Inclusion of Synoptic Weather Forecast Data in Decision Support Systems for Agriculture

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EXTENDED ABSTRACT

Models for agricultural decision support inform grower management strategies with the goals of increasing product quality, limiting expenditures, and reducing the amount of chemical released to the environment. Plant disease risk systems are often used to estimate environmental conditions that are favourable for risk of disease epidemics and fungicide recommendations appropriate to that risk. Meteorological data has been included in these systems for well over 50 years. The inclusion of extended range synoptic forecast data into risk estimation models renders such systems even more valuable to growers by providing prediction of risk conditions up to several days in advance of their occurrence.

This paper describes the development and implementation of a series of artificial neural network models to incorporate synoptic weather forecasts into an expert system for potato late blight risk. Potato late blight serves as an excellent test case for such models, as late blight risk systems have included weather variables since the 1960s. Previous attempts to use synoptic weather forecasts in plant pathology have had limited results because of the quality of forecast data. However, since 2003 the National Weather Service (NWS) of the United States has implemented new medium extended (MEX) forecast models that have improved their usefulness for plant pathology applications. The number of stations throughout the US with daily model output statistics (MOS) available publicly has also increased dramatically in recent years.

Initial analysis of the new forecast MOS began in 2005. The twelve NWS stations with the longest MOS archive lengths for the state of Michigan were used to determine what the optimal modelling approach and average accuracy would be. Determinacy analysis, logistic regression, discriminant analysis and artificial neural networks were each examined for their utility in predicting agricultural risk in potatoes from late blight. Model variables taken directly from and derived from the MOS data included spatial, temporal, and weather based variables. The models proved successful in predicting potato late blight risk as estimated by potato late blight disease severity values (DSV) up to four days in advance of their occurrence. Model results were significantly higher than predicting no risk every day, which would yield a state average accuracy of 72 percent. High and low risk periods, optimized as a function of the frequency of risk days through time in the growing season for each station, were significant in every type of model. The artificial neural network models achieved the highest overall accuracy (79 percent) and the highest accuracy in July and August when weather is particularly favourable for the disease in this region.

In recent years, as longer data records of MOS have become available and additional station locations have been added to the network, it has become important to examine the usefulness of generalized state models, developed from regional locations with long archive records, at a more local scale. The south central region of Michigan was chosen for this analysis as ten prediction locations have been added in close proximity (within 70 km) of one of the first order stations (JXN).

Lack of archive data for the newer stations is the main cause of concern when using the same modelling approach at a local level, especially with regard to station specific variables such as high and low risk time period. Preliminary analysis of the regional scale showed that station specific risk time periods resulted in lower accuracies than those derived from regional normals when archive records of only one year were available.

In general, the artificial neural network model developed at the scale of the state did not appear be acceptable at the regional scale. Further research will focus on regional scale variables that may be used to increase the range of usefulness of such a model without requiring respecification for every station location individually.

1. INTRODUCTION

Expert systems to aid in plant disease prevention have become the norm in agriculture and other industries (United States Department of Agriculture [USDA], 2006). Weather data has been an important component of models for plant growth and disease for decades. Previous attempts to use synoptic weather forecasts in plant pathology have had limited results because of the quality of forecast data for predictions more than 24 hours in advance (Wilks and Shen, 1991; Raposo et al., 1993). Developments in meteorology, such as improvements in synoptic forecasts and NEXRAD (Next Generation Radar) precipitation estimates, have direct implications for industries with close ties to biological systems whose model inputs rely on meteorological data (USDA, 2006).

This paper describes the feasibility of incorporating recently improved synoptic forecast data into plant disease expert systems in the United States (Carrol and Maloney, 2003). We examine the National Weather Service (NWS) forecast data within the context of a common plant disease model for potato late blight. This weather-based model can be used to calculate daily disease risk values, or disease severity values (DSV's), that are accumulated throughout a growing season. Because late blight in potato can be devastating to yields and marketability of a crop within a very short time frame and has close ties to weather predictions, growers have used Wallin-type weather based potato late blight models for over 50 years to inform their management practices (irrigation timing, fungicide sprays, etc) (Wallin, 1962).

