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Turbulence for different background conditions using fuzzy logic and clustering

K. Satheesan and S. Kirkwood

Swedish Institute of Space Physics, Kiruna, Sweden

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Abstract. Wind and turbulence estimated from MST radar observations in Kiruna, in Arctic Sweden are used to characterize turbulence in the free troposphere using data clustering and fuzzy logic. The root mean square velocity, v_{fca}, a diagnostic of turbulence is clustered in terms of hourly wind speed, direction, vertical wind speed, and altitude of the radar observations, which are the predictors. The predictors are graded over an interval of zero to one through an input membership function. Subtractive data clustering has been applied to classify v_{fca} depending on its homogeneity. Fuzzy rules are applied to the clustered dataset to establish a relationship between predictors and the predictant. The accuracy of the predicted turbulence shows that this method gives very good prediction of turbulence in the troposphere. Using this method, the behaviour of v_{fca} for different wind conditions at different altitudes is studied.

Keywords. Meteorology and atmospheric dynamics (Polar meteorology; Turbulence) General or miscellaneous (Techniques applicable in three or more fields)

1 Introduction

Turbulence in the atmosphere is a phenomena affecting the transport and diffusion of trace gases. It also affects the aviation safety. Modelling and prediction of turbulence is a challenge to the scientific community. This is due to the fact that turbulence cannot be measured directly and it is usually not possible to link occurrence of turbulence to any visible phenomena. Moreover, the theory and physical mechanisms that produce turbulence in the atmosphere are not understood well.

Correspondence to: K. Satheesan
(satheesan.k@gmail.com)

MST radar is a useful tool for estimating turbulence. Vertical eddy diffusivity (K_{z}) is commonly used as a measure of turbulence. There are various methods to estimate turbulence using MST radar. Some commonly used methods are the the power method, doppler spectral width method, and variance method. The assumptions involved and the strengths and weaknesses of various methods are explained elsewhere (Wilson, 2004; Satheesan and Krishna Murthy, 2002, 2004). Turbulence in the atmosphere is affected by the background conditions. For example, generation of turbulence in the boundary layer is strongly influenced by the wind direction due to boundary layer heterogeneity (Klipp, 2007). Nastrom and Eaton (2005) found that there is significant correlation between turbulent parameters and wind speed while Kirkwood et al. (2010) have shown that turbulence in the free troposphere can be caused by the interplay of synoptic wind shear and mountain waves. Long records of radar observations can be used to study the climatology of turbulence and its relation to the background wind conditions. In the present work, using a nonlinear technique, turbulence observed by radar is clustered for different background conditions. Non linear system identification methods are used in many geophysical problems (Basu et al., 2005a,b). The nonlinear method used in this study is based on the combination of fuzzy logic and data clustering techniques. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data. Fuzzy logic is one of the major approaches towards nonlinear system identification and has been applied successfully in the areas of communication, control systems, signal processing, chemical process control, biological processes, and atmospheric parameter retrievals (Center and Verma, 1998; Sugeno, 1985; Ajil et al., 2010). In the fuzzy based method, data clustering is applied to classify the predictants depending on their homogeneity. Following data classification, fuzzy rules are applied to establish a relationship between predictors and the clustered

