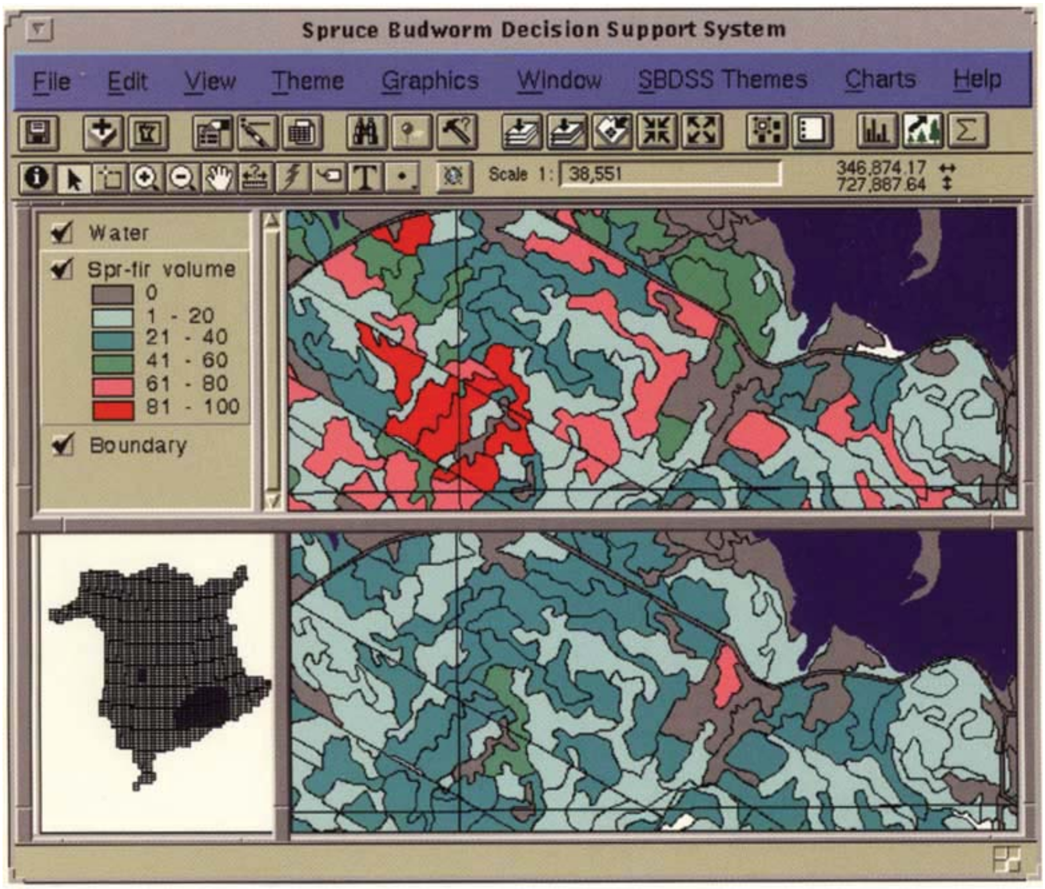
Decision Support Systems for Forest Pest Management

Proceedings of a Workshop at the Joint Meeting of the Entomological Societies of Canada and British Columbia, October 17, 1995, Victoria, BC, Canada



Edited by
Terry L. Shore
Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, Victoria, BC

David A. MacLean
Natural Resources Canada, Canadian Forest Service, Atlantic Forestry Centre, Fredericton, NB

November 1996
FRDA Report No. 260

CANADA-BRITISH COLUMBIA PARTNERSHIP AGREEMENT ON FOREST RESOURCE DEVELOPMENT FRDA II

Canada

BC

Decision Support Systems for Forest Pest Management

Proceedings of a Workshop at the Joint Meeting of the Entomological Societies of Canada and British Columbia, October 17, 1995, Victoria, BC, Canada

Edited by

Terry L. Shore
Natural Resources Canada, Canadian Forest Service,
Pacific Forestry Centre, Victoria, BC

David A. MacLean
Natural Resources Canada, Canadian Forest Service,
Atlantic Forestry Centre, Fredericton, NB

November 1996

FRDA Report No. 260

CANADA-BRITISH COLUMBIA PARTNERSHIP AGREEMENT ON FOREST RESOURCE DEVELOPMENT FRDA II

Canada

BC

Funding for this publication was provided by the Canada-British Columbia Partnership Agreement on Forest Resource Development: FRDA II - a five year (1991-96) $200 million program cost-shared equally by the federal and provincial governments.

Canadian Cataloguing in Publication Data

Main entry under title :

Decision support systems for forest pest management

(FRDA report, ISSN 0835-0752 ; no. 260)
"Proceedings of a workshop at the Joint Meeting of the Entomological Societies of Canada and British Columbia, October 17, 1995, Victoria, BC, Canada."
Issued under Canada-British Columbia Partnership Agreement on Forest Resource Development: FRDA II.
Co-published by the BC Ministry of Forests.
ISBN 0-662-25177-6
Cat. no. Fo29-19/260E

1. Forest insects — Control — Congresses. 2. Pests — Control — Congresses.
I. MacLean, David A. II. Shore, Terrence Leckie, 1951- . III. Pacific Forestry Centre.
IV. British Columbia. Ministry of Forests. V. Canada-British Columbia Partnership Agreement on Forest Resource Development: FRDA II.

SB950.A2D42 1996 634.9'695'028543 C96-980441-5

This is a joint publication of the Canadian Forest Service and the British Columbia Ministry of Forests.

For additional copies and/or further information about the Canada-British Columbia Partnership Agreement on Forest Resource Development: FRDA II, contact:

Canadian Forest Service
Pacific Forestry Centre
506 West Burnside Road
Victoria, BC V8Z 1M5
250-363-0600

or

B.C. Ministry of Forests
Research Branch
31 Bastion Square
Victoria, BC V8W 3E7
250-387-6721

Landscape-Wide Projection of Temperature-Driven Processes for Seasonal Pest Management Decision Support: A Generalized Approach

Jacques Régnière
Natural Resources Canada, Canadian Forest Service, PQ
Jesse A. Logan
U.S. Forest Service, Forest Sciences Laboratory, UT

Abstract

A new approach to the landscape-wide projection of temperature-driven simulation model outputs has been incorporated into a software package named BioSIM. The package is intended for two user groups: ecologists studying poikilothermic systems through the analysis of temperature-driven models; and governmental or industrial organizations responsible for optimizing the efficiency, efficacy, and innocuousness of pest management programs. Essentially it consists of a generalization of the t-function method of Schaub et al. (1995). In this paper, the approach used in BioSIM and the structure of the BioSIM software are briefly described. Current and potential applications in ecological research and pest management decision support are discussed.

Introduction

Insects, pathogens, and their host plants are affected by climate through most of the key biological processes, and population-level processes determine their abundance patterns in space and in time. The ability to understand, model, and predict the outcome of weather-dependent ecological processes is key to efficient and effective ecosystem management.

By far the most pervasive weather factor that influences natural ecosystems is temperature, because most of the organisms involved (plants, microbes, invertebrates and many vertebrates), are poikilotherms (or exothermic). Temperature can affect basic ecological processes directly through development (rates and pathways), mortality (prostration, desiccation, freezing), reproduction (ovogenesis, mating, oviposition, adult longevity), and migration (triggers, rates of departure and arrival). It can also have complex indirect effects through its influence on the synchrony between organisms (host plants, consumers, pathogens, natural enemies), on the activity (efficacy) of natural enemies as well as on the quality of host plants (palatability, nutritional value, defences).

