DETERMINING WHICH POLARIMETRIC VARIABLES ARE IMPORTANT FOR WEATHER/NON-WEATHER DISCRIMINATION USING STATISTICAL METHODS

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ABSTRACT

Weather radar is a useful tool for the meteorologist in examining the atmosphere and determining what types of weather are occurring, how large an area a weather event might cover, and how severe that event might be. It is also widely used for automated applications. However, weather radar can pick up on objects other than just weather, causing the data to become cluttered and harder for forecasters to decipher. Quality control algorithms can help to identify which echoes returning to the radar are meteorological and which are not, and they can then remove such contaminants to create a clearer image for the meteorologist. With the recent widespread upgrade to dual polarization technology for the WSR-88D (Weather Surveillance Radar 1988 Doppler) radars, polarimetric variables can be used in these quality control algorithms, allowing for more aspects of the data to be analyzed and more of the contamination to be removed. This study analyzes those polarimetric variables in order to determine which are the most important for weather/non-weather discrimination. Such research serves to help rank variable importance and prevent the quality control algorithm from being overfit, thus aiding in developing the most efficient algorithm for operational use.

1. INTRODUCTION

Radar data provides useful information for the meteorologist. It is helpful in determining the severity and coverage of storms, aids in accurate forecasts, and thus helps to relay the most reliable and detailed information to the public in order to help ensure safety and preparedness. Useful applications using weather radar data include estimating precipitation amounts (Fulton et al. 1998) and aiding in hail detection (Ortega et al. 2009). But sometimes the radar beam can detect non-meteorological objects (i.e., contaminants), resulting in a more cluttered view for the meteorologist to decipher when looking at the weather radar display. Types of contaminants include the presence of birds, insects, and dust. Contamination may also result from anomalous propagation, which involves the bending of the radar beam outside of what is expected. When the radar beam bends in this way, it can detect near-surface obstacles such as terrain or buildings and cause an erroneous echo return.

Quality control algorithms have been developed by researchers and scientists that serve to identify which radar echoes are meteorological and which are non-meteorological (e.g., by Steiner and Smith (2002); Kessinger et al. (2003); Zhang et al. (2004); Lakshmanan et at (2007a, 2012)). Lakshmanan et al. developed an algorithm in 2007 which operated on three radar moments, including velocity (V), reflectivity (Z), and spectrum width (SPW). Information on the identity of radar echoes taken from these quality control algorithms can be used to remove such clutter from the weather radar data. This would create an overall clearer image for the

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meteorologist and forecaster to look at and discern what is happening in the atmosphere in a more efficient way.

With the recent widespread operational use of dual polarization radar, new quality control algorithms can be developed that incorporate polarimetric variables. Dual polarization radar allows for a greater number of variables to be utilized in such algorithms that were before unavailable with non-polarimetric radars. One such algorithm has been developed for dual polarization radar data (Lakshmanan et al. 2013). This algorithm utilizes the three moments from the previous non-polarimetric quality control algorithms, in addition to three others including correlation coefficient (RhoHV), differential reflectivity (Zdr), and differential phase shift (PhiDP). From these six radar moments, other polarimetric variables can be calculated.

One downfall of non-polarimetric quality control methods is that they tend to focus only on removing the anomalous propagation and ground clutter, since these contaminants have high reflectivity values (Lakshmanan et al. 2013). With the more diverse collection of variables available through polarimetric radar data, biological targets can also be better detected and thus removed from the contamination in the data.

The recent Lakshmanan et al. (2013) quality control technique was developed in such a way that allows for statistical methods to be applied to the data. The present study seeks to use such statistical methods to examine which of these polarimetric variables are the most important in weather/non-weather discrimination. A combination of three different statistical methods are employed, including a permutation-based test, the Kullback-Leibler method known as the J-measure, and a χ^2 statistics-based test. In total, 17 different polarimetric variables were utilized for the research, as will be described in Section 2, as will the specific cases from which the data for the study were taken. Section 3 will discuss the various statistical methods that were used, leading to the analysis of such data in Section 4, and concluding thoughts presented in Section 5.