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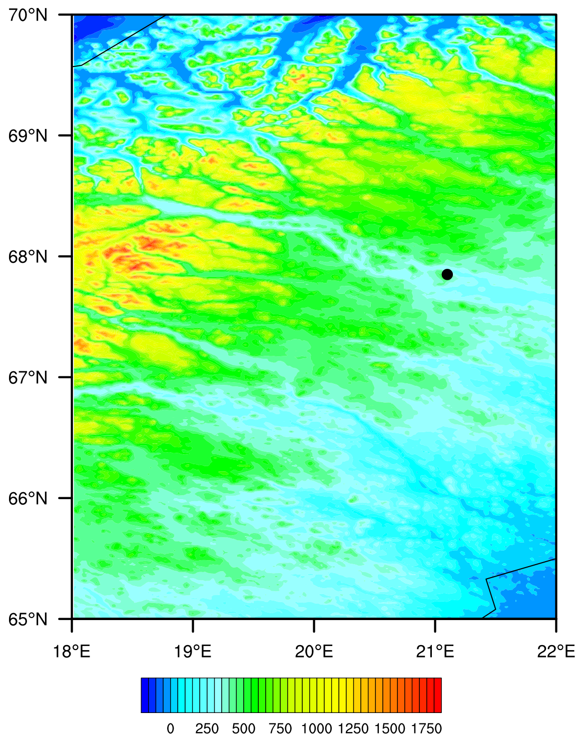

Fig. 1. Location of the MST radar at ESRANGE is marked by a dark circle. The colour shading show the height above mean sea level.

datasets (predictant). The predictor values are graded over an interval of zero to one through fuzzy membership functions, as a prelude for a fuzzy based approach.

2 Data used

Wind and turbulence observed by ESRAD (ESrange RADar) are used in the present study. ESRAD is a VHF radar with an operating frequency of 52 MHz located at ESRANGE (67°53′ N, 21°06′ E) in northern Sweden near Kiruna. The peak transmitted power of ESRAD is 72 kW. The antenna array is made up of 284 five-element yagis, providing a beam width (two-way half-power-width) of about 5°. The atmospheric parameters are retrieved from the returned signal from 6 spaced antenna receivers using full correlation analysis (FCA) (Briggs, 1984; Holdsworth and Reid, 1995). A complete description of the radar system is given by Chilson et al. (1999). (Note that the antenna array was extended in 2004 to twice the original area.) The radar operates continuously cycling between modes optimized for troposphere and mesosphere. For the present study, hourly averaged data of wind and turbulence from ESRAD for for the year 2007 between the altitudes 2 and 12 kms were used. In the troposphere and lower stratosphere, the vertical resolution of the data is about 150 m and the time resolution is ∼2 min. The data are first subjected to a quality check with data corresponding to Signal-to-Noise Ratio (SNR) greater than –2 dB being selected. Note that we used only the vertical wind speed, i.e., magnitude of vertical velocity. The correlation coefficient (R) between the observed and the predicted ν_{fca} improved by ∼10% when vertical wind speed is considered instead of vertical velocity. Further, only wind speed in the range 4–42 m/s and vertical wind speed higher than 0.1 m/s are considered. When the data with vertical velocity less than 0.1 were also used, R between the observed and predicted ν_{fca} was deteriorated by ∼20% compared to when they were not used. The histogram of all the data used are displayed in Fig. 2. There is less data available at the higher altitudes as the SNR becomes very low in dry, neutrally stable air masses which are common in the upper troposphere (see e.g. Rao and Kirkwood, 2005).

3 Method

3.1 Estimation of turbulence

The turbulent root mean square (rms) velocity (ν_{fca}), usually referred to as FCA turbulent velocity, is estimated from the radar using the equation

$$\nu_{\mathrm{fca}} = \frac{\lambda\sqrt{2\ln 2}}{4\pi T_{0.5}} \qquad (1)$$

where $T_{0.5}$ is FCA pattern life time, the corrected fading time in the reference frame of the mean background wind. The pattern life time provides the means for estimating turbulent velocities (Holdsworth et al., 2001). The advantage of using $T_{0.5}$ for turbulent studies over traditional spectral width methods is that the effects of horizontal winds on spectral width (due to finite beam width) are removed. From ν_{fca}, K_{z} is estimated using the the relation,

$$K_{\mathrm{z}} \approx 0.1\frac{\nu_{\mathrm{fca}}^2}{N} \qquad (2)$$

where N is the Brunt-Väisälä frequency. The vertical profile of temperature is required to calculate N. This information is not generally available and therefore we use ν_{fca} as a measure of turbulence. We use horizontal wind speed (U), wind direction (ϕ), magnitude of vertical velocity (w) obtained from the radar, and altitude (Z) of the observations as the predictants and ν_{fca} as the predictor. Note that the vertical velocity at this site is primarily an indicator of mountain-wave activity (Kirkwood et al., 2010).