Because of the importance of temperature as a driving variable in ecology and pest management, considerable effort has been devoted to the development and use of temperature-driven models to predict plant, pathogen, and insect seasonal biology (phenology and population dynamics). A wide diversity of modelling approaches has been used (Wagner et al. 1984a, l984b; Schaalge and van der Vaart 1988; Wagner et al. 1991) and model-development tools are available (Logan 1988, 1989; Dallwitz and Higgins 1992).

There have been several recent attempts to use these models to forecast seasonal biology of poikilothermic organisms over large heterogeneous areas (landscape level) (Gage et al. 1982; Ross et al. 1989; Pickering et al. 1990; Rock et al. 1993; Russo et al. 1993; Schaub et al. 1995). Much of this work has been concerned with wide-area pest management planning (efficient deployment of human and material resources for monitoring and control operations). Consideration of landscape-level processes in ecology is only beginning. These efforts have had to deal with two problems:

providing models with adequate input weather data, and projecting model predictions to the landscape level.

The first problem has two main components. First, there is usually a paucity of sources of weather data, and there are several causes of geographical variation in weather (particularly temperature). These include location (latitude and longitude), elevation, slope and aspect, cold-air drainage, and terrain shading (Rosenberg et al. 1983). Another source of variation is the proximity of a significant body of water, the maritime effect. Thus, methods to identify adequate data sources and to compensate for differences in geographical context must be developed. Second, methods must be available to forecast daily temperature fluctuations from normals.[1] This problem stems from the so-called Kaufmann effect (Worner 1992): insect responses to temperature are most often nonlinear, with discontinuities near the extremes (thresholds). This prevents the use of normals as input to seasonal biology models because normals are averages and do not represent the natural variability of actual weather. This problem has only recently been fully recognized, and few methods are available to restore daily variation around normals (Bruhn 1980; Régnière and Bolstad 1994).

This paper is a review of the methods that have been proposed to project the outcome of temperature-driven seasonal models to the landscape level. It is also a general discussion of BioSIM, a software tool (Régnière et al. 1995a) designed to facilitate the development of landscape-wide projections of seasonal model outputs for pest management and ecological research.

Review of Available Landscape Projection Methods

The first concerted effort to project seasonal model output to the landscape level was published by Russo et al. (1993). Their approach consisted in using multiple regression to relate daily minimum and maximum air temperature to the latitude, longitude, and elevation of all weather data sources in an area and generating a temperature regime for each grid cell on a digital elevation model (DEM) of the area (Figure 1).

The same approach was used whether real-time data or long-term averages (normals) were being used. The resulting temperature regimes were then used as input to their seasonal biology model. Thus one set of temperature data was generated and one model run was carried out for each cell of the DEM. The output produced was a map of the date at which 50% gypsy moth, *Lymantria dispar* (L.), egg hatch should have occurred (the "target event"). While this is clearly a feasible technique, it presents three main drawbacks. First, the computational cost can be prohibitive when a relatively complex simulation model is being used. For example, running the spruce budworm, *Choristoneura fumiferana* (Clem.), seasonal biology model (Régnière 1987; Régnière and You 1991) on a computer with a Pentium-133 processor requires about 3 seconds. To produce a modest 400 x 400 grid-cell map would require at least 133 hours! Second, this approach does not take into consideration sources of geographical variation in temperature other than latitude, longitude, and elevation. Finally, the Kaufmann effect is not considered when generating temperature regimes from normals to predict future events.

A second approach published by Schaub et al. (1995) consisted of four steps (Figure 2). First, the seasonal biology model was provided with temperature data from a single nearby source, the base station. The model was run for an array of elevations, compensating for differences between the simulation point and the source of weather data, with a constant elevational lapse rate (-0.5°C per 100 m). A linear regression model was used to relate the predicted target event (the date at which gypsy moth should reach 50% second instar) to elevation. That relationship was then applied to a DEM of the area of interest to generate a target-event map by simple algebraic transformation. Schaub et al. (1995) coined the term t-function to name the regression between the target event and elevation. This simple and efficient approach presents three main weaknesses. First, the criteria used to select an adequate base weather station are not clearly defined, and selection of a single source implies a loss of information associated with dropping the other potential sources of weather data from an area. Second, the only source of geographical variation in temperature considered is elevation, although the approach can be generalized. Finally, Schaub et al. (1995) did not address the Kaufmann effect.

A third approach was proposed by Régnière (1996). It borrows some concepts from Russo et al. (1993) and is a generalization of the t-function concept of Schaub et al. (1995) that allows the consideration of additional sources of geographical variation in temperature (Figure 3). It also deals explicitly with issues of weather-station selection and the Kaufmann effect. In this approach, simulations are run for a limited series of locations scattered throughout the area of interest. For example, simulation points can constitute a low-density rectangular grid, or can correspond to the location of weather stations in the area. At each location, elevation, slope and aspect are varied systematically. The number of simulations required is thus considerably reduced compared with the Russo et al. method. For example, simulations with the spruce budworm seasonal biology model for a rectangular grid of 25 points, with five

[1] Normals are statistics (averages, extremes) taken over long periods. The standard normal-generating period is 30 years, starting at the beginning of a decade. The most recent is 1961-1990.

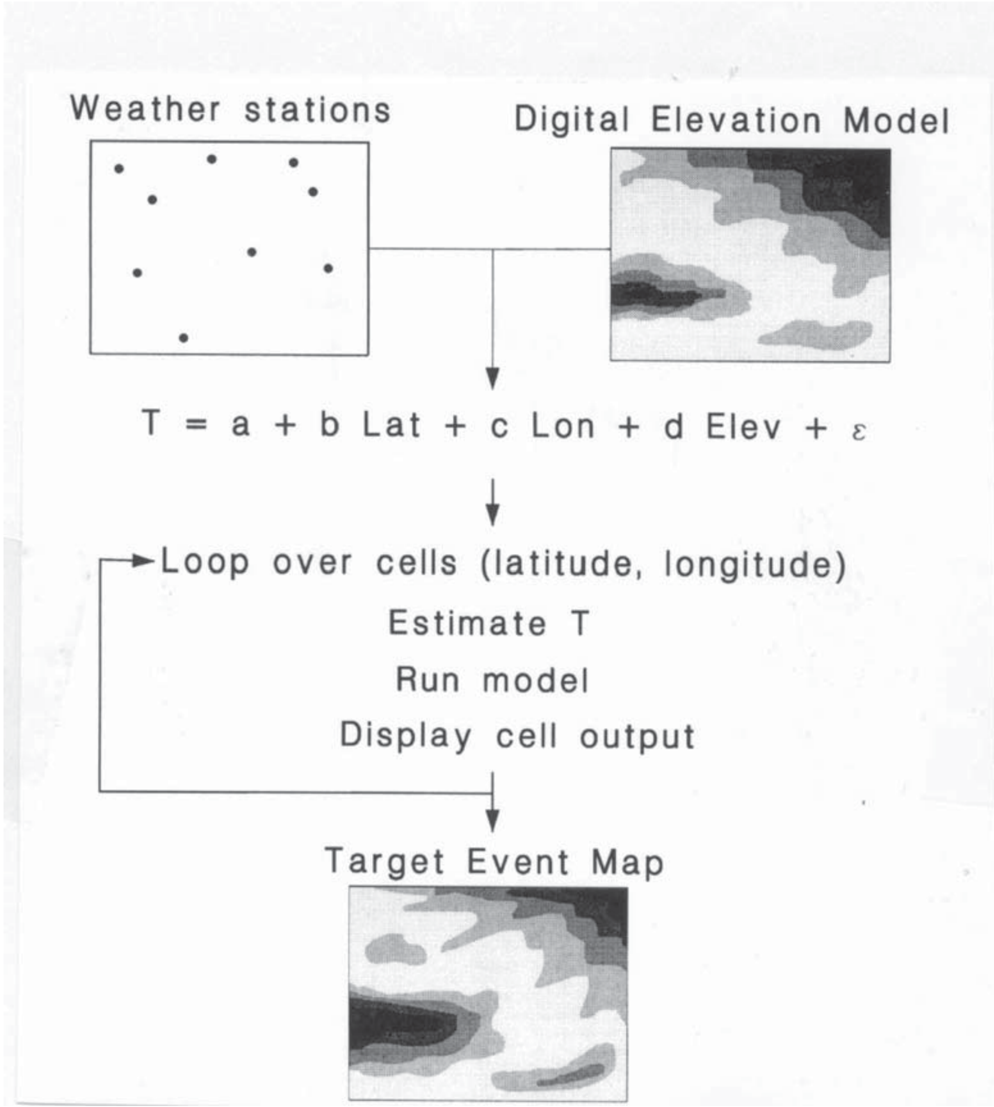


Figure 1. Diagram of the Russo et al. (1993) approach to landscape-wide simulation of temperature-driven processes. T: temperature; Lat: latitude; Lon: longitude; Elev: elevation; e: error.

elevations and seven combinations of slope and aspect, would require less than 45 min with a Pentium-133 processor.

