Assessment of long term spatial-temporal variability of wind speed

Abstract

A pure and non-polluting renewable energy source is wind power. Accurate wind power estimates (based on variable wind speeds) are necessary for successful planning and investment in wind power development. In order to inform the development of wind energy, it is essential to acquire a trustworthy quantification and spatiotemporal characteristics of wind speeds. This research used the ArcGIS, Mann-Kendall (MK) test, and Sen's slope to analyse long-term wind speed data from 7 stations in the Kalburgi District, North Eastern Region of Karnataka State, from 1981 to 2018. The findings of this study contribute to our knowledge of how wind speeds in Kalburgi District vary and are distributed over long time scales. Over 35 years, there has been a slight and steady rise or decrease in the average wind speed (aveWS). Second, over a span of about 35 years, the annual aweWS varied greatly at various points within the Kalburgi District. Additionally, the annual aveWS at each station showed a rising tendency. Last but not least, values of wind speeds varied geographically were not very consistent throughout the year, and gradually decreased.

Keywards : Spatial Variability, MK test, Sen’s Slope, trend analysis

Introduction

The renewable energy sector has been tasked with providing a reliable power supply to industry, commerce, and society at large. The motivation is not only to supplant a diminishing fossil fuel resource but also to bring about cleaner air and meet net-zero carbon emission targets at globally varying time horizons. Globally, most research in this field occurs in Asia, with China, India, and Iran being the top three countries for total publications produced (Mazzeo et al., 2021). In coastal and offshore areas, especially for marine research and development, the demand for electricity has risen. Offshore wind power is particularly appropriate for high-demand coastal cities, lighthouses, and marine-weather buoys (Zheng and Pan, 2014).

A variety of time scales, including monthly, yearly, seasonal, and decadal, as well as maximum or extreme values within a particular time frame, can be used to analyze wind speed characteristics. Fu et al. (2011) investigated the various temporal patterns of annual wind speed variation at 597 observational sites across China based on the yearly mean wind speed and connected the variability to the Inter decadal Pacific Oscillation. Rehman (2013) used the MK test to analyze the trends in the regression lines and calculated the annual net yield of wind energy using the wind power law and long-term yearly and monthly mean wind speeds. Bierstedt et al. (2015) evaluated the spatial structure and temporal variability of mean and extreme wind speed data using principal component (PC) analysis, also referred to as EOF, to identify the dominant patterns of variability.

Our knowledge of the spatiotemporal distribution and variation of wind speeds over long time scales in Kalburgi District, North Eastern Region of Karnataka State, was to be improved by the current research. The possible links between these traits and the recognized patterns of climate variability were then confirmed. As a result, the analysis and findings offer significant insights that may guide choices regarding the location of wind farms and the orientation of wind turbines, helping to assess the offshore renewable energy sector. In the context of seasonal outlooks or long-range wind power generation forecasting, these findings may also be interesting. (Yu et al., 2019). The study of fitting probability density distributions, such as gamma, Weibull, Gumbel, and truncated normal or mixed distributions, can also benefit from understanding of wind speed distributions with various characteristics. (Jung and Schindler, 2018; Mazzeo et al., 2019; Ouarda and Charron, 2018).

Material and Methods

Description of Study Area

Location

The area selected for the present study comes under the north eastern dry zone of agro climatic condition of Karnataka state, India (Fig. 1). The entire district located on Deccan plateau and altitude ranges from 300 to 750 m above Mean Sea Level (MSL). Most of the area is covered with black soil and to some extent red soil as well. The study area lies between 17˚12′ and 17˚46′ N latitude and 76º 04′ and 77˚54′ E longitude.

Data collection

The long-term wind speed (ms^{-1}) data obtained from the National Aeronautics and Space Administration prediction of worldwide energy resource (NASA POWER) project. Historical data of wind speed collected for 7 weather stations *viz.* Aland, Afzalpur, Chincholi, Chittapur, Kalaburgi, Sedam and Jewargi, for the periods of 1981-2018.

Statistical analysis

Statistical analysis of long-term wind speed (ms^{-1}) data executed. For statistical data analysis spreadsheet package of MS Excel was used. The analysis was carried out by using Mann- Kendall Test and Sen's slope estimator for collected wind speed (ms^{-1}) data from the study area.