3.2 Fuzzy logic

Fuzzy set theory (Zadeh, 1965) was born out of the realization that the world that surrounds us is defined by non-distinct boundaries. It is a mathematical tool to deal with linguistic variables (i.e., the concept described in natural language). A fuzzy set is defined as a set without a crisp, clearly

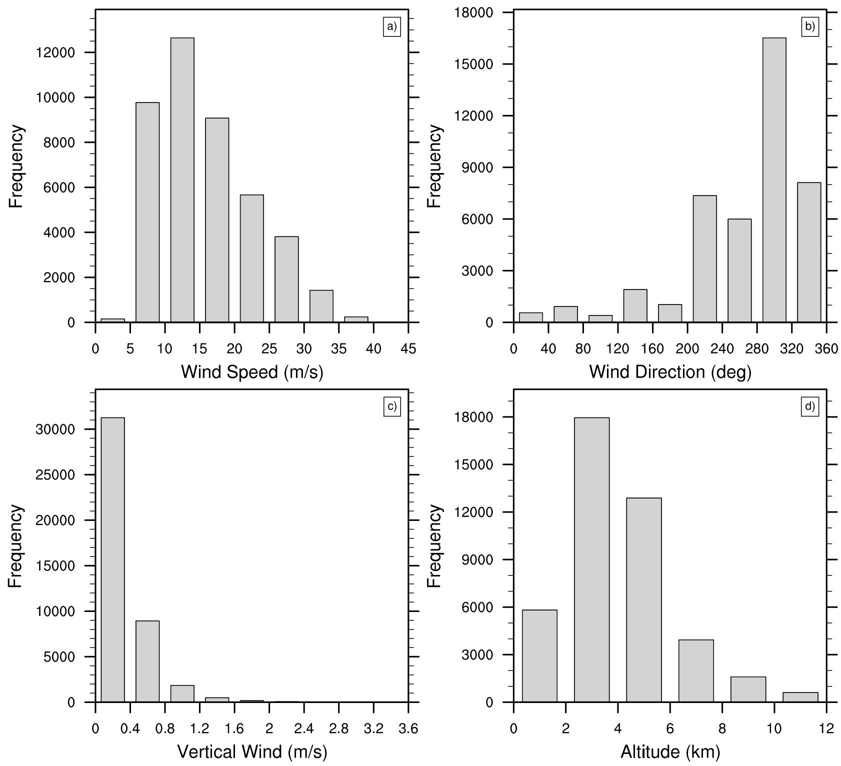

Fig. 2. Histograms of **(a)** wind speed, **(b)** wind direction, **(c)** vertical wind speed, and **(d)** altitude of observations of data used.

defined boundary and is an extension of the classical sets. If $\mathbb{X}$ is a universal set and its elements are denoted by x, then fuzzy set A in $\mathbb{X}$ is defined as the set of ordered pairs.

$$\mathrm{A} = \{x, \mu_\mathrm{A}(x) | x \in \mathbb{X}\} \tag{3}$$

where $\mu_\mathrm{A}(x)$ is called the membership function and maps universal set $\mathbb{X}$ to the real interval [0 1]. The closer $\mu_\mathrm{A}(x)$ is to 1, the more x belongs to A. We may, therefore, view $\mu_\mathrm{A}(x)$ as the degree of membership of x in A. It must be noted that the membership function is different from the Probability measure. Fuzzy membership function is based on the set theory, while the probability measure is based on measure theory. Fuzzy sets are based on vague definitions of sets, not randomness. Fuzzy logic is specifically designed to deal with imprecision of facts (fuzzy logic statements), while probability deals with chances of that happening still considering the result to be precise. The set-theoretic operations of union, intersection and complement for fuzzy sets are defined through membership functions. Let A and B denote the pair of fuzzy sets in $\mathbb{X}$ with membership functions $\mu_\mathrm{A}(x)$ and $\mu_\mathrm{B}(x)$ respectively. The membership function $\mu_{\mathrm{A}\cup\mathrm{B}}(x)$ of union A∪B and the membership function $\mu_{\mathrm{A}\cap\mathrm{B}}(x)$ of intersection A∩B are defined as