Sources of weather data for each simulation are selected on the basis of three criteria: climatic zones partitioning the area according to broad climatic considerations such as the maritime effect, elevational difference between simulation location and weather data source, and Cartesian distance. Differences in latitude and elevation between source and simulation point are compensated for by variable elevational and latitudinal lapse rates (Régnière and Bolstad 1994). The influence of slope and aspect on air temperature is simulated from incident radiation calculations (Paltridge and Platt 1976; Hottel 1976; Bolstad et al. 1996; Régnière 1996). Temperature forecasts from normals are generated stochastically to restore natural daily variation (Régnière and Bolstad 1994) and thus accommodate the Kaufmann effect. Once the series of simulations has been run, a polynomial regression model is used to relate the "target event" to latitude, longitude, elevation, and slope and aspect. This multivariate "t-function" is then used to transform a DEM of the area into a target-event map. This approach is in no way limited to the issue of timing. However, for the sake of simplicity and to maintain terminology used by other authors, the term "target event" is intended here to represent any feature of simulation model output that is of interest.

Description of BioSIM

The generalized approach developed by Régnière (1996) offers considerable flexibility in the types of proc-

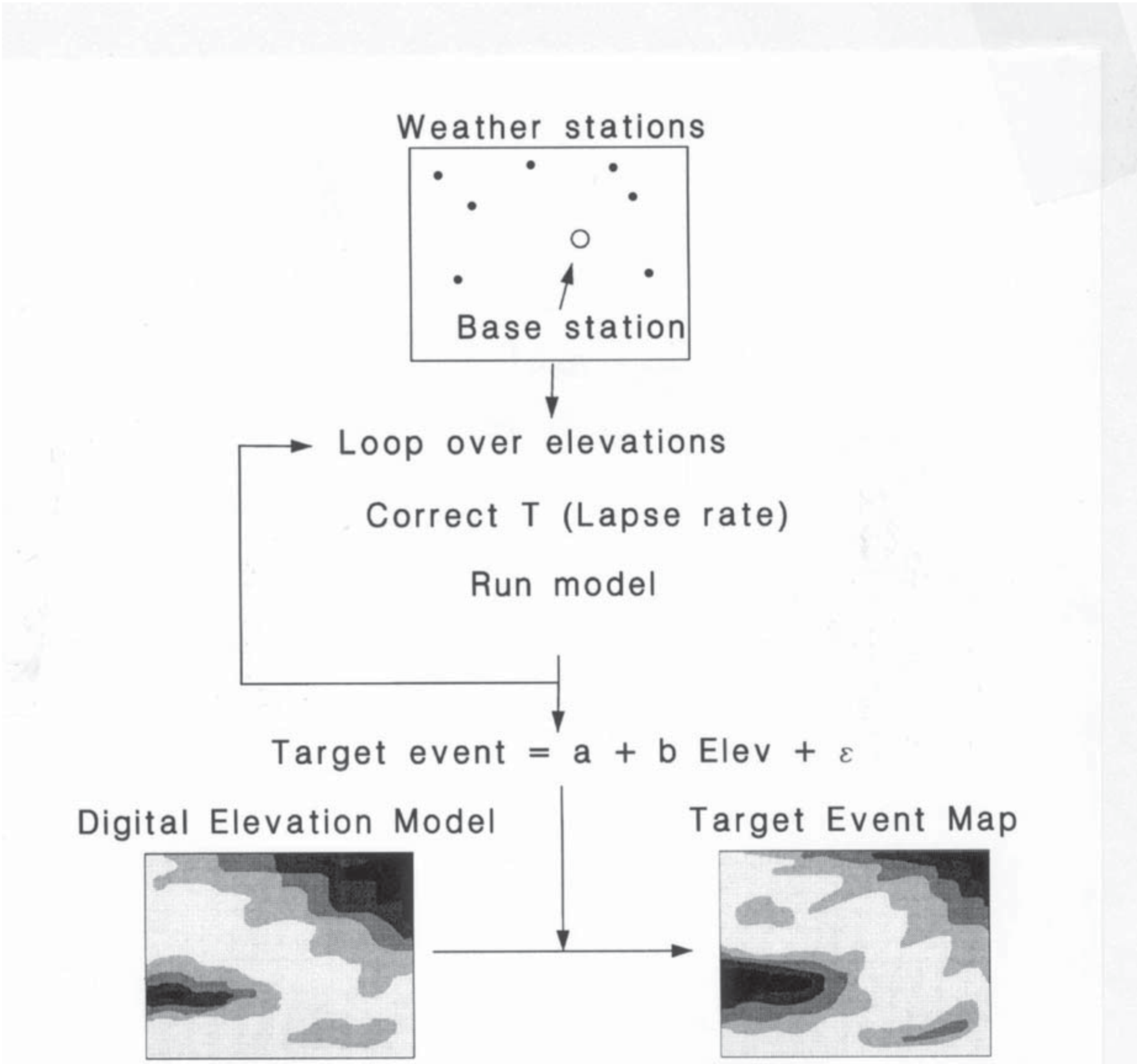


Figure 2. Diagram of the Schaub et al. (1995) approach to landscape-wide simulation of temperature-driven processes. T: temperature; Elev: elevation; e: error.

esses that can be investigated. Because of its large application potential in ecological research and pest management, this method has been implemented in a versatile and user-friendly computer software package called BioSIM (Régnière et al. 1995a). This package is intended for two user groups: ecologists studying poikilothermic systems through the analysis of temperature-driven models, and government or industry organizations responsible for optimizing the efficiency, efficacy, and innocuousness of pest management programs.

BioSIM consists of four modules, integrated through a graphical user interface (GUI). The first module is a database manager designed to develop and maintain weather databases, as well as the simulation models themselves. The second module controls the simulation models, allowing the user to run large numbers of simulations while systematically varying model parameters. The third module is a set of analytical tools used to generate graphs, compile summary tables, and fit regression equations (t-functions) to features extracted from model output. The fourth is an interface between analysis results and geographical information systems (GIS), for further integration into the decision-making process.

