ANALYSIS OF EXTREME WIND SPEED TREND IN THE TYPHOON-VULNERABLE PREFECTURES OF JAPAN

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Abstract. This paper is an observational study that evaluates historical trend changes of extreme wind speed in Japan’s top three typhoon-vulnerable prefectures according to Japan Meteorological Agency (JMA), namely, Kagoshima, Kochi, and Wakayama. Recorded historical average daily data from 35 wind stations were collected from as early as 1979 until late 2021. Extreme wind speed deterministic trends were calculated using Kendall’s τ and their significance was tested using the Mann-Kendall test, confirming whether the trend is significantly monotonically increasing or decreasing. Mann-Kendall test results across the wind stations were then corrected using the Benjamini-Hochberg method to rectify the false discovery rate. Moreover, Local Indicators of Spatial Association (LISA) method was used to determine the existence of significant spatial correlation of extreme winds across wind stations and their *k*-nearest neighbours. We also tested for trend-stationarity using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to determine whether extreme winds from these stations can be characterized with stochastic trend, i.e., if there is evidence of extreme wind speed trend fluctuations over time. Finally, we also provide spatial interpolation of extreme wind speed using the inverse distance weighting (IDW) technique to provide insight into how extreme wind speeds are clustered and spread and was also applied to every season (domain) to understand better the spatial distribution of extreme winds as season changes.
Keywords: *extreme wind speed, trend analysis, stationarity, spatial interpolation, spatial correlation*

Introduction

Japan is included in the list of countries belonging to the Pacific Ring of Fire; countries that are vulnerable to extreme disasters such as volcanic eruptions, earthquakes, and tsunamis. The country is also exposed to a number of typhoon landfalls. Historical records from 1951 until 2023 by the Japan Meteorological Agency (JMA) show an average of 2.34 annual landfalls where the most number of 19 landfalls occurred in 1960, 1966, and 2004. Extreme winds brought by these strong typhoons pose a major concern as it plagues and wreaks havoc to the community and bring fatalities. The Guardian (2023) reported that heavy rains and strong winds by the Typhoon Khanun that occurred in 2023, lashed Okinawa and Kagoshima prefectures causing 166,000 homes without power and two fatalities. In fact, the typhoon reached its maximum wind speed at 220 km/h which is equivalent to a Category 4 status on the Saffir-Simpson scale. This is also already beyond the violent storm status set by JMA where, trees, power poles, and streetlights fall,

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concrete block walls collapse, wooden houses begin to collapse, and steel frame structures can buckle or deform.

Over the years, intensity of tropical cyclones and super typhoons is seen to get stronger and climate change is a major contributor for this (Pandey and Liou, 2022). Super typhoons bring extreme winds, and extreme winds cause storm surge that bring devastating damages especially in coastal areas. The direct effect of climate change to the increasing intensity of tropical cyclones was investigated by Tsuboki et al. (2015) predicting future wind speeds reaching 85-90 m s^{-1} which is quiet what is happening already in the present. Hence, it is of interest to evaluate how extreme wind speed changes over time with respect to its trend as well as its variability.

In this paper, we analyze and evaluate the evolution of extreme wind speed dynamics over time in the typhoon-vulnerable prefectures of Japan. In particular, the prefectures of Kagoshima, Kochi, and Wakayama. These prefectures were identified by JMA as prefectures with the most landings. Evaluating extreme wind speed changes in the typhoon-prone prefectures is crucial for enhancing safety, resilience, and preparedness in the face of these powerful storms. It supports better forecasting, infrastructure planning, risk management, and overall disaster response efforts. The study may not be able to cover the entire Japanese archipelago however we believe this supplements the paper of Maeda (2009) on his investigations about extreme wind events and damage assessment in Japan in a much more recent manner. As of the present, there is little to no discussion and critical observational analysis on the evolution of extreme winds in Japan. This paper intends to address that gap but is specifically intended to Japan prefectures that are prone to typhoon landfalls.

Therefore, we intend to achieve the following objectives in the pursuit of analyzing comprehensively the long-term extreme wind speed trend along the typhoon-vulnerable prefectures of Japan, based on sound statistical techniques:

1. Describe the statistical characteristics of the extreme wind speed from the selected wind stations of Kagoshima, Kochi, and Wakayama.
2. Test for evidence of significant deterministic and stochastic trends.
3. Map the spatial trend and measure spatial correlation.

Literature review

Over the years, literature has offered insights on significant trends of wind speed all over the globe, i.e., there are numerous evidence of significant increasing and decreasing trend of wind speed changes that gives us a clearer picture how wind speed dynamics vary from one country to another. One of the major reasons why the research paradigm on wind speed trend analysis and more specifically, the evolution of extreme winds over time is continually pursued because of its relevance on wind farming as a renewable source of energy, clearly emphasized as one of the identified sustainable development goals (SDGs) set by the United Nations (Parra et al., 2020). Literature also recognizes and discusses the link between climate change, wind as a renewable source of energy, and the evolution of extreme wind. We can trace it back as far as Griffin et al. (2010) where they analyzed the trend of extreme winds from 92 meteorological wind stations in Canada, and they found out that the extreme wind speed behavior across the wind stations vary in behavior and more particularly, they identified that extreme wind speeds around the coastal areas follow an eight to nine-year cyclic pattern while mainland sites have a small, linear downward speed trend. Presence of extreme winds over coastal areas were also highlighted by De Winter et al. (2013) in the case of North Sea Basin region, in the

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context of climate change. They confirmed that there are no projected changes in annual extreme winds, and that extreme winds are coming more often from western directions.

Similarly, Jiang et al. (2013) projected decreases annual and seasonal extreme wind speed changes in the southeast coastal areas of China, which is related to reduced intensity of cold waves and decreasing frequency of typhoon landfalls from the Northwest Pacific Ocean. But aside from climate change, Waliser and Guan (2017) also associated presence of extreme winds as well as extreme precipitation to atmospheric rivers based from their analysis of western North America and northern Europe climate data through global detection algorithm. They concluded that landfalling atmospheric rivers can represent a significant hazard around the globe, because of their association with not only extreme precipitation, but also extreme winds.

In the case of Brazil, Pes et al. (2017) highlighted positive trend for extreme wind speed which is consistent with IPCC AR5 (Stocker, 2014), asserting an increase in the maximum extreme winds in Brazil mainly in mid-latitudes. On the other hand, spatiotemporal long-term trends of extreme wind characteristics were analyzed by Islek et al. (2020) in the case of Black Sea from ECMWF and NCEP/CFSR reanalysis data. They found out that there is consistency with the spatial distribution of extreme wind speed dynamics from both reanalysis with slightly larger wind speeds in the CFSR wind data, where southwestern part of the Black Sea is characterized by higher wind speeds, longer storm durations, stronger wind energy potential, and lower variability whereas the southeastern side of the Black Sea (around Turkïye), is characterized by weaker wind speeds, shorter storm durations, lower wind energy potential, and higher variability.

We also include in this section literature that discuss evolution of non-extreme wind speed. For instance, an investigation also in Turkïye showed significant wind speed trends downward and upward trends which were seen to have relevant implications to wind energy sources and hydroclimatic systems (Dadaser-Celik and Cengiz, 2014). On the other hand, a significant positive trend in most regions of Antarctica and the Southern Ocean was observed from observing the gridded ERA-Interim reanalysis (Yu et al., 2020). These findings were insightful as it was concluded that the continent was suitable for development of wind power. The same was said by Natarajan et al. (2021) and Srinivas et al. (2022) for wind power development in India as there were proof of significant increasing trend in various locations in Tamil Nadu and in some Indian coasts.

Storm surge phenomenons can also be understood clearly by evaluating changes in the wind and wave climates since the roughness of the air-water interface is mostly determined by ocean waves. This interrelationship between extreme conditions of wind, waves, and rising sea-levels and temperatures was studied extensively in a global scale by Young and Ribal (2019) using data observed from 31 satellite missions. Results of their investigation reveal that largest increases of wave height occurs in the Southern Ocean due to the significant increasing wind speed trends confirmed from three satellite systems. Zheng et al. (2022) also supports these results using ERA5 reanalysis data. Aside from wind-wave interaction, there is also evidence of trend relationships between wind speed, humidity, and temperature as presented in Zakaria et al. (2020) in the case of windstorms of Klang Valley area in Malaysia. In relation to this study, significant trend relationship between air temperature and wind speed exists in Iran using ECMWF reanalysis (Molaei and Lashkari, 2020).

However, although the nexus between wind speed trend and other climate variables exists under the changing climate, Li and Irwin (2018) emphasized that in the case of Canada, there are other external factors that may affect the significant trends on wind

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speed aside from climate change such as data transformations for terrain effects and other large scale cyclical effects such as El Niño and thus, these factors must be taken into account as well. These findings are similar with that of Wohland et al. (2019) in the case of 20CR, ERA20C, and CERA20C reanalyses global data as they found inconsistencies. Moreover, a criticism regarding the use of reanalysis datasets for wind energy production from evaluating land surface wind speed trend on a global scale was reported by Fan et al. (2021) as they found inconsistencies on the observations analyzed. More discussion regarding uncertainties and anomalies in using reanalysis for evaluating wind speed trend can be found on Wen et al. (2019) (tropical Pacific region), Zhang et al. (2019) (China), Cortesi et al. (2019) (Euro-Atlantic region), Ramon et al. (2019) (global), Yu et al. (2019) (China), Shen et al. (2022) (China), and Gualtieri (2022) (global).