2. BACKGROUND

The data for this study were taken from a series of specific cases, each of which represented a specific type contaminant which should be removed. These cases are listed in Table 1.

The quality control algorithm used for this study operates on six moments available from the WSR-88D polarimetric radar. These include the absolute velocity (absvel), correlation coefficient (RhoHV), differential reflectivity (Zdr), differential phase shift (PhiDP), reflectivity (Z), and spectrum Width (SPW).

Based on these six radar moments listed above, eleven additional variables were computed using the data, resulting in a total of 17 different polarimetric variables for the dataset. The additional variables calculated are as follows: the gate-to-gate shear computed from velocity (azshear); the composite of dBZ, providing the maximum dBZ that is found in the vertical column (dbzcomp); the maximum height at which the reflectivity value is greater than -14 dBZ, which is considered a weak echo (height); the reflectivity value found at 3 km from tilts greater than 1 degree (dbz3km); the maximum height at which the reflectivity value is greater than 0 dBZ (htgood); the difference between the reflectivity value at the lowest tilt and the next higher tilt, at an elevation greater than 1 degree (delta); the local variance of the reflectivity computed in a 5x5 neighborhood centered around the range gate (refvar); the local variance of differential reflectivity computed in a 5x5 neighborhood centered around the range gate (zdrvar); the variance of the correlation coefficient (rhohvvar); a simplified hydrometeor classification algorithm, or HCA (metsignal); and the absolute value of differential reflectivity (abszdr).

A neural network was also used on the data for this study. Neural networks are computer programs that operate on a specific set of data and become trained on that data in order to

Radar	Location	Date/Time (UTC)	Description
KAMA	Amarillo TX	20120411 14	Rain and bioscatter
KAMA	Amarillo TX	20120412 12	Rain and bioscatter
KAMA	Amarillo TX	20130215 18	Rain and ground clutter
KBMX	Birmingham MS	20130130 11	Lines of storms
KCLE	Cleveland OH	20130215 17	Snow
KDMX	Des Moines IA	20130129 03	Widespread convection
KILX	Lincoln IL	20130129 21	Rain and clutter
KLVX	Louisville KY	20130215 16	Snow
KMHX	Morehead City NC	20110827 01	Hurricane
KMHX	Morehead City NC	20110827 19	Hurricane
KOUN	Norman OK	20100511 05	Anamalous propagation
KOUN	Norman OK	20100519 11	Supercell and insects
KTLH	Tallahasee FL	20130226 11	Squall line and clutter
KTLX	Norman OK	20130309 23	Squall line and clutter
KVNX	Vance AFB OK	20120520 09	Storms and bioscatter
KVNX	Vance AFB OK	20120529 23	Artifacts and bioscatter
KVNX	Vance AFB OK	20130129 11	Storms

Table 1. List of cases from which data were obtained (Lakshmanan et al. 2013)

develop a type of pattern-recognition. Neural networks can thus look through large datasets and find patterns within them in an efficient manner. The neural network used for this study was trained on a set of cases that were chosen due to their association with specific types of non-weather echoes (Lakshmanan et al. 2013). These cases are listed below in Table 2.