Because weather-based expert systems are potentially most useful in areas where weather is not predictable, the study focuses on the state of Michigan in the Great Lakes region of the U.S. Because of the influence of the Great Lakes, daily weather patterns in this region and, specifically, precipitation is inherently difficult to predict.

Preliminary analysis focused on the 12 NWS station locations across the state with relatively long archived records (first order stations) of the new medium range forecast (MRF MEX) model output statistics (MOS). Disease severity values calculated with the MRF MEX MOS were compared with the unedited local climate data (ULCD) for the same stations and days for the growing seasons of 2001-2004. This data was used to compare a variety of modelling techniques to improve the accuracy of using the forecast data to predict potato late blight DSV's.

The objectives of this portion of the project were to:

1) Develop baseline data for a region using the first order NWS stations with the longest archive records
2) Compare the accuracy of various statistical models with that of artificial neural network models that incorporate the baseline data
3) Examine model accuracy spatially and temporally.

Since 2004, the NWS has increased the density of prediction locations across the country. Although these most recent additions to the network have little archived data available from the new MOS (1-2 years at most) they represent new sites for model implementation. Therefore, results from the state-wide model analysis were used to explore techniques for comprehensive integration of all regional NWS locations. The south central region of Michigan was chosen for this analysis as ten prediction locations have been added in close proximity (within 70 km) of one of the first order stations (JXN) in this area.

The objectives of this portion of the project were to:

1) Examine data availability and disease risk characteristics of the new station locations.

2) Assess the quality of the state-wide model at the regional scale.

3) Compare the usefulness of station specific variables derived from relatively short archive lengths to similar variables based on regional norms.

2. METHOD

Initial analysis of the new forecast MOS began in 2005. The twelve NWS stations with the longest MOS archive lengths for the state of Michigan were used to compare modelling approaches. The model resulting in the highest accuracy at the state scale was then used as a base to test new station locations on a regional scale.

2.1. Source Data and Variable Derivation

Five day predictions for potato late blight DSVs were calculated from NWS medium range forecasts for each of the 12 first order stations in Michigan for each growing season (1 May – 30

Sept) from 2001 to 2004. In total 24,573 predictions were tested.

A modified-Wallin DSV model (Wallin, 1962) is currently used to calculate the risk of potato late blight by Michigan State University (MSU) for daily distribution to Michigan potato growers through a web accessible management recommendation site (Baker et al., 2005; MSU, 2005). For purposes of this paper the MSU model was simplified to a Boolean scale of 0, no risk, and 1, risk. In the simplified system, days were considered to be risk days for potato late blight infection if relative humidity remained above 80% when temperatures remained between 7.2 and 11.7C for more than 16h, between 11.7 and 15.0C for more than 13h, or between 15.0 and 27.0C for more than 10 h (MSU, 2005).

Model variables including maximum and minimum daily temperature, cloud cover, probability of precipitation and quantity of precipitation were extracted directly from the daily 0000 UTC (Coordinated Universal Time) MEX MOS. Hourly temperature values for DSV calculations were derived from daily maximum and minimum NWS temperature predictions using a sine-exponential model modified to obtain continuity in time (Ephrath et all, 1996). Minimum temperature was used as an estimate of dew point temperature for the calculation of relative humidity.

Although not traditionally included in biologically based models, spatial and temporal variables were included in the analysis as is typical in models involving MOS derived variables (Clark and Hay, 2004). Temporal variables included Julian day, high-risk time periods (when 50% of the days during that time period at a particular station would typically be risk days), and low-risk time periods (when 90% of the days during that time period would typically be non-risk days). Spatially specific variables included station name, latitude and longitude. Potato late blight day typing values from the MSU modified-Wallin method included a dry day DSV (assuming no precipitation), a wet day DSV (assuming enough precipitation throughout the day to keep the relative humidity above 80%, and the range of DSV values between the wet and dry day calculations.

Because station specific time periods of low and high risk are derived variables that depend upon a record of several years for averages, these variables were of most concern when the state wide model was used at the regional scale. Preliminary analysis compared model results with time period variables derived from regional normals with those derived from station records regardless of length.

