PLP 6404 Epidemiology of Plant Diseases
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Lecture 29: Decision support systems

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Overview

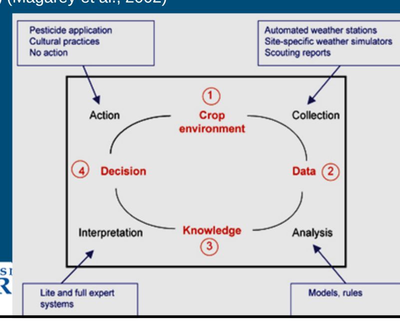
- Introduction to Decision Support Systems
- Computerized disease forecasting systems
  - Stand-alone forecasters
  - Interactive on-line forecasting systems
  - Spatial trajectory systems
  - Expert systems
  - Neural networks
- Summary

Introduction to decision support systems

- A Decision Support System (DSS) integrates and organizes all types of information required for production decisions.
- DSS tools vary in complexity
  - Data component, e.g. automated weather stations or site-specific weather products
  - Tools for processing data: rules, schedules of management, equations
  - Combinations of decision aids
  - Complex computerized expert systems

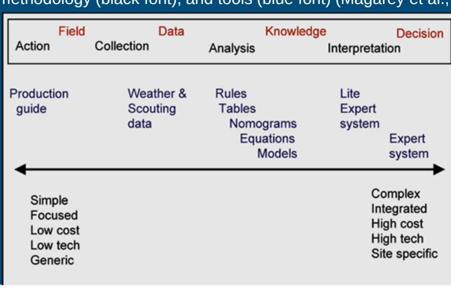
Introduction to decision support systems

- Idealized Decision Support System for plant disease management showing components (red font), methodology (black font), and tools (blue font) (Magarey et al., 2002)



Introduction to decision support systems

- A spectrum of tools for decision support showing components (red font), methodology (black font), and tools (blue font) (Magarey et al., 2002)



Computerized disease forecasting systems

- Stand-alone forecasters: in-field electronic forecasting systems
- Example: Spectrum Technologies Inc. http://www.specmeters.com/home_usa.html
- Example: Weather INnovations Inc. with 'Beetcast' http://www.michiganbeets.com/contact.cfm
  - Microprocessor based
  - Plus environmental monitoring equipment (sensors, gauges, etc.)
  - plus software to: process weather data, predict infection or disease severity, provide management recommendations

Computerized disease forecasting systems

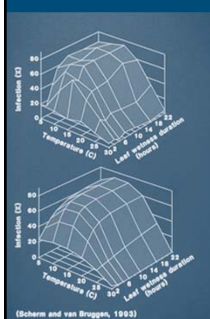
- Electronic units commercially available for forecasting several different diseases on the following crops:
  - Apple/pear, grapes, cherries
  - Turf grass, potatoes, tomatoes, onions etc.
- Advantages of in-field forecasting units:
  - potential to provide more accurate, site-specific information
- Disadvantages:
  - units are relatively expensive ($1000-$3000) and easily damaged (by lightning, field equipment, etc.)
  - require periodic maintenance, sensor calibration, frequent data acquisition

Computerized disease forecasting systems

- Electronic units and interactive systems
- Example: downy mildew of lettuce
- Development of a forecasting system
  - Research results used by a company that developed an in-field classical system
  - Intention: develop an interactive spatial system based on weather forecasts

Lettuce production in California

Controlled environment studies – Temp. & LWD



Gompertz model

$Y(t) = Ymax \exp -\exp(k\,t)$

Ymax = asymptote parameter
k = rate parameter

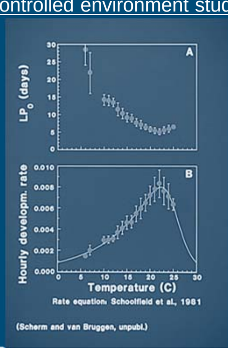
Modified Gompertz model

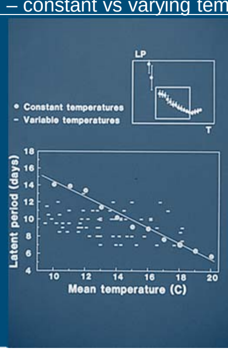
$Y(T,LWD) = Ymax(T) \exp -\exp[k(T)\,LWD]$

