regression results.

Sample Dep. variable	1 All ln(Prod.)	2 All ln(Area)	3 All Yield
Direct			
TMIN _{<i>t</i>}	−3.910* (1.647)	−4.589* (1.789)	0.394** (0.142)
TMIN _{<i>t</i>−1}	−8.881** (2.345)	−9.001** (2.364)	−0.321 (0.203)
TMAX _{<i>t</i>}	0.294 (0.187)	0.361 (0.197)	−0.031 (0.017)
TMAX _{<i>t</i>−1}	0.026 (0.099)	0.022 (0.103)	0.005 (0.015)
RAD _{<i>t</i>}	−0.197* (0.085)	−0.229* (0.092)	0.019* (0.007)
RAD _{<i>t</i>−1}	−0.429** (0.108)	−0.436** (0.110)	−0.015 (0.009)
RAIN _{<i>t</i>}	−0.306 (0.167)	−0.241 (0.173)	−0.066* (0.029)
RAIN _{<i>t</i>−1}	−0.154 (0.108)	−0.159 (0.147)	−0.021 (0.031)
TMIN _{<i>t</i>} × RAD _{<i>t</i>}	0.009* (0.004)	0.011* (0.004)	−0.001** (0.000)
TMIN _{<i>t</i>−1} × RAD _{<i>t</i>−1}	0.021** (0.006)	0.022** (0.006)	0.001 (0.004)
DA _{<i>t</i>}	−0.627* (0.247)	−0.675* (0.280)	−0.001 (0.037)
DA _{<i>t</i>−1}	−0.079 (0.452)	−0.076 (0.433)	−0.016 (0.036)
Spatial ϕ	0.279** (0.004)	0.282** (0.007)	0.277** (0.005)
Observations	2808	2808	2808
R ²	0.04	0.04	0.01

d. Quantitative significance

Our results can be used to determine the recent quantitative importance of typhoons for rice production in the Philippines. For instance, using the mean quarterly total production and our estimated coefficient from column 2, our estimates suggest that, on average, quarterly provincial losses were about 3090 tons over our sample period. This constitutes about 6% of the average provincial quarterly production of rice. Nationally, these losses sum to a median loss of about 46 000 tons per quarter, or a total of 12.5 million tons since 2001. More generally, it is important to note that the implied figures may not only account for damaged rice fields but could also capture other indirect negative effects, such as damage to infrastructure. Unfortunately, the lack of data on the latter aspect does not allow us to disentangle these other factors.

In terms of storm-specific damage, our estimates suggest that each storm has on average reduced rice production by 16 393 tons. In this regard, Typhoon Utor caused the largest damage, totaling about 448 000 tons, whereas, for example, Haiyan resulted in a reduction in