$$\mu_{\mathrm{A}\cup\mathrm{B}}(x) = \max(\mu_\mathrm{A}(x), \mu_\mathrm{B}(x)) \tag{4}$$

$$\mu_{\mathrm{A}\cap\mathrm{B}}(x) = \min(\mu_\mathrm{A}(x), \mu_\mathrm{B}(x)) \tag{5}$$

The complement of fuzzy set A is defined as

$$\mu_{\overline{\mathrm{A}}}(x) = 1 - \mu_\mathrm{A}(x) \tag{6}$$

Fuzzy sets and fuzzy operators are the basic building blocks of fuzzy logic. The IF-THEN rule statements are used to formulate the conditional statements that comprise fuzzy logic. Linguistic rules describing a system consist of two parts: an antecedent part (between the IF and THEN) and a consequent part (following THEN). The approach to a problem using fuzzy logic is facilitated through a fuzzy inference system (FIS). The first step in FIS is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The input is always a crisp numerical value limited to the universe of discourse of the input variable. These crisp values must be transformed into linguistic terms (fuzzy sets). This is called fuzzification. The fuzzification layer in FIS generates membership values for all the inputs through membership functions which lie in the premise part. The fuzzy logic controller in FIS combines all the membership values in the premise part to get a weight called "firing strength". The next step is the generation of qualified consequents for each rule depending on the firing strength. In our case U, ϕ, w, and Z are the inputs and ν_fca is the output. The inputs are classified based on the its dynamic range (low, medium and high). IF-THEN rules are used to combine these inputs for mapping with the output. For example, we illustrate a simple case of only two inputs with the U and ϕ as the inputs and ν_{fca} as the output. Further, assume that we have two fuzzy IF-THEN rules of Takagi and Sugeno (1985) type.

Rule1: if U is C_1 and ϕ is D_1, then $\nu_{\text{fca}} = p_1U+q_1\phi+r_1$.

Rule2: if U is C_2 and ϕ is D_2, then $\nu_{\text{fca}} = p_2U+q_2\phi+r_2$.
where C_i and D_i are the linguistic labels (low, medium, high etc.) associated with the inputs U and ϕ coded in the form of membership functions through fuzzification. The parameters p_i, q_i, and r_i will be referred to as consequent parameters. The consequents (outputs) are aggregated to produce a crisp output. This step is called defuzzification.

3.3 Data clustering

Data clustering by definition is grouping of data into similar categories and it is one of the major approaches to unsupervised learning. In an unsupervised learning algorithm provided with just data points and no labels, the task is to find out a suitable representation of the underlying distribution of the data. Many data clustering algorithms are available. The hard-c means algorithm (HCM) tries to locate clusters in multidimensional feature space. The objective is to assign each point in the feature space to a particular cluster. The HCM algorithm tries to minimize the objective function j

$$j=\sum_{i=1}^{c} j_i=\sum_{i=1}^{c}\left(\sum_{k,u_k\in c_i} \parallel u_k-c_i \parallel^2\right) \tag{7}$$