$Ymax(T) = a_0 + a_1 T + a_2 T^2 + a_3 T^3$

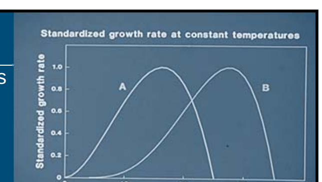
$k(T) = b_0 + b_1 T + b_2 T^2$

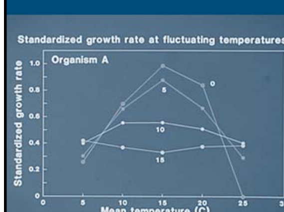
Controlled environment studies – constant vs varying temps

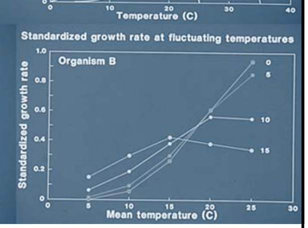




Simple deterministic model – constant vs varying temps

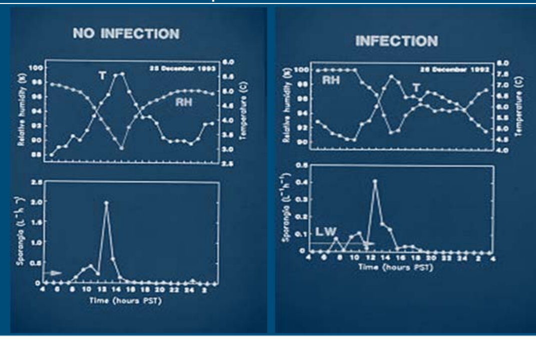




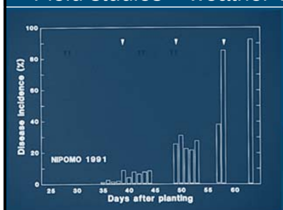


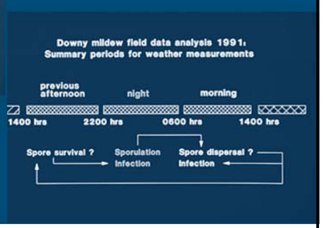
Field studies – microloggers & spore trap

Field studies – Temp, RH, LW



Field studies – weather variables -> infection





Field studies – weather variables -> infection

EXPLAINING VARIABLES

Afternoon (14:00 to 21:59 hrs):
- mean wind speed
- mean and max. temperature
- mean and min. relative humidity
- mean and max. shortwave irradiance
- mean vapor pressure deficit
- leaf wetness duration

Night (22:00 to 05:59 hrs):
- mean wind speed
- mean temperature
- mean relative humidity
- hours RH >= 90%
- mean vapor pressure deficit
- leaf wetness duration

Morning (06:00 to 13:59 hrs):
- mean wind speed
- mean temperature
- mean relative humidity
- hours RH >= 90%
- mean and max. shortwave irradiance
- mean vapor pressure deficit
- leaf wetness duration

CLASSIFICATION VARIABLE

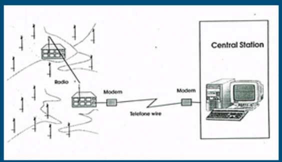
0 = Day without infection
1 = Day with infection

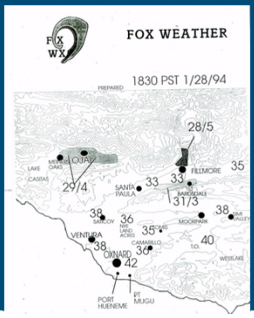
The most important weather variables for infection of lettuce by downy mildew as determined by stepwise discriminant analysis

Pajaro	Rio Del Mar	Nipomo	Castroville	Combined Data Set
AM-LWD	AM-LWD	AM-LWD	AM-VPD	AM-LWD
PM-RH	PM-SOL	MAX-TEMP	AM-LWD	PM-RH
AM-RH90	AM-TEMP	PM-RH	MAX-TEMP	NI-RH95
NI-WIND	NI-VPD	AM-WIND	NI-RH	
AM-WIND	NI-RH95			
PM-RH90	PM-VPD			
PM-SOL				
0.894	0.886	0.839	0.745	0.711

• positive effect • negative effect • correlation too low for interpretation

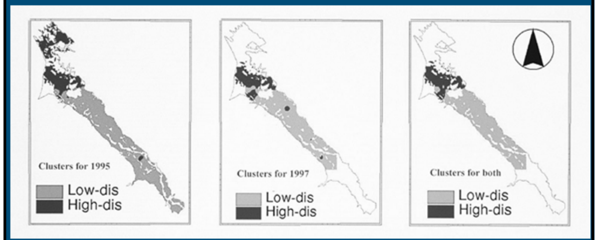
Field studies – weather and disease forecasts





