Long-Range Violent Typhoon Forecasting: A Machine-Learning Approach

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Abstract

The enormous devastation caused by typhoon Haiyan (2013) led us to consider recent Japan Meteorological Agency (JMA) violent typhoons (sustained wind speeds of at least 105 knots) as a special category of research. Using JMA best-track data for the years 2009-2013 as training data, we construct a quasi-operational MATLAB machine learning model which uses best track data for the first 24 hours of an emerging tropical storm as predictors, and has the storm category, as well as a latitude, longitude, and maximum sustained wind speed as responses. The model is trained using 2009-2014 best track data, and validated by quasi-operational ("hind-casting") of 2015-2017 best tracks. Prediction error is reported as a confusion matrix for the category of the storm. and in comparison with a baseline climatological regression model for violent typhoon position and maximum wind speed errors.

Keywords JMA best track, MATLAB machine learning model, confusion matrix, regression model

1. Introduction

The enormous devastation caused by typhoon Haiyan (2013) led us to consider quasi-operational prediction ("hindcasting") of JMA Grade 5 violent typhoons (maximum sustained wind speeds of at least 105 knots or 194 km/hr) as a special category of research. As has been the case for decades (Epstein 1969; Hope and Neumann 1970; Leith 1974; Anthes 1982; Krishnamurti et al. 1991; Wu and Emmanuel 1993; Elsberry 1995 and Leslie et al. 1998), in recent years, understanding of physical processes (Chan, 2005; Cap 2006; Rozanova et al. 2010; Yanase et al. 2010 and Yang et al. 2012) combined with advanced numerical, statistical ensemble and other data assimilation methods (Krishnamurti et al. 1999; Williford et al. 2003; Weber 2005; Meng et al. 2007; Chan 2010; Cecelski et al. 2014; Chang et al. 2014 and Higaki et al. 2015) have resulted in steady improvement of operational typhoon forecasting (Korean Meteorological Administration 2013 and Japan Meteorological Agency 2015). At the same time, sensitive dependence on initial conditions (Lorentz 1963, 1965; Kamaromi et al. 2011; Yamaguchi et al. 2012 and Chang et al. 2014) and 'busted cases' with large track position errors (Ito and Wu 2013), have kept the door open for new approaches to improve both operational and no-skill baseline long range typhoon forecasting models. In this study, a MATLAB machine learning model (MMLM) built from best track data for the first 24 hours of a tropical storm as predictor variables, and the category of the storm, as well as location and maximum wind speed as responses,

In developing a new model for this special category of research, we considered only best track data for the years 2009-2016 published by the Japan Meteorological Agency (JMA 2009-2016) which is downloadable at http://www.jma.go.jp/ jma/jma-eng/ jma-center/ rsmc-hp-pub-eg/trackarchives.html. Data for the years 2009-2013 were used to train the model, and 2014-2016 to test the model. A confusion matrix is used to analyze error in quasi-operational storm category predictions. For the position and maximum wind speed, we considered only the violent typhoon category for which the MML model response was compared to a multiple linear regression (MLR) model developed in an earlier stage of this project.

In Section 3 we describe an MLR model for long-range violent typhoon predictions. We identify each violent typhoon by a three coordinate *genesis point* (GP) (latitude, longitude, pressure) giving the respective JMA best track point latitude, longitude and central pressure values at time $t = 0$. We require a genesis point to have a recorded best track wind speed of 0 since wind speed is not one of the GP coordinates. The best track of each violent typhoon must have at least one *violent point* whose coordinates (time, latitude, longitude, pressure, wind speed) are the respective time (in hours), latitude, longitude, central pressure (in hPa) and sustained maximum wind speed (in knots) best track values at any time point when the storm's maximum wind speed is at least 105 knots. A *most violent point* (MVP) of a storm is defined to be any violent point with highest sustained maximum wind speed among the storm's violent points. Our goal was to create a simple 'GP/MVP' multiple linear regression model, meaning one which uses just a storm's GP to predict an MVP under the assumption that the storm becomes violent.

A default GP/MVP model is introduced, one which uses data for the seven violent typhoons between 2009-2012 to 'hindcast' MVPs of the 5 violent typhoons in 2013. To check robustness of the default GP/MVP model, 2010-2013 data was used to predict MVPs of the 4 violent typhoons in 2014. In Section 3, we explain how an annual average predicted MVP track position error (EGP) compared favorably with a related JMA PER model error EP. In Section 4, strategies are introduced to reduce EGP by filtering the data used in regression. Monte Carlo simulation is used to assess the likelihood the EGP error was achievable by chance rather than information contained in past violent typhoon data.

