Remote sensing and interpolation methods can obtain weather data for disease prediction

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Abstract The risk of the appearance or the intensification of a crop disease can be assessed using information about the weather, the pathogen or the crop. Weather data for use in disease risk prediction can be obtained from measurements at a nearby weather station. While weather measurements can represent accurate weather conditions at the site where the weather station is located, these data are representative only of a small area near the station. To obtain weather information over a larger area, spatial interpolation and remote sensing can be used to estimate the likely weather conditions in other locations. It is crucial to obtain weather data at an appropriate temporal resolution (e.g. daily or hourly) for a given disease in order to predict the disease. A weather database system is being constructed to provide high-quality climatic data (e.g. daily temperature, humidity and rainfall), which can be used to quantify the link between weather conditions and disease outbreaks.

Keywords spatial interpolation, remote sensing, disease management.

INTRODUCTION

Weather plays an important role in the epidemiology of many fungal and bacterial pathogens (Seem & Russo 1984). Temperature, humidity and rainfall have been used to predict the risk of plant diseases (Weltzien 1972, Coakley et al. 1999). These weather data have been obtained from automated weather stations (AWSs) equipped with electrical sensors whose outputs are recorded by data loggers. Although electrical sensors are durable enough to provide continuous weather information over a growing season (Sutton et al. 1984), the high purchase and maintenance costs of weather stations limit the number that can be practically deployed in a region.

Estimation of site-specific weather conditions using spatial interpolation data from a limited network of stations and satellites can be used to

provide weather data without on-site sensors. This paper will review the currently available technologies for obtaining site-specific weather data using spatial interpolation and remote sensing for disease management.

SITE-SPECIFIC ESTIMATION USING SPATIAL INTERPOLATION

Spatial interpolation estimates weather variables for a site by mathematically analysing measurements from surrounding weather stations. These estimates are known as “simulated observations” (Magarey et al. 2001). There are many approaches to spatial interpolation, including use of inverse distance weight and ordinary kriging (Snell et al. 2000). Inverse distance weight provides no measure of precision or accuracy for estimates,

while ordinary kriging produces the variance of the error of estimates, which can indicate the uncertainty associated with these estimates (Meyers 1994). To obtain reliable estimation, variables of elevation, aspect and proximity to ocean have been used (Jarvis & Stuart 2001).

The temporal scale of weather data is important in site-specific decision making (Magarey et al. 2001). Spatial interpolation approaches can be applied to weather data at different temporal scales including hourly, daily and with 30-year average data. The hourly and daily estimates of weather data are suitable for daily disease risk warnings (Gleason et al. 1997). On the other hand, the long-term weather data are useful for identifying areas where the climate conditions are favourable for a certain disease, e.g. soybean rust (Pivonia & Yang 2004).

In the USA, the DAYMET model (Thornton et al. 1997) has been used to interpolate daily weather variables including temperature and precipitation over large areas of complex terrain. The daily data products are publicly available through the DAYMET U.S. Data Center (DAYMET 2010). Such daily data would help growers gain spatial perspectives of weather conditions and associated disease risks, e.g. botrytis bunch rot on grapes (Kim et al. 2007), if they were freely available in New Zealand.

For climatic risk assessment studies, gridded climate surfaces at a global scale have been used. For example, a climate surface product can be obtained from the Climatic Research Unit (CRU), University of East Anglia, Norwich (New et al. 2002). The spatial resolution of the surfaces is 10 arc min. The CRU surfaces were derived from 30-year station records from 1961 to 1990. These long-term climate data are commonly used in climate matching models such as CLIMEX, which has been used to produce risk prediction maps for Swiss needle cast disease (Rosso & Hansen 2003) and soybean rust (Pivonia & Yang 2004).

Weather estimates using spatial interpolation can be used in site-specific disease management (Magarey et al. 2001). For example, a natural neighbour interpolation method was used to estimate weather variables associated with the

risk of botrytis bunch rot on grapes, such as air temperature and leaf wetness duration (Kim et al. 2007). When estimated or measured data were used as inputs to the disease model to assess the risk of the disease, the predicted risks were similar to each other, which suggested that reliable disease risk assessment could be achieved using site-specific estimates obtained from spatial interpolation.