Field studies –spatial analysis

Results of cluster analysis in GIS



Computerized disease forecasting systems

- Online forecasting systems – Examples:
  - Enviro-weather - Michigan State University
  - http://www.enviroweather.msu.edu/home_map.asp
  - AU-PNUT for early and late leaf spot of peanut – Auburn University, AU-PECAN for pecan scab – University of Georgia
  - http://www.awis.com
  - UC IPM Online: Statewide integrated pest management program – University of California, Davis
  - http://www.ipm.ucdavis.edu/GENERAL/tools.html

Computerized disease forecasting systems

- Interactive forecasting systems
- Example: EPIPRE (epidemiology, prediction, prevention) since 1980s for pest control in winter wheat (Zadoks, 1981)
  - Information about at least 6 diseases & insect pests
  - Crop, soil and weather taken into account:
  - Participation fee, enter own field monitoring, received forecast info from centralized location where info was processed.
  - A pesticide application recommended when predicted severity was above chosen threshold for a specific disease or pest.
  - EPIPRE now replaced by CERDIS predicting fungal diseases and making management recommendations for wheat and barley (from Opticrop)
  - Recently: EPIWHEAT for leaf rust and Septoria leaf spot by S. Savary

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Computerized disease forecasting systems

- Interactive forecasting systems
- Example: Plant-Plus by Dacom company since 1990s for disease control on potato (Raatjes et al., 2003)
  - Interactive, spatial DSS for management of late and early blight and irrigation management
  - Communication of data and info between farmer, consultant, and processor
  - Choice of interface and output (SMS, Fax or Email)
  - Five day weather forecast -> predictive risk assessment
  - Disease models require on-farm, automatic, weather data
  - Uses a biological model based on the lifecycle of the fungus
  - Combines infection events with unprotected tissue area
  - Recommends when to apply a new spray and what type of chemical to use: contact, translaminar or systemic.

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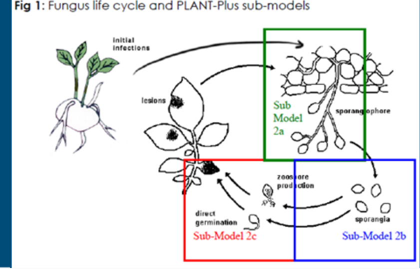
Computerized disease forecasting systems

- Example: Plant-Plus by Dacom company

Fig 1: Fungus life cycle and PLANT-Plus sub-models



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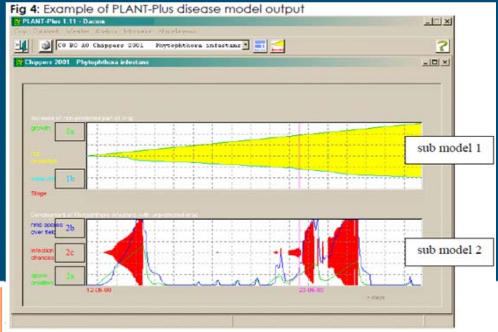
Computerized disease forecasting systems

- Example: Plant-Plus by Dacom company

Fig 4: Example of PLANT-Plus disease model output



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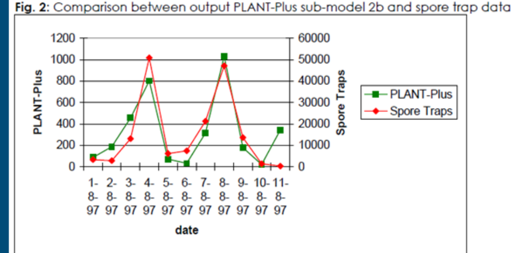
Computerized disease forecasting systems

- Example: Plant-Plus by Dacom company

Fig. 2: Comparison between output PLANT-Plus sub-model 2b and spore trap data



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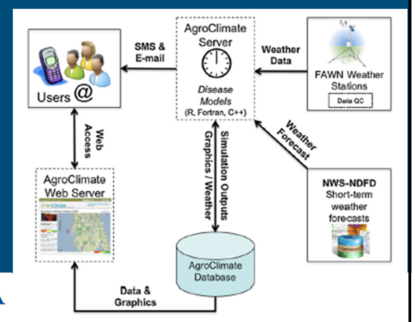
Computerized disease forecasting systems