Understanding extreme wind speed trends is one of the many ways we monitor the effects of climate change and more importantly, inform authorities immediate discernable patterns key for disaster prevention and response in typhoon-vulnerable communities. Moreover, a record of historical patterns on the seasonal variation of extreme winds along with updated monitoring is crucial for policymakers to craft relevant policies on mitigating the effects of typhoons.

Material and methods

As mentioned from the first chapter, the area of interest for this study are the top three typhoon- vulnerable prefectures in Japan, with the most number of recorded landfalls over the years namely, Kagoshima, Kochi, and Wakayama, according to JMA. These three prefectures are all situated in the south with relatively warmer climates compared to the northern regions, and more notably, each prefectures have significant coastline located along the Pacific Ocean. Thus, it is not surprising how these three prefectures are the ones having the most number of typhoon landfalls. For instance, we see in *Figure 1* the trajectory of Typhoon Shanshan (as of 2024/08/22 00:45 UTC) moving slowly towards Japan, and is projected to have a landfall in the three prefectures mentioned.

To achieve the objectives set in this study, a series of statistical tools were identified to grasp as much as information possible with regard to the long-term trend of extreme winds in the selected prefectures. We enumerate below the statistical procedures to be implemented:

1. Select wind stations coming from Kagoshima, Kochi, and Wakayama.
2. From every wind station, collect the highest daily average wind speed for every month from 1979 to 2021.
3. Plot the time series which is scaled according to the monthly coefficient of variation.
4. Generate box plots of extreme wind speed values for every wind stations grouped according to prefectures.
5. Compute the summary statistics of the extreme wind speed values; mean, median, maximum, standard deviation, and kurtosis.
6. Plot the spatial distribution of the extreme wind speed values by domains in terms of seasons; spring, summer, autumn, and winter.
7. Test the extreme wind speed values for presence of deterministic trend using the Mann-Kendall test.
8. Correct the p-values obtained from (4) using the Benjamini-Hochberg field correction approach.

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9. Test the extreme wind speed values for presence of stochastic trend or trend-stationarity using the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.
10. Measure the spatial correlation of extreme wind speed values and test whether this correlation is significant up to the nearest k neighbors using Local Indicators of Spatial Association (LISA).
11. Finally, plot the overall and seasonal spatial trend using the Inverse Distance Weighting (IDW) method.

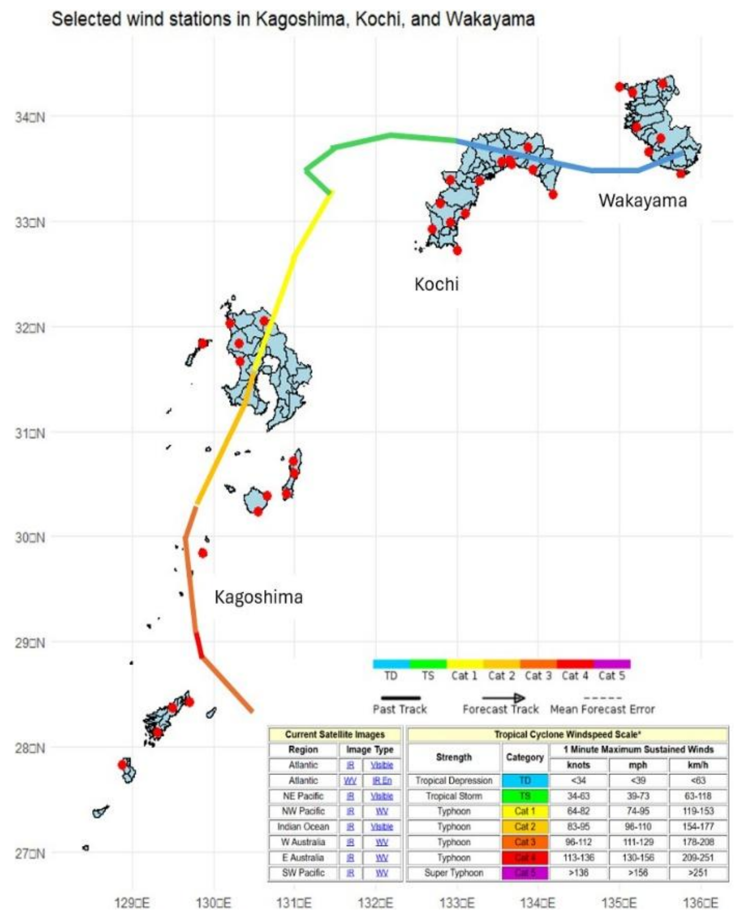

Figure 1. *Typhoon Shanshan trajectory and the selected meteorological wind stations. (Source: Tropical Storm Risk at tropicalstormrisk.com)*

Data

Daily mean wind speed data from selected JMA wind stations are used, spanning from, as early as 1979, until 2021. In this study, we define extreme monthly wind speed as the highest observed and recorded wind speed for every month. Also note that stations with missing data were not considered as it will give us spurious estimates, and data imputation is beyond the scope of the study. Also, note that some wind stations' wind speed record started later than the rest of the meteorological wind stations. We present in *Tables 1 and 2*, the list of wind stations detailing the station ID, address, and coordinates (also plotted in *Figure 1*). In total, 35 stations were considered for this study; 15 from Kagoshima, 13 from Kochi, and 7 from Wakayama. Location details of the wind stations including the address and coordinates are found in *Table 1*.

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Table 1. *Location details of the selected wind stations*

Wind station	Station address	Latitude	Longitude
Akune	Akune Special Regional Weather Observatory	32°1.6’	130°12’
Okuchi	Okuchi Harada, Isa City	32°2.8’	130°37.6’
Nakakoshiki	Nakakoshiki, Kamikoshikicho, Satsumasendai City	31°50.1’	129°52’
Sendai	Nakago, Satsumasendai City	31°50’	130°18.9’
Higashiichiki	Yuda, Higashi City, Hioki City, Kimachi	31°40.1’	130°19.7’
Tanegashima	Tanegashima Special Region Weather Observatory	30°43.2’	130°58.9’
Nakatane	Tanegashima Aviation Meteorological Observatory	30°36.3’	130°59.5’
Kaminaka	Nakanoshita, Minamitane-machi, Kumage District	30°24.4’	130°54.1’
Yakushima	Yakushima Special Region Weather Observatory	30°23.1’	130°39.5’
Onoaida	Idenojiri, Onoma, Yakushima-machi, Kumage District	30°14.1’	130°33.3’
Nakanoshima	Nakanoshima, Toshima Village, Kagoshima District	29°50.4’	129°52’
Kasari	Amami Air Meteorological Observatory	28°25.8’	129°42.7’
Naze	Naze Minato-cho, Amami City Naze Weather Station	28°22.7’	129°29.7’
Koniya	Koniya Funatsu, Setouchi Town, Oshima District	28°8.6’	129°18.9’
Amagi	Tokunoshima Aviation Meteorological Observatory	27°50.1’	128°52.8’
Odochi	Kami City, Monobe Town, Otochi Kaminishi River	33°41.9’	133°52.5’
Hishima Town	Kochi Local Meteorological Observatory	33°34’	133°32.9’
Gomen	Nankoku City, Mashie	33°35.4’	133°38.6’
Nankokunishou	Kochi Aviation Meteorological Observatory	33°32.7’	133°40.1’
Aki	Iogi, Aki City	33°29.3’	133°56’
Yusuhara	Kawanishiji, Yusuhara Town, Takaoka District	33°23.4’	132°55.3’
Susaki	Nishimachi, Susaki City	33°23.1’	133°16.6’
Murotomisaki	Muroto Misaki Special Regional Weather Observatory	33°15.1’	134°10.6’
Ekawasaki	Shimanto City, Nishitosayoi	33°10.2’	132°47.5’
Saga	Saga, Kuroshio Town, Hata District	33°4.7’	133°6.1’
Sukumo	Sukumo Special Region Weather Observatory	32°55.2’	132°41.7’
Nakamura	Chozenji, Irita, Shimanto City	32°59.4’	132°55.2’
Shimizu	Shimizu Special Regional Weather Observatory	32°43.3’	133°0.6’
Katsuragi	Myoji Temple, Katsuragi Town, Ito District	34°18.6’	135°31.7’
Tomogashima	Wakayama City, Kada, Tomagaoki Island	34°16.8’	134°59.9’
Onoshiba Town	Wakayama Local Meteorological Observatory	34°13.7’	135°9.8’
Kawabe	Wasa, Hidakagawa Town, Hidaka District	33°53.6’	135°13’
Kurisugawa	Kurisugawa, Nakahechi Town, Tanabe City	33°47.5’	135°30.8’
Nankishirahama	Nanki Shirahama Aeronautical Weather Observatory	33°39.7’	135°21.8’
Shionomisaki	Shionomisaki Special Regional Weather Observatory	33°27’	135°45.4’

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Table 2. *Wind force scale*

Average Wind speed	Classification	Description
10-15 m/s	Moderate gale	It finds it hard to walk against the wind. It's difficult to hold umbrellas. Trees and electricity cables begin to swing. Cars travelling at speed are blown off course by strong winds. Gutters begin to shake.
15-20 m/s	Gale	It's difficult to walk against the wind. It's easy to fall down. Electricity cables begin to make noise. Signs and galvanized sheet irons begin to come off. Car drivers experience their cars being blow off course by strong winds. Roof tiles and roofing materials begin to come off. Shutters rattle.
20-25 m/s 25-30 m/s	Storm	It's difficult to stand without holding onto something. Thin trees break or fall over. Signs fall and are blown away. It becomes difficult to drive a car at normal speed. Roof tiles and roofing materials begin to come off. Shutters rattle.
30-35 m/s 35-40 m/s >40 m/s	Violent storm	Thin trees break or fall over. Signs fall and are blown away. Insufficiently fixed metal roofing materials turn over. Being outside is extremely dangerous. Moving trucks are blown over. Roofing materials on metal roofs come off. Damage is extensive. Trees, power poles, and streetlights fall. Concrete block walls collapse. Wooden houses begin to collapse. Steel frame structures can buckle or deform.