Trend Analysis

Long term wind speed (ms^{-1}) collected data from the National Aeronautics and Space Administration prediction of worldwide energy resource (NASA POWER) project (https://power.larc.nasa.gov / data-access-viewer/), these data available freely worldwide in gridded form with 0.5 degree resolution. Trend analysis of were carried out to assess the long-term variability and trend slope by Mann-Kendall test and Sen's slope estimator.

Mann- Kendall Test

The Mann- Kendall test is often used to identify a trend in a series (Siddaram et al 2020). The test is of non-parametric trend test is proposed by Mann (1945), further studied by Kendall (1975) and improved by Hirsch *et al.*, (1982). The Mann-Kendall statistic (S) measures the trend in the data. Positive values indicate an increase in constituent concentration over time, whereas negative values indicate a decrease in constituent concentrations over time. The strength of the trend is proportional to the magnitude of the Mann-Kendall statistics (*i.e.*, large magnitudes indicate a strong trend). Data for performing the Mann-Kendall analysis should be in time sequential order.

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} Sgn(X_j - X_k) \qquad (1)$$

Where,

X_j and X_k = sequential data values for the time series data of length n.

The sum of the Sgn function and the mean-variance Var(S), under the null hypothesis (H_o) of no trend and independence of the series terms are given in equations (3) and (4) respectively.

$$\mathrm{Sgn}(X_j - X_k) = \begin{cases} 1 \text{ if } Xj > Xk \\ 0 \text{ if } Xj = Xk \\ -1 \text{ if } Xj < Xk \end{cases} \quad (2)$$

$$\mathrm{Var}(S) = \frac{N(N-1)(2N+5) - \sum_{i=1}^{m} U_i(i)(i-1)(2i+5)}{18} \quad (3)$$

Where,

N = Length of the data set,

m = Number of tied groups

U_i= Size of the M^{th} group

i = Integer

The standard normal test statistic Z_S (Equation (4) indicates a trend in the data series with a positive or negative value indicating increasing or decreasing trends respectively. The trend result was evaluated at 5 % significant level (corresponding threshold value of ±1.96) and the null hypothesis (H_o) is rejected, when $/Z_S/ \geq Z_\alpha/2$ at $\alpha = 0.05$ level of significance.

$$Z_S = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}}, \text{ for s} > 0 \\ 0, \quad \text{for s} = 0 \\ \frac{S+1}{\sqrt{VAR(S)}}, \text{ for s} < 0 \end{cases} \quad (4)$$

Sen's slope estimator

Linear trend in a time series can be estimated using a simple non-parametric procedure developed by Sen (1968). Mann-Kendall test is used to evaluate a significant increase or decrease in parameter under consideration. Kendall's correlation of coefficient is (Kendall's tau), an effective and general measurement of correlation between two variables. (Mann, 1945; Kendall, 1975), this type is extensively used for testing the trend in hydrological data, however, it does not estimate a trend slope. Therefore, the non-parametric Sen's method, is a linear model (Gilbert, 1987), is used to estimate the value and confidence interval for the slope of an existing trend. The statistic- Sen's Slope estimates the slope (unit change per time period) or the magnitude of the trend. This approach involves computing slopes for all the pairs of time points and then using the median of these slopes as an estimate of the overall slope. As such, it is insensitive to outliers and can handle a moderate number of values below the detection limit and missing values.

Sen’s method calculates the slope of the line using all data pairs, as shown in the following equation (5).

$$Q_i = \frac{X_j - X_k}{j - k} \tag{5}$$

Where,

X_j and X_k = sequential data values for the time series data of length n

J and k= If there are n values x_j in the time series, we get as many as slop estimate

Q_i = Sen´s estimator of slope is simply given by the median of these N values of Q_i’s.

$$Q_i = \begin{cases} Q_{[(n+1)/2]} & \text{If N is odd} \\ Q_{\frac{n}{2}} + Q_{\frac{N+2}{2}} & \text{If N is even} \end{cases} \tag{6}$$

Where,

Q_i is the slope between data points X_j and X_k, Q_{med} is median slope estimator which reflects the direction of the trend in the data.

Spatial analysis

A Spatial Analysis Tool in the ArcGIS V. xx software was used for investigating spatial patterns in data. The Spatial Analysis Tool in the ArcGIS V. xx software used for interpolation creating and analysing the map of long term wind speed (ms^{-1}) data. The Inverse Distance Weighting (IDW) interpolation technique used to create the map of the study area. We used this technique because IDW technique takes the less neighbouring unknown location points and it will give more accurate than the kriging and spline or any other interpolation technique. The spatial interpolation by IDW performed with the assumption that the attribute value of an unknown location with weighted average of a known location by assigning values to the unknown location using values from known neighbouring locations based on the concept of distance weighting (Po *et al.*, 2017). The collected wind speed (ms^{-1}) data analyzed from 1981-2018 using deterministic IDW interpolation technique available in ArcGIS V. xx software.