Multiple regression based typhoon models are of course far from new. They were introduced over 50 years ago (Arakawa 1964) and later employed in both climatology persistence (CLIPER) and statistical typhoon intensity prediction (STIPS) models (Neumann 1972; Knaff et al. 2005 and Jin 2008). The real-time availability of global weather data together with super computer execution of physics-based models used in current operational typhoon prediction has in general relegated statistically-based position forecasts using past climatological records to 'no-skill' baseline predictions. Position errors in climatological models serve as a baseline for prediction accuracy and an indicator of the relative difficulty in forecasting a particular storm. Improvement of the baseline 'no-skill' forecast motivates improvement in operational forecasting. The GP/MVP model uses only initial ($t = 0$) latitude, longitude and pressure as predictor variables and so is simpler than the National Hurricane Center's (2009) CLIPER5 model, another multiple regression based climatology model for predicting typhoon position first developed in 1972 and extended in 1998 to provide forecasts out to 120 h (5 days). CLIPER5 uses more input variables than GP/MVP. In addition to initial intensity, variables including latitude, longitude, date, and movement in the past 12 and 24 hours are based on evolving rather than solely genesis point data. CLIPER5 is also used to predict entire storms of any intensity rather than just MVPs of violent typhoons. Whereas CLIPER5 is used as a baseline to evaluate the skill of an operational forecast, the GP/MVP model offers a new early warning data point not currently provided by operational forecasting.

Since the GP/MVP model uses only initial data (time $t = 0$), it offers a different type of prediction than the physics based operational models which depend on continuous updates to evolving local and global weather conditions. Moreover, GP/MVP forecasting requires only extremely small violent typhoon data sets and the simplicity of the default linear regression model makes GP/MVP forecasting easily adoptable as a new information point in early-warning operational typhoon forecasting.

1.1 The Default GP/MVP Model

We begin by considering the color-coded 3 dimensional data visualization of 2009-2012 JMA grade 5 typhoon best track data shown in Figure

1. Best track latitude, longitude and pressure (in hPa) are used for the geometric coordinates, and maximum sustained wind speed (in knots) is represented by color. The JMA best tracks begin at $t = 0$ at which time the wind speed is usually recorded as 0. We call these points *genesis points* (GPs) and they appear in dark blue. Since the terminal best track points also have wind speeds recorded as 0, the dark blue points form two clusters, with genesis points in the right cluster and terminal points clustered towards the left. Points in between the genesis point and terminal point are separated by 6 hour time intervals. Since pressures are highest at the beginning and end of the best track, all the dark blue points appear in the top layer of the scatter plot's "funnel". The light green and yellow layers in the funnel correspond to typhoons (63-84 knots), the orange layer to very strong typhoons (85-104 kts), and the red layer to violent typhoons ($\geq$105 kts). Violent points (wind speeds at least 105 kts) appear in the red layer at the bottom of the funnel. Figure 2 gives a 2 dimensional representation of these violent points. Note in particular the confinement of violent points to a relatively small geographic region. Fig. 1

A special type of violent point called a most violent point (MVP) is a point(s) in a typhoon's best track which has highest maximum wind speed among the violent points. A violent typhoon may have multiple MVPs as shown in Table 1 which specifies the genesis, violent, and most violent points of the 7 violent typhoons in the years 2009-2012. For the purpose of using just a storm's genesis point (GP) data to predict a most violent point (MVP) by means of multiple regression, the fact that the funnel nar- Fig. 2

rows from the top layer towards the bottom layer in Figure 1, and similarly, the confinement of violent points in Figure 2, is important to achieving reasonable position accuracy.

We consider a multiple linear regression model in which the genesis point latitude (x_1), longitude (x_2) and pressure (x_3) coordinates serve as the predictor variables and the dependent variables are the five coordinates of an MVP, namely time (y_1), latitude(y_2), longitude (y_3), pressure (y_4), and wind speed (y_5). Regression coefficients using the violent typhoon data in Table 1 are shown in Table 2A. Table 1

Denote the 2009-2012 violent typhoon data regression coefficients for latitude $\alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3) = (-708.14, -.254, .167, .699)$ and the regression coefficients for longitude $\beta = (\beta_0, \beta_1, \beta_2, \beta_3) = (-1827.084, -.799, 1.033, 1.807)$. Given only the genesis point (lat_0,lon_0,pressure_0) of a violent typhoon in 2013, the default regression model hindcasts the latitude and longitude of an MVP as

$$\begin{aligned}\text{Predicted MVP latitude} &= \alpha_0 + \alpha_1 \text{lat}_0 + \alpha_2 \text{lon}_0 + \alpha_3 \text{pressure}_0, \\ \text{Predicted MVP longitude} &= \beta_0 + \beta_1 \text{lat}_0 + \beta_2 \text{lon}_0 + \beta_3 \text{pressure}_0.\end{aligned}$$

Table 2

In a similar way, the time, maximum sustained wind speed and central pressure of an MVP can be predicted from just the genesis point for a total of $4 \cdot 5 = 20$ regression coefficients. For example, for Utor, the genesis point is given by

$$(\text{lat}_0,\text{lon}_0,\text{pressure}_0)=(12.1,136.6,1008),$$

and the default regression model predicted MVP is

$$\text{(time,lat,lon,pressure,wind speed)=}$$
$$(130.3\text{(h)},16.6^o,126.1^o,898.9\text{(hPa)},114.9\text{(kts)}).$$

We call this method of predicting a storm's MVP from its GP the *(default) GP/MVP model*.