Source: https://www.data.jma.go.jp/multi/cyclone/cyclone_wind_advisory.html?lang=en

Test for significant trend

The World Meteorological Organization (WMO) recommends using the nonparametric Mann- Kendall test to evaluate data patterns in time series of environmental variables (Rustum et al., 2017). This can test the variation trend of the time series of variables. This is important since we want to know the variation trend of wind speed over time that may suggest seasonality. Given a wind speed time series $x_1, x_2, \dots, x_t$ of size t, the Mann-Kendall statistic S_t is given by

$$S_t \coloneqq \sum_{j=1}^{t} \sum_{k=j+1}^{t} sgn(x_k - x_j) \quad \text{(Eq.1)}$$

where,

$$sgn(x_k - x_j) \coloneqq \begin{cases} 1; & x_k - x_j > 0 \\ 0; & x_k - x_j = 0 \\ -1; & x_k - x_j < 0 \end{cases} \quad \text{(Eq.2)}$$

This trend test tests for the null hypothesis of no significant upward or downward trend over time. In this study, the Mann-Kendall test will be used to test the presence of a monotonic increasing or decreasing trend. This trend test will be implemented for each

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wind station however, there is evidence of spatial relationships of wind speed in the real world (Lv and Wang, 2023). This cannot be ignored since variables such as wind speed with inherent spatial correlation across wind stations can lead to a falsely-discovered significant trend. Therefore, to control the false discovery rate (FDR), we apply the Benjamini-Hochberg correction by Benjamini and Hochberg (2000). The method was shown to be powerful in controlling FDR in multiple hypothesis testing with independent statistics.

The procedure rejects all $H_i, i = 1, \dots, k$ where k is the largest i for which $P_i \leq \frac{i}{m} q$, given a set of ordered p-values $P_{(1)} \leq \cdots \leq P_{(i)} \leq \cdots \leq P_{(m)}$ and the corresponding hypothesis tests $H_{(1)} \leq \cdots \leq H_{(i)} \leq \cdots \leq H_{(m)}$With this, we will be able to prevent reducing the likelihood of detecting true significant trends which can happen with spatially distributed wind stations.

Test for non-stationarity

Confirming stationarity for extreme wind speed is crucial since GEV models require that the observations be independent and identically distributed (i.i.d.). For this regard, we choose to use the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test by Kwiatkowski et al. (1992) to test for presence of non-stationarity. The choice of this test is due to its procedure in testing trend-stationarity which we find to be appropriate and fit compared to other tests of stationarity.

The test is based on the linear regression model of the form

$$x_t = r_t + \beta_t + \epsilon_t \quad \text{(Eq.3)}$$

where $\boldsymbol{r_t}$ is a random walk, $\boldsymbol{\beta_t}$ is a deterministic trend, and $\boldsymbol{\epsilon_t}$ is the error term. This tests the null of the series being trend-stationary.

The tests uses OLS and we say that data is stationary if $\beta \neq 0$. Although there are numerous tests available for testing non-stationarity, we find KPSS test to be the most appropriate test since it tests for presence of trend-stationarity, fit for extreme wind speed trend analysis.

Local indicators of spatial association

Spatial correlation of extreme winds from the selected wind stations will be implemented using Local Indicators of Spatial Association (LISA) (Anselin, 1995) to measure the spatial relationship of extreme winds from every neighboring wind stations as well as their localized impacts. LISA will also reveal significant clusters (if any). It is based from the local Moran's I statistic where, for a given location i, is computed as:

$$I_i = z_i \sum_j w_{ij} z_j \quad \text{(Eq.4)}$$

where,

- $z_i = x_i - \bar{x}$ is the deviation of the observed value at wind station i from the mean,
- w_{ij} is the spatial weight between wind stations i and j,
- x_i and x_j are the observed extreme wind speed values from wind stations i and j, respectively.

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The test is assessed using a Monte Carlo permutation test, testing the null of no spatial (auto)correlation, i.e., the extreme wind speed values' spatial distribution is random. On the other hand, a "high-high" cluster would mean that stations with consistently increasing trend is surrounded by stations with similar increasing trends. Otherwise, the cluster has insignificant clustering. The LISA analysis is done at varying values of k-nearest neighbors ($k = 1, 2, 3, 4$).

Spatial interpolation of extreme winds

Apart from doing individual trend analysis of extreme wind speed for every station, it is also of greater importance that we investigate how extreme winds behave in the spatial sense through spatial interpolation. Since our choice for the wind stations are those coming from typhoon-vulnerable prefectures, then in a geographical sense, we have enough reason to believe that extreme wind values from these wind stations are clustered spatially, that is, areas with higher extreme wind values are clustered together, and are farther apart from areas with lower extreme wind values.

To do the spatial interpolation of extreme winds, we will employ the *inverse distance weighting* (IDW) technique. This technique is quite simple as it does not require prior information to be applied to spatial prediction (Babak and Deutsch, 2009) but was found and shown to be sensitive to the type of database, to the number of neighbors used in the estimate, and to the exponent of distance used in weighting (Weber and Englund, 1994). IDW interpolation is calculated as

$$Z^*(u) = \sum_{i=1}^{n} \lambda_i Z(u_i) \quad \text{(Eq.5)}$$

where u is the estimation location of wind station, $u_i, i = 1, \ldots, n$ are the locations of the wind stations of the sample extreme wind speed values within the search neighborhood, $Z^*(u)$ is the inverse distance estimate at the estimation wind station location, n is the number of extreme wind speed sample points, $\lambda_i, i = 1, \ldots, n$ are the weights assigned to each extreme wind speed sample point, and $Z(u_i), i = 1, \ldots, n$ are the conditioning extreme wind value at sample points.

The weights are determined as

$$\lambda_i = \frac{\left(\frac{1}{d_i^p}\right)}{\sum_{i=1}^{n}\left(\frac{1}{d_i^p}\right)} \quad \text{(Eq.6)}$$

where d_i are the Euclidian distances between estimation location and sample points, and exponent p is the power or distance exponent value.

With the help IDW spatial interpolation of extreme winds, we will be able to highlight local extreme wind patterns and capture their spatial differences and more importantly, it will provide us more insights of extreme wind speed events since we will be able to visualize the spatial distribution of extreme winds, how it spreads, and where it is more intense. We also do this by season to see how extreme winds varies as season changes over the years. Moreover, note that, with the limitation of our data, the period considered for this analysis is from 2007 to 2021 since there are wind stations with no available data prior 2007.

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Results

Monthly mean wind speed and variability

Overall trend and movement of wind speed from the selected wind stations are captured using a time series plot of the monthly average wind speed. While the evolution of wind speed stability over time is presented using a plot of monthly coefficient of variations. In Kagoshima, a general declining trend of monthly average wind speed is seen in the regions of Akune, Nakakoshiki, Higashiichiki, Tanegashima, Kaminaka, and Yakushima. Monthly average wind speed in Akune has a range of approximately 2.0–4.3 m s^{-1}, smaller range of 1.1–2.6 m s^{-1} in Nakakoshiki, 1.3–3.0 m s^{-1} in Higashiichiki, large ranges of 3.8–8.7 m s^{-1}, 1.3–6.5 m s^{-1}, and 2.3–7.8 m s^{-1} in Tanegashima, Kaminaka, and Yakushima, respectively. One particular interesting observable seasonality is that of Onoaida. Monthly average wind speed in Onoaida spikes up during January and June. The data also reveals similar phenomenon in other regions of Kagoshima like Nakatane with spikes every July (summer) and November (winter).

The included regions of the Kochi prefecture on the other hand display a discernible decreasing trend such as Aki, Ekawasaki, Saga, and Nakamura, albeit having relatively smaller monthly average wind speed compared to Kagoshima. Aki's monthly average wind speed range from 1.2–2.2 m s^{-1},0.4–2.7 m s^{-1} in Ekawasaki, 0.8–3.0 m s^{-1} in Saga, and 0.9–2.6 m s^{-1} in Nakamura. Some of the regions exhibited seasonality despite absence of trend like in Odochi and Murotomisaki. Similar observation can be seen in the area of Simizu but with deep troughs or sudden drop fluctuation during spring and autumn as these seasons do not bring much strong winds. This is the same case in the selected regions of Wakayama prefecture exhibiting perceptible seasonality despite only showcasing slight decreasing trend.