where $u_k \in \boldsymbol{R^m}$, the set of real numbers having dimension m, k is the total number of data points and c is the total number of clusters. The partitioned clusters are typically defined by a binary characteristic matrix $\mathbf{M}$, called the membership matrix where each m_{ik} is 1 if kth data point u_k belongs to cluster i and 0 otherwise. The fuzzified c-means algorithm (Jang et al., 1997) allows each data point to belong to a cluster to a degree specified by a membership grade, and thus each point may belong to several clusters. The fuzzy c-mean (FCM) is different from HCM, mainly because it employs fuzzy partitioning, where each point can belong to several clusters with varying degree of membership. To incorporate fuzzy partitioning the membership function matrix $\mathbf{M}$ is allowed to have all values between 0 and 1. The objective function j which is to be minimized is the generalization of Eq. (7) and is given by

$$j=\sum_{i=1}^{c}\sum_{k=1}^{K} m_{ik}^{q} d_{ik}^{2} \tag{8}$$

where, m_{ik} is a membership between 0 and 1, c_i is the center of the fuzzy cluster i, $d_{ik} = \parallel u_k - c_i \parallel$ is the Euclidean distance between ith cluster point and kth data point, K is the total number of data points and, $q\in(0,\infty)$ is a weighting exponent. FCM starts with an initial guess for the cluster center location and iteratively updates the cluster center and the membership grades by minimizing (8). In many situations, FCM is more natural than hard clustering. In FCM, objects on the boundaries between several classes are not forced to fully belong to one of the classes, but rather are assigned membership degrees between 0 and 1 indicating their partial membership. FCM allow the objects to belong to several clusters simultaneously, with different degrees of membership.

FCM is a supervised algorithm because a priori knowledge of the number of clusters is required. If the number is not known beforehand, it is necessary to apply unsupervised algorithms. Subtractive clustering belongs to the category of unsupervised algorithms and is based on the density of data points in the feature space (Jang et al., 1997). The aim is to find regions in the feature space with a high density of data points. The point with highest number of neighbors is selected as the center for a cluster. The data points within the selected cluster are removed (subtracted) to ensure its absence in the next cluster. The algorithm looks for a new point with the highest number of neighbors. This is continued until all the data points are evaluated.

The modeling is realized through data clustering and fuzzy logic. As a first step, a subtractive clustering algorithm, as described above, is applied to cluster the predictant, ν_{fca} into different clusters. Each cluster contains values of almost similar magnitude of ν_{fca}. More precisely it categorizes the entire ν_{fca} into different clusters depending on the characteristic variability of ν_{fca} which are observed at different altitude regions and for different wind conditions. The clustering algorithm takes into account this variability. The number of clusters generated using subtractive clustering depends on the search radius which is the Euclidean distance between the cluster center and the data points. If the search radius is small we will have a larger number of clusters. We set 0.2 as the search radius for clustering. Decreasing the radius may improve the mapping for the training set, but it may not yield good results for the validation using independent data sets. This problem is due to over fitting. So, there must be a trade off between search radius and the desired model accuracy. This radius is determined depending on the characteristics of the variability of the dataset under consideration.

In the present case, the premise part of the fuzzy rule includes U, ϕ, w, and Z whereas the consequent part has the clustered ν_{fca}. The advantage of data clustering prior to the application of fuzzy rules is that rules can be applied for different altitude regions and for different wind conditions separately. As explained earlier, input values are graded between the values 0 and 1 and are coded in the form of fuzzy a membership function. In the present algorithm we have used bell shaped membership functions to represent the input. Takagi and Sugeno's (Takagi and Sugeno, 1985) IF-THEN rules are used, the output of each rule being a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output. The weight is the firing strength which is obtained by combining the membership values on the premise part of each rule through a specific T-norm operator, usually multiplication or minimum.