2.2. Model Comparison

Determinacy analysis, logistic regression, discriminant analysis and artificial neural networks were each examined for their utility in predicting agricultural risk in potatoes from late blight at the state scale. Stepwise techniques were used to identify the predictor variable explaining the most variance in the dependent variable for each model and subsequently increase each model's variables until all those variables that significantly increased the power of the model were included. Only the most successful model was used for preliminary analysis at the regional scale.

3. RESULTS

3.1 Model Accuracies

Total accuracies for the four models and accuracy percentages derived from confusion matrices are shown in Table 1. Model results are compared to the regional normal frequency of non-risk days using the Wilcoxson non-parametric test for related samples. Determinacy analysis, logistic regression and neural network models each predicted daily potato late blight DSV's with a significantly greater accuracy than the regional normal. As also shown in Table 1, the overall accuracy of the neural network model was significantly higher than the overall accuracy of the other models. The neural network also resulted in the highest accuracies on non-risk days and predicted risk days. Both neural network and logistic regression models were statistically significant at P=0.001 level for every aspect of accuracy when compared with the regional normal.

When monthly averages were analysed with respect to station location, a strong trend in accuracy is apparent (Figure 1). As the monthly risk at a particular station increases, model accuracy decreases for all models. Monthly averages for each model are shown in Figure 2. When non-risk days are frequent, such as early and late in the growing season, the models all perform similarly, and have difficulty achieving accuracies higher than can be achieved simply knowing the normal percentage of non-risk days (72%). However, during the high risk months of July and August, the models easily outperform knowledge of regional normals although all model accuracies decrease during these months.

Table 1. Overall accuracy of regional forecast models for potato late blight risk at 12 locations in Michigan, US, from 2001 to 2004.

Accuracy	Determinacy Analysis	Logistic Regression	Discriminant Analysis	Neural Network	Regional[x] Normal
Total	0.755**[y] c[z]	0.773***b	0.743 d	0.798***a	0.720
Risk	0.500***c	0.474***c	0.727***a	0.529***b	0.280
Non-Risk	0.864***b	0.901***a	0.749 c	0.905***a	0.720
Predicted Risk	0.612***b	0.673***a	0.555***c	0.689***a	0.280
Predicted Non-Risk	0.801***b	0.799***c	0.865***a	0.829***b	0.720

Accuracy is reported as a percentage of model predictions that were correct when compared to actual risk calculated from Unedited Local Climate Data (ULCD) for the same date and location.
[x] Regional normals are the average frequency of risk and non-risk days at all stations in the region from 2001 to 2004; [y] Model accuracy is significantly greater than the regional normal at P=0.01(**) and P=0.001(***); [z] Within a single row, values followed by the same letter are not significantly different at P=0.05 (Wilcoxson test for two related samples).

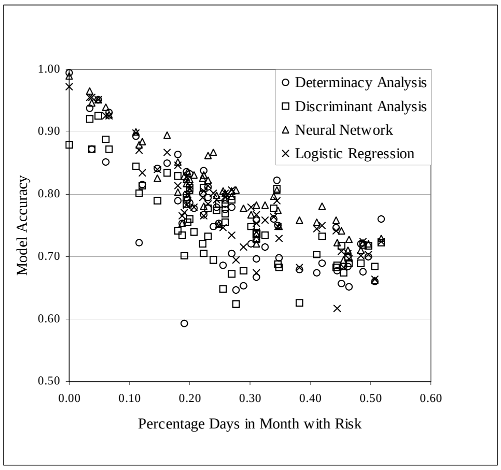

Figure 1. Monthly model accuracy by percentage of days in month categorized as having potato late blight risk.

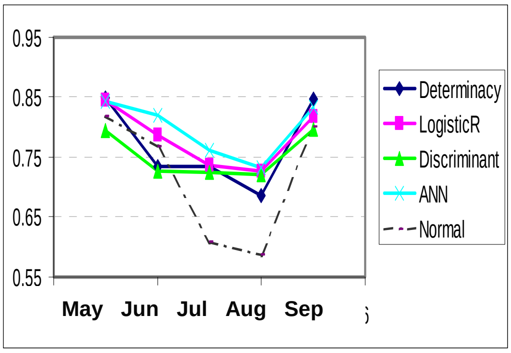

Figure 2. Average monthly model accuracy by model type. risk.