Module 1

This component of BioSIM helps the user to develop and maintain the system's weather databases, lists of simulation location coordinates, and models. BioSIM uses three weather databases:

1) Normals, that are long-term statistics about

Click here for next page

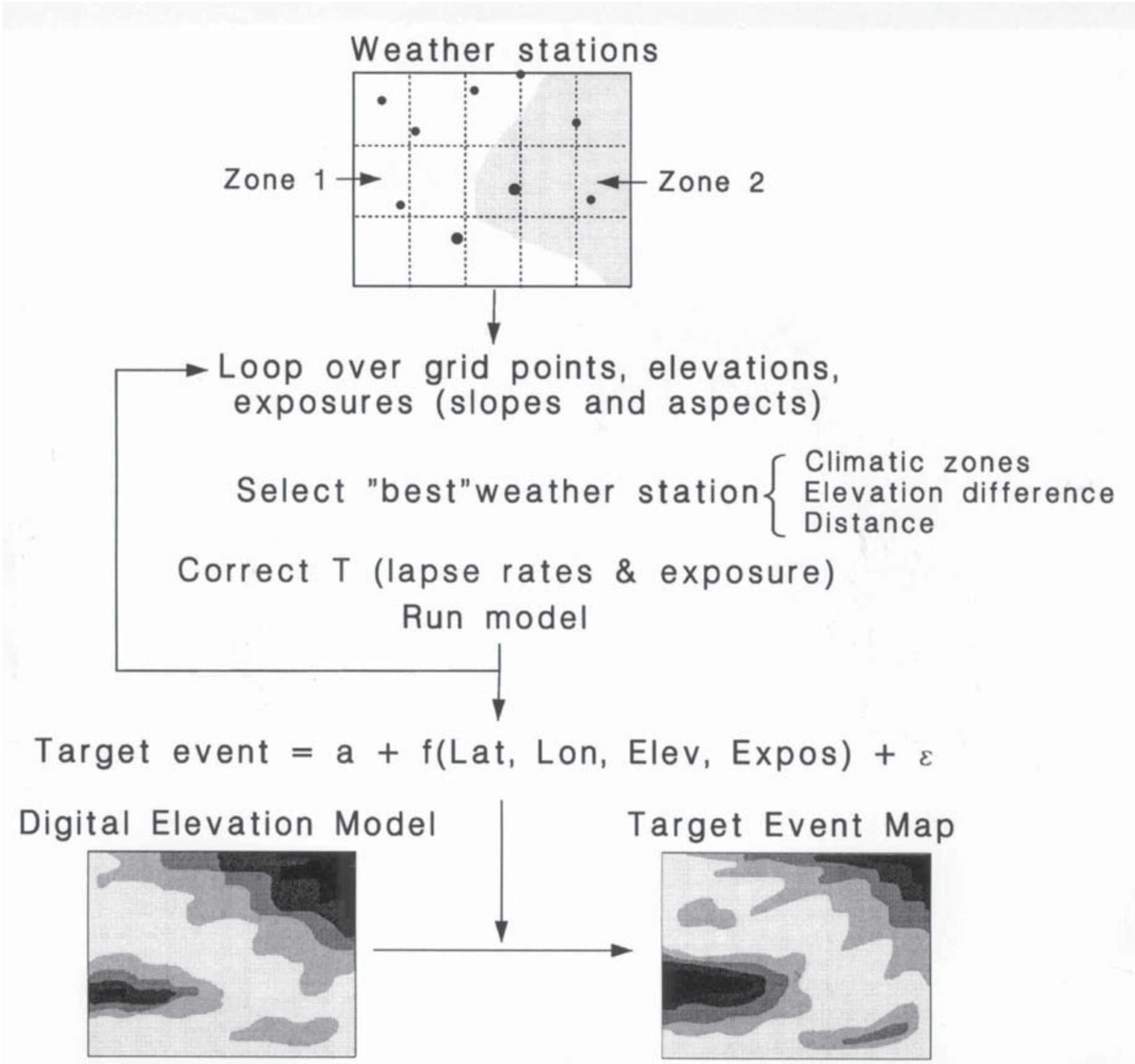


Figure 3. Diagram of the approach adopted in BioSIM to project temperature-driven model output features to the landscape level (adapted from Régnière 1996). T: temperature; Lat: latitude; Lon: longitude; Elev: elevation; Expos: exposure (a combination of slope and aspect); e: error.

monthly extreme and average minimum and maximum air temperatures.

2) Real-time data, including daily observations of minimum and maximum air temperatures.

3) 5-day min. and max. air temperature forecasts.

All data in these databases are geographically referenced by latitude, longitude, and elevation. Also part of BioSIM weather databases is a definition of regional climatic zones delineating the boundaries of areas dominated by drastically different weather influences, such as occur near significant bodies of water. As an example, the province of New Brunswick has been divided into three climatic zones: East-shore, Bay of Fundy, and inland zones (Régnière et al. 1995b) (Figure 4). In defining these zones, the maritime effect was presumed to disappear within 60 km of shore, or above 150 m elevation. Location lists include geographical coordinates for which simulations are to be conducted. They form the basis for control of large simulation tasks, as well as the generation of landscape-wide projections. In the latter case, location lists may constitute a rectangular matrix of points or may list all sources of real-time or normals weather data in an area.

The simulation models are independent executable modules. BioSIM can accommodate any number of simulation models, which can be added or deleted interactively. Each model in the model-base is interfaced with BioSIM through two accessory files that describe input parameters and output variables. BioSIM communicates with simula-

