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Measuring the Impact of Statistical Techniques for Computation of Weighting Factors in Avalanche Forecasting Model

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Abstract: ***Avalanche forecasting is an important measure required for the safety of the people residing in hilly regions. Snow avalanches are caused due to the changes that occur in the snow and weather conditions. The prominent changes, that cause the variations which further culminate into an avalanche, can be given higher significance in the forecasting model by application of appropriate weights. These weights are decided based on the relation of each weather parameter to snow avalanche occurrence by the forecaster with the help of historical data. A method is proposed in the current work that can help in removing this subjectivity by using correlation coefficients. Present work explores the use of Pearson correlation coefficient, Spearman rank correlation coefficient and Kendall Tau correlation coefficient to obtain the weighting factors for each parameter used for avalanche forecasting. These parameters are further used in the cosine similarity based nearest neighbour model for avalanche forecasting. Bias and Peirce's Skill Score are performance measures used to evaluate the outcome of the experimental work.***

Keywords: ***Correlation Coefficient, Forecasting, Nearest Neighbour, Snow Avalanche.***

I. INTRODUCTION

An avalanche is a flow of snow or ice or both which moves rapidly down a steep slope [1]. It is a natural disaster which is frequently observed in the hilly and mountainous territories throughout the world. An avalanche mainly occurs due to a weakening in the snowpack. This is observed when the gravitational force exerted on the snowpack is more than the force holding the snow together. The area where an avalanche begins is the starting zone of an avalanche. The path traced by an avalanche is called as the track and the area where an avalanche slows down and snow is deposited is known as the runout zone [2]. Forecasting of an avalanche is very important for the safety of the people staying in the avalanche prone regions and also for the protection of the infrastructure present in the nearby areas. Avalanche forecasting is defined as predicting snowpack instability in space and time relative to a given triggering level [3].

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Many factors like new snow, water content, snowpack structure, mean slope affect the stability of the snowpack [4]. Hence, it is necessary to study the effect of all these parameters on the occurrence of snow avalanche in order to forecast snow avalanche. For the current work, the data consists of snow and weather parameters of the region under study.

These parameters are computed at, above or near the snow surface [3]. The effect of all these parameters is not same on avalanche forecasting. Some parameters have higher significance than the rest of the parameters. As a result, additional importance is given to some parameters by using the concept of weighting. The objective of the paper is to explore the use of correlation coefficients to obtain these weighting factors for each parameter for an avalanche forecasting model. This is achieved by obtaining the Pearson correlation coefficient, Spearman rank correlation coefficient and Kendall Tau correlation coefficient for all the parameters with regards to the avalanche occurrence condition. These values of coefficients are then used as weighting factors after normalization in the cosine similarity based avalanche forecasting model.

The following paper is divided into six sections. Section I is the Introduction. Section II provides the background. Section III provides details information about the study area and the data used for forecasting. Section IV gives information about the methodology used in the current work. Section V describes the results and the accuracy of the forecasting model. Section VI concludes the paper.

II. BACKGROUND

Avalanche forecasting was suggested by using nearest neighbours[5]. The conditional probability for a point/day whose avalanche occurrence condition has to be found out, is given by

$$\Pr(A) = \frac{nA}{N} \qquad (1)$$

where nA is the number of avalanche days present in the nearest neighbours and N is the total number of neighbours considered. Further the use of Euclidean distance as a distance metric was proposed to find the neighbours [6].

The use of weighting was also suggested which could help in providing additional preference to certain parameters in forecasting model[6]. That work was further extended where the critical factor was decided to be 0.3 and the use of explanatory variable in forecasting was suggested [7], [8]. It was also suggested to consider number of nearest neighbours as ten for calculating the avalanche occurrence probability [9]. Though weighting formed an integral part of avalanche forecasting methods, subjective ranking for different parameters with
regards to their influence in avalanche occurrence was also observed [10]. The concept of automation was observed in the calculation of the weights that were used in avalanche forecasting model [11]–[14]. Automation of weighting factors was achieved with the help of genetic algorithm and Artificial Bee colony algorithm. However, it was observed that even though automation provided optimised results, the weights obtained from them could not be directly interpreted as the significance of a particular parameter in avalanche occurrence. This is because many different combinations could provide an optimal solution. The use of two feature ranking methods: Relief F and Sequential forward generation was explored to provide additional significance to the parameters and remove the involved subjectivity [10].