1.2 MLR Error Analysis

In constructing and improving the default GP/MVP model, we focus on the position error of the predicted MVP. To this end, we used the mathematical concept of distance between a point P and a finite set of points S, namely, the minimum distance between P and the points in S (Figure 3). We define the position error in predicted MVP as the distance between the point P=(Predicted MVP latitude,Predicted MVP longitude) and the set S of actual MVPs for the storm being predicted. Table 3 gives these prediction errors for 2013 MVPs. Figure 3 Table 3

Minimization of the average predicted MVP position error EGP for violent storms in a given year guided development of the GP/MVP model. EGP was compared to JMA's EP (corresponding JMA no-skill PER model baseline error) and EO (average operational forecast position error) for the day closest to the time coordinate of the MVP used in computing the position error. For example, if the time of the actual MVP was 78 hours, we used the EO and EP 72-h (3 day) average position forecast error as comparisons. The default model EGP error of 835.6 km for 2013 was deemed reasonable since it fell between the EO average error of 314.6 km and the EP average error of 850 km.

To check model robustness, we compiled 2010-2013 violent typhoon data for the regression, and analyzed the 2014 MVP predictions. The violent typhoon Genevieve was excluded from analysis since a genesis point was not given (a positive wind speed was reported at $t = 0$). The 2014 EGP error of 680.75 km again fell between the average EO error of 384.75 km and the average EP error of 1332.15 km (Table 3).

Though our focus was on minimization of position error, Table 3 also reports the average wind speed error and error in predicted timepoint of an MVP. We simply note here that these errors were quite reasonable for both 2013 and 2014.

Insight into the size of the 2013 EGP error is given by Monte Carlo simulation. We use random numbers to create data used in regression (DUIR) having the same structure as the DUIR based on 2009-2012 violent typhoons (see Figure 4). In particular, we choose 7 points at random (uniform distribution) from the rectangle bounding 2009-2012 violent typhoon GPs. For each of these randomized GPs, we create an appropriate number of MVPs. For example, for the 1st randomized storm we create 6 randomized MVPs, for the 2nd storm, 3 randomized MVPs and so on. We then used the randomized data set to predict 2013 MVPs and computed the average predicted MVP error. A histogram (see Figure 5) constructed using 1,000 randomized trials show that a predicted average 2013 MVP position error of 821.1 km or less could have been achieved by a random-

Figure 4

ized data structure with empirical probability of roughly **p**=.155.

In what follows, we use Monte Carlo simulation to obtain such $\mathbf{p}$-values to assess strategies which reduce EGP errors. For example, the default GP/MVP model's 2014 EGP error of 680.75 km has a **p** value of .571 (see Table 3B) and the 2015 EGP error of 583 km has a **p** value less than .001. Note that the heavily right-skewed histogram suggests possible occurrence of "busted cases" which greatly increase the value of EGP due to the small number of violent typhoons occurring in any given year. Figure 5

1.3 Distance Filtering of the Data used in Regression

As stated earlier, our primary goal in genesis point prediction of MVPs is the minimization of the average predicted MVP geographic position error for violent typhoons occurring in a given year (EGP). Improving the accuracy of predicted wind speed and the time at which an MVP occurs are also important, but were not considered in this study. One approach to reducing EGP is to filter the data used in regression (DUIR). Several filtering strategies are possible.

An intuitive strategy is to rank the violent storms in the DUIR by geographic proximity of their genesis points to the genesis point of the typhoon being predicted. Table 4 shows the result of filtering the DUIR of 2009-12 violent typhoons and using data from just the 3 storms with closest geographic proximity. This filtering is such that if the genesis point of a storm

‘X’ in the DUIR is too far from the genesis point of the storm being predicted, all MVPs of X are deleted from the DUIR. This approach gave a 2013 EGP error of 608.6 km (**p** =.008). However, since the 2014 predictions using the 3 closest typhoons had an EGP of 1007.2 (**p**=.886) this method was deemed unreliable. One reason is that the number of MVPs is not the same for each violent typhoon; hence fixing the number of violent storms involves variability in the size of the DUIR. Furthermore, the distances to the 3 closest storms in the DUIR may also be quite different from one predicted storm to another. Table 4

A second type of filtering takes into consideration pressure differences between genesis points in addition to the geographic separation. Given two genesis points $U = (u_1, u_2, u_3)$ and $V = (v_1, v_2, v_3)$ there are various possibilities for measuring the “distance” $d(U, V)$ between U and V. One distance measure found to be helpful in various applications is a (weighted) p-norm (Üster, H. and R.F. Love, 2001) defined by

$$d(U,V) = [\Omega_1(\frac{u_1 - v_1}{\sigma_{lat}})^p + \Omega_2(\frac{u_2 - v_2}{\sigma_{lon}})^p + \Omega_3(\frac{u_3 - v_3}{\sigma_{pres}})^p]^{1/p}.$$