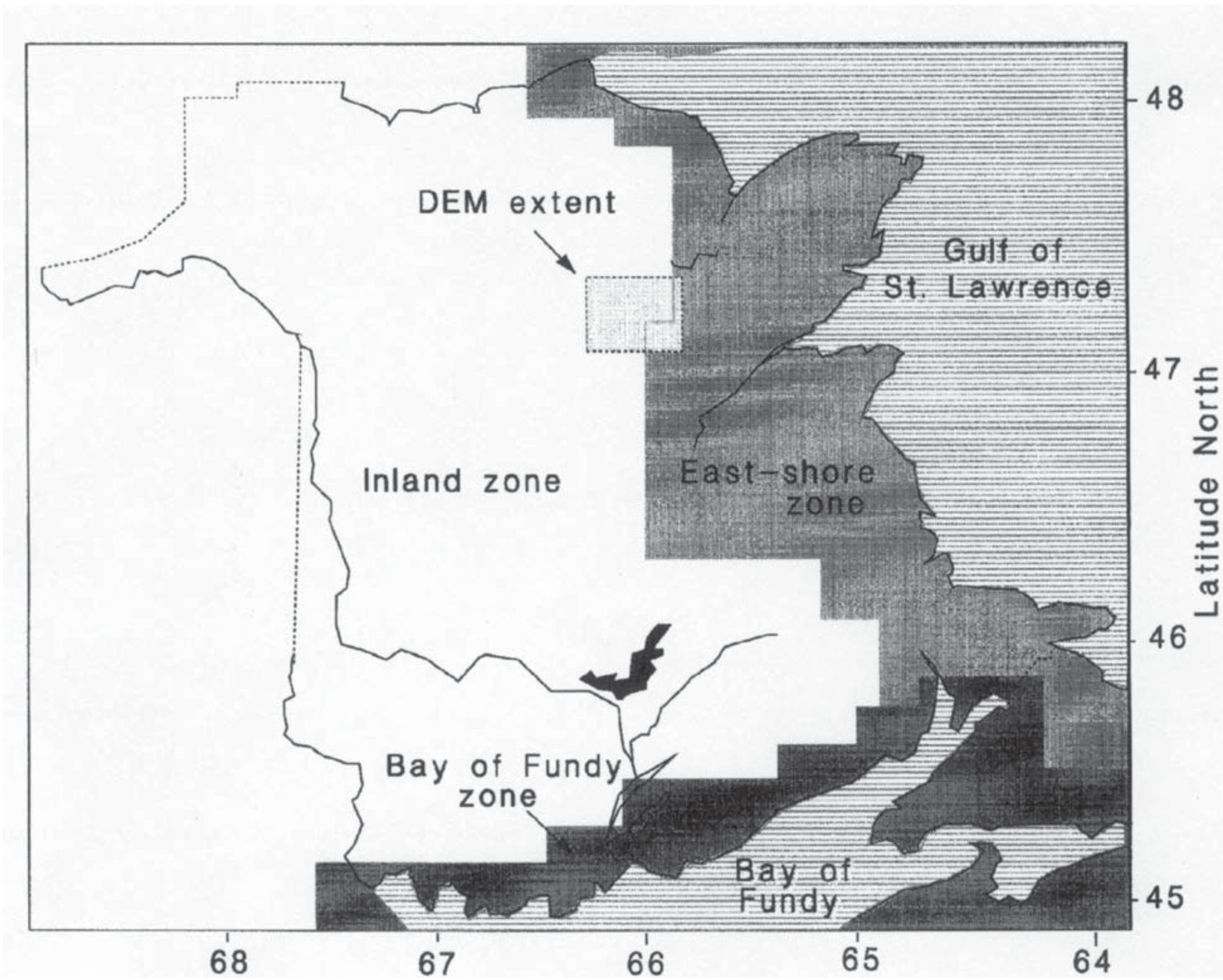


Figure 4. Map showing the three climatic zones defined in the New Brunswick Department of Natural Resources and Energy's implementation of BioSIM (after Régnière et al. 1995b). The area delimited by a dotted line in the north-central portion of the province is that used in the BioSIM application depicted in Figure 7.

tion models via an input-parameter file that a model reads at run time. There are three simple conditions for a simulation model to be compatible with BioSIM (see Régnière et al. 1995a for technical details). First, it must read input daily minimum and maximum air temperatures from a file format compatible with BioSIM. Second, the model must write output to an ASCII file, where columns contain output variables and rows represent time intervals. Third, it must accept the names of the input and output files by reading them from an input-parameter file, whose name is passed from BioSIM to the model as a command line argument. This input-parameter file may also contain any number of other model-specific parameters that the developer intends the user to control via BioSIM.

Module 2

In a single BioSIM session, users may want to run large numbers of simulations using different models, parameter settings, and locations. BioSIM's simulation control module provides considerable flexibility and batch job control.

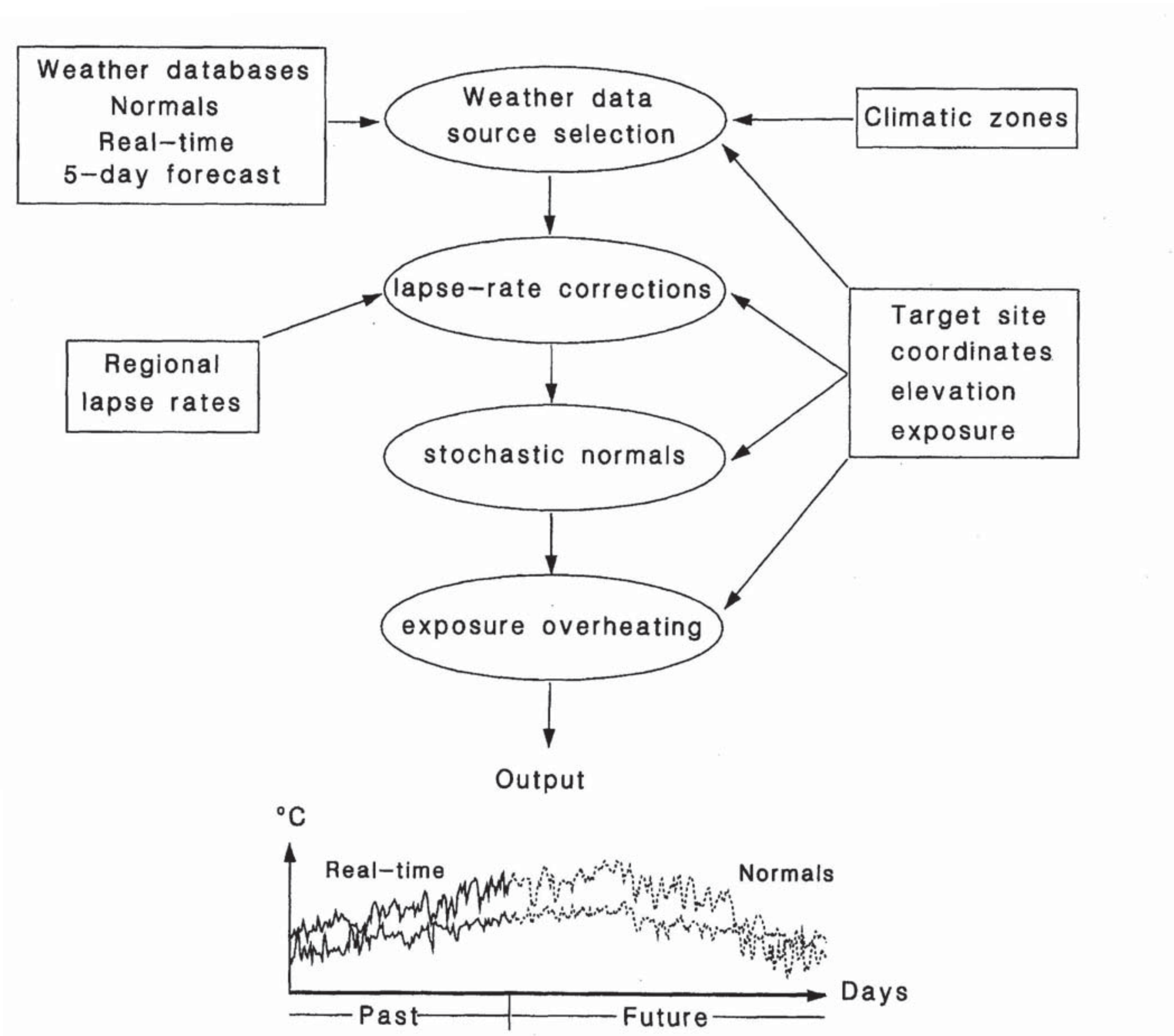


Figure 5. Diagram of BioSIM's temperature-regime assembly procedure.

Each simulation involves two steps: assembly of a temperature regme from the weather databases, and execution of the selected simulation model with the assembled temperature regime as input and using parameter values specified by the user or controlled by BioSIM. The GUI provides the user with access to the temperature-regime assembly parameters (e.g, location, elevation, slope and aspect, weather-station selection criteria) as well as the model's input parameters (file names under BioSIM control).

Temperature-regime assembly is a complex process that is hidden from the user, but that requires explanation. BioSIM's temperature-regime assembler generates a complete series of daily minimum and maximum or hourly air temperatures for a specified period of time and location (latitude, longitude and elevation). Three functions are performed during this task (Figure 5): matching geo-referenced sources of weather data in the three databases to the specified locations, adjusting selected weather data for latitude; elevation, and slope and aspect differences between the source and the specified location; and restoring random daily variation to temperatures estimated from as normals.

Real-time temperature data in BioSIM's databases are referenced by year. Thus, the system can run simulation models using either real-time weather data from past years for historical reconstruction, or current-year data for seasonal forecasting. It can also use normals exclusively, to simulate the "normal" course of events.

Geographical matching. In searching through each of the three weather databases, BioSIM defines the "best" source of data for a specified location as that station with the minimum Cartesian distance among the subset of stations in the same climatic zone, and within a specified range of elevations from that location. The restriction on the elevational range between weather station and specified location provides an opportunity to take elevation into consideration along with Cartesian distance in the station selection process. Whenever an appropriate source of weather data cannot be found using these criteria, the limiting criterion is dropped and the search is repeated.

