Plant Pathol. J. 21(2) : 111-118 (2005)

The Plant Pathology Journal

Simulation of Grape Downy Mildew Development Across Geographic Areas Based on Mesoscale Weather Data Using Supercomputer

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(Received on May 4, 2005; Accepted on May 23, 2005)

Weather data for disease forecasts are usually derived from automated weather stations (AWS) that may be dispersed across a region in an irregular pattern. We have developed an alternative method to simulate local scale, high-resolution weather and plant disease in a grid pattern. The system incorporates a simplified mesoscale boundary layer model, LAWSS, for estimating local conditions such as air temperature and relative humidity. It also integrates special models for estimating of surface wetness duration and disease forecasts, such as the grapevine downy mildew forecast model, DMCast. The system can recreate weather forecasts utilizing the NCEP/NCAR reanalysis database, which contains over 57 years of archived and corrected global upper air conditions. The highest horizontal resolution of 0.150 km was achieved by running 5-step nested child grids inside coarse mother grids. Over the Finger Lakes and Chautauqua Lake regions of New York State, the system simulated three growing seasons for estimating the risk of grape downy mildew with 1 km resolution. Outputs were represented as regional maps or as site-specific graphs. The highest resolutions were achieved over North America, but the system is functional for any global location. The system is expected to be a powerful tool for site selection and reanalysis of historical plant disease epidemics.

Keywords **:** disease model, farecast, high-resolution, mesoscale, simulation, supercomputer, weather

Automated weather stations (AWS) are needed to continuously monitor the near canopy weather conditions and forecast plant disease outbreak based on models and empirical equations. Because the data from one AWS represent only a few square kilometers at most, weather stations are networked for regional disease forecast. However, the cost of installation and difficulties of maintenance make it difficult to compose large AWS network (Kim and Park, 1998, 2000). The problems related with AWS can be resolved by incorporating various methods to create high-resolution weather data for agricultural ecosystems. There are currently two approaches to produce local-scale high-resolution weather data based on numerical interpolation and physical weather models. Numerical interpolation methods can easily produce high-resolution weather data; however, they are dependent largely on the density of the weather network. Alternatively, physical weather models can be operated completely absent from AWS data and require large amount of computing power. In areas of high variations of elevation and water bodies, as the Finger Lakes region of New York State, interpolated weather data tended to exhibit too much smoothing. On the other hand, a physical mesoscale model, LAWSS (MESO, 1999) finely captured farm-scale weather conditions without on-site AWS data (Magarey et al., 2001).

Local weather information can be defined as representing a scale between 1 and 250,000 ha or between 0.1 and 50 km on a horizontal scale (Oke, 1987). Although any plant in a field has unique weather conditions, a reasonable scale of detail needed for farm management would be about the size of 1 ha (Magarey et al., 2001). Local weather conditions based on the LAWSS model were utilized in agriculture for cold injury analysis and site selection of vineyard sites (Magarey et al., 2000). However, plant disease infection models require seamless hourly weather data throughout the disease monitoring period instead of one or two target days per cold event analysis.

The physical mesoscale weather model, LAWSS can simulate local scale hourly weather conditions for several weeks. By incorporating a supercomputer, running hours of the model can be reduced to a reasonable level. Each data point from the local scale weather model is equivalent to one AWS installed in the field. Therefore, a robust data management and presentation routines would be needed for a local scale plant disease simulation system. Seasonal

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disease forecasting with high-resolution hourly weather data and regional mapping of infection risks were the challenging subjects of this study.

Materials and Methods

LAWSS model. The Local-area Agricultural Weather Simulation System (LAWSS), which was designed to run local-area simulation on a moderate cost personal computer running the Linux operating system, has been described in detail elsewhere (MESO, 1999). It was created by simplifying the Mesoscale Atmospheric Simulation System (MASS; Kaplan et al., 1982; MESO, 1995; Manobianco et al., 1996) into a single layer model using many of the approximations and assumptions employed by Mass and Dempsey (1985). It simplified the representation of processes that are usually unimportant in determining surface temperature (especially in nocturnal clear sky, light winds scenarios) such as the parameterization of grid-scale precipitation processes and cumulus convections. It retained the relatively sophisticated Surface Energy Budget, Radiation, Planetary Boundary Layer and Hydrology (SRPH) model currently used in MASS. It accounted for the four most important factors in determining nighttime temperatures in agricultural fields: (1) radiation cooling, (2) turbulent mixing, (3) down slope flow of radiatively cooled air, and (4) the effects of nonuniform surface properties (i.e. variations in vegetative cover, bodies of water, etc.) on heating and cooling rates. The LAWSS model was designed to optimize the simulation of the ground and near surface conditions important to agriculture. It did so by concentration its highest resolution in the lowest 2-3 km of the atmosphere over a limited horizontal domain with a horizontal resolution of less than 1 km.