Standard deviations of the latitude, longitude and pressure (respectively denoted σ_{lat}, σ_{lon}, and $\sigma_{pressure}$) for the data used in regression (DUIR) are used to standardize differences, accounting for the differences in scale of the coordinate axes. Note that when $p = 2$, if the (non-negative) parameters Ω_1, Ω_2, and Ω_3 called “weights” are all set equal to one, ($\Omega_1 = \Omega_2 = \Omega_3 = 1$), the distance $d(U, V)$ becomes the usual Euclidean norm for the normalized data. If the value of p is changed to $p = 1$, the so called "taxi-cab" metric is obtained where one is constrained to move parallel to a coordinate axis in measuring the (normalized) distance from U to V. Although pressure is not a geographic coordinate, Figure 1 suggests that a Euclidean or taxi-cab norm might be appropriate for measuring the distance between two genesis points. Similar to the previous section which used geographic distance to rank violent storms in the data used in regression (DUIR), one can use a p-norm (or other measure of distance) to filter the DUIR in an attempt to reduce the EGP error according to the algorithm shown in Table 5. Note that the data used in regression (DUIR) includes only storms whose genesis points are within a specified distance r to the genesis point of the storm being predicted. If r is sufficiently large, distances are immaterial and the model reverts to the default model. Table 5

In Table 6, we compare the default model EGP errors for 2013 - 2015 with those filtering the DUIR via the taxicab and Euclidean norms. In some cases, a particular norm can greatly reduce the default model error (eg. 2013 taxi-cab metric with $r = 3$ has an EGP error of 537.9 (**p** $< .01$)). However, the errors for both these p-norms fluctuate dramatically from year to year. The default model was more stable over the years tested (2013-2015). Table 6

Varying the weights allows one to place different amounts of importance on differences between coordinates. For example, if a latitude difference in genesis points is deemed more important than either longitude or pressure difference, one would increase the value of Ω_1 in relation to the weights Ω_2 and Ω_3. Note that one can use a different p norm measure for each of the 5 predicted MVP variables (time, lat, lon, pressure, wind speed). Since each distance measure has 4 parameters ($\Omega_1, \Omega_2, \Omega_3$ and p), and the radius r is a 5th parameter specifying how close GPs must be for inclusion in the DUIR, there are a total of $5 \cdot 5 = 25$ p-norm model parameters that can be tuned in an attempt to improve MVP predictions. Finding the best distance measure for filtering the data used in regression is a difficult problem open to further investigation.

2. MML models

2.1 Confusion Matrix for Storm Category Prediction

2.2 MVP Prediction Error

3. Summary and Conclusions

Early prediction of most violent points of violent (JMA Grade 5) typhoons has humanitarian value in that such predictions seek to give the earliest advance warning of the most violent track points during a typhoon season. Basic machine learning (ML) models ehnhance prediction of storm category, maximum wind speed and location.

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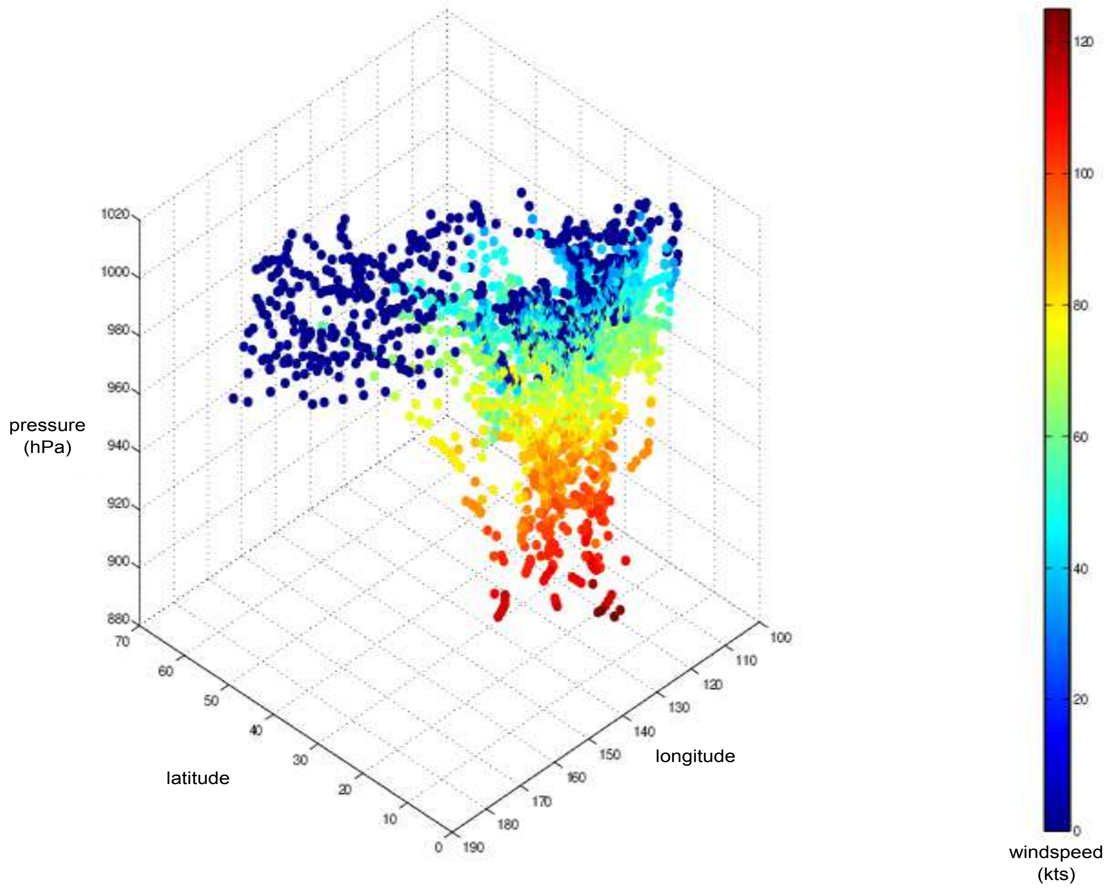