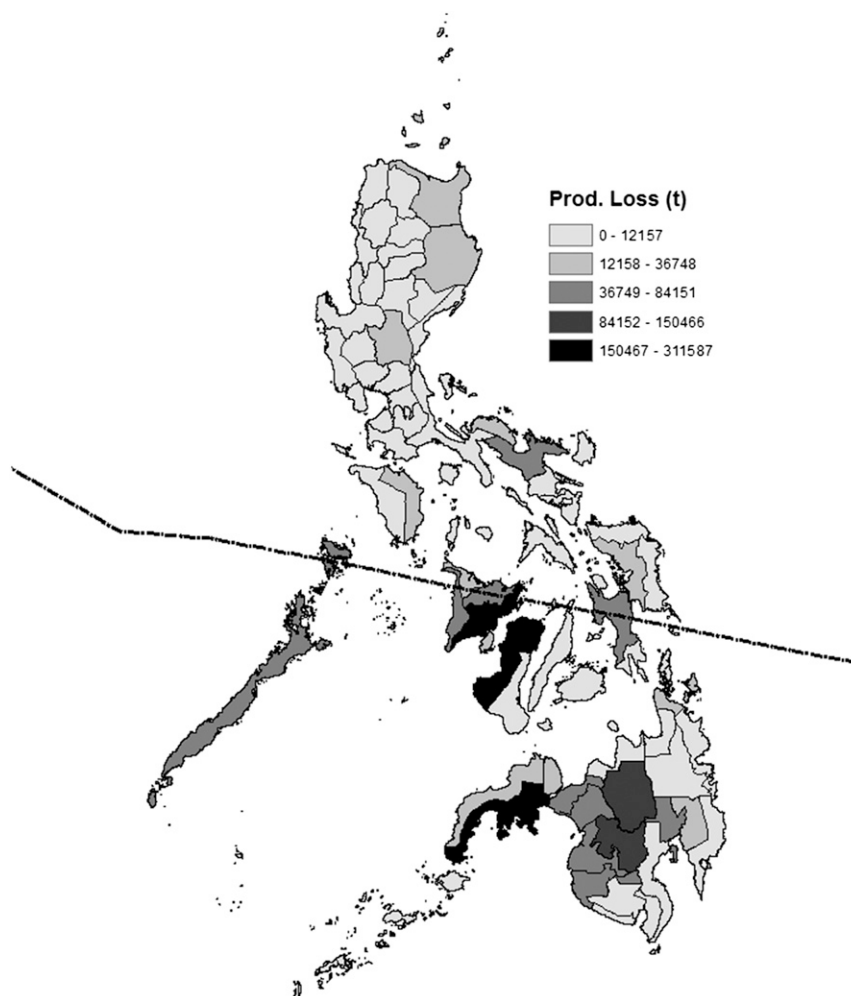


FIG. 6. Distribution of damage to rice (production loss) due to Haiyan. Data are derived from regression estimates (see [section 3](#)).

production of about 260 000 tons of rice. As an example of the regional distribution of losses, we depict the percentage of rice production lost due to Haiyan in [Fig. 6](#). Accordingly, much of the loss was in the southern part of the country.

In considering how the implied losses stand relative to what production could have been over time, it is important to realize that there have been considerable changes in production, area harvested, and yields over our sample period. More specifically, examining the aggregate data shows that production and yields have grown by 42%, 17%, and 22%, respectively, since 2001. Thus some of the losses in the earlier period may have been small in part also because yields were smaller. To take account of these changes in our loss estimations, we thus used the coefficient estimated from the sixth column of [Table 3](#) to calculate the implied loss in harvested area, and then converted this to the current

equivalent of production by using the average yields by province over 2009–13.¹³ This suggests that average losses might have been much greater if past yields had been as high as they are today. For instance, the average yield quarterly adjusted losses would have been 3325 tons, while the median quarterly and total national adjusted losses over our period would have been 49 000 and 1.3 millions of tons, respectively. We depict in [Fig. 7](#) these adjusted losses relative to potential production, which is measured as the average potential production in that quarter over our sample period. As can be seen, the quarterly impact varies considerably over our sample period, with relatively loss heavy

¹³ The assumption behind this approach is that rice farmers would have planted the same number of fields even if they could have benefitted from greater yields.

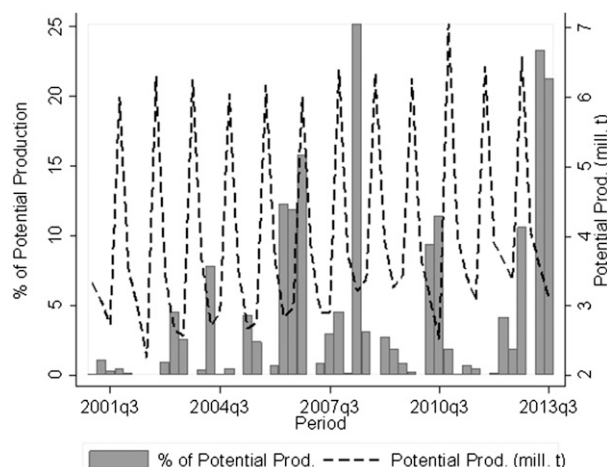


FIG. 7. Percent reduction in potential quarterly production. Data are derived from regression estimates (see section 3).

quarters in the years 2006, 2008, 2010, and 2013. The largest loss was estimated in the second quarter of 2008, where production was more than 25% below its potential.