RESULTS AND DISCUSSION

This section includes result and discussion of the assessment of long term spatio temporal variability of wind speed from 1981 to 2018 for seven recording stations of Kalaburgi district using Mann-Kendall test and Sen’s slope estimator method.

Spatial variability analysis of wind speed data from 1981-2018

The spatial variability maps of wind speed data prepared to display its spatial distribution in the study area. The spatial variability analysis of wind speed carried out in ArcGIS Vr.xx in spatial analyst tool by IDW interpolation technique.

Wind speed

The spatial variability maps of average wind speed (Henceforth aveWS) over the last 38 years from 1981-2018 prepared and shown in Fig. 2 (a to e) and Table 1. The spatial distribution of aveWS from 1981-1990 Fig. 2 (a) observed lower in Kalaburgi, Chincholi, Chittapur, Sedam and some part of Aland and Jewargi between 3.42 to 3.71 ms^{-1} as compared to Aland and Afzalpur with a range of 3.71 to 4.13 ms^{-1}. During1991-2000 Fig. 2 (b) the spatial distribution of aveWS observed similar with slightly lower than the previous decade with a range of 3.25 to 3.98 ms^{-1}. The spatial distribution maps of aveWS from 2001 to 2010 presented in Fig. 2 (c) and analogous to previous decade the aveWS also observed slightly lower compared with the first decade and similar to the second decade with a range of 3.23 to 3.95 ms^{-1}. The spatial variability of aveWS from 2011 to 2018 Fig. 2 (d) found more sparsely distributed over the study area with a range from 3.24 to 3.93 ms^{-1}. The maximum aveWS observed at the outside boundary of Afzalpur, Aland and Jewargi with 3.6 to 4 ms^{-1}. The aveWS of the last 38 years from 1981 to 2018 Fig. 2 (e) observed spatially distributed over the study area in the range of 3.33 to 4.00 ms^{-1}. The maximum aveWS observed at the outside boundary of Afzalpur, Aland and Jewargi because these areas topographically plane and the Aland is udulating, and temperature in these areas is more.

Time series analysis

Long term trend analyses of seven locations from study area were studied for the period of 38 years for wind speed. Long term trend analysis of wind speed (Henceforth, aweWS) from 1981 to 2018 shown in Fig 3 (a to g), and Table 2. Longterm average, yearly highest and lowest values of wind speed is presented in Table 2 (a) for Aland, Afzalpur, Chincholi, Chittapur, Kalaburgi, Sedam and Jewargi respectively. In the Aland aweWS recorded highest with 3.59 ms^{-1} in 1982 and lowest with 3.04 ms^{-1} in 2008, average aweWS with 3.32 ms^{-1}, Mann- Kendall test (Z) with -0.79 and Sen's slope (Q) is 0.009 shown in Fig 3 (a). The average aweWS with 3.32 ms^{-1}, Mann- Kendall test (Z) with -0.07, Sen's slope (Q) with 0.011, highest with 3.73 ms^{-1} in

1983 and lowest with 3.22 ms^{-1} in 2016 observed over the Afzalpur presented in Fig 3 (b). In the Chincholi aweWS reported highest with 3.56 ms^{-1} in 1982 and lowest with 3.02 ms^{-1} in 2008 shown in Fig 3 (c). Also, the WS observed average with 3.42 ms^{-1}, Mann- Kendall test (Z) with -4.4, Sen's slope (Q) with -0.01 in the Chincholi. In the Chittapur aweWS recorded highest with 3.58 ms^{-1} in 1986, lowest with 3.03 ms^{-1} in 2008, average with 3.42 ms^{-1} and statistical analysis results observed for Mann- Kendall test (Z) with -4.4 and Sen's slope (Q) with -0.01 shown in Fig 3 (d). The aweWS observed over Kalaburgi average with 3.36 ms^{-1}, highest with 3.64 ms^{-1} (1982), lowest with 3.17 ms^{-1} (2008), and statistical results for Mann- Kendall test (Z) with -4.31 and Sen's slope (Q) with 0.009 presented in Fig 3 (e). The Fig 3 (f) displayed the aweWS over the Sedam highest with 3.59 ms^{-1} in 1990, lowest with 3.03 ms^{-1} in 2003, average with 3.34 ms^{-1}, and also statistical results for Mann- Kendall test (Z) with -4.4 and Sen's slope (Q) with -0.01. The average aweWS with 3.40 ms^{-1}, highest with 3.64 ms^{-1} in 1982 and lowest with 3.11 ms^{-1} in 2008 with the statistical analysis results for Mann- Kendall test (Z) with -4.31 and Sen's slope (Q) with 0.009 for Jewargi shown in Fig 3 (g). The WS observed decreasing trend linearly in all weather stations for last 38 years and observed similar trend with statistical analysis of Sen's estimate.