Moreover, we cite the use of coefficient of variation for representing variability of monthly wind speed from the study of Kainkwa (2000) that defines a coefficient of variation of at least 30% to be unstable or unsteady winds. This is particularly relevant for identifying regions suitable for wind farming since wind farms must have strong but calmer or stable wind speed. Majority of the graphs (see *Figure 2*) show that wind stations from these selected areas have unstable wind speeds as most of the monthly coefficient of variations exceeded the threshold of 30%. Although, a different case is seen in the regions of Kochi Meteorological Observatory, Susaki, and Saga, all located in the Kochi prefecture. Wind speed around these areas are more stable than the rest of the regions and prefectures. But may not be suitable for wind farms as monthly wind speed is not that strong. Therefore, all regions included from the three prefectures are either having unstable wind speed or stable but weak wind speed. However, differences as seen in the boxplots from *Figure 3* among the three prefectures also suggest regional variability in wind speed extremes across Japan.

Summary statistics of extreme wind speed

This section covers descriptive statistics of extreme wind speed from the three prefectures to describe and get initial insights of its fundamental characteristics. For concise discussion, we do not consider regions with extreme wind speed below 10 m s^{-1} (see *Table 2*). According to their scale, a wind speed of 10–15 m s^{-1} is defined as moderate gale.

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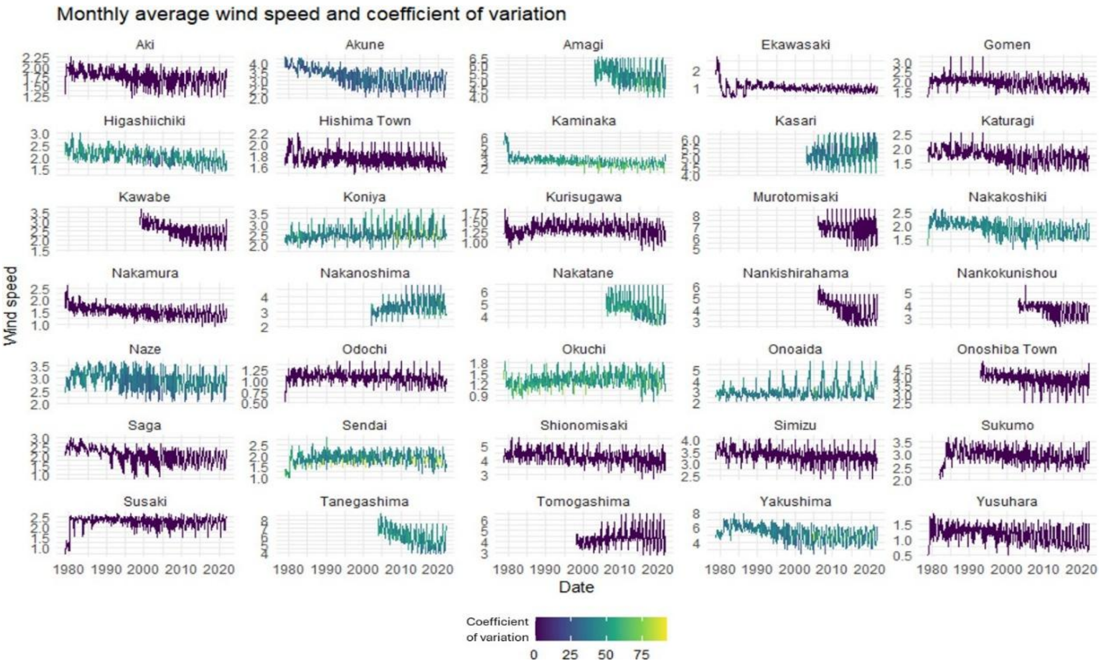

Figure 2. *Scaled time series plot of monthly mean wind speed from the selected meteorological wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

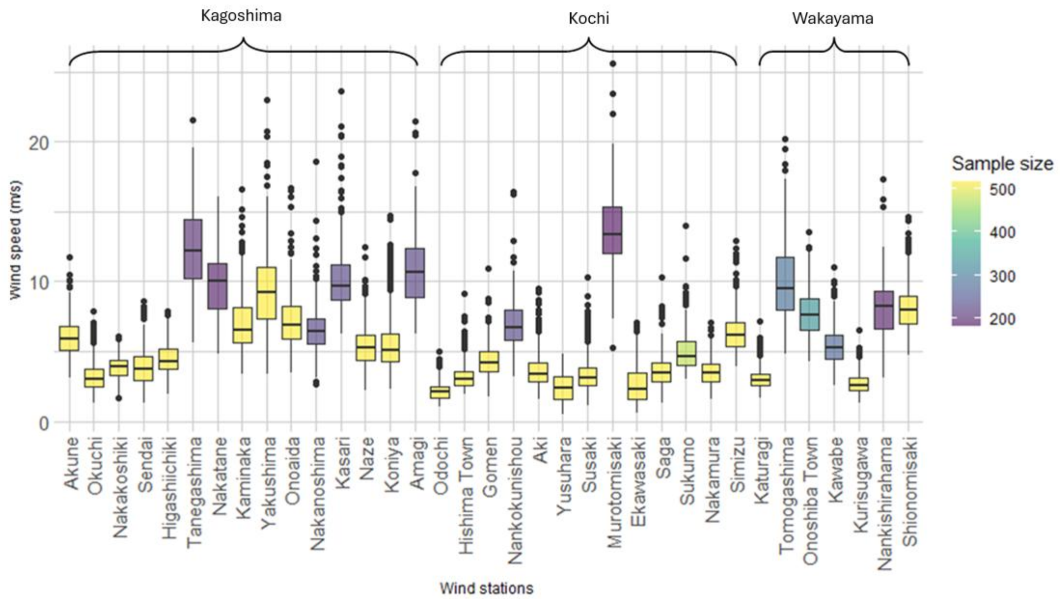

Figure 3. *Boxplots of monthly extreme wind speed from selected wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

The distribution of the observations for extreme wind speed is shown in *Figure 3* illustrated through boxplots for every wind stations showing the outliers as well as the observation counts. Complete summary statistics are presented in *Table 3*. Moreover, domain (seasonal distribution) average is estimated as well, i.e., the mean for every season for seasonal comparison (illustrated in *Figure 4*).

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***Table 3.** Summary statistics of monthly maximum wind speed from selected wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

Wind Station	Period	Mean	Median	Maximum	SD	Kurtosis
Akune	1979-2021	6.062597	5.90	11.8	1.3113457	0.76225112
Okuchi	1979-2021	3.194961	3.00	7.9	1.0077437	2.08269696
Nakakoshiki	1979-2021	3.852907	3.90	6.1	0.7907298	0.17157199
Sendai	1979-2021	3.856977	3.70	8.6	1.3225930	0.92914621
Higashiichiki	1979-2021	4.467442	4.30	7.9	1.1065674	−0.0414502
Tanegashima	2004-2021	12.332683	12.20	21.6	2.8110348	−0.3215867
Nakatane	2006-2021	9.791579	10.00	16.1	2.2366672	−0.28489961
Kaminaka	1979-2021	7.094574	6.50	16.6	2.1293168	1.26874362
Yakushima	1979-2021	9.291860	9.20	23.0	2.7780435	1.77726123
Onoaida	1979-2021	7.233140	6.90	16.7	1.9289332	2.94350467
Nakanoshima	2002-2021	6.613974	6.40	18.6	1.9372562	7.09087420
Kasari	2003-2021	10.428509	9.70	23.6	2.7768114	4.24316807
Naze	1979-2021	5.372868	5.30	12.5	1.3736212	2.31203939
Koniya	1979-2021	5.669186	5.05	14.7	2.0794977	2.46250584
Amagi	2003-2021	10.796460	10.70	21.5	2.5581740	2.05375139
Odochi	1979-2021	2.181202	2.10	5.0	0.6132955	1.2810791
Hishima Town	1979-2021	3.250969	3.00	9.1	0.9639014	4.7938726
Gomen	1979-2021	4.357752	4.20	10.9	1.2108402	1.6946152
Nankokunishou	2003-2021	6.951316	6.75	16.4	1.9341467	4.2584872
Aki	1979-2021	3.673256	3.40	9.5	1.2374660	3.1801377
Yusuhara	1979-2021	2.451357	2.40	4.8	0.9590540	−0.7710218
Susaki	1979-2021	3.252713	3.10	10.3	1.1993576	4.6913287
Murotomisaki	2006-2021	13.760440	13.40	25.6	3.0477010	2.1844914
Ekawasaki	1979-2021	2.674225	2.30	7.1	1.3887392	0.1717774
Saga	1979-2021	3.591860	3.50	10.3	1.1805756	2.9509509
Sukumo	1982-2021	5.005870	4.60	14.0	1.4027311	4.2864504
Nakamura	1979-2021	3.521124	3.50	7.1	0.9258108	0.2504728
Simizu	1979-2021	6.423062	6.20	12.9	1.3984010	2.4110360
Katuragi	1979-2021	3.068992	2.90	7.2	0.7272823	3.1692515
Tomogashima	1998-2021	10.045455	9.50	20.2	2.9523164	0.3225819
Onoshiba Town	1993-2021	7.728783	7.60	13.6	1.6467237	0.1165244
Kawabe	1999-2021	5.441606	5.30	11.0	1.3589019	1.1215338
Kurisugawa	1979-2021	2.711047	2.60	6.5	0.7564699	1.7136020
Nankishirahama	2006-2021	8.069474	8.20	17.3	2.1084649	2.3079334
Shionomisaki	1979-2021	8.197674	8.00	14.6	1.6043492	1.0177936

Calculations show that on average, Tanegashima, Kasari, and Amagi experience moderate gale extreme winds with an average extreme wind speed of 12.33, 10.43, and 10.80 m s^{-1}, respectively. Between these three stations however, only Kasari does not experience moderate gale at least fifty- percent of the time, only Tanegashima and Amagi with median extreme wind speed of 12.20 and 10.70 m s^{-1}, respectively, along with Nakatane with median extreme wind speed of 10 m $s^{−1}$.