4 Results

The hourly averaged data contains 42 781 points for the altitude range considered. Only values of U in the range 4–42 m/s and w in the range 0.1–3.5 m/s were used. Values of $w<0.1$ m/s are also important, but R between the observed and predicted ν_{fca} was improved by about 20% when they were not used. So we are not considering those cases. We used data with values of w greater than 1.0 m/s also for training, but the number of data points with such values is small and therefore we do not discuss these cases. In order to have representation from all the ranges in the data, every fifth data point was selected for training to generate the fuzzy membership functions. This will help in representing all the variabilities of the data within the whole dynamic range. There were 8557 data points used for the training which is 20% of the total data points. The remaining data are used for the validation. Fuzzy rules were generated using the training dataset as explained in the previous section. Using a search radius of 0.2 there were 413 fuzzy rules. These rules represent the data for the altitude range 2–12 km, and for all U, ϕ, and w.

Figure 3a shows the scatter plot of the ν_{fca} for the training data. The R for training data is 0.742 with a root mean square error (RMSE) of 0.1 and a bias close to 0. Figure 3b shows the same for the validation data. It has an R of 0.695, RMSE of 0.012 with no bias. In fact, the data shows a small positive bias for low values and a small negative bias for higher values. There is not much variation for R with altitude in the lower and middle troposphere. But R is high ($\sim$0.8) near the tropopause for both training and validation data sets. The validation with independent data sets, with very good R shows that the turbulence in the region is represented very well by the fuzzy membership functions. We use these to study turbulence under different conditions of wind in different altitude ranges.

The training data set consisted of U in the range 4–42 m/s, direction in the range 5–355°, w in the range 0.1–1.0 m/s, and Z in the range 2–12 km. We generated ν_{fca} for the same ranges using the fuzzy membership functions and the results of the outputs are discussed in this section. We use the notation $\widehat{\nu_{\mathrm{fca}}}$ for the generated ν_{fca} hereinafter.

Figure 4 shows the $\widehat{\nu_{\mathrm{fca}}}$ values generated using the fuzzy membership function. The columns in the figure show the $\widehat{\nu_{\mathrm{fca}}}$ for different w ranging from 0.1 to 0.9 m/s with steps of 0.2 m/s. It can be observed that turbulence is low for low vertical and horizontal wind conditions. Further, weak turbulence is observed for a wide range of horizontal wind conditions at the lower altitudes while strong turbulence is observed at higher altitudes but only for higher wind speeds and for wind from north and west directions. Turbulence is comparatively weaker for the rest of the wind speeds and directions at higher altitudes. The first row in Fig. 4 shows the $\widehat{\nu_{\mathrm{fca}}}$ at 2 km for w from 0.1 to 0.9 m/s. $\widehat{\nu_{\mathrm{fca}}}$ is low with maximum values less than 0.7. $\widehat{\nu_{\mathrm{fca}}}$ increases gradually with the wind speed from 15 m/s upwards. For higher wind speed,

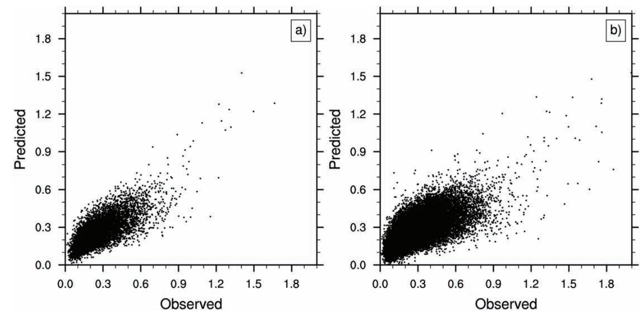

Fig. 3. RMS turbulence observed and predicted for the training data(left panel) and validation data set (right panel).

above 30 m/s, the turbulence is stronger for wind from all directions. Similar behaviour is observed for all the w values, with the turbulence becoming stronger for higher values. At 2 km altitude, the effect of complex surface heterogeneity may be generating turbulence for wind coming from any side. The Scandinavian mountains are situated on the western side of the radar location as seen from Fig. 1. This leads often to wave generation. Turbulence is generally expected associated with these waves (Kirkwood et al., 2010). At the next level at 4 km (second row, Fig. 4), turbulence is stronger for wind speed higher than $\sim$30 m/s and wind direction between 200 and 360°. This strong turbulence is observed for wider range of wind conditions with increased values of w.