SUMMERY AND CONCLUSION

The wind speed is the most important parameters for harnessing the renewable energy which influence the availability of electrical power. About 38 years wind speed data of study area were analyzed to determine its variability. The non-parametric statistical methods Mann Kendall test and Sen's slope estimator were used to establish the trend in wind speed.

The major conclusions drawn from the study are;

- The spatial variability of aveWS from 2010 to 2018 found more sparsely distributed over the study area with a range from 3.24 to 3.93 ms^{-1}. The aveWS of the last 38 years from 1981 to 2018 observed densely distributed over the study area in the range of 3.33 to 4.00 ms^{-1}.
- The aweWS observed decreasing trend linearly in all recording stations for last 38 years and also observed similar trend with statistical analysis of Sen's estimate.

REFERENCES

Alam, A., Sultan, B. M. and Maheen, M., 2019, Using landsat satellite data for assessing the land use and land cover change in Kashmir valley. *GeoJournal*., 5(4): 1-15.

Anamika, T. S., Ghosh, M., Pandey, A. C. and Shekhar, S., 2017, Assessment of climate extremes and its long-term spatial variability over the Jharkhand state of India. *Egyptian J. Remote Sensing and Space Sci.*, 21(1): 49-63.

Anonymous, 2017, Annual report on Kalaburgi district at glance, Department of Agriculture Kalaburgi, pp:25-40.

Bierstedt, S.E., Hünicke, B., Zorita, E., 2015. Variability of wind direction statistics of mean and extreme wind events over the Baltic Sea region. Tellus 67, http://dx.doi.org/10.3402/tellusa.v67.29073.

Fu, C., Yu, J., Zhang, Y., Hu, S., Ouyang, R., Liu, W., 2011. Temporal variation of wind speed in China for 1961–2007. Theor. Appl. Climatol. 104, 313–324. http://dx.doi.org/10.1007/s00704-010-0348-x.

Hassan, A., Mostafa, M. and Gamal, A., 2019, Assessment of agroclimatology NASA POWER reanalysis datasets for temperature types and relative humidity at 2 meters against ground observations over Egypt. *Advan. in Space Res.*, 5(2):1-20.

Hatzianastassiou, N., Papadimas, C. D., Lolis, C. L., Bartzokas, A., Levizzani, V., John D. P. and Katsoulis, B. D., 2016, Spatial and temporal variability of precipitation over the mediterranean basin based on 32-year satellite global precipitation climatology project data, part-I: evaluation and climatological patterns. *Int. J. Climatol*., 20(5): 1-14.

Hirsch, R. M., Helsel, D. R., Cohn, T. A. and Gilroy, E. J., 1982, Statistical treatment of hydrologic data. In: *Handbook of Hydrology* (ed. by D. R. Maidment), 17.1–17.52. McGraw-Hill, New York, USA. Hollander, M. and Wolfe, D.A., 1973.

Huang, H., Han, Y., Song, J., Zhang, Z. and Xiao, H., 2016, Impacts of climate change on water requirements of winter wheat over 59 years in the huang-huai-hai plain. *Soil and Water Res.*, 11(1): 11-19.

Huang, Y., Wang, H., Xiao, W., Chen, L., Yan, D., Zhou, Y., Jiang, D. and Yang, M., 2018, Spatial and temporal variability in the precipitation concentration in the upper reaches of the Hongshui river basin, Southwestern China. *Adv. Meteorol*., 4(32): 1-20.

Huntington, T. G., 2006, Evidence for intensification of the global water cycle: review and synthesis. *J. Hydrol*., 319 (4): 83-95.

