Estimation of the damage area due to tropical cyclones using fragility curves for paddy rice in Japan

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Abstract
A method for estimating the area of crop damage due to tropical cyclones (TCs) by using fragility curves (FCs) is proposed. FCs, which represent the probability of damage caused by external forces, are one method considered appropriate for estimating structural damage caused by natural disasters. Here, FCs are applied to estimate the area of damage to paddy rice resulting from typhoons in Japan. The FCs for paddy rice are assumed to vary with growth stage. Statistical data on areas damaged by 42 typhoons that have struck Japan between 1991 and 2007, together with observed meteorological data, are used to derive the FCs. In general, our estimates agree with the reported areas of damage for the 42 typhoons, especially for typhoons that affected large areas of paddy rice. Moreover, from statistical data on crop damage due to typhoons, the proposed method successfully shows that the heading stage of paddy rice is the stage most vulnerable to typhoons, as found in earlier experimental studies and post-disaster investigations.

Keywords: tropical cyclone, damage area, fragility curve, paddy rice

1. Introduction

Tropical cyclones (TCs), which include tropical storms, severe tropical storms, typhoons, hurricanes and cyclones, have caused substantial damage to crops in parts of the world. For example, hurricane Katrina in 2005 decreased sugarcane production in Louisiana by 8.7% and the total economic damage to crops in the United States was estimated at $705 million (USDA 2005); cyclone Sidr in 2008 decreased aman rice production in Bangladesh by approximately 15%, and the total damage in the crop sector was estimated at $412 million (GoB 2008); and in 1991 typhoons Kinna and Mireille, together with severe tropical storm Luke, decreased paddy rice production in the Kyushu region of Japan by 11.8% (MAFF 1991–2007a, 1991–2007b). Hence, crop damage due to TCs is currently a significant issue in TC-prone regions.

A recent spate of severe TCs has raised public concern about a probable relation between TCs and global warming. Although it remains uncertain whether that relation holds for past decades, future projections based on theory and high-resolution dynamical models consistently indicate that global warming may increase the globally averaged intensity of TCs by 2–11% at the end of this century (Knutson et al 2010). Therefore, changes in crop damage due to TCs under global warming are of considerable concern to the scientific community, as well as to the public.

To understand these changes, it is necessary to develop a model for estimating crop damage due to TCs. However, no attention has been paid to estimating the area of crop damage resulting from TCs, and there have been only a few studies on the estimation of crop yield losses (Tsuboi 1961a, Moore and Osgood 1985, Iizumi et al 2008).
In contrast, in the field of civil engineering, there have been many studies on the estimation of damage to structures caused by natural disasters (e.g. Mitsuta 1997, Sill and Kozlowski 1997, Klawa and Ulbrich 2003, Watson and Johnson 2004), and changes in damage under global warming have also been estimated in a number of the studies (Leckebusch et al 2007, Pinto et al 2007, Schwierz et al 2010, Donat et al 2011). The majority of these studies have derived correlations between external forces and the amount of damage (or the probability of damage occurring) by using reports from post-disaster investigations or from available insurance claim data. Moreover, a component approach, which explicitly accounts for the resistance of various components to deformation and breakage within structures, has been presented (Pinelli et al 2004). In particular, a function relating external forces and the probability of damage is called a fragility or vulnerability curve (or function), and this function has been used in many studies on the assessment of damage (e.g. Mitsuta 1997, Sill and Kozlowski 1997, Khanduri and Morrow 2003, Calvi et al 2006, Li and Ellingwood 2006, Colombi et al 2008).

In this letter, a method that uses fragility curves (FCs) for estimating the extent of crop areas damaged by TCs is proposed. Specifically, FCs are derived and tested on paddy rice damage in Japan due to typhoons. Paddy rice, a staple of the Japanese diet, is affected by typhoons almost every year, largely because in Japan the growing season corresponds to the typhoon season. The average proportion of areas damaged between 1991 and 2007 was 9.6%, with a maximum of 29.1% in 1991. Hence, both current and future damage caused by TCs is a pressing issue in Japan.