High and low risk periods, optimized as a function of the frequency of risk days through time in the growing season for each station, were significant in every type of model.

Because the artificial neural network model demonstrated the highest accuracy spatially and temporally, it was used as the model to the feasibility of using the state wide model at a regional scale. The artificial neural network model was developed using Stuttgart Neural Network Software (Stuttgart Neural Network Software [SNNS], 2005). A total of 49 variables were included in the neural network model. A resilient propogation (Rprop) learning function with a topological order update function resulted in the highest accuracy. The optimal number of hidden nodes for the model was 10. Random noise added to all the links in the network most increased model accuracy when it was bounded between -0.0005 and 0.0005. The model is shown in Figure 3.

3.2 Regional Scale Data Characteristics

In testing the state model at the regional scale, station record length was of primary concern. For five of the stations, including JXN, archived data was available beginning in 2000 or 2001. The remaining stations, however, had shorter archive

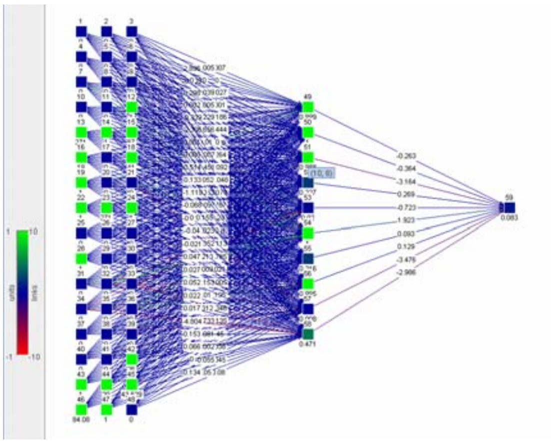

Figure 3. SNNS schematic of the completed showing 49 input values and 10 hidden nodes. Approximately 18,000 DSV predictions made for 2001-03 growing seasons were used to develop the model. The 2004 season was used for preliminary validation. Validations will continue through 2007.

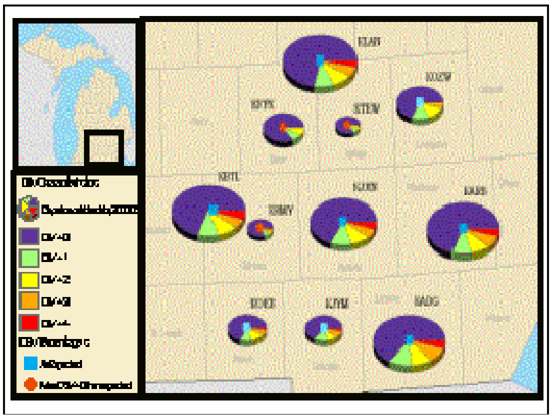

Figure 4. Station characteristics for south central Michigan stations used in scale analysis. Size of pie indicates archive record length breakdown for that data as calculated by the ULCD.

lengths, with KRMY and KTEW data records beginning only in May of 2005. Figure 4 shows relative quantity of growing season data available for each station as well as the actual DSV values. Because the region is relatively small, DSV breakdowns were expected to be similar among all 11 stations. However, three stations (KFPK, KTEW, KRMY) showed a higher percentage of no-risk days (DSV=0) than would typically be expected in the region. It is interesting to note that KRMY and KTEW were also among those stations with the only one year of archived data included in the analysis, resulting in skewed results.