Iglesias, A. and Garrote, L., 2015, Adaptation strategies for agricultural water management under climate change in Europe. *Agril. Wat. Manage*., 155: 113-124.

INCCA, 2010, Indian Network for Climate Change Assessment, Climate Change and India: A 4x4 Assessment, Ministry of Environment and forests, Government of India.

IPCC, Climate Change, 2007, Climate change impacts, adaptation and vulnerability. Working Group II contribution to the Intergovernmental Panel on Climate Change Fourth Assessment Report. Summary for policymakers, pp:23.

IPCC, 2014, Contribution of Working Group I to the *IPCC Fifth Assessment Report Climate Change-2014. The physical science basis,* pp:26.

Jung, C., Schindler, D., 2018. Sensitivity analysis of the system of wind speed distributions. Energy Convers. Manag. 177, 376–384. http://dx.doi.org/10. 1016/j.enconman.2018.09.078.

Kambale, J. B., Singh, D. K. and Sarangi, A., 2017, Modelling climate change impact on crop evapotranspiration. *Nat. Environ. and Pol. Tech.*, 16(3): 953-958.

Kendall, M. G., 1975, Rank correlation methods. Charles Griffin: London.

Li, C., Wu, P. T., Li, X. L., Zhou, T. W., Sun, S. K., Wang, Y. B., Luan, X. B. and Yu, X., 2017, Spatial and temporal evolution of climatic factors and its impacts on potential evapotranspiration in Loess Plateau of Northern Shaanxi, China. *Sci. of the Total Environ*., 3(2): 1-8.

Po, Y. N., Lawin, E. A., Yao, B. K., Oyerinde, G. T., Attogouinon, A. and Afouda, A. A., 2017, Decreasing past and mid-century rainfall indices over the Queme river basin, Benin (West Africa). *Climate*., 4(5): 74-80.

Mazzeo, D., Matera, N., Luca, P.De., Baglivo, C., Congedo, P.M., Oliveti, G., 2021. A literature review and statistical analysis of photovoltaic-wind hybrid renewable system research by considering the most relevant 550 articles: An upgradable matrix literature database. J. Clean. Prod. 295, 126070. http: //dx.doi.org/10.1016/j.jclepro.2021.126070.

Mazzeo, D., Oliveti, G., Labonia, E., 2018. Estimation of wind speed probability density function using a mixture of two truncated normal distributions. Renew. Energy 115, 1260–1280. http://dx.doi.org/10.1016/j.renene.2017.09.043.

Manasa H. G. and Anand V. S., 2016. implications of climate change on crop water requirements in hukkeri taluk of Belagavi district, Karnataka, India. *Int. J. Res. in Engg. and Tech*., 5(6): 1-6.

Mann, H. B., 1945, Non-parametric tests against trend. *Econometrica1*., 3:245 - 259.

Pathak, H., Aggarwal, P.K. and Singh, S.D., 2012, Climate change impact, adaptation and mitigation in agriculture: methodology for assessment and application. ISBN 978-81-88708-82-6.

Ouarda, T.B.M.J., Charron, C., 2018. On the mixture of wind speed distribution in a Nordic region. Energy Convers. Manag. 174, 33–44. http://dx.doi.org/10. 1016/j.enconman.2018.08.007.

Rehman, S., 2013. Long-term wind speed analysis and detection of its trends using Mann–Kendall test and linear regression method. Arab. J. Sci. http: //dx.doi.org/10.1007/s13369-012-0445-5.

Rawat, J. S. and Manish, K., 2015, Monitoring land use/cover change using remote sensing and GIS techniques: A case study of Hawalbagh block, district Almora, Uttarakhand, India. *The Egyptian J. Rem. Sen. and Space Sci*., 18:77-84.

Sen, P. K., 1968, Estimates of the regression co-efficient based on Kendall's tau. *J. Am. Stat. Assoc.*, 63:1379–1389.

Siddharam, Kambale JB, Basavaraja D, Nemichandrappa M, Dandekar AT. Assessment of long term Spatio-temporal variability and Standardized Anomaly Index of rainfall of Northeastern region, Karnataka, India. Climate Change, 2020, 6(21), 1-11

Yu, L., Zhong, S., Bian, X., Heilman, W.E., 2019. The interannual variability of wind energy resources across China and its relationship to large-scale circulation changes. Int. J. Climatol. 39, 1684–1699. http://dx.doi.org/10.1002/joc.5909.