2. Method and data

2.1. Model

2.1.1. FCs and estimation of damaged areas. An FC is represented by a cumulative distribution function describing the probability of TC damage as a function of the external force. The total area of paddy rice damage in Japan due to typhoons is estimated by applying an FC to each prefecture in Japan. Here, the damage area denotes the area in which yield decreases due to a typhoon. In this study, each FC is assumed to be a Weibull distribution, which is related to the failure rate. Thus, the FC for paddy rice damage by typhoons is

\[ \Pr_{ij}(I_{ij}) = 1 - e^{-\left(\frac{I_{ij}}{\lambda_{ij}}\right)^k}, \]

where \( \Pr_{ij} \) is the probability that damage is caused by intensity \( I_{ij} \) (m s\(^{-1}\)) of typhoon \( i \) in prefecture \( j \), and \( \lambda_{ij} \) and \( k \) are model parameters. The assumption that the FC can be represented by a Weibull distribution is discussed in section 3.1. The typhoon intensity is explained in section 2.1.2.

Note that typhoon damage to crops in the proposed model is the total damage caused by floods and strong winds. Strong winds often lead to the lodging, injury and stripping of organs of plants, in addition to inducing water stress due to enforced transpiration (Maki 1991). Furthermore, strong winds in coastal areas blow tides inland, which may result in salt damage to the crops. In contrast, floods can cause a decrease in photosynthesis and respiration (Hayakawa 1991). Typically paddy rice is unaffected by inundation, but continual submergence eventually begins to cause damage (Kubo 1990). Thus, crops are harmed through several processes. However, only the damage caused by the combination of these processes is considered in our study, because separate statistics are not available.

The two parameters of the Weibull distribution, \( \lambda_{ij} \) and \( k \), define the scale and shape of the distribution, respectively, and the parameters are related to the mean of the distribution, \( E_{ij} \):

\[ E_{ij} = \lambda_{ij} \Gamma \left(1 + \frac{1}{k}\right), \]

where \( \Gamma \) is a gamma function. According to equation (2), \( \lambda_{ij} \) indicates the resistance of paddy rice to typhoons for fixed distribution shape \( k \), since large \( \lambda_{ij} \) implies a low probability of damage. The resistance of paddy rice to environmental change is reported to vary with the growth stage (Welch et al 2010); in particular, resistance to strong winds and floods is reported to be lowest in paddy rice during the heading stage (Tsuboi 1961b, Yamada 1959, Funaba et al 1997). Thus, from these considerations, \( \lambda_{ij} \) is assumed to be a quadratic function—one of the simplest functions having a minimum or maximum—of the number of days between the day when the maximum wind speed is observed, \( WD_{ij} \), and the heading day of the rice, \( HD_{ij} \):

\[ \lambda_{ij} = a(wd_{ij} - HD_{ij})^2 + b(WD_{ij} - HD_{ij}) + c. \]

Here, \( a \) and \( b \) are model parameters. The sign of \( a \) signifies whether the distribution contains a day when the rice has maximum or minimum resistance to typhoon damage, and the values of \( a \) and \( b \) define the day when the rice attains this maximum or minimum. In addition, \( c \) is the value of \( \lambda_{ij} \) when \( WD_{ij} \) is the heading day. Note that so far four model parameters have been introduced: \( a, b, c \) and \( k \). Values for these parameters are statistically selected by the method explained in section 2.2. The assumption that \( \lambda_{ij} \) is a quadratic function is discussed in section 3.1.

Finally, the total damage area in Japan, \( EA_i \), attributed to typhoon \( i \) is calculated by using \( \Pr_{ij} \) and the area of paddy rice planted in prefecture \( j \) in year \( yr \), \( PA_{ij,yr} \):

\[ EA_i = \sum_j \Pr_{ij}(I_{ij})PA_{ij,yr}. \]

2.1.2. Typhoon intensity. In the proposed model, typhoon intensity, \( I_{ij} \), is expressed as a linear combination of the maximum normalized wind speed, \( W_{ij} \), and the accumulated rainfall, \( P_{ij} \) (mm):

\[ I_{ij} = lW_{ij} + mP_{ij}. \]

Here, \( l \) and \( m \) are translation parameters from the normalized wind speed and from the accumulated rainfall to typhoon intensity, respectively. In this study, \( l \) is set to be 1, because one parameter among \( l, m, a, b \) and \( c \) can be deleted in the
fraction of the exponential in equation (1). The value of m is statistically selected as explained in section 2.2.