Avalanche forecasting models have been suggested and implemented throughout the globe. Factors affecting avalanche activity are common at the base. However, depending on each region, the importance of a particular factor on avalanche activity may change. A new method was proposed that found the nearest neighbour of a particular day by using cosine similarity instead of Euclidean distance as a distance metric [15]. This work was further extended by using the concept of weighting with the cosine similarity based avalanche forecasting model[16]. The results of this model are encouraging, but as mentioned earlier, subjectivity is observed in the decision of the weighting factors that are to be applied for each parameter. The present work suggests the use of correlation coefficients to remove this subjectivity involved in deciding the weighting factors. The present work uses the correlation coefficients to find the relation between the parameters used for forecasting and the avalanche condition and thereby tries to remove the subjectivity present in assignment of weighting factors. This work has been currently carried out for the Bahang village present in Himachal Pradesh, India. However, it could be extended to any region where the avalanche condition and historical information about the weather parameter is present. The correlation coefficients used for the current work are Pearson correlation coefficient, Spearman rank correlation coefficient and Kendall Tau correlation coefficient. The weighting factors obtained after applying these coefficients are used in the cosine similarity based nearest neighbour model for avalanche forecasting [16].

III. STUDY AREA AND DATA

The snow and meteorological data for the Bahang (32.2727° N, 77.1823° E) region is obtained from the weather station installed at Bahang (2192 m above sea level) [17]. 10 parameters are selected from the data obtained from this observation station and are used for the current study. The data is obtained for the months of January, February and March from the year 2005 to 2013. For the current study, data recorded at 0830 hrs (GMT+5.30) is used. The missing values that are observed in the dataset are calculated by using the relation between dry temperature, wet temperature and humidity presented by [18]. The list of parameters used for the current study is provided in Table 1 and the geographical location of Bahang region is given in Figure 1.

Table 1: List of parameters used for the current work

Sr. No	Variable	Unit
1	Wet temperature	°C
2	Average wind speed	kmph
3	Humidity	%
4	Amount of fresh snow	cm
5	Fresh snow water equivalent	mm
6	Height of snow	cm
7	Snow temperature	°C
8	Penetration of snow	cm
9	Sunshine	Hrs: min
10	Rate of snow fall	cm/min

