SOUNDING–DERIVED INDICES FOR FORECASTING HAILSTORMS USING ENSEMBLES OF ARTIFICIAL NEURAL NETWORKS

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I. INTRODUCTION

A method based on neural networks for forecasting thunderstorm and rain from sounding–derived indices in Friuli Venezia Giulia has been presented in the ECSS–2004 conference (Manzato 2007). This time, a similar approach, but using neural network *ensembles*, will be applied to the hail forecasting problem.

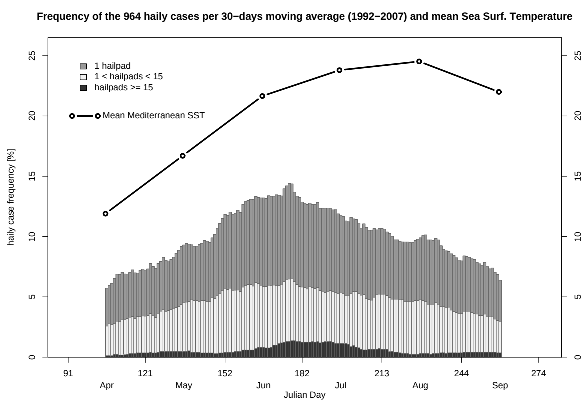

fig. 1: *The distribution of the number of hit hailpads clustered in three classes for the different Julian days of the hail season (30–days moving average).*

II. DESCRIPTION

In this work, more than 50 different sounding-derived indices are used for forecasting the occurrence and extension of hailstorms in the Friuli Venezia Giulia region (NE Italy) during the 6h after the sounding launch. A hailpad network collects data from April to September in the plain of this region since 1988, but only data after 1992 have been used, because the sounding database starts in 1992. A climatology of hail in the 1992-2007 period is presented, stratifying the 6h cases per Julian day (Fig. 1), per period of the day (6h-long, because it is associated to the 4 daily soundings) and per number of hit hailpads in 6h (Fig. 2).

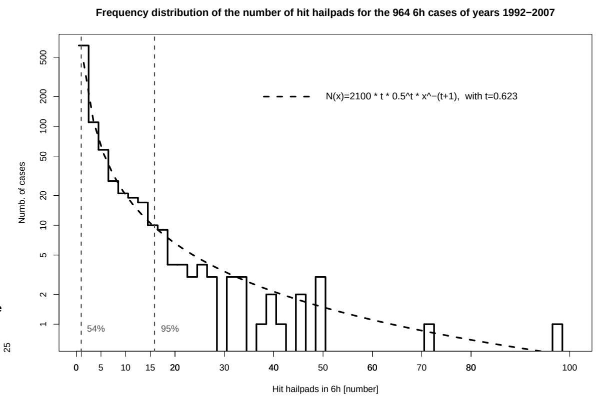

fig. 2: *The total number of hit hailpads distribution in 6–hours. The bin width is 2, that is, the first bin shows the 68% of cases with 1 or 2 hit hailpads, the second one shows the cases with 3 or 4 hit hailpads and so on. The dashed line is a Pareto distribution fit, which underestimates the first bin.*

52 different sounding-derived indices (8 out of which newly developed for this work), plus the Sea Surface Temperature, the Julian day and the period of the day, are used as candidate predictors for forecasting hail. Two problems are studied: the first is to classify the occurrence of at least 2 hailpads hit in 6h, while the second is to estimate the number of hit hailpads in 6h.

Linear *bivariate* methods (discriminant analysis and regression) are applied to the whole database, finding a maximum Pierce Skill Score as high as 0.46 (for UpDr and Hail Diameter, followed by CAPE, DTC –Manzato 2003–, DT500 and SWISS –Huntrieser et al. 1997–) for the classification and a linear correlation as high as $R = -0.32$ (for Showalter Index –Showalter 1953–, followed by DT500 and UpDr) for the number of hit hailpads regression problem.

After that, a neural network non-linear approach is chosen, dividing the database in 3 samples: training, validation and independent test. The candidate predictors are preprocessed transforming them to their empirical posterior probability for the classification problem and to their Z–scores (standardization) for the regression problem. In this *multivariate* approach a subset of 5 to 9 predictors, chosen by a stepwise algorithm, can usually optimize the neural network in terms of validation error (Cross Entropy for classification and Mean Square for regression).

To avoid overfitting, the training/validation sample division is made in different ways (*resampling*), leading to 17 different lists of selected predictors. Varying also the number of hidden neurons and the sounding-derived index database (computed with the 3 thermodynamic schemes described in Manzato and Morgan 2003) a total of 238 classification and 204 regression networks are built, respectively for the hail occurrence and the hailstorm extension problem.

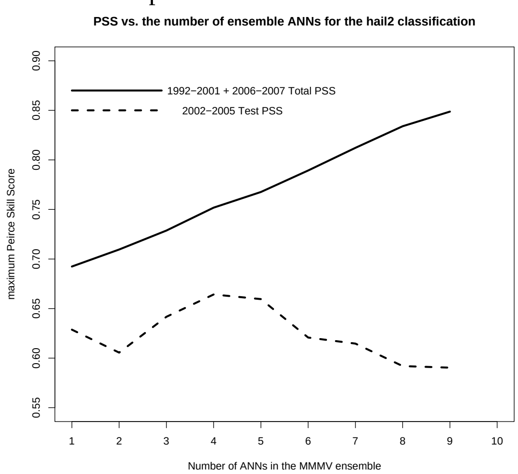

fig. 3: *Modified Mojirsheibani Major Voting ensemble using different number of ANN members for classifying the occurrence of at least two hit hailpads in 6h. The independent Test dataset start to decrease the Pierce Skill Score after that more than 5 neural networks are selected.*

Lastly, a subset of these networks are combined together in an ensemble using a newly proposed variant of the Mojirsheibani Major Voting (Mojirsheibani 1999) for the classification problem and a linear multiregression of the network outputs for the regression problem. In the first case, just 4 networks are used (Fig. 3), while in the second, the first 7 networks chosen by the stepwise model selection algorithm are combined together.

III. CONCLUSIONS

The final results using the neural network ensemble are better than the simpler linear methods and than the best neural networks used alone. For the classification, the indices which seem to be chosen more frequently in the neural network first input positions are the SWISS index, the surface-850 bulk shear and the period of the day.

On the other hand, the indices which seem to be more important for the neural networks of the regression ensemble are the SWISS index, the Showalter Index and the mean wind between 6 and 12 km of height.

IV. REFERENCES

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