In equation (5) absolute wind speeds are not used, since the values measured at wind stations represent only small regions around the stations. To exclude local dependency of measured wind speeds, normalized wind speeds are used. These normalized wind speeds are derived by dividing the absolute wind speed by the 98th percentile of wind speeds during the period 1991–2007 (Klawa and Ulbrich 2003).

Wind speeds averaged over 10 min are used for the calculation of normalized wind speeds. While gust wind speed, which is averaged over 3 s, might be considered more suitable for the estimation of typhoon damage, long-term observations of gust wind speed in Japan are limited and the measurement method was changed in 2007. Hence, the gust factors, which are the ratio between gust and average wind speeds, are also limited. Conversely, more stations have been observing 10 min averaged wind speeds using the same method for a number of years.

Moreover, Donat et al (2010) showed that little difference is found between damage estimated by normalized wind speeds calculated using gust wind speeds or wind speeds with large time resolution. This similarity in damage estimates is advantageous when data of gust wind speeds are not available, which often occurs (as in this study).

2.2. Parameter selection

2.2.1. Optimal model. The parameters a, b, c, k and m are statistically selected by minimizing the summation of the difference between reported, RA\textsubscript{i}, and estimated, EA\textsubscript{i}, areas of rice paddy damage in Japan for each typhoon \textit{i}. Hence, the objective function is

\[
\sum_{\textit{i}} |EA_{\textit{i}} - RA_{\textit{i}}|,
\]

and this is minimized by adjusting parameter values using the downhill simplex method (Nelder and Mead 1965). To avoid local minima, the method is repeated 10 000 times for different initial values of parameters, and the parameters producing the lowest value are selected. The estimation model parameterized by the above procedure will henceforth be called the ‘optimal model’. In the calibration, the majority of the 10 000 optimizations found parameters close to those of the optimal model. For RA\textsubscript{i}, actual data are taken for typhoons that caused damage to paddy rice in Japan between 1991 and 2007. Excluding typhoons for which individual damage areas are not reported and those for Okinawa Prefecture (the southernmost prefecture in Japan), because a different cropping system for paddy rice is used there, left the data on the 42 typhoons listed in table 1.

2.2.2. Model uncertainty. Generally, models have uncertainty due to factors that are not considered in their formulation. Quantifying model uncertainty is vital for users of a model and of estimates from a model. Uncertainty in the proposed model is quantified by using the bootstrap method (Efron 1979). First, new damage areas for the 42 reported data are produced by adding to each reported damage area individual samples extracted at random with a replacement from the residuals between the reported damage areas and those estimated by the optimal model. If the new damage area is negative, it is set to be zero. Then, the parameter selections described in section 2.2.1 are conducted once more using the new 42 damage areas to obtain a new parameter set. Repeating these procedures 1000 times, the model uncertainty is quantified by calculating the 95% confidence interval of each parameter.