Radar	Location	Date/Time (UTC)	Description
KABR	Aberdeen SD	20120811 08	Insects and light rain
KARX	La Crosse WI	20120626 19	Insects and light rain
KARX	La Crosse WI	20120926 20	Insects
KCLE	Cleveland OH	20120224 13	Rain
KCLE	Cleveland OH	20120224 18	Rain
KCLE	Cleveland OH	20120224 23	Snow
KDLH	Duluth MN	20120926 17	Insects
KEWX	Austin TX	20120506 06	Instr. artifacts and storms
KEWX	Austin TX	20120506 09	Instr. artifacts and storms
KFSD	Sioux Falls SD	20120804 00	Line of storms
KFTG	Denver CO	20130224 21	Snow
KGYX	Portland ME	20130224 18	Snow
KHTX	Huntsville AL	20120811 00	Storms
KJAX	Jacksonville MS	20120923 08	Birds
KJAX	Jacksonnville MS	20120926 18	Ground clutter and storms
KJGX	Robins AFB	20120920 02	Birds
KLOT	Chicago IL	20120804 20	Storms
KLSX	St. Louis MO	20120926 19	Storms
KLSX	St. Louis MO	20130224 20	Insects
KLTX	Wilmington NC	20120917 16	Storms and sea clutter
KMHX	Morehead City NC	20120919 22	Storms
KMRX	Knoxville TN	20120624 23	Insects and storms
KNQA	Memphis TN	20120921 10	Storms and AP
KOTX	Spokane WA	20120926 16	Ground clutter
KPDT	Pendleton OR	20120720 10	Rain
KRLX	Charleston WV	20121001 08	Ground clutter and rain
KSGF	Springfield MO	20120229 06	Line of storms
KTFX	Great Falls MT	20120926 15	Insects and rain
KTYX	Ft Drum NY	20130224 19	Snow
KVNX	Vance AFB OK	20110520 08	Convection
KYUX	Yuma AZ	20120723 15	Ground clutter
KYUX	Yuma AZ	20120723 16	Insects and rain
KYUX	Yuma AZ	20120926 21	Insects
KYUX	Yuma AZ	20120928 09	Ground clutter

Table 2. List of cases from which the neural network was trained (Lakshmanan et al. 2013)

3. METHODS

Three different statistical methods were employed in order to assess the importance of each of the polarimetric variables. These include a permutation test, a calculation of the Kullback-Leibler distance called J-measure, and a χ^2 statistics-based measure. These three methods are described in more detail in the following sub sections.

a. Permutation Test

The first test that was utilized involved a permutation-based approach. This process involved running the dataset through a computer program that would take one column of data at a time, corresponding to one of the polarimetric values, and randomize the values so that all of the data values for that specific variable are out of place. With these values randomized, the data for that variable, within the frame of the entire training dataset, has no significance.

With this new dataset, the data are then run through the trained neural network using the WDSS-II program (Warning Decision Support System – Integrated Information). The w2scoreTrainedNetwork was used through the WDSS-II program for this permutation test. This specific algorithm in the program produces an output which can be used to calculate a forecast skill using a contingency table, giving a set of values for different thresholds, including the number of hits, misses, false alarms, and accurate null forecasts. Only the threshold at 0.5 was taken for each run for this dataset, because operationally, only the threshold at 0.5 is examined when determining whether or not to keep a range gate (Lakshmanan et al. 2013).

From this information, the Heidke Skill Score (HSS; Heidke 1926) was calculated. The HSS is a statistical test used to test the accuracy of forecast. A hit is characterized as a forecast for an event that did occur; false alarms correspond to a forecast for an event that didn't occur; misses represent a forecast for an event that didn't accurately predict the event; accurate null forecasts represent agreement between the forecast and non-events. In reference to Figure 1, the "a" corresponds to the number of hits, the "b" is the number of false alarms, the "c" is the number of misses, and the "d" is the number of accurate null forecasts.

The steps above were repeated for each of the columns of data in the dataset so that the accuracy of each polarimetric variable could be tested and a Heidke Skill Score could be calculated. The skill score was also calculated for the dataset before any permutation had been performed. When the skill score of the permuted dataset is compared to the skill score of the un-permuted dataset, the loss in skill score can be assessed. This process provides useful information about how well the dataset does at forecasting weather/non-weather echoes. If a polarimetric variable is important in distinguishing between weather and non-weather echoes, then the skill score of that dataset should reduce when the values for that variable are randomized. The more important the variable in distinguishing between echoes, the more of a negative impact should occur on the overall skill when those values are randomized.