Zheng, C.W., Pan, J., 2014. Assessment of the global ocean wind energy resource. Renew. Sust. Energ. Rev. 33, 382–391. http://dx.doi.org/10.1016/j.rser.2014.01.065.

https://power.larc.nasa.gov

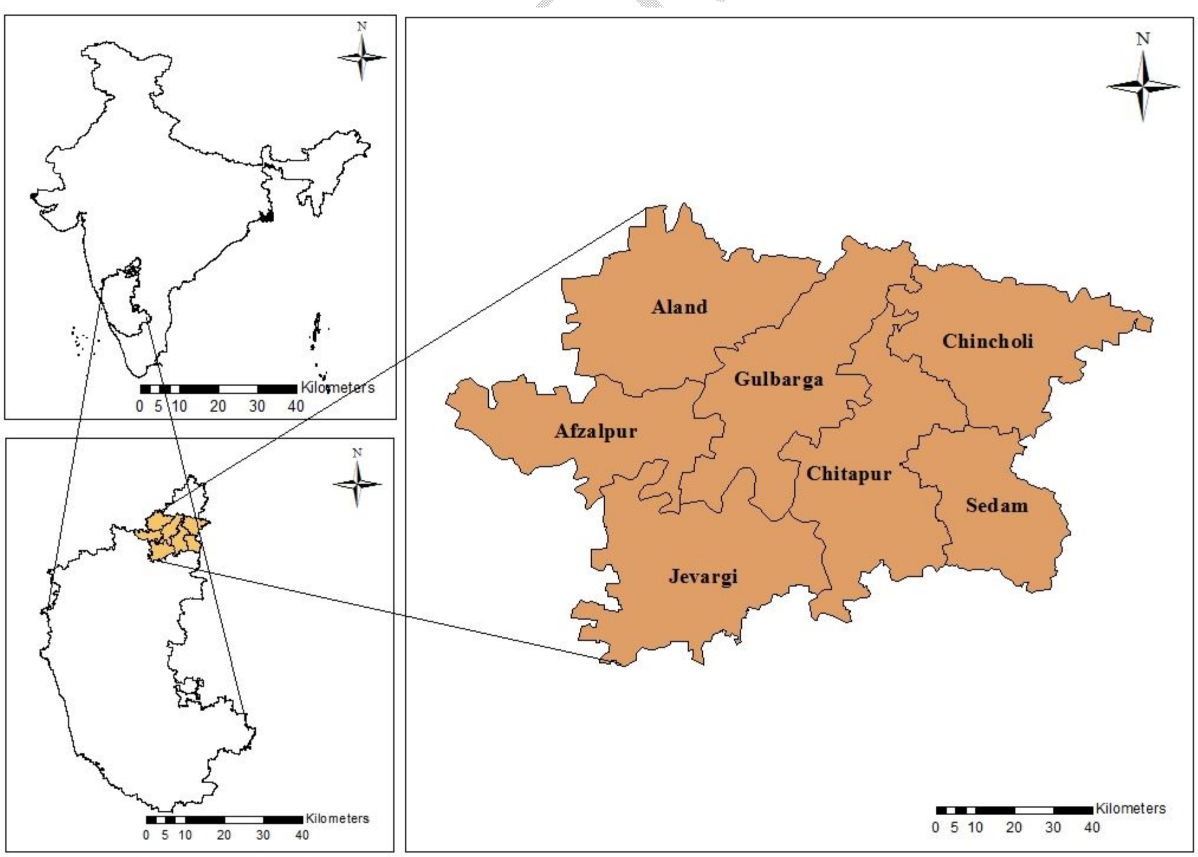
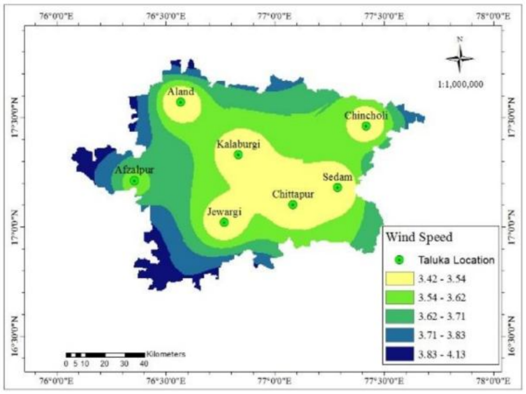
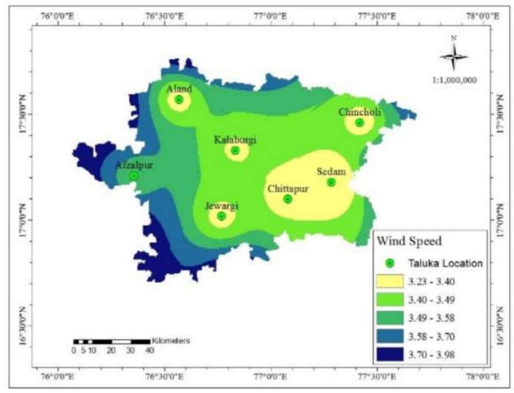