Implementation of LAWSS on a supercomputer. The LAWSS model can be implemented on grids with resolutions as high as about 100 meters (1 ha) over a domain of 100×100 grid points or even larger. Domain size for the Finger Lakes agricultural region is about 10,000 km^2 or 1000×1000 grid points with 100 m horizontal resolution. A supercomputer was needed to run the model at sub-kilometer resolution over the Finger Lakes region for two-month-long weather and disease simulations per grape growing season.

The supercomputer at Cornell Theory Center is a Windows cluster. Each node in the '*vplus*' cluster, which was used in this study, has two 733 MHz CPUs and 2 GB main memory. The maximum number of available nodes at one time was 64. Because LAWSS was originally run on a Linux workstation, Cygwin (http://cygwin.com) environment was adopted to provide the functionality of UNIX shell scripts on Windows. Various FORTRAN compilers from Cygwin (GNU g77, http://cygwin.com), HP (f77, http://hp.com/go/fortran), Portland Group (pgf77, http://www.pgroup.com), and Intel (ifc, http://intel.com) were tested on Windows. Cygwin FORTRAN compiler was selected for preprocessor programs of LAWSS because they required UNIX conventions for path names of input and configuration files. Intel FORTRAN compiler was used for the main program of LAWSS. The '/Qsave' compiler flag was needed for LAWSS to work correctly since it depended on persistent local variable values between subroutine calls.

Through the Cluster Controller System (CCS), a node from the supercomputer could be allocated and jobs be executed. A split-and-run system was developed to create and submit batch jobs to CCS (Fig. 1). The system included several key features such as (1) managing domain areas in hierarchical 5-level nested grids to use the output of parent (coarser) grids as the input for child (finer) grids (Fig. 2); (2) splitting the time domain into 24- or 12- or 6-hour segments depending on the grid level so that one segment can be finished within the runtime limit of 24 hours per job; and (3) sequentially arranged jobs based on parent-child relationships of grid levels and time segments within a grid level. Multiple jobs at the same grid level and time segment were independent of each other and launched in parallel. Jobs in nested domains were also run in parallel once the relevant time segment jobs of their parents have finished.

Target sites. Grape-growing regions of the Finger Lakes and Chautauqua Lake of New York State were selected as

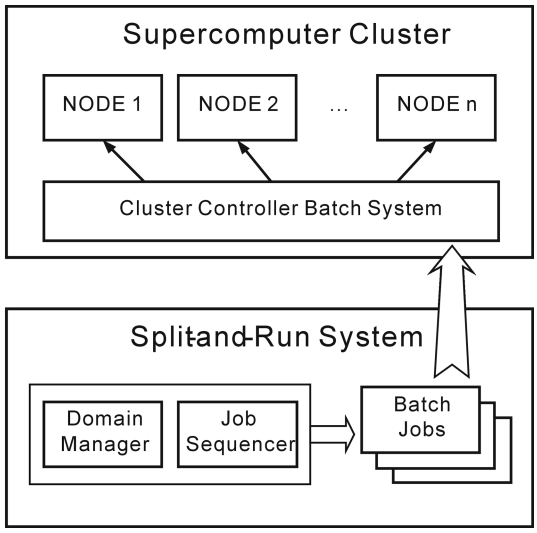

Fig. 1. Schematic view of the supercomputer at Cornell University with cluster controller batch system (CCS) and the split-and-run system for the management and submission of jobs in temporal and spatial domains.

target sites. For each test case of the model for the Finger Lakes region, initial runs of the LAWSS model were made at a 9 km horizontal resolution for a 656,100 km^2 domain (Grid-A: 90 × 90 grid cells), which included the entire State of New York with the Finger Lakes region in the middle of the domain. Subsequent runs were nested inside their parent domains. Grid-B was at 3 km resolution (90,000 km^2 domain with 100 × 100 grid cells) and Grid-C at a 1 km resolution (10,000 km^2 domain with 100 × 100 grid cells). The Grid-C domain encompassed the Finger Lakes region. It was further split into nine Grid-D's at a 0.333 km resolution (1,109 km^2 domain each with 100 × 100 grid) to allow coverage of the entire region (Fig. 2). Each Grid-D was further split into four Grid-E's to achieve the system's highest resolution of 0.150 km (225 km^2 domain each with 100 × 100 grid). The same methods of down-scale nesting were used for the Chautauqua Lake site.

Input data and output processing. The input data for the LAWSS model consisted of upper atmospheric and geographic data. The upper atmospheric data were obtained from the NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research) reanalysis project (http://www.cdc.noaa.gov) and transformed for the LAWSS model. The spatial coverage of the database was 2.5 × 2.5 degrees latitude/longitude global with 144 × 73 points, and temporal coverage was from 1948 to present with data values every 6 hours. Digital terrain data or digital elevation models were obtained from the United States Geological Survey (USGS) at a 100 m horizontal resolution (Anonymous, 1989). Landuse data were also obtained as polygon coverage at 1:250,000 scale from USGS (Anonymous, 1991). Each polygon in the database represented a homogenous area and had a minimum area of 4 ha for urban features and 16 ha for non-urban features. The polygon coverage was converted to a 100 m raster grid in Arc Info Grid 8.0 (http://esri.com).