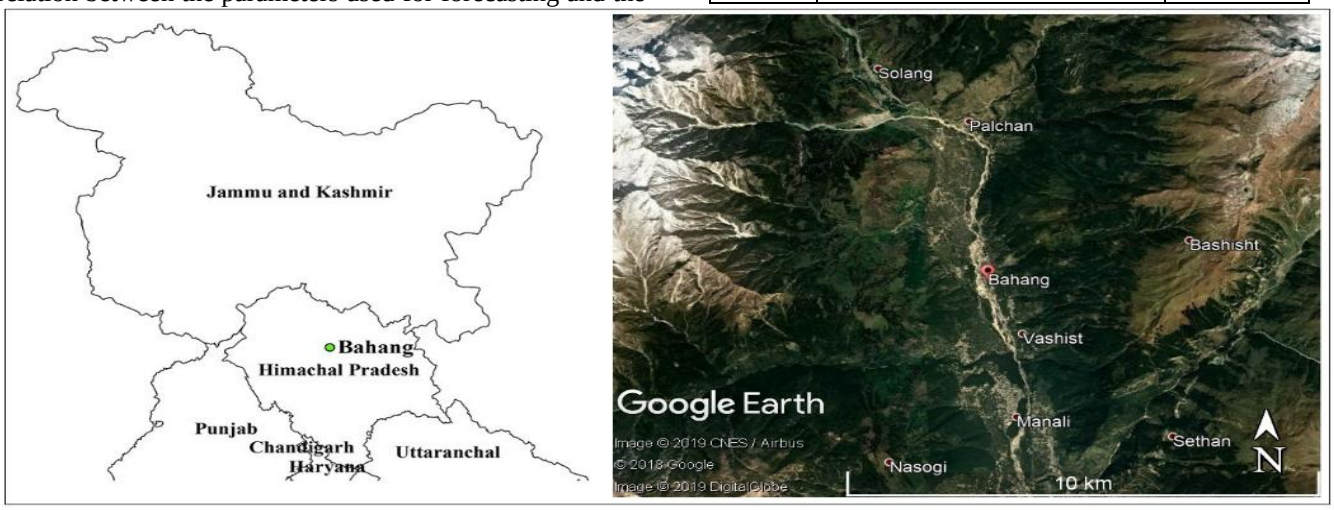

Figure 1: Geographical location of Bahang village (32.2727° N, 77.1823° E)

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IV. METHODOLOGY

A. Calculation of correlation coefficients

A correlation coefficient depicts a statistical relation between two variables. Normally, it mirrors the monotone association amongst the variables [19]. It can be positive or negative. Pearson correlation coefficient estimates the degree of linear association between two variables [20]. However, sample Pearson correlation coefficient, r is given by

$$r = \frac{\sum_{i=1}^{n}((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (2)$$

where, $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$ *and* $\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$

Similarly, Spearman rank correlation is a rank-based version of the Pearson's correlation coefficient [19]. This is equivalent to performing the Pearson's correlation coefficient on the ranks of the data rather than using the original data. The sample correlation coefficient of Spearman's rank correlation coefficient, (r_s) is given by

$$r_s = \frac{\sum_{i=1}^{n}((rank(x_i) - \overline{rank(x)})(rank(y_i) - \overline{rank(y)}))}{\sqrt{\sum_{i=1}^{n}(rank(x_i) - \overline{rank(x)})^2 \sum_{i=1}^{n}(rank(y_i) - \overline{rank(y)})^2}} \quad (3)$$

where rank(x_i) and rank(y_i) are the ranks of the observation in the sample. The ranks are assigned for each x and y based on its value with regards to other values present in x and y respectively. In case of identical values, ranks are given by calculating the average with respect to number of positions having the same value.

Lastly, Kendall Tau correlation coefficient assesses the degree of similarity between the two sets of ranks given to a same set of objects [21]. The Kendall Tau correlation coefficient is calculated in simple case [22], in absence of any tied ranks as

$$\tau = \frac{n_c - n_d}{n_0} \quad (4)$$

where, $n_0 = 0.5n(n-1)$ and n_c are the number of concordant pairs and n_d are the number of discordant pairs. However, in cases where tied ranks are present, another formula termed as τ_b is used. τ_b is given by

$$\tau_b = \frac{n_c - n_d}{\sqrt{(n_0 - n_1)(n_0 - n_2)}} \quad (5)$$

where, $n_1 = 0.5\sum_{i=1}^{p} t_i(t_i - 1)$ and $n_2 = 0.5\sum_{j=1}^{q} u_j(u_j - 1)$

For all these correlation coefficients, the values fall between the range of +1 to -1 where, +1 is the highly correlated and -1 is inversely correlated. The values for Pearson correlation coefficient, Spearman rank correlation coefficient and Kendall Tau correlation coefficient are found out by considering the relation of each parameter used in forecasting with the avalanche occurrence condition. Accordingly, the values for all three correlation coefficients are summarised in Table 2.

Table 2: Correlation coefficients values for all the parameters with respect to the avalanche occurrence condition

	Pearson's correlation coefficient	Spearman rank correlation coefficient	Kendall Tau correlation coefficient
Wet temperature	-0.093804	-0.115568	-0.096675
Average wind speed	-0.160188	-0.189192	-0.154780
Humidity	0.186917	0.203304	0.168340
Amount of fresh snow	0.343670	0.349685	0.341410
Fresh snow water equivalent	0.465734	0.367240	0.358233
Height of snow	0.335141	0.262225	0.243249
Snow temperature	0.181335	0.227638	0.197889
Penetration of snow	0.531704	0.414645	0.346387
Sunshine	-0.188408	-0.179108	-0.151796
Rate of snow fall	0.267249	0.343880	0.335550

B. Calculation of weighting factors

These values of the correlation coefficients are further normalized between 0 to 1 by using the following equation [23],

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (6)$$

where, x is the value obtained after applying correlation coefficient and x_{min} and x_{max} are the minimum and maximum values obtained for each correlation coefficient respectively. The normalized values for all three correlation coefficients are summarized in Table 3.