WEATHER INFORMATION DERIVED FROM SATELLITE DATA

Satellites have been used to provide a wide range of weather observations in a large area. For example, Wan et al. (2004) showed that daily land surface temperature measured from the Earth Observing System (EOS) Moderate Resolution Imaging Spectroradiometer (MODIS) on board the Terra satellite was similar to that at weather stations. Wylie et al. (1994) used the High Resolution Infrared Sounder (HIRS) data to estimate cloud cover. In addition, remote sensing data usually provide information on crop canopy, including leaf area index and primary productivity. These data derived from satellites could be used to estimate the risk of disease, e.g. dwarf bunt of wheat (Peterson et al. 2009).

Satellites can be used to obtain weather data for variables that are rarely measured at local weather stations. For example, leaf wetness duration is rarely measured at AWSs although is an important variable in the development of many fungal diseases (Gleason et al. 1997). Satellite data can also be used to detect free water on crop surfaces. For example, Kabela et al. (2009) used passive microwave observation of the land surface using the Coriolis satellite to detect dew on crop surfaces. However, the Coriolis satellite data are only available for short periods of time in a given day, which requires a modelling approach to predict leaf wetness duration data for disease management.

Some satellite data can be obtained freely through the internet. For example, the MODIS data, including land surface temperature, are freely available through the Level 1 and Atmosphere and Distribution system (LAADS 2010) at Goddard Space Flight Center in National Aeronautics and

Space Administration, USA. National Oceanic and Atmospheric Administration's Comprehensive Large Array-data Stewardship System (CLASS 2010) contains a wide range of satellite products, which can be easily downloaded to endusers. These satellite products could be useful in disease management in New Zealand because they provide estimates for crop canopy conditions as well as weather conditions.

INTEGRATED WEATHER DATABASE SYSTEMS FOR DISEASE MANAGEMENT

To manage a wide range of weather data including measurements and estimates using spatial interpolation and satellites, it would be useful to develop an integrated weather database system. This system could be constructed using modules for weather data management, disease risk assessment, decision support and information distribution. The architecture of the database system would include multiple layers that are connected independently to each other.

A prototype of a system to provide information for daily disease management in vineyards using weather information has been developed for New Zealand. This consists of components that obtain weather information from weather stations, estimate weather information using a model and predict disease risk of botrytis bunch rot on grapes (Figure 1). These components are contained in four layers – data, information, knowledge and presentation.

In the data layer, weather data are collected from different data sources, including AWSs (Figure 1). At sites where no weather data are available, spatial interpolation is performed to generate site-specific data. In the prototype system, a natural neighbour interpolation method has been implemented although the data layer could be connected to an external database system. For example, National Institute of Water and Atmospheric Research (NIWA) has developed a weather data management system, EcoConnect. The large set of weather data in the EcoConnect system, including weather forecasts, could be accessed for disease risk prediction using the data layer in the future.

In the information layer, the site-specific weather data are processed to prepare a set of input data for disease risk prediction models. For example, leaf wetness duration is estimated using the site-specific weather data (Gleason et al. 1997; Kim et al. 2002; Kim et al. 2004). In the information layer, a risk assessment model for botrytis bunch rot was also embedded for daily risk assessment in vineyards using leaf wetness and temperature data (Kim et al. 2007). Kim et al. (2008) showed that cost of spray application using a risk assessment model could be compared between different approaches. The information layer could give an objective assessment to select the most cost-effective approaches for disease management.

In the knowledge layer, an expert system is used to provide decision support for growers using the predicted risk of botrytis bunch rot. The expert system is based on rules that describe management options under a given risk (Gleason et al. 1997).

Information in these layers is provided through the internet using a user interface on the presentation layer. When this system is fully developed and validated for management of botrytis bunch rot on grapes, it could be of great utility in keeping New Zealand's wine production competitive and protected.

CONCLUSION

A wide range of weather data have been used to predict the risk of plant diseases. Using spatial interpolation and satellites, it is possible to obtain estimates of weather data without on-site sensors. The spatial and temporal scale of these data is suitable for daily operation of disease management. An integrated weather database system can be used to manage weather data available from local weather stations and satellites in order to operate daily disease management programmes. The disease modules embedded in the database system can be developed and validated for a specific crop and disease. The integrated weather database system for disease management could provide optimal management recommendations under a given risk of a disease.

Figure 1 Framework of an information system to predict disease risk.

It merits further studies for its development and validation.

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