The LAWSS model outputs 2-dimensional distribution of various fields including but not limited to 2 m temperature, 2 m relative humidity, 10 m wind speed and direction, and net radiation. It would be also possible to compute many other derived variables from the basic variables. The output could be saved at any interval based on the model time step. Hourly data were saved for plant disease simulation.

To properly manage a large amount of data from hourly output, the plain text of the LAWSS output was transformed to NetCDF format (http://my.unidata.ucar.edu/content/software/netcdf/) using Ferret (http://ferret.pmel.noaa.gov/) and NCO (http://nco.sourceforge. net) software. Analysis and mapping of the model output were conducted using Ferret on the NetCDF data files.

SWEB model. Surface Wetness Energy Balance (SWEB) model is a simple surface wetness model for grape vines

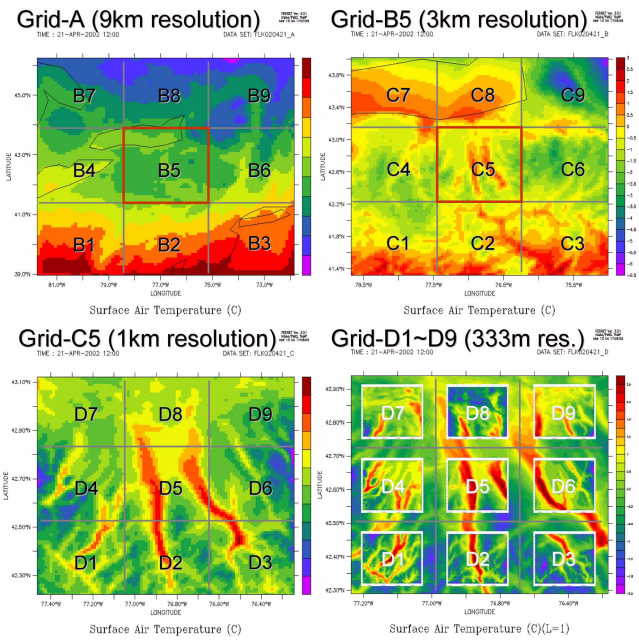

Fig. 2. Surface air temperature maps demonstrating the nesting of domain grids by four levels from 9 km to 333 m horizontal resolutions. At 333 m resolution, nine sub-domains are merged after model runs using output processors.

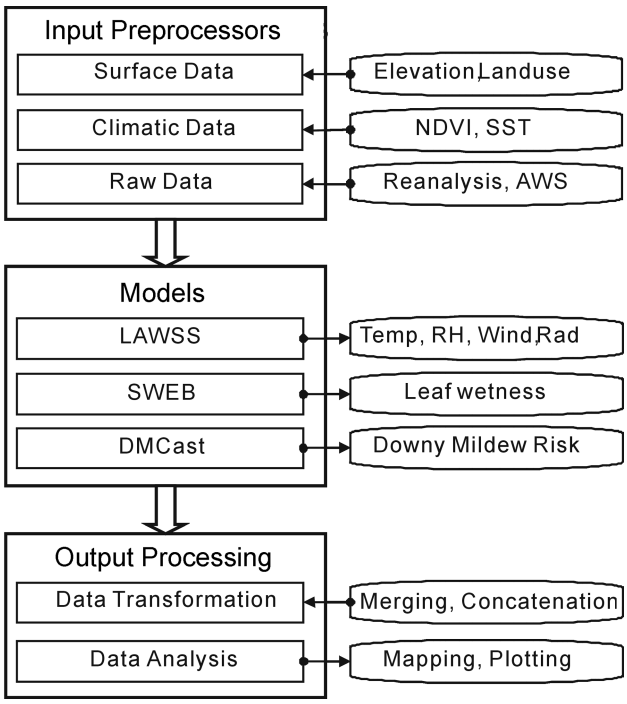

Fig. 3. Schematic data flow in the high-resolution weather and plant disease forecasting system from the input processors to the models and to the output processors.

(Magarey, 1999 and Magarey et al., 2005). It is based on a 'big leaf' approach and consists of four sub-modules describing: (1) surface water distribution based on an observed wet fraction; (2) canopy water budget; (3) an energy balance module based on a combination equation; and (4) a simple transfer function calibrated to determine surface wetness under controlled conditions. The SWEB model can be adapted to the physical characteristics of a particular crop by adjusting four plant parameters: leaf area index (LAI); maximum fraction of canopy allowed as wet surface area (W_{max}); crop height and maximum water storage.

Vineyard leaf area index (LAI) was estimated as LAI = –0.25198 + 5.70850 × NDVI (Johnson et al., 2001). NDVI (Normalized Difference Vegetation Index) was available in LAWSS as a standard climatological dataset. W_{max} and other configurable plant parameters were established by Magarey (1999) and Magarey et al. (2005). Input data for the model are temperature and relative humidity (RH) at canopy height, precipitation and wind speed collected above the canopy and the net radiative flux for the canopy. Simulated hourly data from LAWSS were used as the input except for precipitation, which was omitted in LAWSS as a simplification. The canopy wet area (CWA) can be estimated by SWEB and it was used as an input for the DMCast model, a disease forecasting model for grape downy mildew (Park et al., 1997).