2.3. Upscaling

\(W_{ij}, P_{ij}\) and \(WD_{ij}\) are prefectural meteorological inputs to the proposed model and, therefore, it is necessary to upscale the values measured at meteorological stations. The upscaling procedure for \(W_{ij}\) is as follows. First, wind speeds measured at various heights in stations are corrected to those at 2 m in height, by using the logarithmic wind profile (Kondo 2000) and the roughness length around stations (Kuwagata and Kondo 1990, 1991). Second, the corrected wind speeds are normalized by the 98th percentile values, as explained in section 2.1.2. Third, the normalized wind speeds are spatially interpolated into grid-cells at 0.1° × 0.1° (≈83 km²) from consideration of the spatial density of the stations (≈one station per 512 km²). To perform the spatial interpolations, the inverse of the distance from a grid-cell to each station is used to weight the interpolation, and only stations within a distance of 30 km from a grid-cell are used in interpolations (Seino 2008). For cases where no station is within 30 km, values for the nearest station are used. Fourth, the maximum value of the interpolated wind speeds is selected for each grid-cell during the period of typhoon \textit{j}. Here, a typhoon period starts when a grid-cell is entered by the circular region with radius twice that of the region of strong wind (over 15 m s\textsuperscript{−1}), and the period ends when the typhoon changes to a tropical depression. Note that observed wind speeds are used to define the typhoon period. Last, \(W_{ij}\) is obtained by taking the weighted average of the maximum interpolated wind speeds for all grids within prefecture \textit{j}, where the weight, \(PA\textsubscript{\textit{j},yr}\), is the planted area of each grid in year, \textit{yr}, in which typhoon \textit{i} occurs:

\[
PA_{\textit{j},yr} = GPA_{\textit{j}}RPA_{\textit{yr},\text{pref}} / \sum_{\textit{pref}} GPA_{\textit{j}} .
\]

Here GPA\textsubscript{\textit{j}} is the area of paddy rice planted in grid-cell \textit{j}, and RPA\textsubscript{\textit{yr},pref} is the reported area of paddy rice planted in prefecture (pref) in year (yr).

\(P_{ij}\) is obtained as follows. First, rainfalls observed at stations are spatially interpolated into grid-cells at 0.1° × 0.1°. Second, interpolated rainfalls during the period of typhoon \textit{i} for each grid-cell are accumulated. Last, \(P_{ij}\) is obtained by taking the weighted average of the accumulated rainfalls for all grids within prefecture \textit{j} in the same manner as the upscaling of wind speed. \(WD_{ij}\) is obtained as follows. First, the day is selected for each grid-cell on which the maximum wind speed is observed during the period of typhoon \textit{i}. Then,
Table 1. 42 typhoons used for parameter selection.