These normalized values are applied as weighting factor for the parameters in the avalanche forecasting model [16]. The basic idea behind this model is that, if an avalanche had occurred for a given set of weather conditions, then an avalanche can occur again if similar weather conditions are met again. The algorithm aims to find the ten nearest days to the day for which the avalanche situation is to be forecasted [9]. The concept of weighting has been explored [6], [10]. A weighting factor is decided for each parameter based on the influence of the parameter on avalanche occurrence. For the current study, the weighting factors are decided by using the correlation coefficients.

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Table 3: Values for all the correlation coefficients after normalisation

	Pearson's correlation coefficient	Spearman rank correlation coefficient	Kendall Tau correlation coefficient
Wet temperature	0.131374	0.121928	0.113262
Average wind speed	0.039188	0.000000	0.000000
Humidity	0.521204	0.650003	0.629848
Amount of fresh snow	0.738882	0.892422	0.967207
Fresh snow water equivalent	0.908390	0.921494	1.000000
Height of snow	0.727038	0.747581	0.775865
Snow temperature	0.513453	0.690302	0.687447
Penetration of snow	1.000000	1.000000	0.976908
Sunshine	0.000000	0.016699	0.005818
Rate of snow fall	0.632759	0.882808	0.955783

C. Avalanche forecasting algorithm:

The steps followed in the avalanche forecasting algorithm as are follows:

Step 1: The similarity between the day to be forecasted and the rest of the days from the dataset is found by

$$\text{Similarity between neighbouring days} = \frac{\sum_{i=1}^{n} w_i P_i Q_i}{\sqrt{\sum_{i=1}^{n} P_i^2}\sqrt{\sum_{i=1}^{n} Q_i^2}} \quad (7)$$

where, P and Q are vectors with P_i and Q_i as their components respectively and w is the weighting factor where w_i is the weighting factor for each parameter.

Step 2: The days from the rest of the dataset are arranged in the decreasing order with regards to the similarity value obtained in step 1. Hence, higher the similarity, closer is the past day from the dataset to the particular day.

Step 3: The first 10 days from the order obtained in step 2 are taken as ten neighbouring days.

Step 4: The avalanche occurrence situation for all the ten neighbours is found.

Step 5: Probability of avalanche occurrence Pr(A) is found out by (1)

Step 6: If the probability of avalanche occurrence is greater than or equal to threshold value, then the particular day is considered as an avalanche day.

The threshold value for the current work is considered as 0.3 [7]. Hence if 3 out of the ten neighbouring days are avalanche days, then the day whose forecast is to be found, is considered as an avalanche day. The outcome of the forecasting model is either a "Yes" event or "No" event. Confusion matrix is used to find the correct predictions and the errors in the current work [24]. The values of the confusion matrix used for binary events are given in Table 4.

Table 4: Confusion Matrix for binary events

Observed / Forecasted	Yes	No
Yes	True Positive (a)	False Positive (b)
No	False Negative	True Negative (d)

V. RESULTS AND DISCUSSIONS

For the current work, data from 2005 to 2010 is used as a training dataset and 2011-2013 is used as a testing dataset. Bias and Peirce's skill score (PSS) are used as verification measures for the forecasting model. Bias is the ratio of the number of forecasts of occurrence to the number of actual occurrences [25]. Hence Bias indicates whether a forecast has a tendency to over forecast (bias>1) or under forecast (bias<1) [26]. It is given by

$$\text{Bias} = \frac{a+b}{a+c} \quad (8)$$

Pierce Skill Score(PSS) measures the skill relative to an unbiased random reference forecast [27]. It is given by

$$\text{PSS} = \frac{(ad-bc)}{(a+c)(b+d)} \quad (9)$$

The value of PSS is between -1 to 1 where perfect forecast is indicated by 1. After applying the weights in the cosine similarity based avalanche forecasting model, the values for a, b, c and d are found. The change in the values of a, b, c and d after application of weighting factors are summarised in Table 5.