DMCast model. Grape downy mildew (*Plasmopara viticola*) is one of the most wide spread diseases in New York State grape growing regions as well as other grape regions of the world. The DMCast model simulates primary and secondary infection events by the grape downy mildew fungus based on air temperature, RH and leaf wetness and estimates hourly risk values on a scale of 0-1 for sporulation, spore survival, and infection. These values are multiplied to determine the overall disease risk (DMrisk). If DMrisk for a given hour is greater than zero, then an hourly disease warning (DMW) is issued. In this study, only the secondary infection cycle was simulated due to unavailable site-specific cultivar and phenological data (date of dormancy break, etc) (Fig. 4). Also, LAWSS has a limitation in producing rainfall events so that leaf wetness, one of the driving variables of DMCast, was determined based on dew formation only.

Test seasons for differential mapping and validation. To demonstrate the differences of favorable and unfavorable weather conditions for infection, we chose three years: 1987, 1994 and 2003 for unfavorable, favorable and ordinary years, respectively, for disease development. Active growing seasons of June 15 to August 15 each year

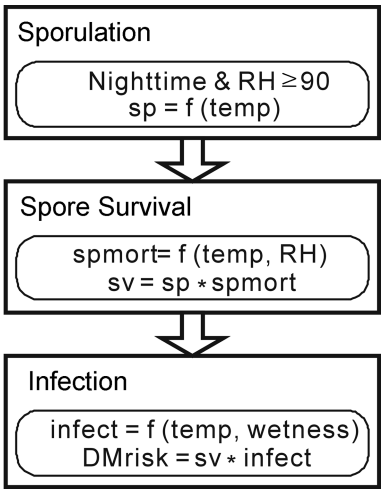

Fig. 4. Flowchart of the secondary infection model of DMCast for disease risk warnings (DMrisk) of grape downy mildew.

were selected to run the model. Daily DMW was set to 1 if there was any hour with DMW in a day. Total DMCast warning days (DMWD) was calculated from the daily DMW for 1987 and 1994. To present the relative risk of grape downy mildew infection on a map, the DMWD of 1994 was subtracted from that of 1987 for each grid cell. These procedures were repeated for two target sites.

To verify the system's fidelity to real weather conditions and to show its capability of site-specific analysis, weather data monitored by AWS at Geneva (42.873N, 77.028W) and Fredonia (42.450N, 79.233W), New York were obtained from the North East Weather Association (NEWA: http://newa.nysaes.cornell. edu). Site-specific time series data were extracted from the simulation outputs saved in the NetCDF format using Ferret. The data were automatically interpolated in Ferret if specified coordinates were pointed off the center of a grid cell. Daily mean air temperature, relative humidity (RH), canopy wet area (CWA) and DMCast risk (DMrisk) at Geneva and Fredonia were extracted and compared to the data from AWS observations in 2003.

Leaf wetness sensors of AWS detected the length of wetting period (WP) whereas CWA was an estimate of wet area of canopy. In other words, a 0.5 hourly wetness from an AWS is 0.5 hour of wetting period whereas a 0.5 CWA represents half of the canopy is wet at the time of the model calculation. Since WP and CWA are different measures of leaf wetness that cannot be directly compared, and there is no rainfall input for the SWEB model, criteria were set up for the comparison of the wetness and DMrisk variables. The agreement ratios on wetness and DMrisk from the AWS observation and the prediction by simulation model were compared for non-rainy days (32 days for Geneva and 37 days for Fredonia) as well as for the entire season.

Table 1. Domain size and running hours per one 24-hour period domain over the Finger Lakes region. The region is about the same size of one Grid-C, nine Grid-D, and 36 Grid-E domains

Grid	Horizontal Resolution	# Grid points	Domain Size (km^2)	Hours/Domain	# Domains for Finger Lakes
A	9 km × 9 km	90 × 90	656100	2	1
B	3 km × 3 km	100 × 100	90000	7	1
C	1 km × 1 km	100 × 100	10000	12	1
D	333 m × 333 m	100 × 100	1109	25	9 (parallel)
E	150 m × 150 m	100 × 100	225	50	36 (parallel)

Results

Each node of the supercomputer cluster used in this study was very similar to ordinary computers except for the Cluster Controller System (CCS) for node allocation and non-interactive batch job submission. The split-and-run system successfully submitted the 24- or 12- or 6-hour batch jobs to CCS based on the nesting and job sequence. In the batch jobs, input data files were copied from the file server to a local hard drive of the node and the simulation system was operated to produce hourly output.