Latitude, elevation, and exposure adjustments. Weather data obtained from the three databases are adjusted automatically for differences in elevation and latitude between the data source and the specified location, by the method of Régnière and Bolstad (1994):

$$T'n_t = \Delta n_l + \Delta n_e + Tn_t \quad (1)$$

and

$$T'x_t = \Delta x_l + \Delta x_e + Tx_t \quad (2)$$

where Tn and Tx are source minimum and maximum air temperatures on day t, and Δn_l Δx_l Δn_e and Δx_e are differences in minimum and maximum temperatures due to any differences in latitude *(l)* or elevation *(e)* between the specified location and the data source. Differences are calculated from latitudinal and elevational lapse rates, both of which vary with time of year. Because elevational lapse rates can vary considerably on a large geographical basis, BioSIM allows the user to specify regional lapse rates.

BioSIM combines slope and aspect into a single "exposure" term that takes into account the amount of solar radiation that a sloped surface receives, relative to a level surface, on average during the year. Exposure is expressed by BioSIM in degrees of northern exposure (algorithm of Bolstad et al. 1996, adapted by Régnière 1996). Direct and diffuse sunlight is integrated between 11:00 and 15:00, based on solar trajectory calculations and under the assumption of a clear, cloudless sky. Cloudiness is taken into account by reducing the radiation differential between sloped and level surfaces proportionally to the range in daily temperature. This is based on the observation that small ranges in temperatures are often associated with cloudy even rainy conditions. On a clear sunny day at latitudes around 40-45°N, the algorithm computes differentials of ±4°C between sloped surfaces and level ground (which is commensurate with observations in forest canopies). The most pronounced effect of exposure is found on steep north-northeast slopes, where temperatures can be as much as 6-8°C lower than level surfaces.

Use of normals. After selecting the best normals station, BioSIM generates a year's daily minima and maxima based on extreme monthly and mean monthly minimum and maximum air temperature taken from the normals database. Régnière and Bolstad (1994) showed that daily temperature fluctuations about the normals are very important in many seasonal processes, because of the nonlinear nature of developmental responses to temperature, i.e. the Kaufmann effect. Even degree-day summation is nonlinear around the threshold. BioSIM generates normally distributed and serially autocorrelated random deviations around normal minimum and maximum temperatures $(\delta_t, \varepsilon_t)$:

$$Tn_t = Mn_t + \delta_t \quad (3)$$

and

$$Tx_t = Mx_t + \varepsilon_t \quad (4)$$

where Mn_t and Mx_t are daily mean minimum and maximum normals. In addition, δ_t and ε_t are correlated with each other to simulate warm or cold days. The autocorrelation simulates the tendency to oscillate between cold and warm periods that is characteristic of the temperate zone. The degree of autocorrelation, as well as the variance of these deviations, varies systematically with latitude and time of year (Régnière and Bolstad 1994).

Module 3

BioSIM is interfaced with the general-purpose graphics package PLT, available for DOS and Unix platforms (Régnière 1989, 1990, 1992), for examination of model output. BioSIM also offers a sophisticated output-analysis tool that can extract various types of features from model output files, compile summary tables and estimate multivariate regression models relating parameter values controlled by BioSIM during simulation to the features of interest. Features that BioSIM can extract from output files include univariate statistics such as minimum or maximum values, the time at which these occur, the value of a variable at a particular time or, conversely, the time at which a specific value is reached. Relationships between output-variable features can also be established (e.g., the ratio of two maxima, the difference between two times).

As an example, a series of simulations with the spruce budworm seasonal biology model was run, varying the survival rate of sixth instar larvae between 0.05 (corresponding to a declining outbreak population) and 0.95 (far higher than the natural survival rate even during the outbreak development phase). The input temperature regimes were assembled from normals, with coordinates corresponding to the Acadia Forest Experiment Station in New Brunswick (45°59'N, 66°22'W, 61 m elevation). Because temperature regimes generated from normals by BioSIM are stochastic in nature, the series was replicated five times. From the output, BioSIM"s analysis module derived a predicted relationship between sixth instar survival (the parameter varied systematically by BioSIM during the simulation series) and end-of-season defoliation, specified as the maximum value of the output variable containing cumulative defoliation (Figure 6).

Module 4

The fourth module of BioSIM is used to algebraically transform a digital elevation model of an area into a map of a specific feature of model output. This transformation is based on a multivariate, polynomial relationship established by the model-output analysis tool (Module 3) between latitude, longitude, elevation, exposure, and the output feature defined by the user. For example, the spruce bud moth, *Zeiraphera canadensis* Mutuura and Freeman, phenology model of Régnière and Turgeon (1989) was run for a series of nine locations (in a 3 by 3 grid) over an area of northern New Brunswick between 47°00'N by 65°00'W and 48°00'N by 65°00'W. For each location on this grid, elevation was varied from 100 to 600 m, and exposure from -45 to +45° north. Real-time weather data from that area in 1993 were used as model input. The output of this simulation series was then submitted to multivariate regression analysis to express the relationship between geographical coordinates *(Lat, Lon),* elevation *(Ele),* exposure *(Exp),* and the date at which the frequency of third instar larvae in the simulated populations reached its maximum value *(Y:* date of peak third instar). The regression model used was:

$$Y = a + b_1 Lat + b_2 Lon + b_3 Ele + c_3 Ele^2 + b_4 \mathrm{Exp} + c_4 \mathrm{Exp}^2 \quad (5)$$

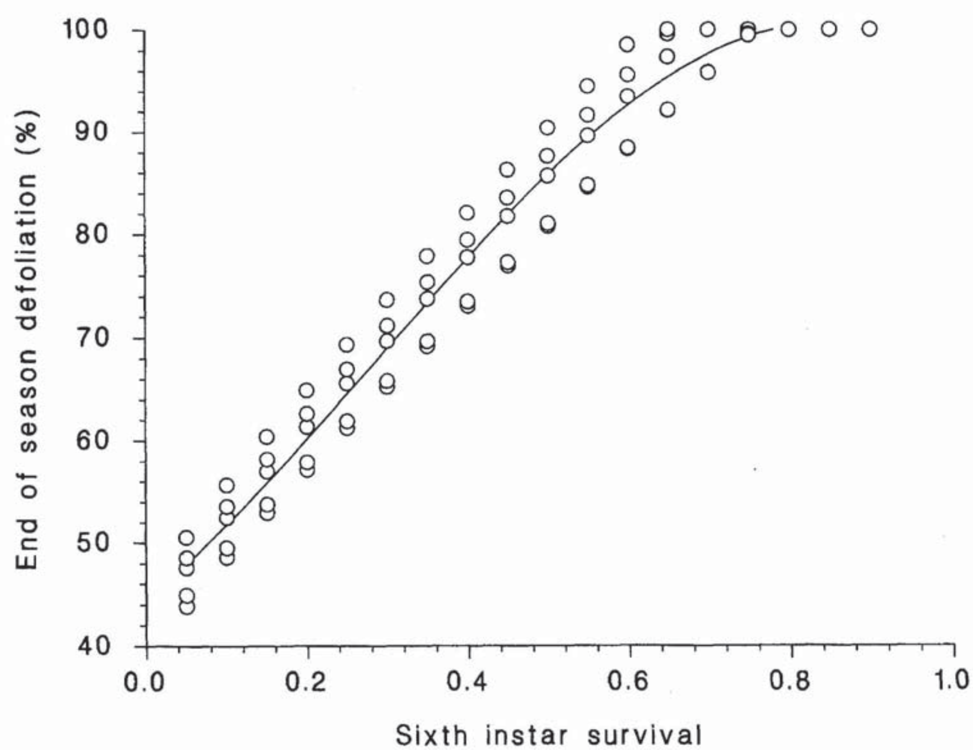


Figure 6. Relationship between simulated end-of-season defoliation and stage-specific survival during the sixth instar of the spruce budworm. Variation between simulations comes from stochastic air temperature data generated from normals for the Acadia Forest Experiment Station, New Brunswick.