- Example: Plant-Plus by Dacom company
- Now in 10 countries
- Results:
  - Netherlands: potato late blight model tested at many locations since 1994, 10,000 participating farmers in 2001
  - on average 28% reduction in sprays (no difference in disease/yield)
  - USA: *Phytophthora* model tested 7 States at 14 locations in 2003, 2004, 2005
  - on average 4 fungicide applications recommended versus 7.4 in standard practice (46% reduction, no significant difference in protection or yield.
  - Canada: Alternaria in potatoes, one test site in 2005
  - Dacom advised 2 sprays, WISDOM and TOMCAST recommended 4 sprays (no difference in disease or yield)

Computerized disease forecasting systems

- Interactive forecasting systems: Strawberry Advisory System (University of Florida) (Pavan et al., 2011)

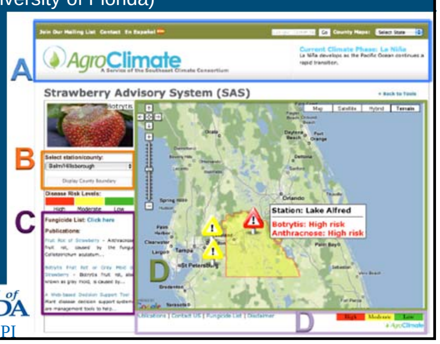
- Disease models: anthracnose and Botrytis fruit rot
- Agroclimate data base and FAWN
- Interface with user
- Controller (model management and view requests



Computerized disease forecasting systems

- Interactive forecasting systems: Strawberry Advisory System (University of Florida)

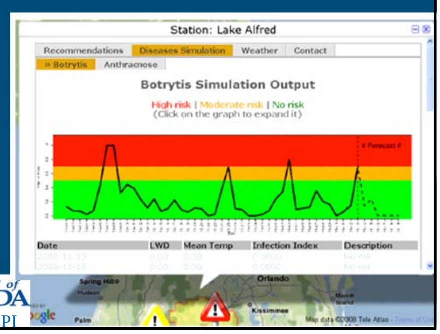
- Simulation models in R
- Anthracnose: temp > 18C, wetness
- Botrytis rot: temp 15-22C, wetness>4hr (RH>95%)



Computerized disease forecasting systems

- Interactive forecasting systems: Strawberry Advisory System (University of Florida)

- Results:
- Tested in 3 farms (weather not conducive; 2009/10)
- Fungicide applications reduced by 50%



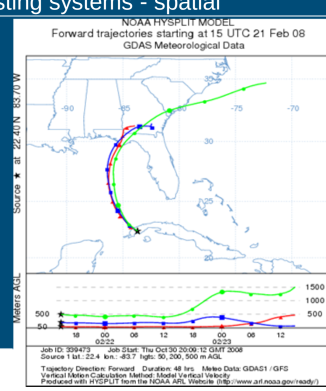
Computerized forecasting systems - spatial

- Forecasting by trajectory analysis
  - Example: Forecasting blue mold of tobacco (NC State Univ.)
  - Tobacco blue mold (*Peronospora tabacina)* forecast is based on mean temperature for January. If mean temperature is <45 °F, light occurrence of blue mold is predicted. If mean temperature is >62 °F, severe epidemics are predicted. Reason: temperature affects the survival (overwintering) of the oospores or fungal colonies on a weed host.
  - http://www.ces.ncsu.edu/depts/pp/bluemold/

  - Based on trajectory analysis of airborne inoculum and probability of favorable weather conditions for spore production and spread, and weather conditions

Computerized forecasting systems - spatial

- Forecasting of tobacco blue mold (NC State Univ.)
- Multi-level trajectories from western Cuba for February 20, 2008



Computerized forecasting systems - spatial

- Forecasting by trajectory analysis
  - Example: Soybean rust (Univ. Florida /NC State Univ.)
  - Soybean rust (*Phakopsora pachyrhizi*) forecast is based on availability of inoculum (spore release from 8 AM through 1 PM; trajectory start at 10 AM)
  - Survival on kudzu in winter
  - http://www.ces.ncsu.edu/depts/pp/soybeanrust/
  - http://sbr.ipmpipe.org/cgi-bin/sbr/public.cgi
  - Based on trajectory analysis of airborne inoculum and probability of favorable weather conditions for spore production and spread, and weather conditions for infection (6-7 hours of leaf wetness at a dew temperature between 18 - 26.5 °C; no infection 27.5 °C.