Event forecast	Event observed		
	Yes	No	Marginal total
Yes	a	b	a + b
No	c	d	c + d
Marginal total	a + c	b + d	a + b + c + d =n

Figure 1. Contingency table representing the four different values that are taken into account in order to calculate the Heidke Skill Score, based on the correlation between event forecasts and actual events that were observed. (European Virtual Organisation for Meteorological Training)

b. Kullback-Leibler distance

A second test that was performed dealt with the Kullback-Leibler distance, known as the J-measure (Jeffreys 1946; Lin 1991). Data that were used for this method were not permuted or changed in any way. The basis for this method, and for the χ² statistics-based test that will be described later, is the distinction that was set for each data value as to whether or not that data value represents a weather echo or a non-weather echo, corresponding to a value of 1 for weather echoes and a value of 0 for non-weather echoes. The Kullback-Leibler distance is given by the equation

$$J_i = \sum_x (P(X_i = x|Y = 0) - P(X_i = x|Y = 1)).\log_2 \frac{P(X_i = x|Y = 0)}{P(X_i = x|Y = 1)}.$$

Histograms were created for each of the polarimetric variables in order to find the probability distributions for the equation. Separate histograms were created for those data points that were weather (assigned a 1) and non-weather (assigned a 0).

c. χ² statistics-based measure

The last test that was performed was similar to the J-measure test, in that the probability distribution for each polarimetric variable were taken from histograms and then applied to the equation, represented as,

$$\chi^2 = \sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(O_{i,j} - E_{i,j})^2}{E_{i,j}}.$$

This method differs from the J-measure calculation in that a third histogram is used which combines the sets of data for both weather and non-weather, giving a set of combined probability distributions.

4. ANALYSIS

a. Permutation Test

After calculating the loss in skill score of the training dataset after each of the polarimetric variables had been permuted individually, two separate graphs were created in order to assess the results. Fig.2 and Fig.3 illustrate the results of these permutation-based calculations. The training dataset was shown to have the most significant drop in skill score after the dbz3km had been permuted. As mentioned earlier, dbz3km is a variable that reflects the reflectivity value at three kilometers in height from tilts greater than one degree. Non-weather contaminants such as birds, insects, and other ground clutter are found at low levels and wouldn't be present in locations as high as three kilometers above the ground. Thus data values in dbz3km are less likely to contain values reflecting non-weather targets. Using data values that are from a tilt greater than 1 degree also help to reduce the amount of ground clutter that would otherwise be picked up at lower levels.

The height variable also showed to have a notable negative impact on the skill score of the dataset. This result makes sense as well. Because the height values are representative of reflectivity values greater than -14 dBZ, such data would not include weak echoes and areas where no targets are present. The height variable would thus do well at distinguishing areas of isolated contaminants. Such areas outside the proximity of a weather event would show low height values, where the only reflectivity returned is that of the contaminants, commonly found at lower levels in the atmosphere.

While the randomization of PhiDP is shown in the graph to have one of the more significant drops in the overall skill score, it was realized that PhiDP on its own is a rather arbitrary variable to look at. This is because PhiDP, or the differential phase shift of the radar, has an arbitrary starting value. Thus the range derivative of PhiDP, called Kdp, should be taken in its place for an accurate reflection of its impact.