Fig. 1. Best tracks of JMA Grade 5 typhoons (2009-2012) with points colored by recorded best track wind speeds (in knots). Genesis points are shown in dark blue (at the right half) and violent points in red. Track points separated by 6 hour intervals form a “funnel” which narrows with increased wind speeds and decreased pressure.

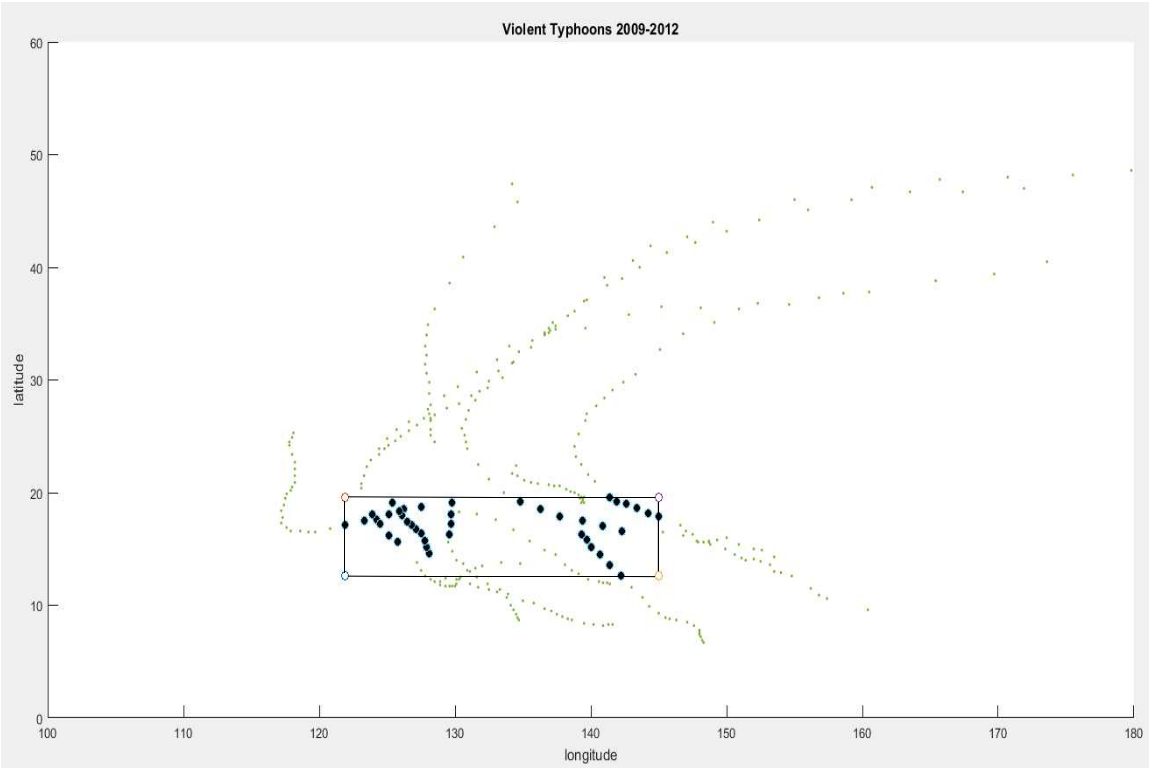

Fig. 2. Violent points of 2009-2012 typhoons (shown in bold) are confined to a rectangle [122°E,145°E] x [12.5°N,20°N].

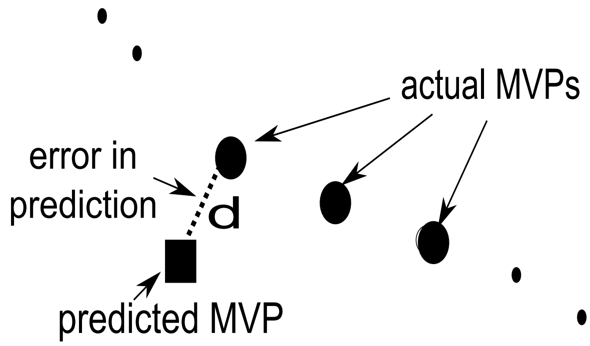

Fig. 3. Distance used to compute the error in a predicted most violent point (MVP).