Kasari has the highest maximum wind speed ever recorded at 23.6 m s^{-1}. This is followed by Yakushima, Tanegashima, and Amagi with 23.0, 21.6, and 21.5 m s^{-1}, respectively. Highest maximum wind speed classified was recorded in the regions of Nakatane, Kaminaka, Onoaida, and Nakanoshima with maximum extreme wind speed range of 16.1–18.6 m s^{-1}. Akune and Naze's highest extreme wind speed were gales recorded at 11.8 and 12.5 m s^{-1} respectively.

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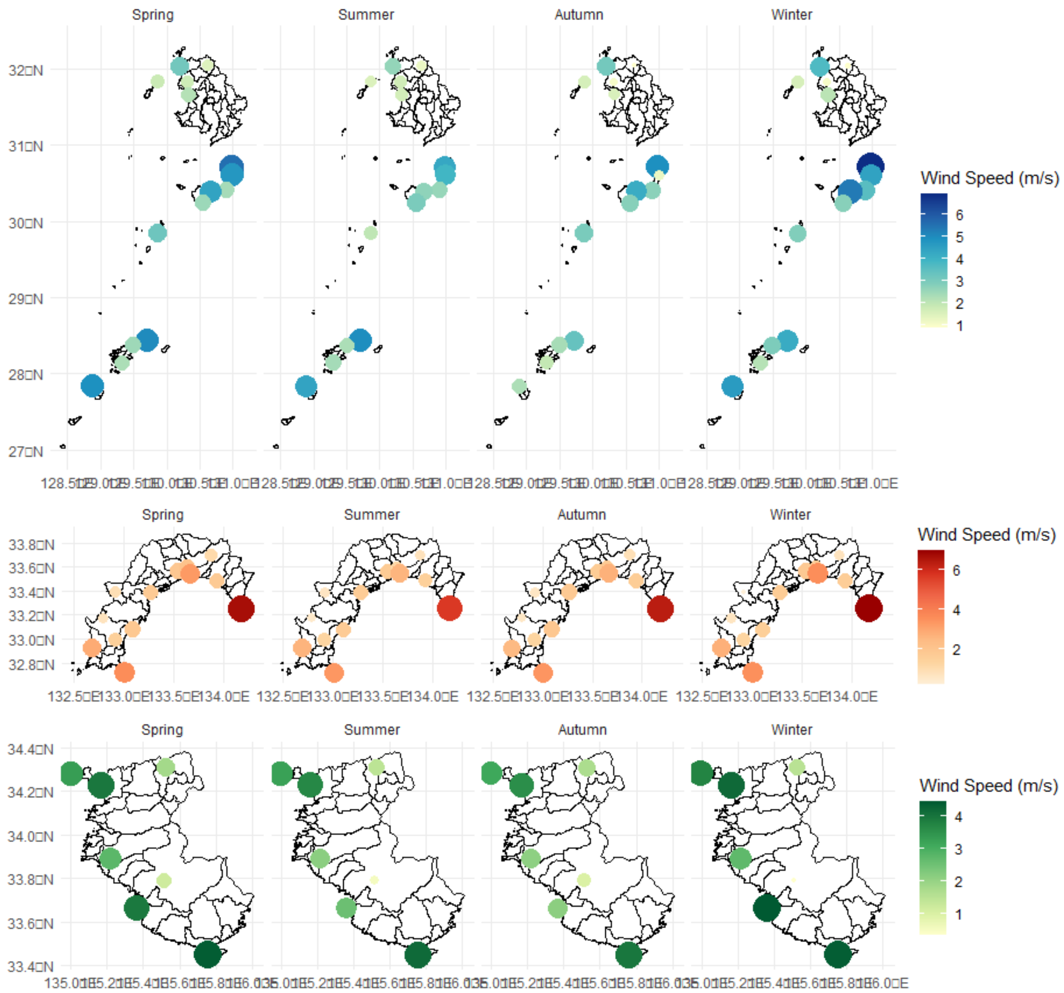

Figure 4. *Spatial distribution of domain monthly average maximum wind speeds from selected wind stations in Kagoshima (top), Kochi (center), and Wakayama (bottom), (1979-2021)*

Then, Tanegashima has the highest variability of 2.81 in terms of standard deviation followed by Yakushima and Kasari with standard deviation value of 2.78 indicating that these areas have high varying wind patterns. We also point out that only Murotomisaki experiences moderate gale extreme winds on average, with a mean extreme wind speed of 13.76 m s^{-1}. It also has a median extreme wind speed value of 13.40 m s^{-1} which means extreme wind speed in the area is at least 13.40 m s^{-1} fifty-percent of the time. We also emphasize that the highest recorded wind speed there is 25.6 m s^{-1}.

Meanwhile, Tomogashima is the region in the Wakayama prefecture that stands out having a monthly gale mean extreme wind speed of 10.05 m s^{-1} while the rest of the selected regions fall below the gale category. Although its median extreme wind speed falls slightly short below the gale category, the region has experienced the highest wind speed at 20.2 m s^{-1} and it comes along with a high varying wind pattern of 2.95 which supports the wind instability behavior seen from *Figure 2*. The shape of the extreme wind speed distribution is similar to that of Murotomisaki suggesting that extreme wind speed in Tomogashima are generally gales with rare instances of storm-like winds.

Furthermore, we report that 32 out of 35 stations (91.43%) have recorded positively-skewed extreme winds while 31 out of 35 wind stations (88.57%) have kurtosis value

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greater than zero indicating that at least 30 of the wind stations have extreme wind speed distributions that are asymmetric clustering on the right side of the distribution (i.e., majority of the values are lower) and also have heavier tails with sharper peak than normal. These are indications that extreme wind values are not normally distributed.

Finally, as observed in the heat map from *Figure 4*, extreme wind spatial distribution suggests visible seasonal trends, with peak wind speeds typically occurring in late summer and early autumn, likely due to typhoon activity. The pattern varies slightly across the three locations, reflecting regional climatic differences. Meanwhile, in a more broader scope, *Figure 5* illustrates how coastal and island stations tend to record higher extreme wind speeds, likely due to greater exposure to typhoons and open sea winds. Inland or more sheltered stations tend to have lower average extreme wind speeds. The southern and southwestern islands (e.g., Okinawa) show particularly high values, consistent with their exposure to frequent typhoons and tropical storms.

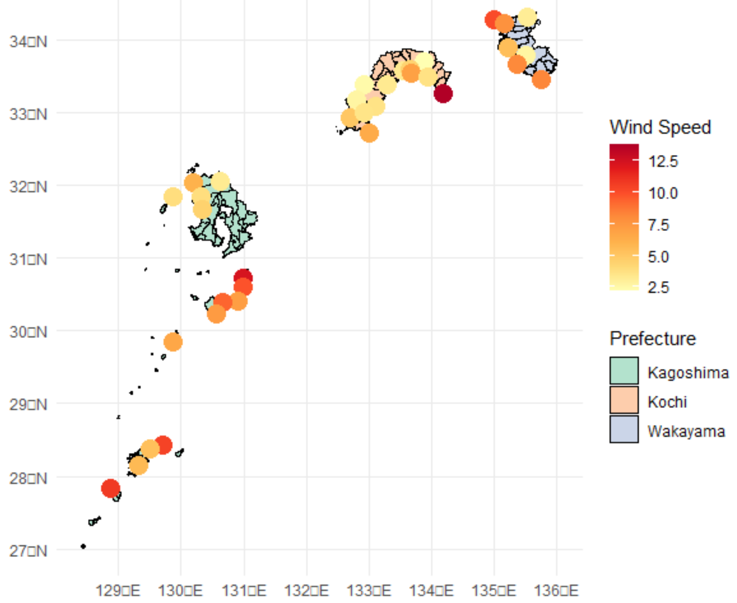

Figure 5. *Spatial distribution of monthly average maximum wind speeds from selected wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

Extreme wind speed trends over time

Trends in the extreme wind speed data for the selected wind stations from Kagoshima, Kochi, and Wakayama prefectures were determined using the Mann-Kendall test and was assessed at $\alpha = 0.05$ level. Furthermore, Kendall's τ coefficient was estimated using the formula

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} sgn(x_j - x_i) sgn(y_j - y_i) \quad \text{(Eq.7)}$$

where $sgn(\cdot)$ is the signum function. The value of τ ranges from −1 to 1 that implies strong negative or positive trend. Chen et al. (2022) discussed how it should be properly used and interpreted, and has linked its relevance to early warning mechanisms for ecological regime shifts.