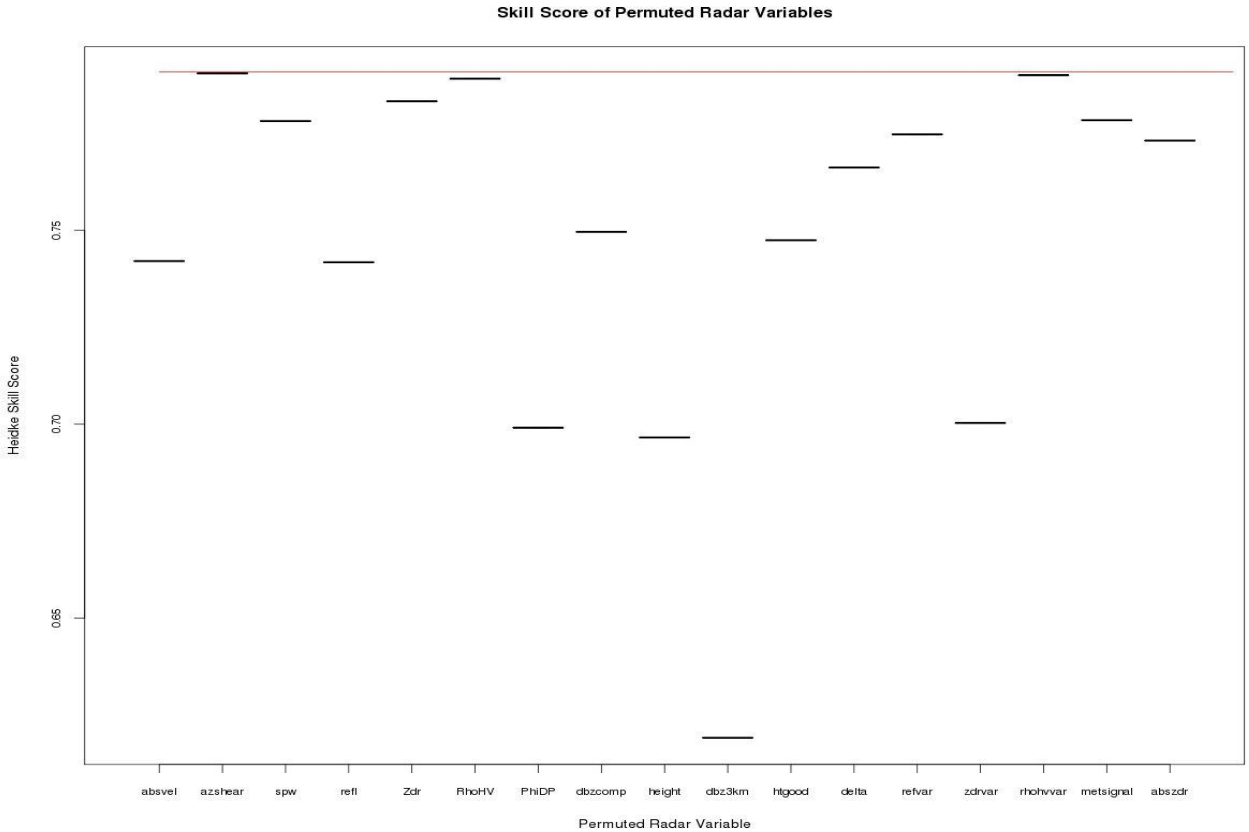

Figure 2. Heidke Skill Scores for the entire dataset calculated after the individual polarimetric variables had been permuted. The red line near the top of the graph illustrates the original Heidke Skill Score of the training dataset calculated before any of the variables had been permuted.