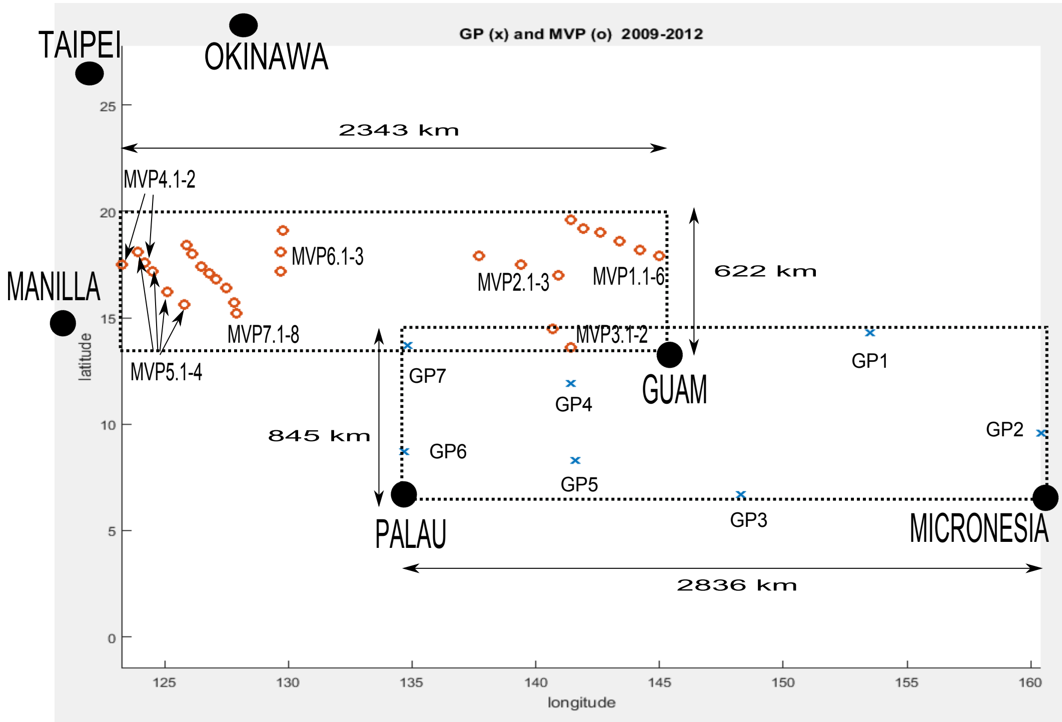

Fig. 4. Genesis points (GPs) and most violent points (MVPs) of 2009-2012 violent typhoons. GP Window:[134.7^{o}E x 160.4^{o}E]x [6.7^{o}N,14.3^{o}N]; MVP Window: [123.3^{o}E x 145.0^{o}E]x [13.6^{o}N,19.2^{o}N]

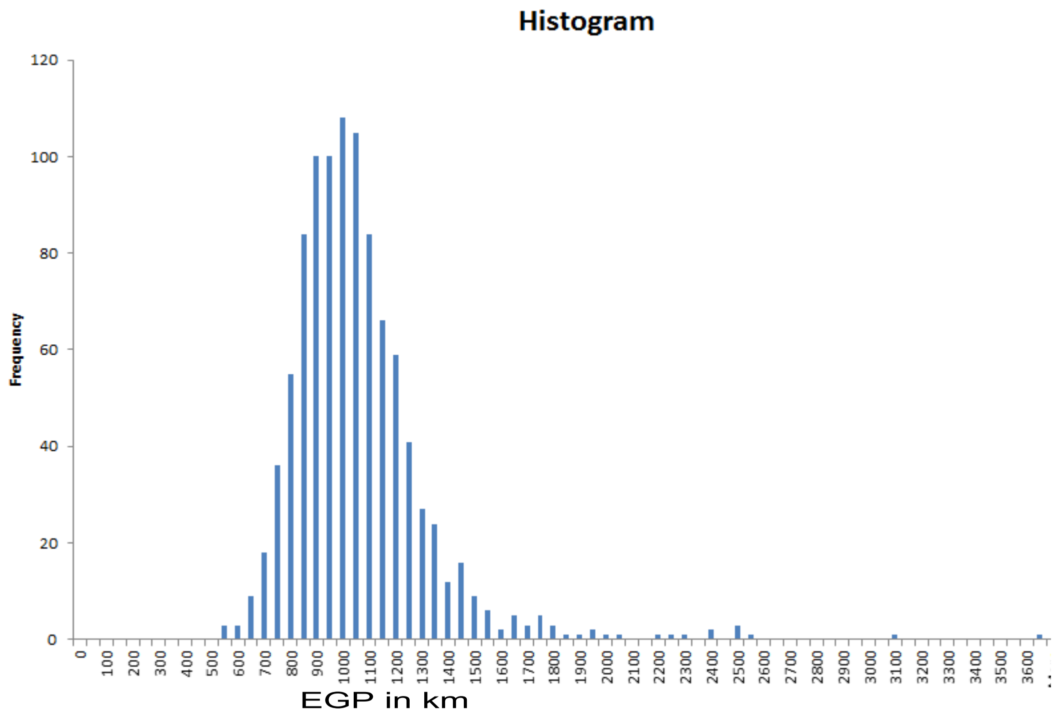

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Table 1. Genesis Points and Violent Points of 2009-2012 Violent Typhoons