At 6 km (Fig. 4, third row), the turbulence is low when U is below 20 m/s. Same pattern is seen for all w with $\widehat{\nu_{\mathrm{fca}}}$ increasing and spreading to more wind conditions as w increases. An important observation is that, compared to lower altitudes, lower turbulence is observed for wind direction 90–180° and wind speed <25 m/s . Turbulence is always high when the wind direction is from north and west sides of the radar and speed is above 25 m/s. Figure 4, fourth row, displays $\widehat{\nu_{\mathrm{fca}}}$ at 8 km. This shows the same structure as that at 6 km. But the transition from low to high $\widehat{\nu_{\mathrm{fca}}}$ is sharper. $\widehat{\nu_{\mathrm{fca}}}$ in the regions from 8 to 12 km shown in the Fig. 4 shows quite similar behaviour. Strong turbulence is observed for wind speed above 30 m/s. An interesting point observed here is that the strong turbulence observed for wind from the north is only from the western side (270–360°) and not from the eastern side (0–90°) showing total absence of periodicity in according to wind directions (for the 330–30°). This may look like an artefact. But, most of the time, the wind direction at the radar location is in the range 200–360° as can be seen from Fig. 2. Fuzzy rules are applied to the clustered data of ν_{fca}. The cyclic nature of wind direction is not considered in the data which may cause to have clusters of different dynamic ranges in the data ranges (330–360°) and (0–30°). The high turbulence observed for the range (270–360°) may be associated with jet streams in the upper troposphere. Strong turbulence is usually observed associated with jet streams which are characterized by wind speed in excess