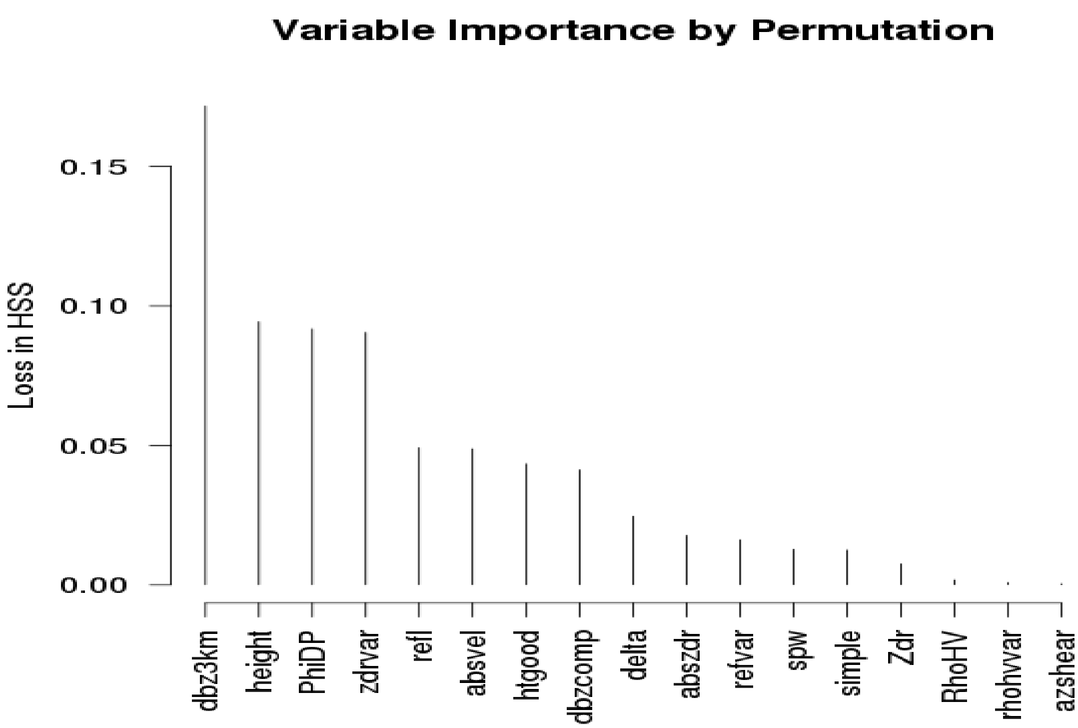

Figure 3. Loss in skill score of the entire training dataset after each variable was permuted, as compared to the Heidke Skill Score computed for the original un-permuted data

The Zdrvar variable was one other parameter to show a significant effect on the skill score of the dataset once permuted. Zdr takes into account the ratio between the horizontal and vertical reflectivity of the targets, thus the variance of such a measure would aid in understanding the consistency of the field of targets present. A more consistent field would be more representative of hydrometeors, as ground clutter, anomalous propagation, and biological targets should only be found isolated from the rest of the field or in a smaller area within the larger area of hydrometeors.

This permutation test was performed only once on the training dataset due to restricted time; however, multiple runs of such a test would provide a valuable range of results, thus showing the distribution and trend of the loss of skill score for each polarimetric variable.

b. J-measure and χ^2 *statistics-based tests*

Data from the histograms yielded similar results for both the J-measure calculation and the χ^2 statistics-based measure. As can be seen in Figure 4 and Figure 5, the variables associated with correlation coefficient, RhoHV and rhohvvar, show the most importance in distinguishing between weather and non-weather compared to the other variables. Such a large separation in importance between these variables and those of the rest of the training set, while quite vast, does make sense with the type of data that RhoHV and rhohvvar represent. Both variables provide an idea of the type of shape that a target has, as it measures the correlation between the horizontal and vertical echo returns of that object. Non-weather objects will have a lower correlation than meteorological targets due to their complex and non-uniform shapes. Thus RhoHV and rhohvvar on their own are good at distinguishing between meteorological and non-meteorological targets.

Metsignal also has a notable importance in discriminating between weather and non-weather targets in the data. Again, metsignal is like a simplified HCA, thus it takes into account multiple parameters that can identify the types of hydrometeors present within the return radar echoes. On its own, the metsignal, similar to the RhoHV variables, is good at distinguishing between weather and non-weather targets.

That being said, it is important to note that the J-measure and the χ^2 statistics-based test are both univariate tests, meaning that they take into account and examine only one variable at a time without comparing its usefulness within a larger group of variables. Thus univariate skill is not necessarily a reflection of a variable's uniqueness. Through univariate tests, some variables may show importance in discrimination on their own, but when compared to other variables, they show a similar discrimination; thus, that variable is not unique within the frame of the entire set of variables in terms of discrimination. The permutation-based test, however, takes into account the skill score of the entire dataset after each of the variables has been permuted, thus the efficacy of the variables is assessed in relation to the whole of the collection of data. Results from such tests provide a more accurate depiction of variable importance, as they reveal a unique way of assessing the performance of the data as a whole from the perspective of each individual polarimetric variable.