| International number<sup>a</sup> | Name   | Time of occurrence | Time of disappearance |
|----------------------------------|--------|--------------------|-----------------------|
| 9109                            | Caitlin | 9:00 on 24 July    | 21:00 on 30 July      |
| 9112                            | Gladys  | 9:00 on 16 Aug     | 9:00 on 24 Aug        |
| 9114                            | Harry   | 9:00 on 30 Aug     | 21:00 on 31 Aug       |
| 9115                            | Ivy     | 3:00 on 3 Sep      | 3:00 on 11 Sep        |
| 9121                            | Orchid  | 9:00 on 4 Oct      | 12:00 on 14 Oct       |
| 9210                            | Janis   | 3:00 on 4 Aug      | 12:00 on 9 Aug        |
| 9211                            | Kent    | 15:00 on 6 Aug     | 15:00 on 19 Aug       |
| 9217                            | Ryan    | 9:00 on 2 Sep      | 9:00 on 12 Sep        |
| 9311                            | Vernon  | 15:00 on 22 Aug    | 15:00 on 28 Aug       |
| 9313                            | Yancy   | 9:00 on 30 Aug     | 21:00 on 4 Sep        |
| 9426                            | Orchid  | 3:00 on 19 Sep     | 15:00 on 30 Sep       |
| 9512                            | Oscar   | 3:00 on 13 Sep     | 3:00 on 18 Sep        |
| 9514                            | Ryan    | 15:00 on 16 Sep    | 18:00 on 24 Sep       |
| 9606                            | Eve     | 15:00 on 14 July   | 15:00 on 19 July      |
| 9612                            | Kirk    | 3:00 on 6 Aug      | 9:00 on 16 Aug        |
| 9617                            | Violet  | 9:00 on 13 Sep     | 21:00 on 23 Sep       |
| 9709                            | Rosie   | 9:00 on 20 July    | 6:00 on 28 July       |
| 9711                            | Tina    | 15:00 on 31 July   | 18:00 on 9 Aug        |
| 9719                            | Oliwa   | 9:00 on 4 Sep      | 6:00 on 17 Sep        |
| 9810                            | Zeb     | 3:00 on 11 Oct     | 9:00 on 18 Oct        |
| 0003                            | Kirogi  | 15:00 on 3 July    | 6:00 on 9 July        |
| 0014                            | Saomai  | 21:00 on 2 Sep     | 15:00 on 16 Sep       |
| 0111                            | Pabuk   | 21:00 on 14 Aug    | 3:00 on 23 Aug        |
| 0115                            | Danas   | 9:00 on 4 Sep      | 15:00 on 12 Sep       |
| 0121                            | Haiyan  | 21:00 on 12 Oct    | 21:00 on 18 Oct       |
| 0213                            | Phanfone| 9:00 on 12 Aug     | 9:00 on 21 Aug        |
| 0215                            | Rusa    | 9:00 on 23 Aug     | 9:00 on 1 Sep         |
| 0221                            | Higos   | 3:00 on 27 Sep     | 15:00 on 2 Aug        |
| 0306                            | Soudelor| 15:00 on 13 Jun    | 0:00 on 20 Jun        |
| 0310                            | Etan    | 15:00 on 3 Aug     | 3:00 on 10 Aug        |
| 0314                            | Maemi   | 15:00 on 6 Sep     | 6:00 on 14 Sep        |
| 0404                            | Conson  | 3:00 on 7 Jun      | 18:00 on 11 Jun       |
| 0406                            | Dianmu  | 21:00 on 13 Jun    | 3:00 on 22 Jun        |
| 0421                            | Meari   | 3:00 on 21 Sep     | 9:00 on 30 Sep        |
| 0422                            | Ma-on   | 15:00 on 4 Aug     | 9:00 on 10 Aug        |
| 0423                            | Tokage  | 9:00 on 13 Oct     | 3:00 on 21 Oct        |
| 0511                            | Mawar   | 3:00 on 20 Aug     | 9:00 on 28 Aug        |
| 0514                            | Nabi    | 21:00 on 29 Aug    | 15:00 on 8 Sep        |
| 0613                            | Shanshan| 21:00 on 10 Sep    | 21:00 on 18 Sep       |
| 0704                            | Man-yi  | 9:00 on 9 Jul      | 9:00 on 16 Jul        |
| 0705                            | Usagi   | 15:00 on 29 Jul    | 15:00 on 4 Aug        |
| 0709                            | Fitow   | 9:00 on 29 Aug     | 9:00 on 8 Sep         |

<sup>a</sup> International numbers consist of four digits; the last two digits of the year followed by the two-digit serial number of the TC.

WD<sub>j</sub> is obtained by taking the weighted average of the selected days for all grids within prefecture <i>j</i> similar to the upscaling of the wind speed and rainfall.

2.4. Source data

Observational data on wind speeds and rainfalls are from the Automated Meteorological Data Acquisition System (AMeDAS) developed by the Japan Meteorological Agency (JMA 1991–2007). Wind speeds from AMeDAS stations that satisfy the two following criteria only are used to conduct the normalization and height correction: (1) observations were conducted since 1991 and (2) roughness length around the station was identified (Kuwagata and Kondo 1990, 1991). As a result, data from 738 stations are used for wind speeds, whereas data from 1553 stations are used for rainfall. For the tracks of the 42 typhoons, JMA’s ‘Best Track Data’ are used (JMA 2010).