The statistical results from this analysis are listed in Table 1. Elevation (both terms combined) explained 51% of the variation in predicted date of peak third instar, and was by far the most important factor. Next came exposure, with 21.5% of variation. Latitude accounted for 8.4%, and longitude for only 2.7%. The overall coefficient of determination was 83.6%. Thus, the regression model provided a sufficiently accurate description of model output to proceed with map transformation (Figure 7). It is interesting to note the pronounced effect of exposure of predicted phenology, particularly along the steeper banks of rivers.

BioSIM uses the standard USGS Digital Elevation Model format (U.S. Geological Survey 1990) in input DEM as well as output TEM (target-event maps). This ensures compatibility of the system with most commercial or public-domain geographical information systems. Maps (either DEM or their transforms) can be displayed and printed by BioSIM, which provides extensive flexibility of scales and colour maps. However, the most important use of output TEMs involves their integration with other GIS databases. This can be done, for example, with ARC/INFO command scripts (Geodat Inc. 1995).

Conclusions

BioSIM is a very powerful tool for the study of temperature-driven seasonal models in ecology (e.g., Thireau and Régnière1995; Cooke 1995). It can also be very useful in planning pest management activities (Régnière et al. 1995b). Its implementation requires an initial investment in the development and maintenance of temperature databases; modification of existing models to conform to system requirements, or development of new models when none exist for the organisms of interest; and acquisition of digital elevation models. Yet the benefits of using this system can vastly outweigh implementation costs.

BioSIM is currently being used in Quebec by the Department of Natural Resources and the Société de Protection de Forêts contre les Insectes et Maladies (SOPFIM) to assist in monitoring of spruce budworm, spruce bud moth, jack pine budworm *(Choristoneurapinus* Freeman) and the yellowheaded spruce sawfly *[Pikonema alaskensis* (Rohwer)]. It has been implemented in pest management activities against spruce budworm in New Brunswick (Régnière et al. 1995b) and the New Brunswick Department of Natural Resources and Energy has developed ARC/INFO procedures to integrate landscape-wide projections produced by BioSIM with their other geo-referenced forestry databases (Geodat Inc. 1995). BioSIM has also been used to investigate the developmental potential of gypsy moth in Florida (Allen et al. 1993) and British Columbia (unpublished), and plans are in place to establish BioSIM as a timing tool in the "slow the spread" gypsy moth control program in the southeastern USA. Negotiations are in progress concerning the use of BioSIM for planning purposes in agricultural pest management in South Korea.

Currently, models that have been linked to BioSIM include a general-purpose degree-day model that can accommodate multiple sequential thresholds, and specific models for the spruce budworm, spruce bud moth, gypsy moth, hemlock looper *[Lambdinafiscellaria fiscellaria* (Guénee)], mountain pine beetle *(Dendrochtonus ponderosae* Hopkins), yellowheaded sawfly, fall armyworm *(Mythimna anipuncta* Haw.), the spruce budworm parasitoid *Meteorus trachynotus,* as well as a model of the interactions between *Bacillus thuringiensis,* spruce budworm, and its parasitoid *Apanteles fumiferanae.*

BioSIM is also being used to investigate the impact of climate change on the seasonality and population dynamics of the mountain pine beetle (Logan et al. 1995). These researchers are using BioSIM to determine the probable shift in vertical distribution of mountain pine beetle in the mountains of the western U.S. as temperatures warm up, and the implications of such a shift for white fir, *Pinus albicaulis* Engelm., a tree species that has not been exposed to beetle damage.

Table 1. Regression analysis of the influence of latitude, longitude, elevation, and exposure on the predicted date of peak third instar spruce budmoth, *Zeiraphera canadensis,* in northern New Brunswick (based on 1993 air temperature data).

Term	Sequential SS	Partial R^2	P	Value	St. Dev.
Intercept	—	—	0.021	92.47	39.97
Latitude	2934.9	0.084	0.000	6.825	0.494
Longitude	948.9	0.027	0.000	-3.881	0.494
Elevation	16860.8	0.485	0.578	-0.0032	0.0058
$Elevation^2$	859.7	0.025	0.000	0.000060	0.000008
Exposure	6225.3	0.179	0.000	0.135	0.0067
$Exposure^2$	1265.6	0.036	0.000	0.00235	0.00026
Total	34796.4	0.836	—	—	—

References

Allen, J.C., J.L. Foltz, WN. Dixon, A.M. Liebhold, J.J.Colbert, J. Régnière, D.R. Gray, J.W. Wilder, and I. Christie. 1993. Will the gypsy moth become a pest in Florida? Fla. Entomol. 76: 102-113.

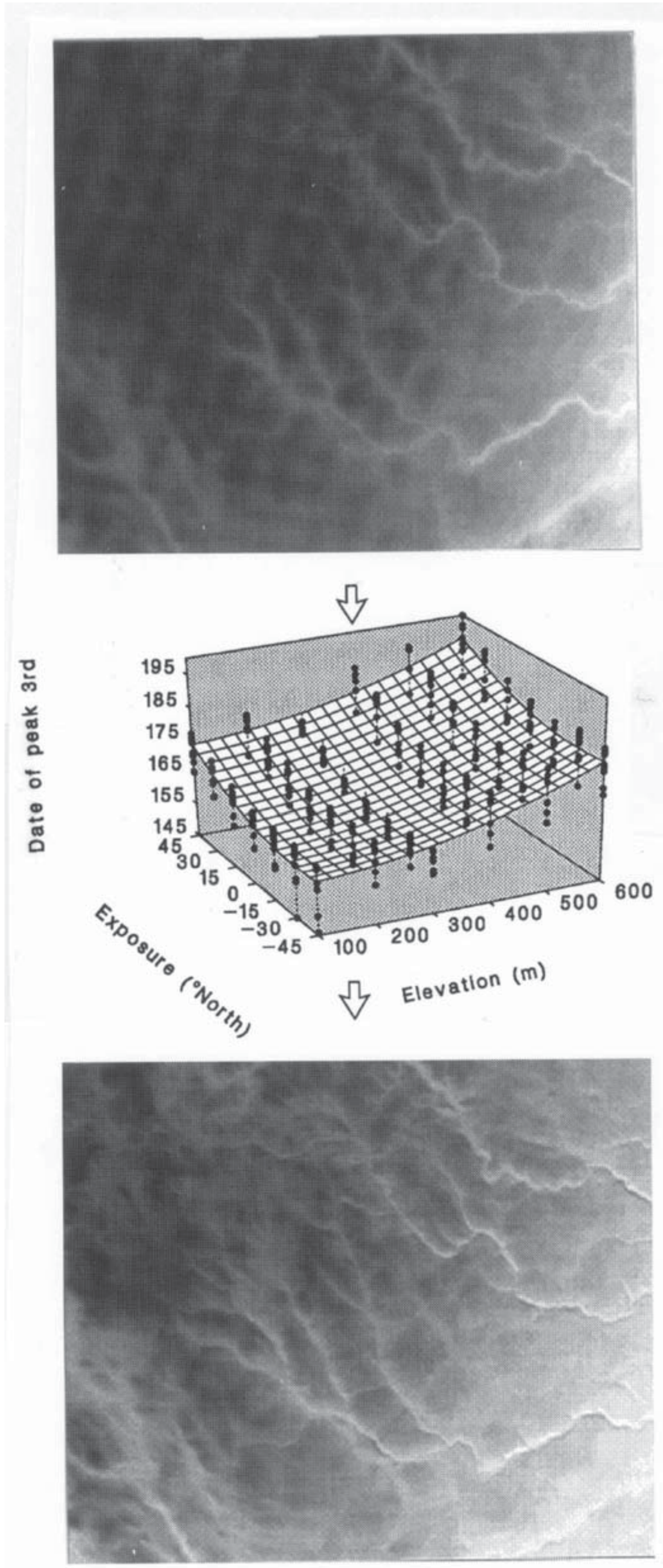


Figure 7. Illustration of the map transformation process, computing a target-event map (bottom) from a digital elevation model (top), using a multivariate regression model. The event depicted: date of peak third instar *Zeiraphera canadensis,* as a function of latitude, longitude, elevation and exposure.