typhoon	data type	time(hrs)	lat	lon	pressure (hPa)	max wind speed (knots)
1. Choi-wan	genesis point	0	14.3	153.5	1008	-
(2009)	most violent point	84	17.9	145.0	915	105
	most violent point	90	18.2	144.2	915	105
	most violent point	96	18.6	143.4	915	105
	most violent point	102	19.0	142.6	915	105
	most violent point	108	19.2	141.9	915	105
	most violent point	114	19.6	141.4	915	105
2. Melor	genesis point	0	9.6	160.4	1002	-
(2009)	violent point	114	16.6	142.3	920	105
	most violent point	120	17.0	140.9	910	110
	most violent point	126	17.5	139.4	910	110
	most violent point	132	17.9	137.7	910	110
	violent point	138	18.5	136.3	915	105
	violent point	144	19.2	134.8	915	105
3. Nida	genesis point	0	6.7	148.3	1002	-
(2009)	violent point	90	12.6	142.2	925	105
	most violent point	96	13.6	141.4	905	115
	most violent point	102	14.5	140.7	905	115
	violent point	108	15.2	140.0	905	110
	violent point	114	15.8	139.7	915	105
	violent point	120	16.3	139.3	915	105
4. Megi	genesis point	0	11.9	141.4	1006	-
(2010)	violent point	96	18.7	127.5	915	105
	violent point	102	18.5	126.2	905	110
	violent point	108	18.1	125.1	895	120
	most violent point	114	17.6	124.2	885	125
	most violent point	120	17.5	123.3	885	125
	violent point	126	17.1	121.9	910	105
5. Songda	genesis point	0	83	1416	1006	-
(2011)	most violent point	156	15.6	1258	920	105
	most violent point	162	16.2	125.1	920	105
	most violent point	168	17.2	124.5	920	105
	most violent point	174	18.1	123.9	920	105
6. Sanba	genesis point	0	8.7	134.7	1008	-
(2012)	violent point	84	16.3	129.6	910	105
	most violent point	90	17.2	129.7	900	110
	most violent point	96	18.1	129.7	900	110
	most violent point	102	19.1	129.8	900	110
7. Jelawat	genesis point	0	13.7	134.8	1010	-
(2012)	violent point	108	14.6	128.1	910	105
	most violent point	114	15.2	127.9	905	110
	most violent point	120	15.7	127.8	905	110
	most violent point	126	16.4	127.5	905	110
	most violent point	132	16.8	127.1	905	110
	most violent point	138	17.1	126.8	905	110
	most violent point	144	17.4	126.5	905	110
	most violent point	150	18.0	126.1	905	110
	most violent point	156	18.4	125.9	905	110
	violent point	162	19.1	125.4	915	105

Table 2. Default Model Regression Coefficients

A) Based on 2009-2012 GP/MVP Data

	PREDICTORS			
FORECAST	constant	lat	lon	pressure
Time	3142.314	0.406	-1.367	-2.808
Latitude	-708.140	-0.254	0.167	0.699
Longitude	-1827.084	-0.799	1.033	1.807
Pressure	-6003.952	-4.693	1.649	6.681
Wind Speed	5339.129	3.236	-1.076	-5.076

B) Based on 2010-2013 GP/MVP Data

FORECAST	constant	lat	lon	pressure
Time	-2247.013	-4.091	-0.988	2.534
Latitude	-246.923	0.275	0.053	0.252
Longitude	-1745.465	0.667	0.879	1.73
Pressure	907.724	0.927	0.125	-0.028
Wind Speed	1053.239	-0.288	0.121	-0.949

Table 3. Default Model Error in Predicted MVPs

A) 2013

Predicted MVP						Closest Actual MVP					Error			JMA	
Storm Name	Time (hrs)	Lat ^{o}N	Lon ^{o}E	Pres (hPa)	Wind Speed (knots)	Time	Lat	Long	Pres	WS	Position	WS	Time	EO	EP
Utor	130.3	16.6	126.1	898.9	114.9	72	15.5	123.5	925	105	300	9.9	58.3	286	572
Usagi	144.3	13.1	113.6	853.6	146.9	108	20.1	123.8	910	110	1340.4	36.9	36.3	235	1236.8
Francisco	114.1	18.2	137.4	911.2	107.2	102	17.4	138.3	920	105	51.8	2.2	12.1	256	624.4
Lekima	93.9	21.6	155.0	954.6	78.1	96	18.6	152.2	905	115	439	36.9	2.1	395	963.4
Haiyan	110.8	18.8	145.2	935.7	92.7	102	10.2	129.1	895	125	1973.8	32.3	8.8	401	853.2
										Average	821.1 (**p**=.155)	23.64	23.52	314.6	850.0