For the reported area of damaged paddy rice (RA), the heading day (HD), and the planted area of paddy rice (RPA), values reported by the Ministry of Agriculture, Forestry, and Fisheries for the years of interest are used (MAFF 1991–2007a, 1991–2007b). Furthermore, the Numerical Information of National Land developed by the Ministry of Infrastructure, Land, and Transportation (MILT) provides 1 km gridded data for paddy rice areas, GPA<sub>j</sub>, for 1976, 1987, 1991, 1997, 2006 and 2010. The gridded data for 1997 (MILT 1997), roughly midway between 1991 and 2007, are utilized in the study. Note that the geographical distribution of paddy rice area did not significantly change between 1991 and 2007, although the total area growing paddy rice decreased by 17.9% during that period.
Note that infinite values of $\lambda$ is discussed next. Given $k$ the values of $\lambda$ calculated from the observed values of the damage area, wind formulation of $\lambda$ seen that the relation between the plotted no damage has occurred, are not plotted in figure 1. It can be seen that a minimum value for $\lambda$ exists, because the sign of $a$ is positive, implying that the rice has a development stage most vulnerable to typhoons. To ascertain the dependence of paddy rice vulnerability on its development, a curve showing $\lambda$ calculated from equation (3) using the optimal model parameter values is given in figure 1. The $\lambda$ values over several days around the heading day are lower than at other growth stages, and the rice has highest vulnerability 2.2 days after the heading day. However, the uncertainty for this day is large, since from table 2 the 95% confidence interval of $b$ is significantly larger than its median. In consideration of the uncertainty of $a$ and $b$, the 95% confidence interval for the most vulnerable day is in the interval (−6.47, 7.33) days, either side of the heading day. Hence, it can safely be said that the heading stage of paddy rice is the stage with the highest vulnerability to typhoons even accounting for model uncertainty. Note that this relation could be derived from statistics on damage data by using the optimal method, whereas similar relations were suggested by earlier research in which experimental studies and post-disaster investigations were conducted (Tsuboi 1961b, Yamada 1959, Funaba et al 1992). Tsuboi (1961b) reported that paddy rice is most vulnerable to strong winds for several days about a week before the heading day, while Yamada (1959) stated similarly for floods about a week after the heading day, whereas according to Funaba et al (1992) paddy rice is susceptible to typhoon damage in the days just after the heading day. That the heading stage poses the greatest risk to damage provides useful information for making adaptive policies; if the rice heading stage is shifted away from typhoon season by adjusting the planting day and variety, the area of typhoon damage can be minimized under current and future conditions.

Note that the above results strongly depend on our formulation of $\lambda$ (equation (3)); therefore, the formulation is discussed next. Given $k$ and $m$ from the optimal model, the values of $\lambda$ for each prefecture and each typhoon can be calculated from the observed values of the damage area, wind speed and rainfall, using equations (1) and (5). In figure 1, the values of $\lambda$ calculated using the above method are plotted. Note that infinite values of $\lambda$, which are found in cases where no damage has occurred, are not plotted in figure 1. It can be seen that the relation between the plotted $\lambda$ and the growth stage is approximately quadratic, and the derived curve from equation (3) agrees well with the plotted $\lambda$. In this study, a quadratic equation was assumed for $\lambda$, since a quadratic is one of the simplest functions to have a maximum or minimum value. Replacing this quadratic with a higher-order equation for $\lambda$ may be a good starting point for improving the proposed model in the future.

Next, the assumption that the FCs can be represented by Weibull distributions is discussed. Figures 2(a)–(e) show the FCs for paddy rice at different growth stages: WD–HD = −60, −30, 0, 30 and 60, respectively. The reported ratios between damaged and crop areas for each prefecture and each typhoon are also plotted for growth stage ranges: WD–HD = 75 to 15, 15 to 45, and 45 to 75 (corresponding to (a)–(e), respectively). It can be observed that the reported data are approximated by the derived FCs. However, the plotted values are spread around the derived FCs. Therefore, use of functions similar to the Weibull distribution (e.g. a lognormal function) may also be possible. Furthermore, figure 2 shows that no plots in (a) and only a few plots in (e) exist for $I > 2.0$. Therefore, the resulting FCs are not compared for strong typhoons in periods far from heading day and this is a limitation of the proposed method. One may have concerns about changes in selected values of parameters when the parameter selection is conducted only for typhoons with $I < 2.0$, where FCs can be compared with reported damage for all growth stages. Selected values of parameters for the restricted model are listed in table 2; a curve of $\lambda$ and FCs for the restricted model are shown in figures 1 and 2, respectively. Note that the value of $m$ for the restricted model is given from the optimal model. It can be seen that the curve

