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Topoclimatic Habitat Models

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Abstract

Topoclimatic models use topographic descriptors (elevation, slope, aspect, landscape position...) as primary input to build climatic surfaces that describe spatial and temporal patterns of such physical factors as temperature, incoming solar radiation (insolation), precipitation, soil moisture, and evapotranspiration. Topoclimatic habitat models translate these physical factors into indices of habitat suitability for a particular species or biotic community. Applications range from explaining observed vegetation patterns to predicting changes in biotic distributions under climate change scenarios. Important issues when developing topoclimatic models include data quality and availability, non-independence of input data, and difficulties of model validation. Use of topoclimatic models to predict potential habitat requires knowledge of biology. Potential habitat dynamically changes over time and actual biotic distributions depend upon factors such as dispersal, history, biotic interactions, and time lags. Empirical approaches to topoclimatic modeling establish significant relations between input parameters and predicted climatic factors, but need not require understanding of mechanisms and system complexity. By contrast, mechanistic approaches are based upon physical principles, and can be applied in cases where few empirical measurements are available. We demonstrate how a combination of empirical and mechanistic submodels can be used to predict spatial and temporal patterns of air and soil temperature at a landscape scale. In topoclimatic studies conducted in the vicinity of Rocky Mountain Biological Laboratory (RMBL), Colorado, we utilized a USGS digital elevation model (DEM) and measurements from four weather stations as input. Air and soil temperature regimes were best explained by a modified lapse rate model, which accounted for deviation from a simple lapse rate based on local heating in proportion to insolation. We calculated insolation maps during the growing season using a mechanistic geometric model (TopoView/Solar Analyst). Vegetation patterns predicted using our topoclimatic model (TopoClimate) were more accurate than patterns predicted based merely on slope, aspect, and elevation.

Keywords

Ecological modeling, habitat modeling, microclimate modeling, topoclimatic modeling.

Introduction

Topoclimate refers to microclimate as it varies according to topographic position in the landscape (Thornwaite 1953, Weiss *et al.* 1988, Brown 1991). Topographic factors such as elevation, slope and aspect, and landscape position influence interrelated microclimatic factors such as incoming solar radiation (insolation), soil temperature, air temperature, wind, precipitation, evapotranspiration, water flow (accumulation and run off), snow accumulation, and snow melt (Wooster 1989, Coughlan and Running 1997). Fine scale variation in topography can cause dramatic variation in microclimate (Geiger 1965). In turn, distributions of all terrestrial organisms ultimately depend on distributions of microclimate that define favorable habitat for survival, growth, and reproduction (Daubenmire 1956, Davis and Dozier 1990, Saving *et al.* 1993, Brown 1994, Rich 2000). Comprehensive theoretical and field studies of microclimate are becoming increasingly important for building spatially explicit landscape models used by biologists, meteorologists, and resource managers (Stoutjesdijk and Barkman 1992, Brown 1994, Running *et al.* 1987, Turner 1989). The challenge for developing microclimate models lies in abstraction of complex processes to minimize input requirements, while producing results with sufficient accuracy. Topoclimatic modeling has the advantage that it can produce relatively accurate estimates of temporal and spatial patterns of microclimate, while using readily available topographic data for input.

In this study first we provide an overview of approaches to topoclimatic habitat modeling. Then we illustrate important principles and highlight future directions based on our experience with topoclimatic modeling in the Rocky Mountains. More specifically, this study has three main objectives:

- **to provide a synthetic view of approaches and issues** involved in topoclimatic habitat modeling;
- **to examine how a combination of empirical and mechanistic approaches are used** in TopoClimate, a new topoclimatic model that incorporates a mechanistic insolation submodel with existing modeling approaches;
- **to highlight important lessons and future directions** that will help us to build increasingly powerful and useful topoclimatic models.

Major approaches to topoclimatic modeling

Two main types of approaches are applied in topoclimatic modeling:

- **Empirical approaches** use observations to build and test relations between input parameters and climatic factors, typically using correlations. Such approaches are indirect, in that they require no knowledge of mechanism, just the ability to make accurate estimates. For example, an empirical temperature model can be derived and tested based solely on correlations between data from temperature sensors and elevation.

- **Mechanistic approaches** derive climatic factors based on physical principles. For example, a mechanistic temperature model may be based on well-understood adiabatic lapse rates that describe how air pressure changes with elevation.

In practice, a combination of empirical and mechanistic approaches can serve to produce the best results. Empirical approaches have the advantage that the complexity of systems need not be understood. Rather, statistically significant relations are established between input parameters and predicted climatic factors. Because empirical data are typically sparse and unevenly distributed, empirical models are often not representative of the landscape. For example, weather stations are biased to distributions in more heavily populated areas at low and mid elevations, and are generally lacking in remote upper elevation areas. Mechanistic approaches facilitate our ability to understand how to relate one or more input parameters in non-linear relations to produce strong relations. For example, elevation, slope, and aspect correlate moderately well with insolation, but a more complete insolation model depends upon understanding combined effects of surface orientation, elevation, and sky obstruction by surrounding topography as they relate to shifting solar angles through the day and season (Dubayah and Rich 1995, Rich *et al.* 1995, Fu and Rich 1999a, Fu 2000, Fu *et al.* 2000, Rich and Fu 2000). Because mechanistic models are based on physical relations, they can be applied to portions of the landscape that are underrepresented by observational data. A combination of empirical and mechanistic approaches can permit efficient use of topographic analysis to generalize limited observational data.