5. CONCLUSIONS

The permutation test reveals that the most important polarimetric variable for weather/non-weather discrimination is dbz3km. This makes sense because this variable focuses on data found at higher heights than most non-meteorological targets would expect to be found.

The J-measure and χ^2 statistics-based tests both revealed similar results. RhoHV and rhohvvar showed the greatest importance in distinguishing between weather and non-weather. These results also make sense, because RhoHV helps in determining the shape of targets being sampled, and non-weather targets are more likely to have a non-uniform shape compared to hydrometeors.

When assessing variable importance from these three tests, it is important to keep in mind that the nature of each test is different. The permutation test takes into account the importance of each polarimetric variable within the set of all variables. Results from the permutation test therefore reveal a unique variable importance within the context of the entire set of variables. The J-measure and χ^2 statistics-based tests are univariate, and thus to do take into account the importance of the variable compared to the rest of the variables being tested. As a result, these tests do not show as much of a uniqueness in distinguishing between weather and non-weather echoes, compared to that of the permutation test.

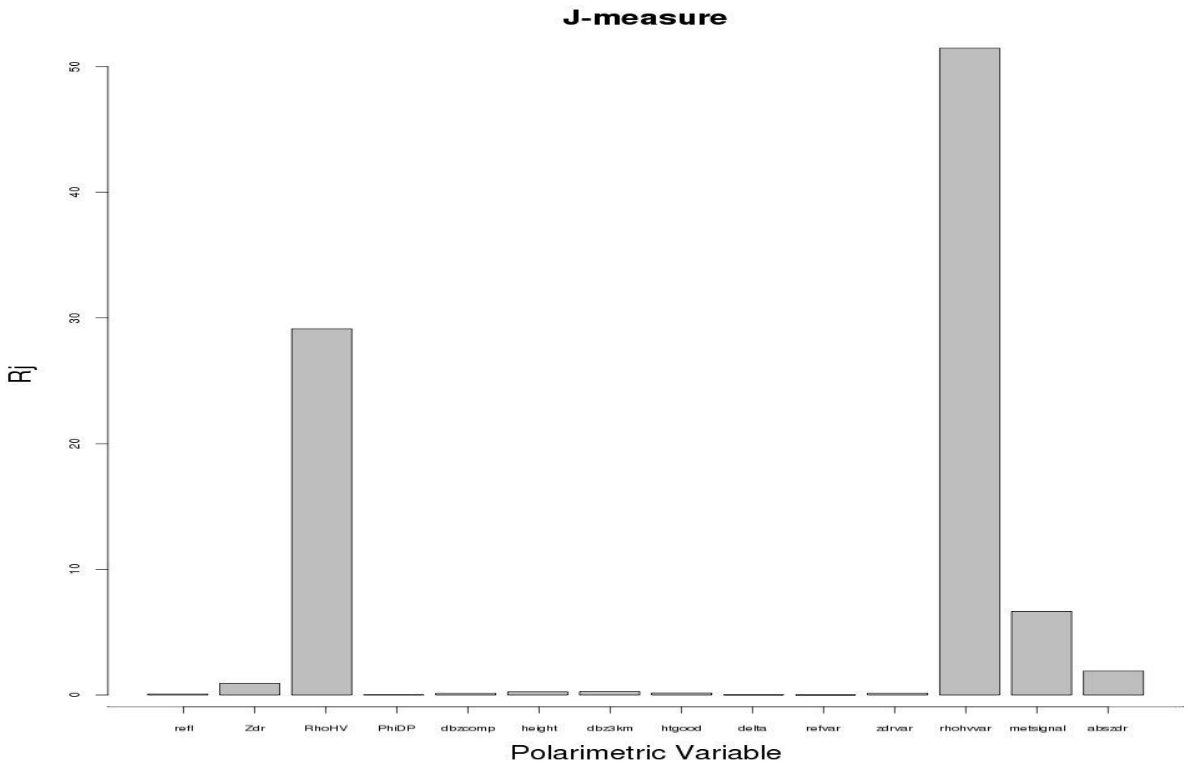

Figure 4. Distribution of J-measure values computed for each of the polarimetric variables, with higher values corresponding to a greater importance in distinguishing between meteorological and non-meteorological targets.