### Table 2. Optimal model value, median, 95% confidence interval and restricted model value for each parameter.

| Parameter | Optimal model | Median | 95% confidence interval | Restricted model |
|-----------|----------------|--------|-------------------------|-----------------|
| $a$       | 0.000 1757     | −0.000 7692 | (0.000 1164, 0.000 339) | 0.000 1809     |
| $b$       | 2.007          | 6.725   | (1.898, 2.183)          | −0.001 9287    |
| $c$       | 2.011          | 6.763   | (5.072, 10.177)         | 1.690          |
| $k$       | 0.001 283      |         | (0.000 025, 0.002 848)  | 12.0698        |
| $m$       | 0.001 283      |         |                         |                 |

#### 3.1. Calibration of FCs

Table 2 shows the parameter values selected for the optimal model, in addition to the median and 95% confidence interval for each parameter. It can be seen that a minimum value for $\lambda$ exists, because the sign of $a$ is positive, implying that the rice has a development stage most vulnerable to typhoons. To ascertain the dependence of paddy rice vulnerability on its development, a curve showing $\lambda$ calculated from equation (3) using the optimal model parameter values is given in figure 1.
Figure 2. Relation between damage area ratios and typhoon intensity for different growth stages (WD–HD = (a) −75 to −45, (b) −45 to −15, (c) −15 to 15, (d) 15 to 45, and (e) 45 to 75). Curves indicate derived FCs for different growth stages (WD–HD = (a) −60, (b) −30, (c) 0, (d) 30, and (e) 30). Thick lines denote FCs for the optimal model; thin lines denote FCs for the restricted model. Plotted points indicate reported ratios between damaged and crop areas for each prefecture and each typhoon. Ratios over 1.0 in (c) and (d) are attributed to errors in reported damaged or planted areas.

Figure 3. Comparison between EA and RA for 42 typhoons. Dashed line indicates $y = x$.

Lastly, table 3 summarizes calculated ratios between the damage areas and planted areas as a function of the growth stage (WD–HD) and typhoon intensity ($I$). The parameter values of the optimal model are used to derive the values in table 3, where missing values indicate that the calculations are beyond the limits of the proposed method. The damage area ratio is strongly dependent on the typhoon intensity and growth stage at which a typhoon hits. Paddy rice begins to be damaged when a typhoon’s intensity is higher than 1.

3.2. Validation

Now, the ability of the proposed method to estimate damage areas is assessed. Figure 3 shows a comparison between reported damage areas (RAs) and the areas estimated by the optimal model (EAs) for the 42 typhoons. It can be seen that EAs typically reproduce RAs, and this is quantitatively confirmed in table 4, which lists the average error between RA and EA for different ranges of RA. In particular, the error for typhoons with damage areas over 100,000 ha is small at 16.8%, and the average for damage areas between 20,000 and 100,000 ha is below 50%. Hence, the proposed method can give highly accurate estimates of damage areas for large typhoons. In contrast, the average error for areas below 10,000 ha is over 100%. These large errors are attributed to the minimization method employed in this study in which the ‘absolute’ error averaged over all typhoons is minimized. Therefore, ‘fractional’ errors for typhoons with small RA will inevitably become large.

Next, the predictive ability of the proposed model is assessed by using the leave-one-out method. In this method,
Table 3. Damage area ratios as a function of growth stage (WD–HD) and typhoon intensity (I). Parameter values of the optimal model are used in the calculation. (Note: ‘—’ denotes beyond the limits of the proposed model.)