B) 2014

Predicted MVP						Closest Actual MVP					Error			JMA	
Storm Name	Time	Lat	Lon	Pres	WS	Time	Lat	Lon	Pres	WS	Position	WS	Time	EO	EP
Halong	105.6	17.2	136.1	908.8	113.7	138	14.9	135.1	920	105	282	8.7	32.4	528	1123.4
Genevieve	(genesis point not available)														
Vongfong	111.7	16.7	142.5	906.4	116.1	126	17.7	133.2	900	115	992	1.1	14.2	329	1827.8
Nuri	105.9	16.5	123.9	908.7	113.9	90	17.8	132.4	910	110	910	3.9	15.9	521	1371.1
Hagupit	137	15.1	134	901.2	116.7	96	11	131.3	905	115	539	1.7	41	161	1006.3
										Average	681.0 (**p**=.57)	3.85	25.9	384.75	1332.15

Table 4. Error in Predicted MVPs Using a Geographic Distance Filter

GP/MVP data for 3 Closest Storms Used in Prediction.

A) 2013

Predicted MVP						Closest Actual MVP					Error			JMA	
Storm Name	Time (hrs)	Lat ^{o}N	Lon ^{o}E	Pres (hPa)	Wind Speed (knots)	Time	Lat	Lon	Pres	WS	Position	WS	Time	EO	EP
Utor	121.4	17.3	126.59	897.8	114.2	72	15.5	123.5	925	105	387.2	9.2	49.4	286	572
Usagi	164.1	15.8	125.4	908.4	104.8	90	18.7	126.4	910	110	343.9	5.2	74.1	235	1236.8
Francisco	106.5	18.5	135.3	903.7	112.7	108	17.8	137.7	920	105	268.6	7.7	1.5	256	624.4
Lekima	130	17.6	139.9	915.6	111.1	126	21.4	146.5	905	115	817.7	3.9	4	395	963.4
Haiyan	123.1	15	139.3	909.1	115.7	102	10.2	129.1	895	125	1225.54	9.3	21.1	401	853.2
										Average	608.6 (**p**=.008)	7.06	30.02	314.6	850.0

B) 2014

Predicted MVP						Closest Actual MVP					Error			JMA	
Storm Name	Time	Lat	Lon	Pres	WS	Time	Lat	Lon	Pres	WS	Position	WS	Time	EO	EP
Halong	95.7	14.7	136.3	912.8	110.4	138	14.9	135.1	920	105	133.2	5.4	42.3	528	1123.4
Genevieve	(genesis point not available)														
Vongfong	111	16.5	142.1	898.6	120.3	126	17.7	133.2	900	115	958.7	5.3	15	329	1827.8
Nuri	105.6	17.6	123.3	877.6	128	90	17.8	132.4	910	110	967.1	18	15.6	521	1371.1
Hagupit	103.6	3.9	114.2	889.9	134.4	102	11.4	130.4	905	115	1969.9	19.4	1.6	161	1006.3
										Average	1007.2 (**p**=.886)	12.03	18.63	384.75	1332.15

Table 5. General Algorithm to Find the GP/MVP Model's EGP Error

1. **READ** (GP(X),MVP(X)), the genesis point and most violent point(s) of storm X, for all X in 2009-2012.

2. **FOR** each violent typhoon S in 2013

    begin

        2a. **READ** GP(S), storm S's genesis point lat, lon and pressure.

        2b. **INCLUDE** (GP(X),MVP(X)) in the data used in regression (DUIR) if distance(GP(X),GP(S)) $< r$.

        2c. **COMPUTE** the regression coefficients for the DUIR constructed in step 2b.

        2d. **COMPUTE** MVP$*$(S), a predicted most violent point of S, using the coefficients in step 2c.

        2e. **COMPUTE** ERROR(S)= the (minimum) geographic distance between the predicted

            MVP$*$(S) and an actual MVP(S).

    end

3. **COMPUTE** EGP, the average of ERROR(S) over all S in 2013.

Table 6. EGP Error (km) Comparisons

Method	2013[1]	2014[1]	2015[2]
Default	821.1 (**p**=.16)	681.3 (**p**=.57)	583.0 (**p**$<$.001)
Taxicab metric (r=3)	537.8 (**p**$<$.01)	609.7 (**p**=.47)	3096.8 (**p**$>$.999)
Taxicab metric (r=4)	851.4 (**p**=.21)	1094.6 (**p**=.92)	779.6 (**p**=.052)
Taxicab metric (r=5)	1065.2 (**p**=.64)	634.0 (**p**=.51)	672.4 (**p**=.005)
Euclidean norm (r=3)	760.7 (**p**=.08)	872.4 (**p**=.79)	611.4 (**p**=.001)
Euclidean norm (r=4)	1070.0 (**p**=.66)	790.8 (**p**=.71)	583.0 (**p**$<$.001)

[1]1000 randomized trials; [2]10,000 randomized trials.