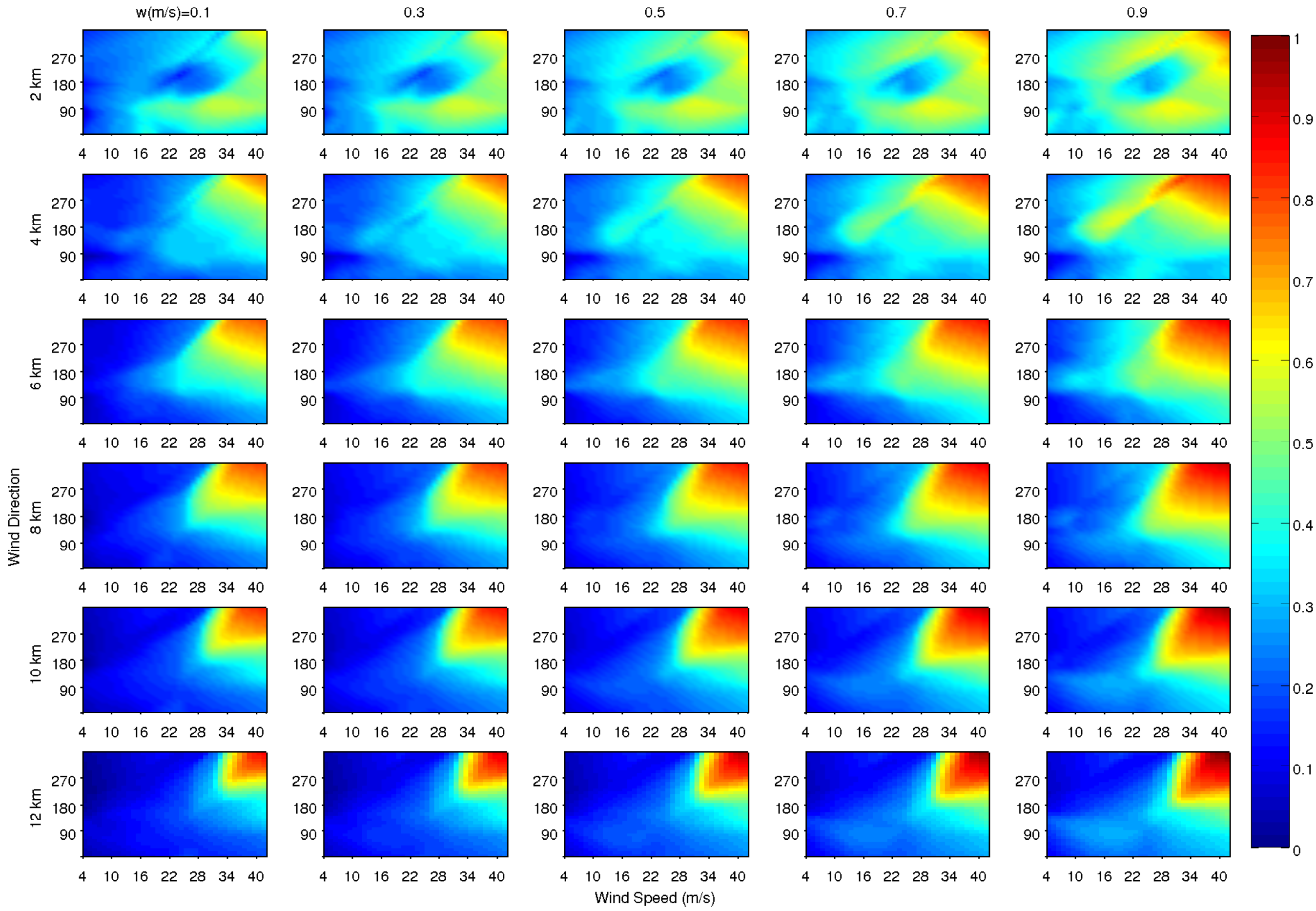

Fig. 4. The ν_{fca} for different wind conditions. Each column represents the ν_{fca} for w ranging from 0.1 to 0.9 with steps of 0.2, while each row is for the altitude regions in the range 2–12 km with steps of 2 km. X-axis is the horizontal wind speed and Y-axis, the wind direction.

of 30 m/s. Strong vertical shears of horizontal wind associated with jet streams give rise to Kelvin-Helmholtz instabilities(KHI) which are important sources for the generation of turbulence. Strong turbulence is observed bordering jet streams over both tropical (Rao et al., 2001; Das et al., 2010) and high latitude (Rao and Kirkwood, 2005) sites while Pepler et al. (1998) found that there is widespread turbulence throughout the jet. Turbulence generated in the lower troposphere is either due to static instability or dynamic instability. Breaking of gravity waves generated due to mountains is also a source of turbulence in the atmosphere. Generally, the turbulence observed in the lower troposphere will be due to a combination of some or all of these processes. On the other hand, turbulence in the upper troposphere and lower stratosphere is generally associated with wind shear created KHI. The differing characteristics of turbulence for different background observations, obtained here with the help of fuzzy clustering are consistent with these mechanisms.

5 Conclusions

In the present study, radar observed turbulence has been studied for different background conditions using fuzzy clustering. The clustering is done for different horizontal wind speed, direction, magnitude of vertical velocity, and the height. The values ν_{fca} are clustered for different values of the above parameters. The clustering is then checked with independent data sets. It is observed that this technique reproduces the ν_{fca} very well with an R of 0.695. Using this method, turbulence in the troposphere is studied. FCA turbulence velocities were characterized for wind speed in the range of 4 to 42 m/s, w in the range of 0.1 to 1.0 m/s for all directions, in the altitude regions 2–12 km. The following points were observed:

1. Strong turbulence is observed when the wind direction is from north and west and the horizontal wind speed is high.

2. Turbulence increases with the magnitude of vertical velocity.

3. Turbulence decreases with increasing altitude for low wind conditions while it increases with altitude for higher wind conditions.

4. Turbulence observed in the lower altitude regions is found to be moderately strong for a wide range of wind speed and direction conditions while that at higher altitude is strong only for a limited range of wind speed and direction conditions.

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