The Finger Lakes region is as large as one Grid-C or nine Grid-D or 36 Grid-E domains. Sub-domains, such as 9 Grid-D domains, were merged into one dataset after parallel simulations. Running hours required to complete job(s) for a 24-hour segment period for one domain are shown on Table 1. It would take approximately 2, 9, 21, 246, and 2,046 hours to complete one-day simulation at 9, 3, 1, 0.333, and 0.150 km resolution, respectively, over the Finger Lakes area if there was only one node available. Hours needed to complete one domain area of a 24-hour segment increased significantly as the horizontal resolution increased because of the shorter time steps and increasing number of grid cells. On the supercomputer, nested

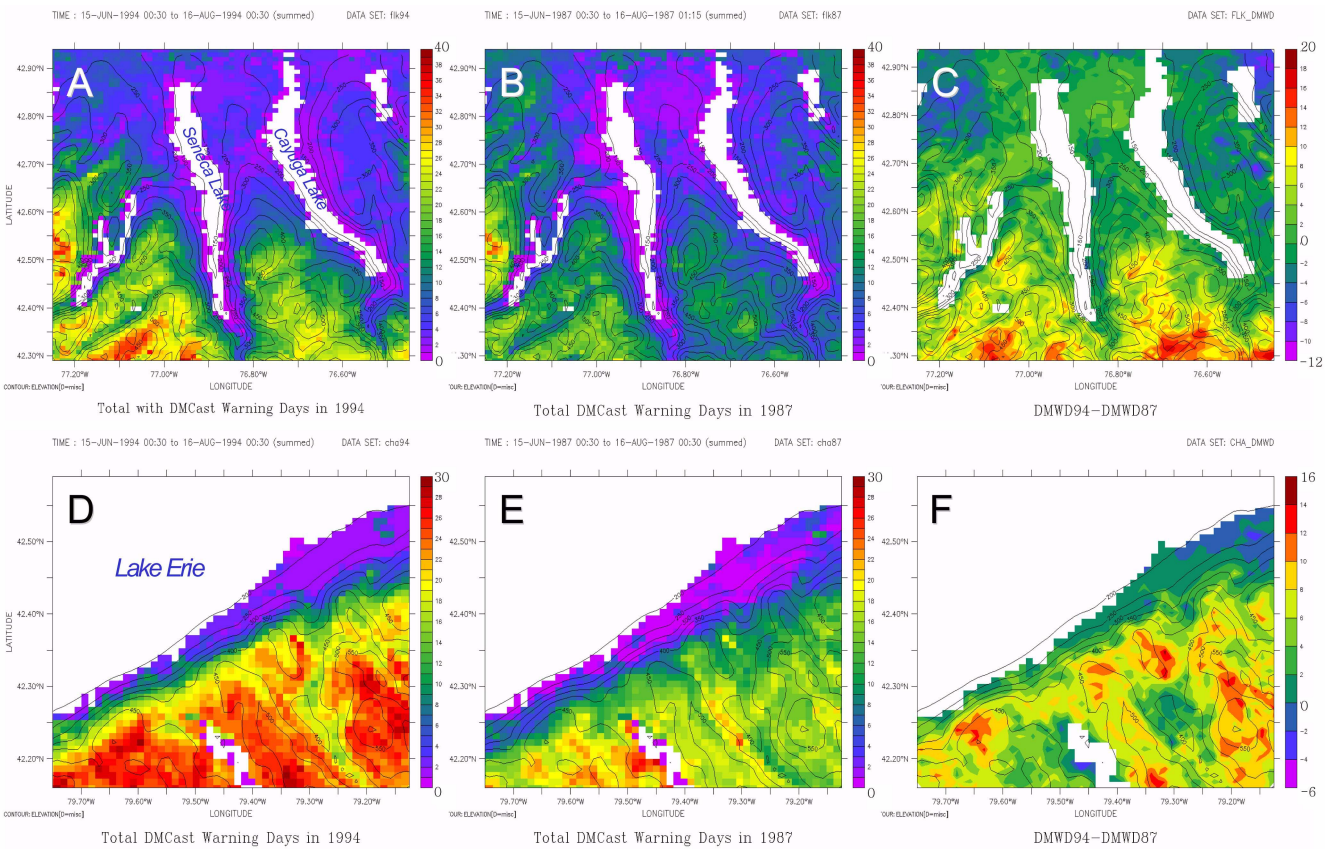

Fig. 5. Total DMCast warning days (DMWD) driven by air temperature, RH, and dew-induced leaf wetness mapped across the Finger Lakes (**A**, **B**, and **C**) and Chautauqua Lake (**D**, **E**, and **F**) grape-growing regions of New York State during June 15-August 15 for the years 1994 (A and D) and 1987 (B and E). The differences of DMWD of the two years are also shown (**C** and **F**).

Table 2. Comparisons of observed and simulated daily wetness and DMrisk during June 15 - Aug. 15, 2003 at Geneva and Fredonia

Location	Criteria of daily comparison	Agreement ratio between observed and simulated data during:	
		the entire simulation	non-rainy days
Geneva (42.87N, 77.03W)	Wetness > 0.1	33/62 (53%)	28/32 (88%)
	DMrisk > 0	41/62 (66%)	28/32 (88%)
Fredonia (42.45N, 79.23W)	Wetness > 0.1	39/62 (63%)	28/37 (76%)
	DMrisk > 0	36/62 (58%)	27/37 (73%)

independent jobs were run in parallel so that it was able to complete a 24-hour simulation at 0.150 km resolution in 5 days. It still required so much time to complete the 62-day simulation per year for three years at its maximum resolution. The system had finished running only up to the 1 km resolution in this study.