Table 5: Change in the value of a, b, c ,d after application of weights (values are in %)

	Pearson's correlation coefficient	Spearman rank correlation coefficient	Kendall Tau correlation coefficient
Change in the value of a	0.3690	0.3690	0.3690
Change in the value of b	7.7491	6.2731	6.6421
Change in the value of c	-0.3690	-0.3690	-0.3690
Change in the value of d	-7.7491	-6.2731	-6.6421

A positive value depicts an increase and a negative value shows a decrease in the value of a, b, c and d. From Table 5, it is observed that there is an increase in the value of True Positive(a) for all the three sets of weighting factors. This means that the application of the weights has increase the values of True Positive(a) which is good. Similarly, a decrease is observed in the values of False Negatives(c) which is again good.

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However, a considerable increase is also observed in the value of False Positives(b). This is not good as it shows that the model is providing a "Yes" forecast for the events where the actual condition in "No". Similarly, a decrease is seen in the values of False Negatives(d) which is again not good.

Subsequently, the values for Bias and Pierce Skill score are calculated for all the three set of weighting factors. The values for verification measures are also calculated for the avalanche forecasting model sans weights. This helps in understanding the change in the accuracy of the model after the application of the weights. These values are summarized in Table 6.

Table 6:Values for Verification measures after the application of weights

Verification measures	Model sans weights	Weights from Pearson's correlation coefficient	Weights from Spearman rank correlation coefficient	Weights from Kendall Tau correlation coefficient
Bias	2.7500	8.2500	7.2500	7.5000
PSS	0.7200	0.8914	0.9064	0.9026

On application of weights, a rise of 23.7971% was observed in the value of Peirce Skill Score(PSS) for the avalanche forecasting model using weights obtained from Pearson's correlation coefficient. A rise of 25.8778% and 25.3576% was observed in the value of PSS in the forecasting model using weights obtained by applying Spearman rank correlation coefficient and Kendall Tau correlation coefficient respectively. The values of the avalanche forecasting model sans weights are used as a reference to see the effect of application of weights on the accuracy of the model. The values of Bias for the model sans weights show that the model is over forecasting. However, after the application of the weights for all the three set of weighting factors, there is a further increase in the tendency of the model to over forecast. This is observed as there is a considerable increase in the values of False Positives(b) after application of weights. However, in case of PSS, an improvement is observed in the values after application of weighting factor for all the three variants. Amongst all the three set of weighting factors, the results provided by the weighting factors obtained by Spearman rank correlation coefficient are better than the rest of the methods. Hence, from the current work, it is observed as the subjectivity involved can be removed by calculating the weights by using the correlation coefficients and applying them in the avalanche forecasting model.

VI. CONCLUSION

Avalanche forecasting is an important aspect in disaster mitigation. Use of cosine similarity with nearest neighbour for avalanche forecasting has been promising. Use of weighting factors helps in further tuning of the model. The current work explored the use of correlation coefficients to remove the subjectivity involved in the decision of the weighting factor. Values for Pearson correlation coefficient, Spearman rank correlation coefficient and Kendall Tau correlation coefficient are calculated by considering the relation of the parameters used for the current study with the avalanche occurrence condition. The weights are then calculated by normalizing the values of the correlation coefficients between 0 to 1 by using the maximum and the minimum values for each correlation coefficient. The accuracy of the model is gauged by using Bias and Pierce Skill Score as verification measures. Improvement is observed after application of weights in the accuracy of the model, however the model tends to over forecast. There is a substantial increase in the False positives after the application of weights. Amongst the three correlation coefficients, weights obtained from Spearman rank correlation coefficient provided better forecast than the weights obtained by using Pearson correlation coefficient and Kendall Tau correlation coefficient. This work is conducted by using the snow and meteorological data of the Bahang village of Himachal Pradesh, India.

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