Bolstad, P.V., B.J. Bentz and J.A. Logan. 1996. Modelling microhabitat temperature for Dendrochtonus ponderosae (Coleoptera: Scolytidae). Ecol. Model. (in press).

Bruhn, J.A. 1980. A stochastic model for the simulation of daily weather. Prot. Ecol. 2: 100-208.

Cooke, B.J. 1995. An Object-Oriented, Process-Based Stochastic Simulation Model of B.t. (Bacillus thuringiensis Berliner var. Kurstaki) Efficacy Against Populations of Spruce Budworm, Choristoneura fumiferana Clem. (Lepiptera: Tortricidae), Parasitized by Apanteles fumiferana Viereck (Hymenoptera: Braconidae). M.Sc. Thesis. Dept. Forestry, Université Laval. Quebec, Canada. 178 p.

Dallwitz, M.J. and J.P. Higgins. 1992. User's Guide to DEVAR: A Computer Program for Estimating Development Rate as a Function of Temperature. 2nd ed. Rep. Div. Entomol. CSIRO, Australia, No. 2. 23 p.

Gage, S.H., M.E. Whalon, and D.J. Miller. 1982. Pest event scheduling system for biological monitoring and pest management. Environ. Entomol. 11:1127-1133.

Geodat Inc. 1995. Investigation of feasibility and development procedures for (1) the conversion of NBGIC digital elevation data for BioSIM software applications; (2) the integration of BioSIM modelling results with DNRE's Arc/Info GIS system. Contract between Forest Protection Ltd. and Geodat. Summary Report, Sept. 29, 1995.

Hottel, H. 1976. A simple model for estimating the transmittance of direct solar radiation through clear atmospheres. Sol. Energy 18: 129-134.

Logan, J.A. 1988. Toward an expert system for development of pest simulation models. Environ. Entomol. 17: 359-376.

Logan, J.A. 1989. Toward an expert system for pest simulation models: lessons learned from application. British Crop Protection Council Monographs 43: 233-243.

Logan, J.A., P.V Bolstad, B.J. Bentz, and D.L. Perkins. 1995. Assessing the effects of changing climate on mountain pine beetle dynamics. Pp. 92-105 in: Proceedings of the Interior West Global Climate Workshop. Edited by R.W. Tinus. USDA, Forest Service. Gen. Tech. Rep. RM-262.

Paltridge, G.W. and C.M.R. Platt. 1976. Radiative Processes in Meteorology and Climatology. Elsevier Scientific Publishing. New York. 318 p.

Pickering, J., W.W. Hargrove, J.D. Dutcher, and H.C. Ellis. 1990. RAIN: a novel approach to computer-aided decision making in agriculture and forestry. Comput. Electron. Agric. 4: 275-282.

Régnière, J. 1987. Temperature-dependent development of eggs and larvae of Choristoneura fumiferana (Clem.) (Lepidoptera: Tortricidae) and simulation of its seasonal biology. Can. Entomol. 119: 717-728

Régnière, J. 1989. PLT: An Interactive Graphics Package for VAX/VMS. For. Can. Info. Rep. LAU-X-88E. 55 p.

Régnière, J. 1990. PLT/2.0: Release Notes. For. Can. Info. Rep. LAU-X-88E 1st Supplement. 15 p.

Régnière, J. 1992. PLT/3D: Three-Dimensional Graphics on VAX-VMS and PC. For. Can. Info. Rep. LAU-X-88E (2nd supplement). 20 p.

Régnière, J. 1996. A generalized approach to landscape-wide seasonal forecasting with temperature-driven simulation models. Environ. Entomol. (submitted).

Régnière, J. and P. Bolstad. 1994. Statistical simulation of daily air temperature patterns in eastern North America to forecast seasonal events in insect pest management. Environ. Entomol. 23: 1368-1380.

Régnière, J. and J.J. Turgeon. 1989. Temperature-dependent development of Zeiraphera canadensis and simulation of its phenology. Ent. Exp. Appl. 50: 185-193.

Régnière, J. and M. You. 1991. A simulation model of spruce budworm (Lepidoptera: Tortricidae) feeding on balsam fir and white spruce. Ecol. Modelling 54: 277-297.

Régnière, J., B. Cooke, and V. Bergeron 1995a. BioSIM: A Computer-Based Decision Support Tool for Seasonal Planning of Pest Management Activities. User's Manual. Can. For. Serv. Info. Rep. LAU-X-116. 50 p.

Régnière, J., D. Lavigne, R. Dichison, and A. Staples. 1995b. Performance Analysis of BioSIM, a Seasonal Pest Management Planning Tool, in New Brunswick in 1992 and 1993. Nat. Resour. Can., Can. For. Serv. Info. Rep. LAU-X-115. 28 p.

Rock, G.C., R.E. Stinner, J.E. Bachelor, L.A. Hull, and H.W. Hogmire Jr. 1993. Predicting geographical and within season variation in male flights of four fruit pests. Environ. Entomol. 22: 716-725.

Rosenberg, N.J., B.L. Blad, and S.B. Verma. 1983. Microclimate, the Biological Environment. 2nd ed. John Wiley and Sons. New York. 495 p.

Ross, D.W, J. Pickering, J.D. Berg, and C.W. Berisford. 1989. Mapping Nantucket pine tip moth (Lepidoptera: Tortricidae) phenology in Georgia. Linnean Entomol. Sci. 24: 405-415.

Russo, J.M., A.M. Liebhold, and J.G.W. Kelley. 1993. Mesoscale weather data as input to a gypsy moth (Lepidoptera: Lymantriidae) phenology model. J. Econ. Entomol. 86: 838-844.

Schaalge, G.B. and H.R. van der Vaart 1988. Relationships among recent models for insect population dynamics with variable rates of development. Pp. 299-312 in: Estimation and Analysis of Insect Populations. Edited by L. McDonald, B. Manly, J. Lockwood, and J. Logan. Lecture Notes in Statistics 55. Springer-Verlag.

Schaub, L.P., F.W. Ravlin, D.R. Gray, and J.A. Logan. 1995. Landscape framework to predict phenological events for gypsy moth (Lepidoptera: Lymantriidae) management programs. Environ. Entomol. 24: 10-18.

Thireau, J.-C. and J. Régnière. 1995. Development, reproduction, voltinism and host synchrony of Meteorus trachynotus with its hosts Choristoneura fumiferana and C. rosaceana. Entomol. Exp. Appl. 76: 67-82.

U.S. Geological Survey. 1990. US GeoData Digital Elevation Models: Data Users Guide. National Mapping Program Technical Instructions. Data Users Guide 5. 51 p.

Wagner, T.L., H.I. Wu, P.J.H. Sharpe, and R.N. Coulson. 1984a. Modeling distributions of insect development time: a literature review and application of the Weibull function. Ann. Entomol. Soc. Am. 77: 475-483.

Wagner, T.L., H.I. Wu, P.J.H. Sharpe, R.M. Schoolfield, and R.N. Coulson. 1984b. Modeling insect development rates: a literature review and application of a biophysical model. Ann. Entomol. Soc. Am. 77: 208-220.

Wagner, T.L. R.L. Olson, and J.L. Willer. 1991. Modeling arthropod development time. J. Agric. Entomol. 8: 251-270.

Worner, S.P. 1992. Performance of phenological models under variable temperature regimes: consequences of the Kaufmann or rate summation effect. Environ. Entomol. 21: 689-699.