Total DMCast warning days (DMWD) in 1994 and 1987 were mapped across the Finger Lakes (Fig. 5A and 5B) and Chautauqua Lake (Fig. 5D and 5E) of New York State. Mountainous areas had higher DMWD in the maps, indicating that those areas were more vulnerable to grape downy mildew than low elevation areas. Most of vineyards in the regions are located on the slopes along the lakes and the maps revealed that they had moderate DMWD during the seasons. The differential DMWD maps (Fig. 5C and 5F) produced by subtracting the DMWDs of 1987 (Fig. 5B and 5E) from those of 1994 (Fig. 5A and 5D) demonstrated that there were 2-10 more days with DMCast warnings in 1994 on the slopes along the lakes.

Air temperature and relative humidity simulated by the

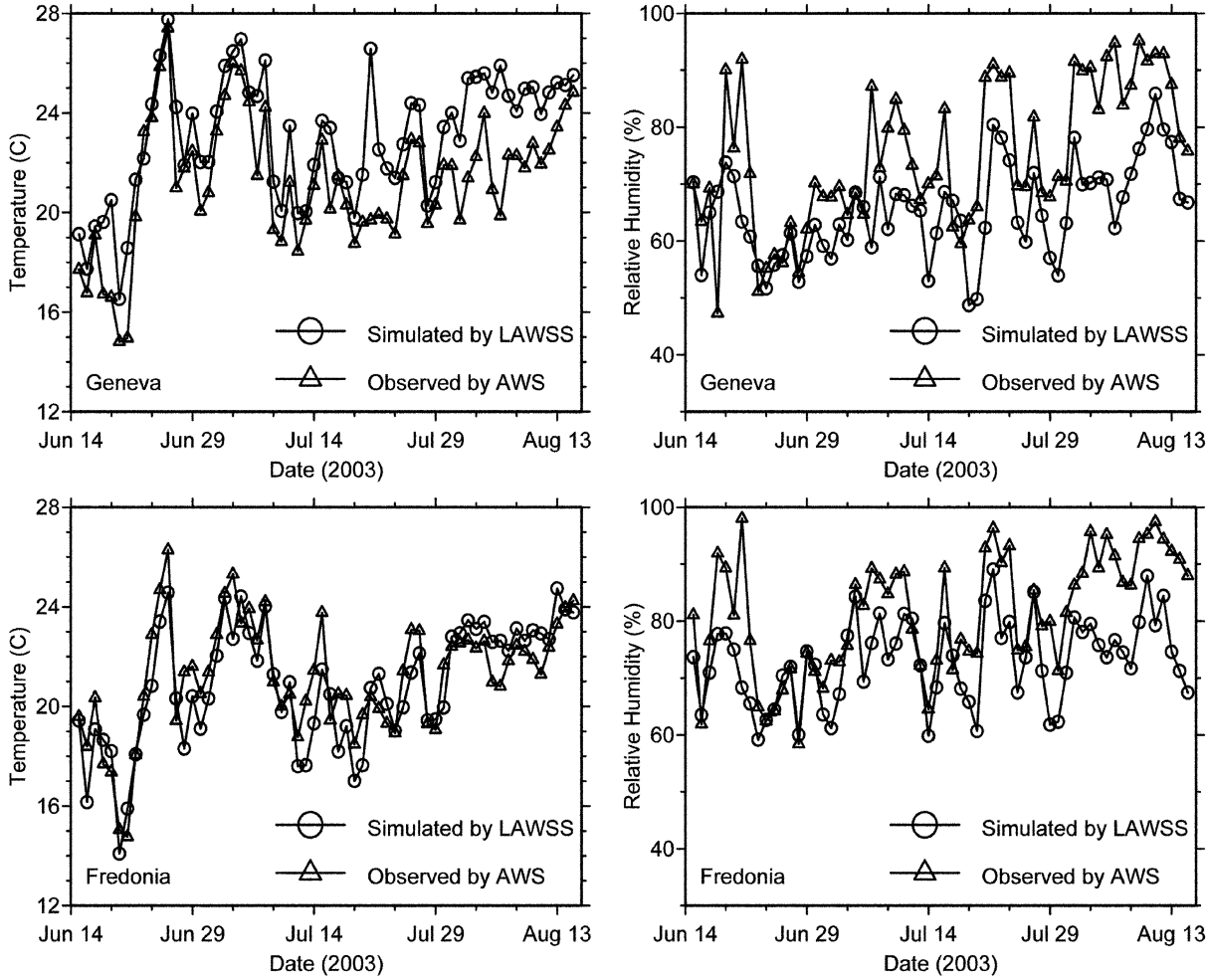

Fig. 6. Comparisons of observed and simulated daily mean air temperature and relative humidity during June 15-Aug. 15, 2003 at Geneva (42.873N, 77.028W) and Fredonia (42.450N, 79.233 W).