One can also compare our results with other climatic shocks. More specifically, our estimated coefficients from the second column in Table 3 suggests that a negative shock to water availability—measured as one standard deviation below the mean—causes a reduction of quarterly rice production of 4818 tons. In contrast, the average damaging storm reduces rice production by 11 039 tons. If we take the effect of the lowest observed water balance value relative to the mean, and compare this with the largest provincial DA over our sample period, then the effects are 8440 and 103 520 tons, respectively.

e. Risk analysis

One can also use our results to provide an indication of the losses expected in the near future. To this end, we need to assume that weather, as it is relevant to the formation of typhoons, remains similar to the last 13 years, so that we can use historical data to predict future damage. In fitting the equation of the parametric bulk model of Behrens et al. (2004) to our implied losses from storms calculated earlier, the threshold was found to be 106 021 tons, while the shape and scale parameter were estimated as 0.289 and 113 142, respectively. We used these fitted parameters to estimate the return periods of typhoons inducing various levels of damage and depict these in Fig. 8. As can be seen, the return period increases with damage levels, although at a decreasing rate. For instance, one should expect a storm causing damages of about 150 000 tons every 5 years, whereas storms causing 400 000 tons are likely

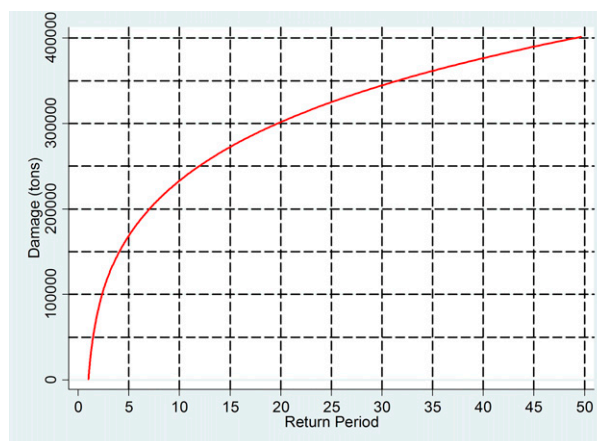


FIG. 8. Estimated return period of damages. Data are derived from risk analysis estimates (see section 3).

every 50 years. In this regard, Typhoon Haiyan was roughly a 1 in 13 year event. However, the accuracy of the return period prediction decreases considerably as one considers more extreme events. For instance, using bootstrapped errors from 500 samples of our data with replacement suggested that for damages of 57 000 tons—which our estimates suggests to be a 2-yr event—the 95% confidence interval was between 1.3 and 2.3 years. For 260 000 tons of damages, that is, a 10-yr event, the 95% confidence band was between 5 and 60 years.

5. Conclusions

We examined the impact of typhoons on rice production at the province level in the Philippines. To this end, we used satellite reflectance data to detect the location and growth phases of rice fields. We then employed typhoon-track data within a wind field model and gridded rainfall data within a fragility curve to drive a provincial rice damage index. Our spatial panel regression model results showed that typhoons have had a large significant impact on rice production, where national losses since 2001 are estimated to have been up to 12.5 million tons. Using extreme value theory to derive return periods under similar weather conditions to compare the relative differences between cyclones suggested that a storm like the recent cyclone Haiyan—estimated to have caused around production losses of 260 000 tons—is likely to recur every 10 years.

More generally, the methodology outlined here could serve Philippine policymakers in making rapid assessments of the likely losses soon after a typhoon occurrence, and therefore guiding their decision to import rice production to counteract the production shortages. This

technique would only require the use of publicly available satellite-derived information and the use of reasonably simple algorithms as employed here. As a matter of fact, the IRRI in the Philippines has already started using satellite data to detect rice fields and used these data to identify flooded areas after Typhoon Haiyan (IRRI 2013). Related to this, the methodology employed here could potentially be used as the underlying tool for introducing a rice insurance product where payouts are triggered according to a parametric index of typhoon-related damage. Again, the IRRI is in the process of introducing the Remote Sensing-Based Information and Insurance for Crops in Emerging Economies (RIICE) to help reduce the vulnerability of rice smallholder farmers in low-income countries globally. The approach here could be one way to incorporate tropical cyclone events as part of such an insurance product. Moreover, the need for such a damage assessment technique may be arguably increasing because of climate-change-induced altering patterns of tropical cyclones and possibly greater exposure due to economic growth in the future.

There are of course a number of aspects of the analysis that could benefit from further work. First, one would ideally like to estimate fragility curves specific to the Philippines. This would require a more comprehensive database of damage for individual cyclones. Second, it must be noted that we were not able to disentangle the effect of typhoons on rice production from other production-reducing factors, such as infrastructure. To isolate such aspects, one would require spatially detailed time series data for these factors.

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