Adapting disease forecasting models to coarser scales: global potato late blight prediction

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Introduction

Many predictive models of plant disease rely upon fine-scale weather data collected in hourly increments, or finer. This data requirement is a major constraint when applying disease prediction models in areas of the world where hourly weather data are unreliable or unavailable. In response to the need to apply predictive models where only coarse resolution weather data are available, we developed a framework to adapt an existing potato late blight forecast model, SimCast. We envision this type of coarser resolution model being useful in long term decision making rather than for within growing season. For long term modeling we may be satisfied with being able to estimate the magnitude of upward and downward trends.

Objectives

1.Develop disease prediction models based on daily and monthly weather means and compare to results based on hourly weather data.

2.Compare risk predictions based on hourly, daily, and monthly weather data to late blight severity data sets from several countries.

3.Predict disease for resistant and susceptible cultivars under climate change scenarios.

Materials and Methods

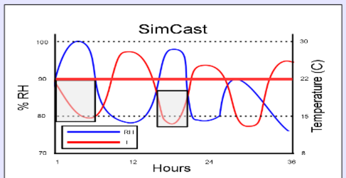
1.Hourly weather data from the US National Climatic Data Center was used in SimCast to calculate blight units, a daily measure of disease risk. Generalized additive models (GAM) were created to estimate blight units based on daily or monthly averages of weather data (Figure 1). We refer to these two models as SimCast Daily Means and SimCast Monthly Means.

2.Although SimCast does not provide direct estimates of disease severity, we compared the AUDPC from 19 cultivar-site-year combinations to SimCast estimates of disease risk to check that there was a general correlation. We also compared estimates of disease risk based on daily weather means to compare the correlations.

3.Maps of disease risk were produced using WorldClim (http://www.worldclim.org/) datasets that include the Intergovernmental Panel on Climate Change (IPCC) A2a (high growth carbon emission) climate change scenario for 2080. We applied SimCast Monthly Means to this data to compare current and future risk estimates.

How SimCast Works

SimCast estimates disease risk based on hourly temperature (T) and relative humidity (RH) inputs. SimCast begins to accumulate blight units, a measure of disease risk, when the RH is above 90%. The number of consecutive hours above 90% RH, T, and cultivar susceptibility to late blight determine the number of blight units accumulated. Averaging T and RH will smooth the patterns that determine disease risk to some extent.



The shaded boxes indicate where blight units will accumulate.

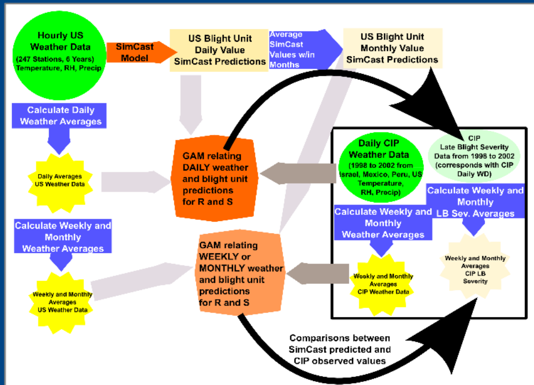


Figure 1: Flowchart of model development process.

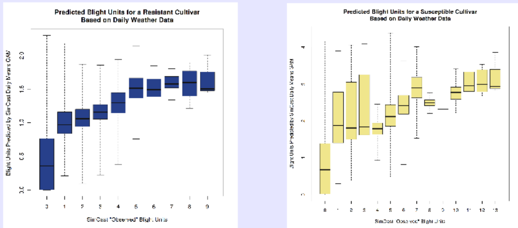


Figure 2: Blight units predicted by SimCast Daily Means for resistant (left) and susceptible (right) cultivars. "Observed" blight units are SimCast estimates based on hourly observations.

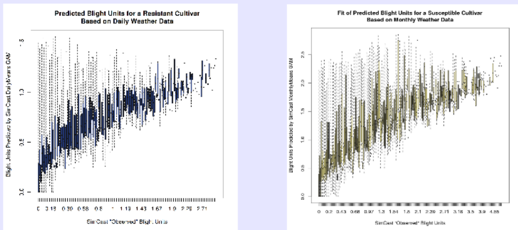


Figure 3: Blight units predicted by SimCast Monthly Means for resistant (left) and susceptible (right) cultivars. "Observed" blight units are SimCast estimates based on hourly observations.

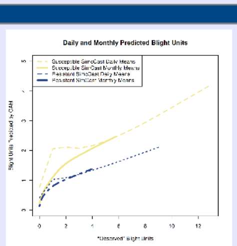


Figure 4: Fitted lines for predictions from SimCast Daily Means and SimCast Monthly Means (from figures 2 and 3) based on US weather data.

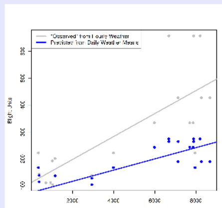


Figure 5: Comparison of estimates for blight units at two levels weather data resolution vs. late blight severity (AUDPC) from 19 cultivar-site-year combinations

Results

1.The models using lower resolution weather data produce results that are correlated with SimCast output but under predict (Figures 2-4).

2.SimCast and SimCast Daily Means produce output that is correlated with observed late blight severity (Figure 5).

3.The relative risk predictions from SimCast Monthly Means were mapped to indicate areas where disease risk will change as illustrated for Peru and Bolivia (Figures 6 and 7).

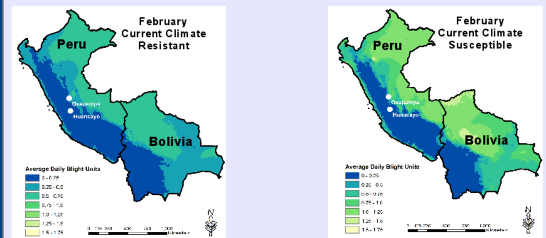


Figure 6: Late blight severity for February under current climate conditions, for resistant (left) and susceptible (right) cultivars.

These maps are model output illustrating the effects of a resistant cultivar and susceptible cultivar and predicted climate change on late blight severity. Not all areas shown are potato growing regions. Oxapampa and Huancayo are locations where late blight severity and weather variables were measured, part of the 19 cultivar-site-year combinations (figure 5).

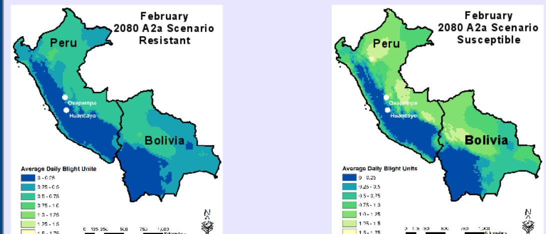


Figure 7: Late blight severity for February under 2080 A2a IPCC climate change scenarios, for resistant (left) and susceptible (right) cultivars.

Discussion

Using this approach we have created models that can quickly estimate late blight risk over large areas using readily available weather data sets.

While it is possible to backcast weather data, our approach can provide quick estimates that are less time and computer intensive. We plan to compare output from the method described in this poster to estimates from using backcast weather data.

Although the models under predict, they are useful for evaluating relative levels of risk.

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