LAWSS model in Geneva and Fredonia were extracted using Ferret and shown on daily comparison graphs in Fig. 6. Simulated air temperature for both locations agreed reasonably well with the AWS observed data. Daily mean relative humidity is often useful for plant disease forecasting to predict pathogen sporulation and infection. Simulated relative humidity followed the daily trend of AWS observations but it was often underestimated at the later seasons (Fig. 6). One of the possible causes of the underestimation might have been partly due to overestimation of saturated vapor pressure by the LAWSS model.

Criteria for the daily comparison of leaf wetness and DMrisk were set as wetness > 0.1 and DMrisk > 0. Agreement ratios between the observed and simulated data are shown in Table 2. In 2003, the observed and simulated data were in agreement for 53-66% of the entire simulation dates. The agreement ratios increased to 73-88% when only non-rainy days were counted during the entire simulation period. Fredonia had more days in agreement during the entire simulation period than Geneva, but it was not true for non-rainy days.

Discussion

We have implemented a regional disease simulation system for grape downy mildew incorporating a mesoscale weather model, a canopy wetness model, and a disease forecasting model in a supercomputer. Using globally archived reanalysis data from 1948 to the present, the system simulates hourly local weather and disease infection warnings over the grape growing areas of the Finger Lakes and Chautauqua Lake up to the horizontal resolution of 0.150 km. It only required a few datasets of geographic and climatological data such as terrain elevation and NDVI to estimate hourly local weather data for disease models. The performance of the LAWSS model in estimating hourly local weather data were reasonably good when compared with the observed data by AWS.

The LAWSS model has the advantage that it does not require a local monitoring network as input data (Magarey et al., 2000 and 2001). However, it is complex, especially compared with the spatial interpolation. Consequently, it takes a substantial time block to run even for a relatively small domain on an ordinary workstation. This drawback was solved in the present study by running the LAWSS model on the supercomputer cluster with parallel model runs over temporally and spatially independent domains.

Since the LAWSS model does not generate rainfall output, estimated daily wetness and DMrisk were more accurate in non-rainy days than in rainy days. This suggested that the disease forecasting system could be improved by incorporating a regional rainfall model. The MASS model (MESO, 1995) is the original model from which the LAWSS model was derived and has the capability of simulating rainfall events. Because MASS requires at least four times more running hours than LAWSS, higher resolution than 1 km is not practical for seasonal operation of MASS over a region as large as the Finger Lakes area. However, it would be possible to run MASS on 1 km grids, generating rainfall output data, which are to be distributed to finer grids for subsequent runs of LAWSS. In this way, the problems due to the lack of rainfall events in the LAWSS output and the long time requirement for the MASS running could be resolved.

As the resolution increased, the spatial variations of the terrain became more influential and more details were visible. Fig. 2 indicated that the Finger Lakes region was not distinguishable in the air temperature maps at 9 km resolution. It became visible at 3 km and higher resolutions and more details of the underlying terrain and vegetation were revealed. Transect graphs of the model outputs showed more spatial details with higher resolution (Fig. 7). They were extracted from the output NetCDF data set at the latitude 42.873N degrees on 08:00 EDT (12:00 UT), July 1,

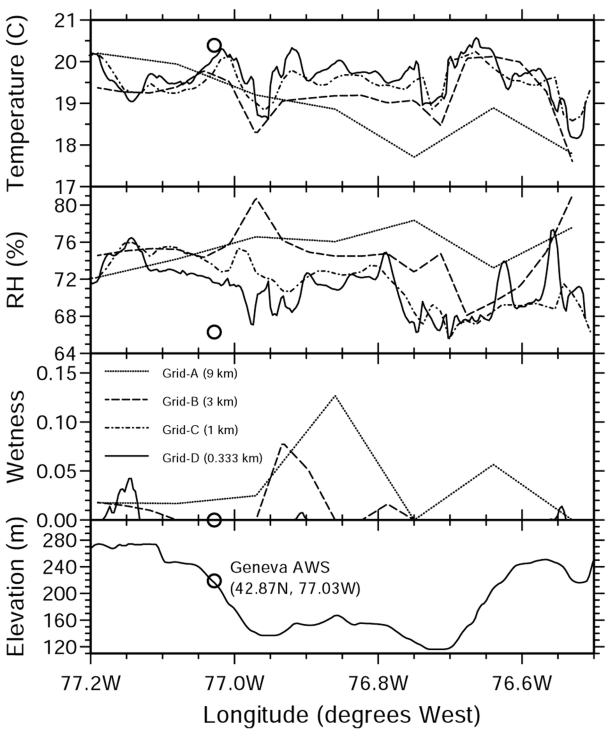

Fig. 7. Latitudinal transect graphs at 42.873N for air temperature, relative humidity (RH), and canopy wetness area (CWA) at 08:00 (EDT) on July 1 2003 as observed by AWS in Geneva or estimated by the LAWSS model at 9, 3, 1, and 0.333 km resolutions. Terrain elevation at 0.333 km resolution is also shown.