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Note that in the illustrations provided for trend analysis in *Figure 6*, ▲ and ▼ implies significant monotone increase/decrease, and insignificant otherwise. So, out of the 15 selected stations in the Kagoshima prefecture, seven locations showed overall decreasing trend namely Akune, Okuchi, Higashiichiki, Tanegashima, Kaminaka, Onoaida, and Kasari. However, only Higashiichiki, Tane- gashima, and Kasari did not exhibit significant downward trends. Higashiichiki and Kasari both have τ values of −0.04 while Tanegashima has −0.05. Meanwhile, Akune, Okuchi, Kaminaka, and Onoaida presented significant decreasing trends overtime at $\alpha = 0.01$ level. Between these four regions, Kaminaka recorded the highest negative τ value at −0.40 with Onoaida coming next at −0.26. Akune and Okuchi have relatively weaker decreasing monotony with τ values of −0.08 and −0.10, respectively, albeit significant.

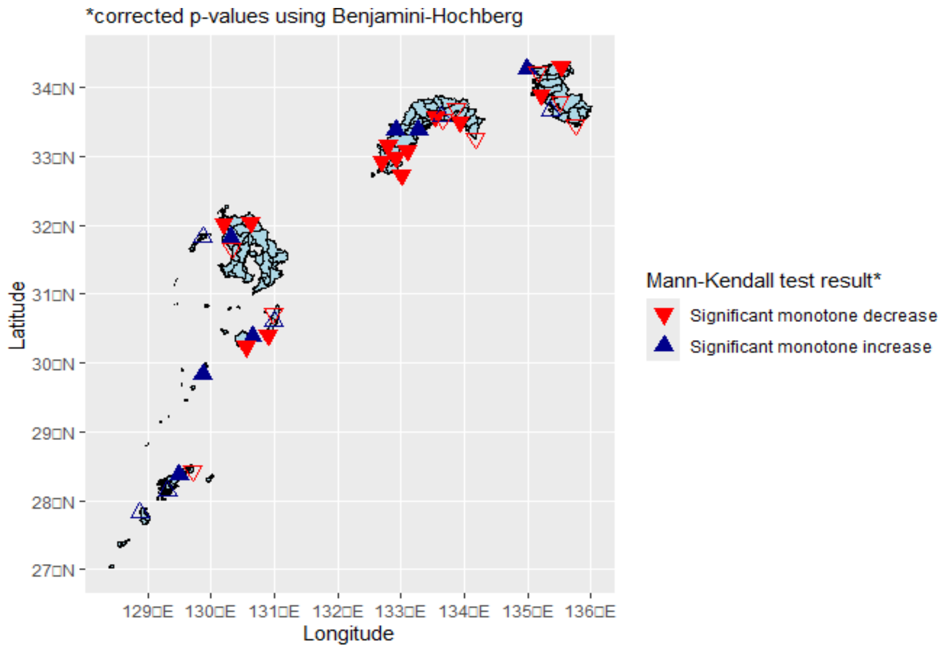

Figure 6. *Trend map of selected wind stations from selected wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

On the other hand, increasing trend was seen in the regions of Nakakoshiki, Sendai, Nakatane, Yakushima, Nakanoshima, Naze, Koniya, and Amagi. But from these eight regions, Nakakoshiki, Nakatane, Koniya, and Amagi have no significant change in their trends. The other 4 regions were not bereft of showing enough evidence of significant increasing trend of extreme wind speed, with Sendai topping first with a τ value of 0.26. Yakushima and Naze are closely-tied with τ values both estimated at 0.19 and lastly, Nakanoshima with a τ value of 0.12. All of these four regions showed significant decreasing trend of extreme wind speed at $\alpha = 0.01$ over time.

Kochi has more regions that showed significant downward trend compared to Kagoshima includ- ing Hishima Town, Aki, Ekawasaki, Saga, Nakamura, and Simizu which all exhibited significance at $\alpha = 0.01$ level. Ekawasaki has the strongest negative correlation having a τ value −0.32 followed by Nakamura which has a 34.375% difference ($\tau = -0.21$). Both Saga and Simizu are closely-tied ($\tau = -0.16$) but extreme wind speed in Hishima Town's value is 12.5% higher $\tau = -0.18$. Then, we have the regions of Yusuhara, Susaki, and Sukumo, that showed significant increasing trend of

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extreme wind speed. The regions of Aki, Odochi, Gomen, Nankokunishou, and Murotomisaki have insignificant decreasing trend. In Wakayama prefecture, Katsuragi and Kawabe have significant downward trend at $\alpha = 0.01$ level ($\tau = -0.11, -0.18$), while Kurisugawa also has a significant downward trend but at $\alpha = 0.05$ level ($\tau = -0.06$). Moreover, Tomogashima showed enough significance of an upward trend of extreme wind speed at $\alpha = 0.01$ level ($\tau = 0.10$) although relatively smaller compared to the regions from Kagoshima and Kochi with significant upward trend. Lastly, the regions of Onoshiba Town, Nankishirahama, and Shionomisaki were found to have insignificant trends.

Then we proceed with testing for trend-stationarity in which, of the 35 wind stations, only 15 were found to have sufficient evidence of trend-stationarity such as Nakakoshiki, Sendai, Kaminaka, Yakushima, Odochi, Hishima Town, Gomen, Nankokunishou, Yusuhara, Susaki, Ekawasaki, Saga, Sukumo, Katuragi, and Kurisugawa. It implies that extreme wind speed observations from these wind stations are not i.i.d. in nature meaning, the extreme wind observations are stochastically-dependent over time as compared to extreme wind values from the other 20 wind stations. However, of these 15, Nakakoshiki, Odochi, Gomen, and Nankokunishou wind stations were not found to have significant trend based on the Mann-Kendall test. This is because, although both tests test trends, Mann-Kendall test tests for deterministic (monotone) trend while KPSS test tests presence of stochastic trend.

One must caution on the difference between the two types of trends being measured by Mann-Kendall and KPSS tests (*Table 4*). A deterministic (monotone) trend may be detected however, it does not necessarily imply that it will have stochastic trend as well. This instance was particularly seen from the extreme wind speed observations from Akune, Okuchi, Onoaida, Nakanoshima, Naze, Aki, Nakamura, Simizu, Tomogashima, and Kawabe. It implies that, extreme wind speed values from these stations have significant trend but are sufficiently and consistently monotone so as not to significantly impact its stationarity.

Non-stationary characteristics of extreme winds from the selected wind stations

Changes in the atmospheric conditions from the effects of climate change is attributed to the inherent non-stationarity of extreme weather data (Kawase et al., 2021). It is a very important insight that needs to be considered as stationarity is an assumption that needs to be satisfied in standard modeling of extreme weather data. Hence in this study, we attempt to provide a more comprehensive statistical analyses that can be evidence of non-stationarity of extreme wind speed, or absence thereof, compared to the existing literature that only provides analysis of trend patterns. For comparison purposes, Mann-Kendall test results with Benjamini-Hochberg field correction as illustrated already from *Figure 5* are indicated alongside KPSS test results. Note however that most of the p-values are not exactly indicated but it still indicates significance at $\alpha = 0.05$ level of significance.

The LISA (Local Indicators of Spatial Association) analysis of extreme wind in selected wind stations across Kagoshima, Kochi, and Wakayama reveals clear patterns of spatial clustering. As the neighborhood size k increases from 1 to 4, the identification of significant clusters becomes more pronounced and geographically widespread. At $k = 1$, only a few high-high clusters appear, mainly in the Kagoshima region, indicating limited spatial context. However, from $k = 2$ onward, more meaningful clusters emerge in all three regions, with notable high-high clusters becoming visible in Kochi and Wakayama as well (*Figure 7*).

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Table 4. Summary of hypothesis tests results

Wind station	Mann-Kendall test		KPSS test	
	τ coefficient	B-H corrected p-value	KPSS trend	p-value
Akune	−0.076	0.0197	0.08195	> 0.10
Okuchi	−0.0993	0.0020	0.11852	> 0.10
Nakakoshiki	0.0151	0.7034	0.3054	< 0.01
Sendai	0.263	0.0000	0.596	< 0.01
Higashiichiki	−0.044	0.2232	0.1404	0.0603
Tanegashima	−0.0542	0.3379	0.0416	> 0.10
Nakatane	0.0286	0.6765	0.0563	> 0.10
Kaminaka	−0.395	0.0000	1.0949	< 0.01
Yakushima	0.194	0.0000	0.2378	< 0.01
Onoaida	−0.257	0.0000	0.1225	0.0936
Nakanoshima	0.117	0.0173	0.1038	> 0.10
Kasari	−0.0391	0.4789	0.0451	> 0.10
Naze	0.189	0.0000	0.0307	> 0.10
Koniya	0.032	0.3659	0.0222	> 0.10
Amagi	0.0597	0.2696	0.0864	> 0.10
Odochi	−0.0105	0.7714	0.4045	< 0.01
Hishima Town	−0.1813	0.0000	0.167	0.0325
Gomen	0.0039	0.9118	0.3018	< 0.01
Nankokunishou	−0.0543	0.3171	0.2162	< 0.01
Aki	−0.0783	0.0173	0.1281	0.0832
Yusuhara	0.1201	0.0003	0.4863	< 0.01
Susaki	0.2745	0.0000	0.5799	< 0.01
Murotomisaki	−0.0056	0.9118	0.0638	> 0.10
Ekawasaki	−0.3197	0.0000	1.2586	< 0.01
Saga	−0.159	0.0000	0.3041	< 0.01
Sukumo	0.2417	0.0000	0.3837	< 0.01
Nakamura	−0.2112	0.0000	0.0569	> 0.10
Simizu	−0.1626	0.0000	0.071	> 0.10
Katuragi	−0.1132	0.0005	0.1799	0.0235
Tomogashima	0.0974	0.0254	0.034	> 0.10
Onoshiba Town	−0.0522	0.2383	0.0319	> 0.10
Kawabe	−0.1776	0.0000	0.0528	> 0.10
Kurisugawa	−0.0603	0.0752	0.221	< 0.01
Nankishirahama	0.0228	0.7034	0.0363	> 0.10
Shionomisaki	−0.0144	0.7034	0.0869	> 0.10

These results suggest that extreme wind events are not randomly distributed, but rather exhibit strong spatial dependence, particularly in Kagoshima and Kochi. The persistence of High-High clusters across increasing values of kk supports the existence of stable, localized areas where high extreme wind values tend to co-occur. This spatial clustering is likely influenced by geographic features such as coastal orientation, mountainous terrain, and regional wind systems.