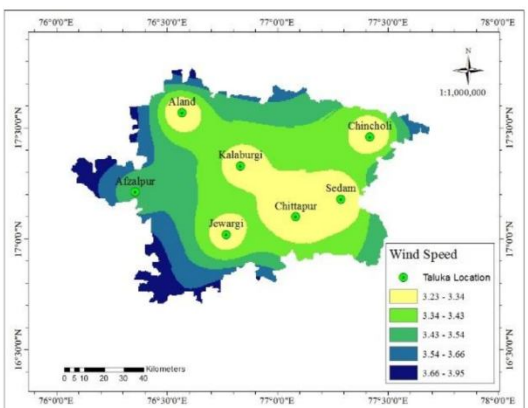
Fig.1. Location of study area.



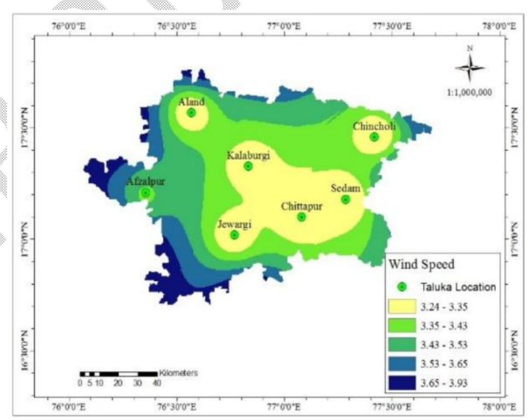
a



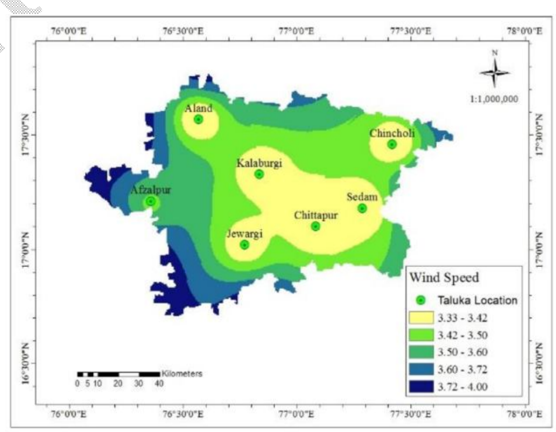
b



c

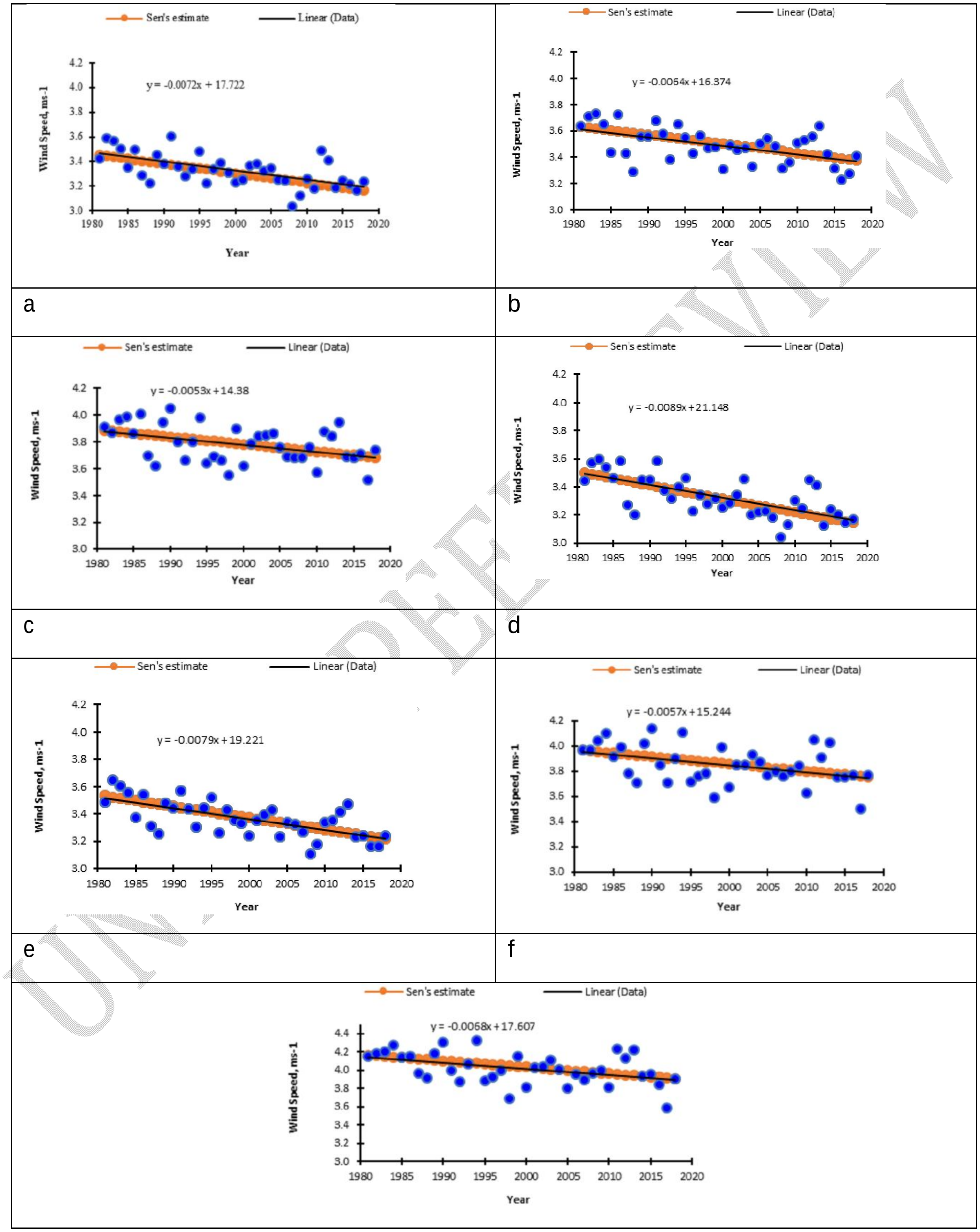


d



e

Fig. 2. Spatial variability maps of wind speed, ms^{-1}, for a) 1981 to 1990, b) 1991 to 2000, c) 2001 to 2010, d) 2011 to 2018 and e) 1981 to 2018.



g

Fig. 3. Long term trend analysis of wind speed, ms-1, from 1981 to 2018, for a) Aland b) Afzalpur, c) Chincholi d) Chittapur e) Kalaburgi f) Sedam and g) Jewargi.

Table 1. Decadal average of wind speed, ms-1

Place	Latitude	Longitude	1981-1990	1991-2000	2001-2010	2011-2018
Aland	17.57	76.5694	3.71	3.95	3.97	4.1
Afzalpur	17.2116	76.3575	4.13	3.94	3.98	4.15
Chincholi	17.4605	77.4188	3.44	3.33	3.26	3.23
Chittapur	17.1002	77.0827	3.46	3.36	3.25	3.21
Sedam	17.1797	77.2869	3.42	3.24	3.28	3.25
Jewargi	17.0197	76.77	3.49	3.37	3.29	3.28
Kalaburgi	17.3297	76.8341	3.47	3.39	3.3	3.29

Table 2. Mann- Kendall trend (Z), Sen's slope value (Q), Long term average, yearly highest and lowest values of various weather parameters

Places/ Indices	Z	Q	Highest	Average	Lowest
Afzalpur	-0.01	-0.011	3.73(1983)	3.49	3.22(2016)
Aland	-0.77	-0.009	3.607(1991)	3.32	3.04 (2008)
Chincholi	-2.35	-0.005	3.62(1983)	3.32	3.03(2008)
Chittapur	-4.4	-0.01	3.6(1983)	3.32	3.03(2008)
Sedam	-2.33	-0.006	3.6(1983)	3.32	3.03(2008)
Kalaburgi	-4.31	-0.009	3.64(1982)	3.36	3.11(2008)
Jevargi	-4.31	-0.009	3.64(1982)	3.36	3.11(2008)