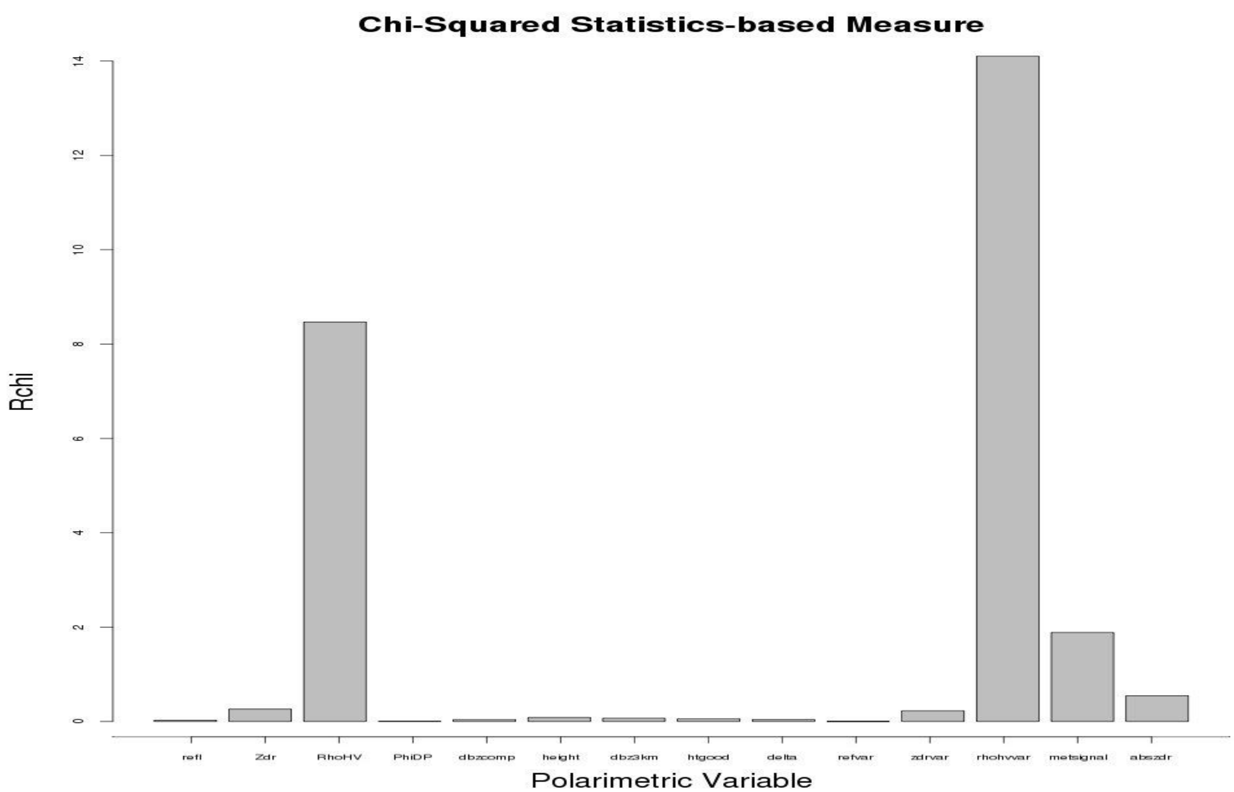

Figure 5. Distribution of r_{chi} values computed for each of the polarimetric variables, where the higher values represent a greater significance in distinguishing between weather and non-weather targets

Realizing the difference between variable uniqueness, as shown by the permutation test, and variable importance as shown by the J-measure and χ^2 statistics-based test, is necessary when assessing which variables are most useful for improving polarimetric quality control algorithms. Variable importance found only through the J-measure and χ^2 statistics-based test may overlook otherwise telling distinctions. The permutation test provides a unique perspective into variable importance by taking into account the skill of variables within the context of an entire diverse variable set.

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