Because high and low risk time periods were of primary importance in the state-wide model, available data was used to optimize risk time periods for the 11 stations in the south central region. The number of days during a growing season included in these periods varied greatly among stations, as shown in Figure 4 would be expected, the three stations with a higher percentage of no risk days than expected also exhibited a longer period of low risk, as did

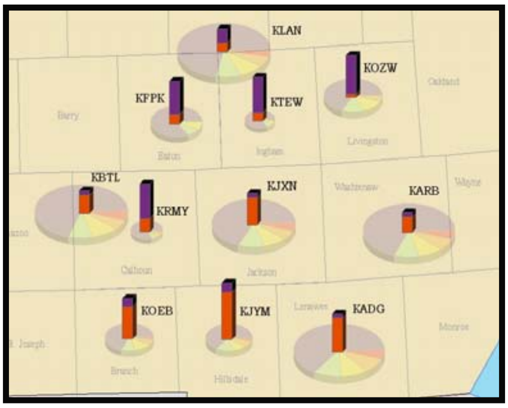

Figure 5. Number of growing season days included in high and low risk time periods per station in the south central Michigan region. Bar graphs are superimposed on characteristics shown in Figure 4.

stations KOXW. Because KLAN also showed a slightly longer low risk period than the remaining stations, there may be a trend of lower risk at stations in farther north within the region. Stations in the southern and eastern portion of the region revealed longer high risk periods in conjunction with very brief low risk periods.

3.3 Regional Scale Use of State Model

Finally, the initial 12 station state-wide model was used for stations in the south central region of the state for 2006. All model specification remained as in the original model except for high and low risk time periods. Because the duration of time periods may have been impacted by length of archive record, a generalized risk period model based on regional norms was compared with the station specific high and low risk period model. The generalized model assumed for every station that low risk periods occurred from May 1 to May 15 and Sept 23 to Sept 30, and high risk periods from July 20 to Aug 19.

Total model accuracy for when regional normals were used to approximate high and low risk time periods was 0.6628. Model accuracy when site specific high and low risk time periods were used, despite issues with archive length was 0.6576. These total accuracies are similar to one another and significantly less than the regional normal percentage of non-risk days (0.7092).

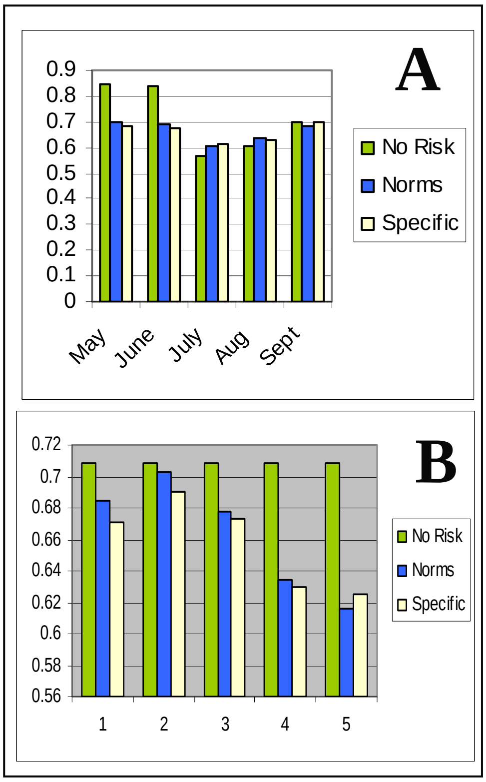

Figure 6. Total accuracy for regional scale model by A) month and B) prediction day. Comparison is made between the normal number of non-risk days for the stations, high and low risk time periods assigned based on regional normals, and high and low risk time periods based on individual station specific values.

Figure 6 shows the model accuracies as broken down by month and prediction day (number of days into the future for which the prediction was made). In both cases, use of regional normals more often gives results slightly over those of the site specific variables.

4. CONCLUSION

The analysis presented in this paper further extends the work of Baker and Kirk (2007). Results indicate that the improved GSFX MEX MOS in the United States seems to yield results with practical applications to agriculture. Artificial neural network techniques were statistically superior to statistical modelling techniques with regard to integrating this data with plant disease expert systems for decisions support. While high accuracies were achieved at stations with relatively long archive record, newly added stations with shorter archive records had lesser accuracies than could be achieved by predicting no-risk every day. This result was somewhat expected given that the model was not respecified for these stations, but used as it was developed for the state scale.

Further research will focus on regional scale variables that may be used to increase the range of usefulness of such a model without requiring respecification for every station location individually. The models will also be tested in various scenarios including different crop disease systems and regions of the country.

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