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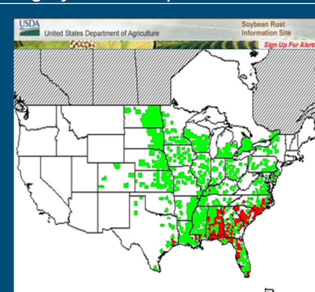
Computerized forecasting systems - spatial

- Soybean rust (USDA and NC State Univ.)
- Surviving on kudzu in Florida
- Trajectories from Florida going North-East



SBR Observation – 12-14-2005

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Forecasting systems – expert systems

- Expert systems are computer programs that use logic and problem-solving of a human expert, using concepts developed in the field of artificial intelligence (AI)
  - can employ heuristics, a problem-solving technique that uses "rules-of-thumb" based on experience to make management decisions.
  - not subject to the constraints of conventional computer programming, encountered with simulation or optimization analysis.
- Expert systems have the ability to:
  - make decisions based on incomplete or uncertain information
  - provide the user with an explanation of how its conclusion was derived

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Forecasting systems – expert systems

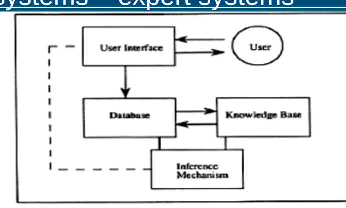

Figure 1 Diagram of expert system architecture.

IF the DISORDER is POWDERY MILDEW, and
WEEKS-BEFORE-HARVEST > 0, and
PREVIOUS-FUNGICIDE-APPLICATIONS = BAYLETON, BENLATE, OR TOPSIN,
THEN recommend the application of BAYLETON 50 DF at 4 oz/acre within the next 24 hours.

Figure 2 An example of a rule for recommending a control action for powdery mildew of muskmelon.

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Forecasting systems – expert systems

- Development of ES
  - interview of human expert by a knowledge engineer, trained in AI and ES.
  - Knowledge engineer organizes info from expert into interconnected rules
  - ES building tool "shell" used rather than a programming language

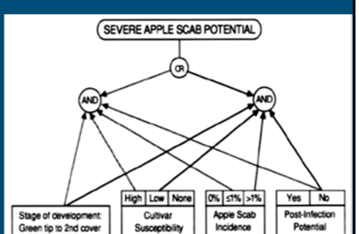

Fig. 4. Dependency network of factors that contribute to severe apple scab potential.

Example: Penn State Apple Orchard Consultant (PSAOC) (Travis, et al. 1992)

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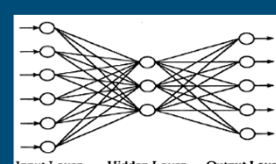
Forecasting systems – neural networks

- Artificial Neural Networks
  - Sophisticated pattern recognition systems that mathematically mimic the biological human learning process and are capable of learning the relationships between system inputs and responses.
- A typical artificial neural network consists of
  - a set of input variables
  - a "hidden layer"
  - a set of output variables
- A training data set is used to adjust the weights of the nodes of the hidden layer to optimize the accuracy of the output



Neural network

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Forecasting systems – neural networks

- Example: Regression and artificial neural network modeling to predict gray leaf spot of maize (Paul and Munkvold, 2005)

Regression was used to identify sets of most important input variables:

LON	longitude
GLSR	gray leaf spot resistance rating
SR	maize residue on soil surface
PD	planting date
CDT4	cumulative hours of daily temperature, period 4 (45-15 days before silking)
AVNT2	average night temperature, period 2 (15 before until 15 days after silking)
NRH904	cumulative hours of nightly RH >=90% period 4

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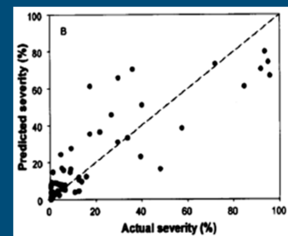
Forecasting systems – neural networks

- Example: Regression and artificial neural network modeling to predict gray leaf spot of maize (Paul and Munkvold, 2005)
- Evaluation with independent data set
- Model underestimated high levels of disease severity and overestimate low levels of disease severity. R^2=0.75



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