LISA analysis confirms that extreme wind behavior in these regions is spatially correlated and varies by location. The consistent presence of High-High clusters implies that targeted mitigation strategies, such as reinforcing wind-sensitive infrastructure, should focus on these high-risk areas. Moreover, the stability of clustering patterns across different spatial neighborhood sizes enhances the reliability of these findings for practical applications in regional planning and hazard management.

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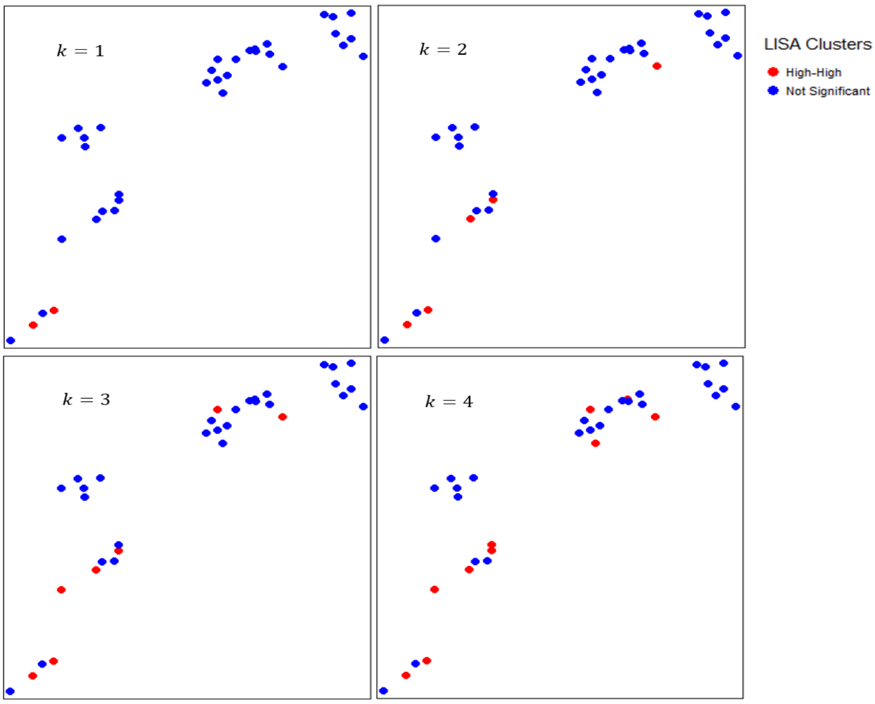

Figure 7. *Spatial correlation map using Local Indicators of Spatial Association (LISA) at different values of k-nearest neighbors from selected wind stations in Kagoshima, Kochi, and Wakayama (1979-2021)*

Spatial trend analysis of extreme winds in Kagoshima, Kochi, and Wakayama

We show in this section the results after we did spatial interpolation of extreme wind speed from the 35 wind stations to show the spatial trend of extreme winds across the selected prefectures from the selected wind stations using the inverse distance weighting (IDW) method. Note again that the data set used for this analysis is for the time period January 2007 – December 2021 as other wind stations have not existed yet prior January 2007 and, the method only accommodates equal number of observations.

Figure 8 reveals how extreme winds were distributed spatially based from the time period considered. In the analysis, various values for the inverse distance parameter (IDP) exponent p were tried ($p = 1.0, 1.5, 2.0, 2.5, 3.0$) and RMSEs of the prediction were compared. However, the differences with the RMSEs were too small, almost infinitesimally small that the RMSEs computed with i.d.p. values from 2 above no longer changes (computationally). Ultimately, an i.d.p. value of $p = 2.0$ was used.

Furthermore, it can be noticed that extreme winds are clustered around the Kagoshima as well as in Wakayama, but not so much in Kochi. In particular, there is a noticeable spread and cluster of extreme wind along the southwestern and central regions, and not so much in the west- ern region. The mentioned regions are geographically facing the Pacific Ocean which is a common trajectory of typhoons coming out of the ocean.

Spatial interpolation of extreme wind was also carried out for every season to capture the cluster and spread of extreme winds as season changes. We present this below in *Figure 9*. Same as what was done earlier, different values of IDP values were utilized to ensure we get the most accurate spatial representations of extreme winds for every season but as it was expected, IDP value of $p = 2.0$ was the most optimal value albeit very small RMSE difference, compared when $p = 1.0$ is used.

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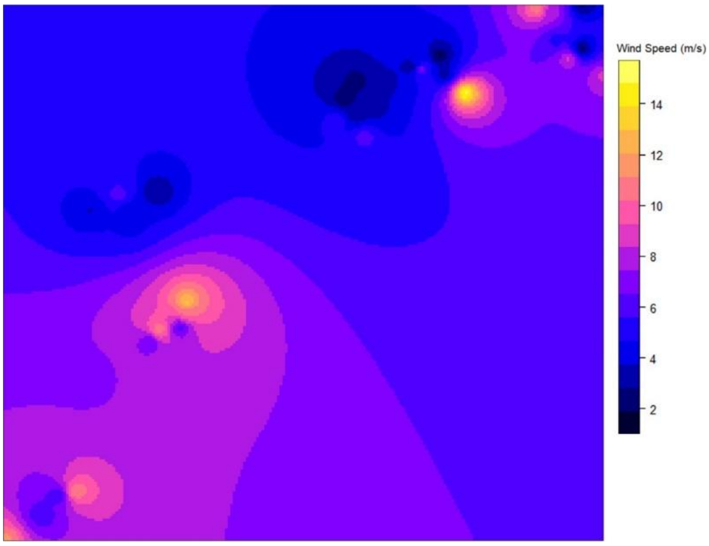

Figure 8. *Spatial map of extreme wind speed from selected wind stations from selected wind stations in Kagoshima, Kochi, and Wakayama (2007-2021)*

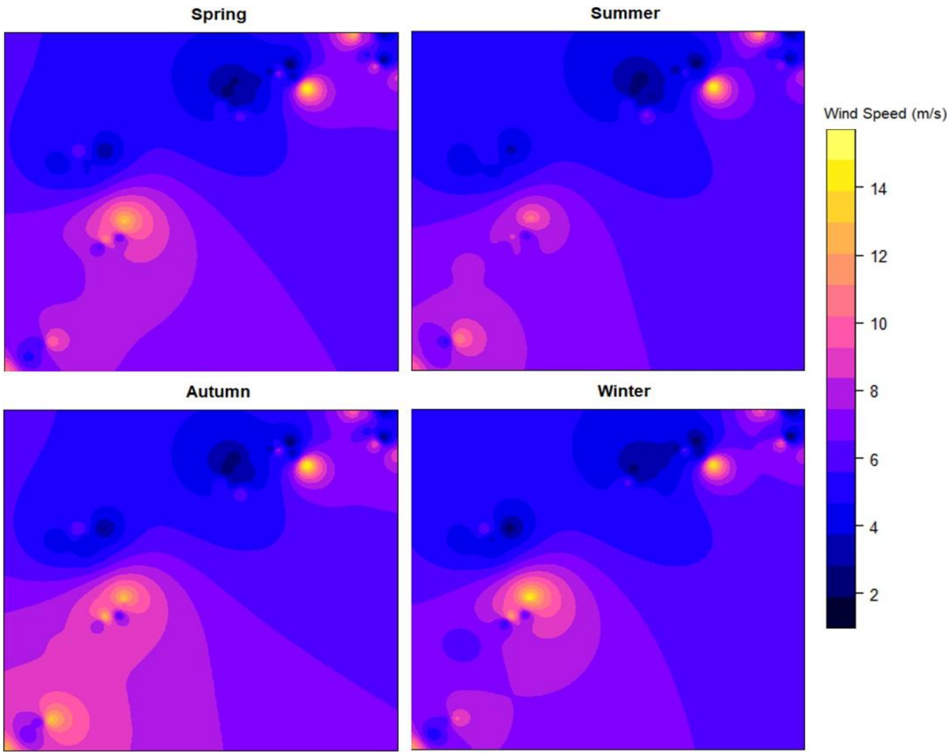

Figure 9. *Seasonal spatial interpolation of extreme wind speed from selected wind stations from selected wind stations in Kagoshima, Kochi, and Wakayama (2007-2021)*

Spatial interpolation of extreme winds for every season from the selected stations reveal that extreme winds are strongest during autumn and it can also be noticed how autumnal extreme winds are mostly clustered around the Kagoshima prefecture. Though the same can be said for the rest of the seasons, this observation is more pronounced during autumn. We also notice how extreme winds are clustered intensely around Muroto

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in Kochi prefecture and extends until the coasts of Wakayama. Hence, in terms of intensity of extreme wind speed clustering, it is strongest during autumn, second strongest in winter, and spring, then weakest during summer.