| WD–HD | −75 | −60 | −45 | −30 | −15 | 0 | 15 | 30 | 45 | 60 | 75 |
|-------|-----|-----|-----|-----|-----|---|----|----|----|----|----|
| I     | 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00|
| 0.25  | 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00|
| 0.50  | 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00|
| 0.75  | 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00| 0.00|
| 1.00  | 0.00| 0.00| 0.00| 0.00| 0.01| 0.01| 0.01| 0.01| 0.00| 0.00| 0.00|
| 1.25  | 0.00| 0.01| 0.01| 0.02| 0.03| 0.04| 0.04| 0.03| 0.02| 0.01| 0.00|
| 1.50  | 0.01| 0.02| 0.04| 0.08| 0.11| 0.13| 0.12| 0.09| 0.05| 0.02| 0.01|
| 1.75  | 0.02| 0.05| 0.11| 0.29| 0.33| 0.30| 0.23| 0.14| 0.07| 0.03|
| 2.00  | —   | —   | 0.26| 0.42| 0.56| 0.62| 0.59| 0.47| 0.30| 0.16| 0.07|
| 2.25  | —   | —   | 0.48| 0.70| 0.84| 0.88| 0.86| 0.75| 0.55| 0.32| 0.15|
| 2.50  | —   | —   | 0.73| 0.91| 0.98| 0.99| 0.98| 0.94| 0.80| —   | —   |
| 2.75  | —   | —   | —   | —   | 1.00| 1.00| 1.00| —   | —   | —   | —   |
| 3.00  | —   | —   | —   | —   | 1.00| 1.00| 1.00| —   | —   | —   | —   |

Table 4. Average error difference, PE and MU for different RA ranges.

| Range of RA (ha) | Average error (%) | Average PE (%) | Average MU (−) | Samples |
|------------------|-------------------|---------------|---------------|---------|
| <5000            | 327.9             | 328.6         | 3.17          | 7       |
| 5000–10000       | 126.5             | 126.8         | 2.21          | 5       |
| 10000–20000      | 81.3              | 88.6          | 1.91          | 8       |
| 20000–50000      | 40.6              | 52.5          | 1.26          | 7       |
| 50000–100000     | 29.9              | 36.1          | 0.75          | 10      |
| >1000000         | 16.8              | 22.1          | 0.34          | 5       |

the reported data for one typhoon are removed, and the damage area for this typhoon is then estimated for comparison by using the optimal model resulting from the remaining data. The procedure is conducted for all 42 typhoons. The error between the reported and estimated damage areas is the ‘predictive error’ (PE), and the average PEs for different RA ranges are shown also in table 4. Average PEs for typhoons with large damage areas of over 50 000 ha are small at below 40%, showing that the proposed model can predict damage areas for typhoons causing large damage.

Finally, the uncertainty in the estimation of damage areas is useful information to know. To this end, damage areas are estimated by using 1000 parameter sets obtained by the bootstrap method. Figure 4 shows a histogram of the frequency of estimated damage areas for typhoon 9313 that had the largest damage area. The probability that the damage area is from 325 000 to 350 000 ha is over 50%. Thus, probabilistic information for estimated damage areas is obtained by considering model uncertainty. Moreover, to quantify the magnitude of the uncertainty for the 42 typhoons, the ratio between the 95% confidence intervals and the medians, ‘MU’, is calculated and the averages MUs for different RA ranges are listed in table 4. It can be seen that the larger RA, the smaller is MU. Thus, model uncertainty is not significant for typhoons with large damage areas.

### 4. Conclusions and future challenges

A method to estimate the area of crop damage due to TCs by using FCs was proposed, taking paddy rice damage in Japan due to typhoons as an example. It was shown that the proposed model has the ability to estimate damage areas with high accuracy, especially for typhoons damaging large areas. In addition, derived curves showed that the heading stage of paddy rice is the stage most vulnerable to typhoons.

A future challenge is to combine the proposed method with TC simulations in order to predict the area of crops that will be affected by a TC under expected global warming conditions. In addition, present the applicability of the proposed method to other crops and regions is unknown.
and this should be addressed. The method was devised for estimating total damage in Japan; however, regional estimates are also considered essential even though additional long-term statistics on damage areas would be necessary to achieve this. As shown in figure 2, uncertainty still exists in the selection of the distribution of FCs. Therefore, various types of distributions must be examined for FCs, as well as non-parametric methods.

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