2003. In Fig. 7, at least 1 km resolution was required to reflect the underlying terrain and vegetation variations. The differential risk maps (Fig. 5) were derived from Grid-C with 1 km resolution. Grid-D or E was required to analyze favorability of weather conditions for disease development at farm or field levels. However, running hours needed to complete three 2-month seasons in sub-kilometer resolution were too long as shown in Table 1. Therefore, certain dates of interest have to be selected first from Grid-C, and then the system is run only for the selected dates.

The NetCDF data files saved from the system could provide hourly and daily data without much difficulty. For example, daily data at a given location (Fig. 6) and transect data at a given hour (Fig. 7) were extracted from the hourly NetCDF data sets. After extracting the weather data, it was possible to perform ordinary data analyses on hourly or daily weather conditions. Other plant disease simulation models than DMCast could also be implemented based on the NetCDF files for regional disease forecasting. Because plant disease forecasting models are often simpler than the LAWSS model, execution and evaluation of new or modified disease models will be possible in short period of time without running the weather model repeatedly.

The regional plant disease simulation system in this study showed the capability of utilizing the global weather database in disease risk assessment. Temporal changes of disease warnings and other variables were presented on maps and graphs for the analysis of disease events from the past. Although the supercomputer cluster was used in this study, higher computing power is still needed to forecast disease development based on high-resolution weather forecasts.

Acknowledgements

This research was conducted using the resources of the Cornell Theory Center, which receives funding from Cornell University, New York State, federal agencies, foundations, and corporate partners. This study was partially supported by a USDA/NRI Competitive Grant No. 2004-35605-14331 and by the Korea Research Foundation Grant funded by Korea Government (MOE, Basic Research Promotion Fund, No. M01-2002-000-00230-0).

References

Anonymous. 1989. User Guide for Digital Elevation Data. United States Geological Survey. Washington D. C.

Anonymous. 1991. Land Use and Land-Cover Digital Data from 1:250,000- and 1:100,000-Scale Maps Factsheet. Data Users Guide 4. 33pp. United States Geological Survey, Reston, VA.

Johnson, L., Roczen, D. and Youkhana, S. 2001. Vineyard Canopy Density Mapping with IKONOS Satellite Imagery, *Third Int'l Conf. Geospatial Information in Agriculture and Forestry*, Denver CO, November 5-7.

Kaplan, M. L., Zack, J. W., Wong, V. C. and Tuccillo, J. J. 1982. Initial results from a mesoscale atmospheric simulation system and comparisons with an AVE-SESAME I data set. *Mon. Wea. Rev.* 110:1564-1590.

Kim, K. R. and Park, E. W. 1998. Rice Disease Forecasting and Information System. http://epilab.snu.ac.kr/rice.

Kim, K. R. and Park, E. W. 2000. Plant disease tracking system for rice – Internet user interface. *Kor. J. Agric. For. Meteorol.* 2:68-73.

Manobianco, J., Zack, J. W. and Taylor, G. E. 1996. Workstation-based real-time mesoscale modeling designed for weather support to operations at the Kennedy Space Center and Cape Canaveral Air Station. *Bull. Amer. Meteor. Soc.* 77:653:672.

Magarey, R. D., 1999. A theoretical standard for the estimation of surface wetness duration in grape. Ph.D. thesis, Cornell University, Ithaca, NY.

Magarey, R. D., Russo, J. M., Seem, R. C. and Gadoury, D. M. 2005. Surface wetness duration under controlled environmental conditions. *Agric. For. Metrol.* 128:111-122.

Magarey, R. D., Seem, R. C. and Zack, J. W. 2000. A Local-area Agricultural Weather Simulation System (LAWSS), for environmental risk assessment. *GIS/EM* 4:47.

Magarey, R. D., Seem, R. C., Russo, J. M., Zack, J. W., Waight, K. T., Travis, J. W. and Oudemans, P. V. 2001. Site-specific weather information without on-site sensors. *Plant Dis.* 85:1216-1226.

Mass, C. F. and Dempsey, D. P. 1985. A one-level, mesoscale model for diagnosing surface winds in mountainous and coastal regions. *Mon. Wea. Rev.* 113:1211-1227.

MESO. 1995. MASS version 5.6 Reference Manual. 118pp. [Available from MESO, Inc., 185 Jordan Road, Troy, NY 12180].

MESO. 1999. LAWSS Users Guide. 37pp. [Available from MESO, Inc., 185 Jordan Road, Troy, NY 12180].

Oke, T. R. 1987. Boundary layer climates. Routledge, London. 435 pp.

Park, E. W., Seem, R. C., Gadoury, D. M. and Pearson, R. C. 1997. DMCAST: a prediction model for grape downy mildew development. *Vitic. Enol. Sci.* 52:182-189.