Discussion

Extreme wind speed trends

In this study, we evaluated extreme wind speed trend changes and variability in the three-most vulnerable prefectures in Japan with daily observations spanning as early as 1979 until late 2021. Data from selected 35 wind stations were used in the analysis. The presence of trends was measured using the nonparametric Mann-Kendall trend test. Kendall's τ were calculated as well to measure the strength of the trend, of which 13 locations have significant decreasing extreme wind speed trend and 8 have significant increasing extreme wind speed trend, and the rest of the 14 locations have no sufficient evidence of discernible and significant trend.

Finding evidence of these significant for extreme winds have several relevant implications in wind farming technologies and environmental studies, not only in meteorological research. Wind stations in Kagoshima, Kochi, and Wakayama detected to have presence of significant extreme wind speed trend that has a monthly coefficient of variation not exceeding the threshold for wind stability of 30% (Kainkwa, 2000) are potential good locations for farming wind energy as a source of renewable source of power in these typhoon-prone areas of Japan.

Locating these potential areas for wind farming using the Mann-Kendall trend analysis technique was implemented by Rehman (2013) in the case of the Kingdom of Saudi Arabia, where they found that the wind stations located in Al-Wejh, Dhahran, Guriat, Turaif, and Yanbo to be preferred locations for wind power development. Similar remarks regarding potential wind farming in locations with significant increasing extreme wind speed strength was presented as well by Lawin et al. (2019) in the country of Burundi. However, these findings must be revisited anew incorporating wind stability criterion by Kainkwa (2000) to minimize risks of inefficiency, power losses, and increased operational costs, especially if those specified areas rely their power mainly from wind energy.

On the other hand, significant increasing trend of maximum wind speed detected in the wind stations of Sendai, Yakushima, Nakanoshima, Naze, Yusuhara, Susaki, Sukumo, Tomogashima, from this study may also have environmental implications in terms of ecological damage, wildlife, agriculture, and to other environmental hazards such as erosions or floods as these can be exacerbated by extreme winds. These identified areas share common geographical characteristics as they are all either coastal islands and/or facing directly the Pacific. Strengthening coastal structures for flood mitigations and other environmental hazards must be prioritized in these areas. This was similarly explained by Ghaedi (2019) in Iran based on weather stations facing the Caspian Sea where they asserted that necessary measures should be put in place to reduce the negative consequences and strong negative impacts of increased maximum wind speed on installations and structures, erosion, human health, evapotranspiration, and wind energy.

In addition, Begin et al. (2021) found that increased strong winds influenced the rising of oxygen concentrations in the lower water column of Ward Hunt Lake that contributed to the movement and break-up of the ice cover in the lake. Also, frequent extreme winds together with extreme rainfall were found to be responsible for the bulk of variability on

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photosynthesis efficiency of phytoplankton assemblages in coastal ecosystems (Helbling et al., 2024).

Non-stationarity of extreme winds

Although the literature on trend analysis of extreme weather variables does not necessarily include trend-non-stationarity, we find it imperative to also identify whether these trends are due to accumulated random factors likely attributed to atmospheric changes and variability. By testing existence of non-stationarity due to random trend fluctuations, a nuanced view on extreme wind dynamics is perceived and can improve our understanding on how extreme winds behave specifically along the prefectures of Kagoshima, Kochi, and Wakayama.

For this matter, the KPSS test was identified to be the appropriate technique to determine presence of significant trend-nonstationarity to be used in this study. Results reveal that 15 out of the 35 stations including Nakakoshiki, Sendai, Kaminaka, Yakushima, Odochi, Hishima Town, Gomen, Nankokunishou, Yusuhara, Susaki, Ekawasaki, Saga, Sukumo, Katuragi, and Kurisugawa showed significant nonstationarity based on trend. This implies that in the long-term, extreme winds from these wind stations fluctuate and drift randomly over time. Hence, disaster mitigation measures that are flexible and adaptive must be implemented in these areas. Since nonstationary extreme winds are responsible for many structural damages (Huang et al., 2015), coastal infrastructures, for instance, should be built knowing that sudden changes in the environment are inevitable in the long-run, to minimize the damages caused by sudden unpredictable changes in the environment.

Non-stationarity of extreme winds have been illustrated already in a few studies emphasizing its relevance in understanding weather patterns and dynamics and its implications in modeling. Huang et al. (2018) for instance found out that there is evidence of time-varying trends of extreme wind speed series in many surface meteorological stations in China. Recent studies have incorporated non-stationarity of extreme winds in modeling extremely severe strong wind such as typhoons and thunderstorms (Hu et al., 2024) and for designing wind power infrastructures in Waglan Island, Hong Kong under non-stationarity assumptions for extreme winds (Dong et al., 2024). Literature in environmental assessment and climate modeling under non-stationarity assumptions is already gaining ground because of the unpredictability of climate due to climate change.

Spatial characteristics of extreme winds in Kagoshima, Kochi, and Wakayama

Aside from testing significant deterministic and stochastic trends, it is also our purpose in this study to capture localized extreme winds and its broad spatial distribution. Capturing localized clusters of extreme winds provides better insights for targeted disaster-mitigation policies, especially for extreme wind-related or typhoon-related disasters, and knowing how extreme winds vary across the prefectures supports regional planning. Hence, the Localized Indicators of Spatial Association (LISA) and Inverse Distance Weighting (IDW) techniques were both utilized in order to detect localized spatial patterns and estimate the continuous spatial trends, respectively.

LISA suggests insignificant spatial correlation in Wakayama prefecture as well as in Kochi and majority of Kagoshima. Opposing extreme wind speed trend from neighboring stations is explained statistically from this insignificant spatial correlation. Although this might seem unusual, there is evidence of opposing climate extreme trends in the literature. For instance, temperature extremes in West Africa were found to have opposing trends

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in-between neighboring stations (New et al., 2006) as well as in eastern and central Tibetan Plateau (Liu et al., 2006). A case for extreme winds is yet to be confirmed but is already initiated in this study.

Furthermore, we found significant high-high clustering or significant spatial correlation along Amami Oshima specifically along Setouchi and Kasari suggesting $k = 1$ nearest neighboring wind station exhibits significant similar increasing extreme wind speed trend. This was also seen along Muroto as well in the Kochi prefecture when $k \leq 2$. Results reveal that for all considered values of k, there is no significant clustering or significant spatial correlation found in the Wakayama prefecture including some areas neighboring Satsumasendai and in most parts of Kochi.

It was also illustrated from spatial interpolation using IDW that extreme winds are more concentrated in the prefectures of Kagoshima and Wakayama and not much in Kochi. Although Kochi was recorded to be the prefecture with the second most number of typhoon landfalls, Wakayama has more concentration of extreme winds compared to Kochi. Moreover, seasonal spatial interpolation of extreme wind revealed that extreme winds are much stronger every autumn and winter than in summer. These findings are also similar with the recent study of Lockwood et al. (2023) where they found out that wind speeds and extreme winds characterized by storms in the United Kingdom are significantly correlated during winter, but not in summer.

Conclusion

This comprehensive analysis of extreme wind speed in the typhoon-prone prefectures of Japan from selected wind stations gave more nuanced insights and detailed information about the extreme wind dynamics by using sound statistical methodology as compared by what is seen in the literature on trend analysis studies. The Benjamini-Hochberg-corrected p-values for the Mann-Kendall test was implemented to make sure that error due to multiple iterations of the MK test is minimized and will give more accurate results. Traditionally, trend analysis studies on weather data ignore this but we believe there MK test results must be field corrected. With that said, MK test results was able to provide new insight regarding the extreme wind speed dynamics in terms of deterministic trend and the KPSS test in terms of stochastic trend. KPSS test is not commonly included in trend analysis studies but we find that the test is appropriate in giving us more depth on understanding regarding the stochastic trend dynamics of extreme wind speed. The results from this test led us to identify wind stations whose extreme wind speed observations that show significant trend fluctuations that may be due to multiple factors such as climate change and changes in instrumentations for weather observations. Later on, this will have implications for modeling studies involving non-stationarity.

Spatial trend of extreme winds using IDW was also implemented to identify where the extreme wind clusters generally based from the observed data. We were also able to identify these clusters according to season to provide us additional key insights on the distribution of extreme winds across domains or seasons. It is quite interesting to note that the prefecture of Kagoshima is where the concentration of extreme wind is as well as parts of Kochi. All in all, we were able to provide a series of results from statistical measurements and techniques we find to be meaningful in giving us more detailed and nuanced insights on long-term extreme wind speed behavior. We hope that these trends that were identified comprehensively from our study can shape better disaster-mitigation policies strengthening the goals of policymakers for a disaster-resilient community.

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