Important issues for topoclimatic modeling

A variety of issues must be considered when developing topoclimatic models:

- **Digital Elevation Model (DEM) quality** can constrain the accuracy of climatic prediction and limit the scale at which models can be applied. DEM quality is limited by a combination of error propagation when the DEM is created, issues of scale inherent in raster representation of continuous surfaces, and methods used for interpolation and calculation of slope and aspect. Most DEMs are available at relatively coarser scales (e.g., 30 m cells), and variation at finer spatial scales can be important for microclimate at particular locations. In general, DEMs can give adequate representation of the major landscape patterns of variation, but not necessarily the details of particular locations.

- **Limits of available field data** may make either empirical or mechanistic modeling more practical, depending upon the circumstance. Empirical modeling is most effective when measurements of microclimate factors are available for a full range of topographic positions. Mechanistic modeling is most effective when measurements of key input parameters are available and either do not vary spatially or vary in predictable ways.

- **Non-independence of input data** can limit the ability to evaluate the importance of different climatic factors. Using the same input parameters does not necessarily lead to problems, because derived factors can still be independent. For example, elevation, slope, and aspect can all be derived from the same DEM, but can generally be treated as independent. On the other hand, non-independence between input parameters and predicted climatic factors can lead to problems with statistical analyses that require independence.

- **Local variation may sometimes dominate** such that the overall patterns predicted from topoclimatic models do not apply. A particular location may have unique geologic, soil, hydrologic, or vegetation characteristics that override the prevailing microclimate.

- **Alternative mechanistic models may give the same results for nonmechanistic reasons.** Practically, we may achieve reasonable results, but may attribute cause to the wrong mechanism. For example, we might predict low snow accumulation along ridges due to snow melt from higher insolation, when the actual mechanism is redistribution by wind. Many physical gradients (temperature, precipitation, air pressure, relative humidity, insolation…) covary with elevation, slope, or aspect. In practice, it is difficult to distinguish whether a single factor may be most important, or a combination of factors may contribute to an observed pattern.

- **Available models are typically not fully validated**, often because rigorous validation is not practical.

Considerations for habitat modeling

Using topoclimatic models to predict habitat requires an additional set of considerations:

- **Habitat suitability is specific to the organisms being studied** and requires an understanding of the biology of the organisms.

- **Habitat models only predict potential biotic distributions**, while actual distributions may depend upon limits to dispersal, history, biotic interactions, and time lags.

- **Potential habitat is not static**, but rather is dynamically changing over both short and long time scales.

A Case Study in the Rocky Mountains

Topoclimatic Studies at Rocky Mountain Biological Laboratory

We conducted studies of topoclimate as it relates to habitat in the vicinity of the Rocky Mountain

Biological Laboratory (RMBL), Gunnison County, CO. The overall goal is to predict spatial and temporal patterns of major microclimate factors as they relate to vegetation distribution and biological implications of different climate change scenarios. We have been developing comprehensive topoclimatic modeling capabilities, in a model we call TopoClimate, which thus far has been applied to predict insolation, air and soil temperature, and soil moisture. Much of the work to date has focused on development of an insolation submodel (TopoView/Solar Analyst) and investigation of the importance of insolation in determing microclimate. Digital maps of the study area (encompassing about 200 km2) are available in USDA Forest Service GIS that includes DEMs and landcover maps. The area has high topographic heterogeneity (~2500 to 4300 m elevation), encompasses a broad diversity of microclimates, and has a correspondingly diverse patterning of vegetation (Langenheim 1962). Four weather stations within the study area provide detailed meteorological data for model formulation and validation. Herein, we present major findings of our insolation and temperature studies.

Insolation patterns

We calculated maps of insolation during the growing season for the RMBL study site using a DEM-based geometric insolation model, implemented as two GIS tools: TopoView (a standalone software program) and the Solar Analyst (an ArcView GIS extension) (Fu and Rich 1999b, 2000, Fu 2000). These tools use an upward-looking hemispherical viewshed algorithm to account for the effects of elevation, surface orientation as it relates to sun-earth geometry, sky obstruction by surrounding topographic features, and atmospheric conditions on direct and diffuse components of radiation (Rich 1990, Rich *et al.* 1994). Viewsheds of sky obstruction are constructed by tracing horizon angles along a specified number of directions for each location in a DEM. Direct radiation is calculated by constructing sunmaps based on a simple transmission model and overlaying the viewsheds on these sunmaps. Diffuse radiation is calculated by constructing skymaps based on simple diffuse models (uniform and standard overcast sky) and overlaying the viewsheds on these skymaps. Major findings include the following:

- **Temporal and spatial patterns of insolation can be predicted accurately using DEM-based geometric insolation models.** Calculated global insolation matched measured values at weather stations ($r2=0.93$, $p=0.018$, mean absolute error $< 2\%$).

- **Other commonly used techniques for estimating insolation from incomplete data are not sufficiently accurate to enable generalization of insolation patterns to landscape scales.** Four approaches are commonly used for estimating insolation: generalization from nearby insolation monitoring, prediction by slope and aspect categories, estimating diffuse from global or direct radiation measurements, and using direct duration to substitute for direct radiation. None of these techniques perform well in complex terrain, where a combination of elevation, surface orientation, and sky obstruction must be considered.

- **Calculated spatial patterns of insolation show considerable and predictable variation with landscape position (figure 1).** Insolation variation is determined by a combination of elevation, surface orientation, and sky obstruction by surrounding topographic features. Insolation increases approximately linearly as a function of elevation due to changes in air mass. Surface orientation influence insolation through its effect on angle of incidence. Also, surface orientation determines self-obstruction, whereby the surface itself blocks direct and diffuse insolation from certain sky directions. Sky obstruction by surrounding topographic features (surrounding-obstruction) has a strong influence on insolation by blocking both direct and diffuse radiation.

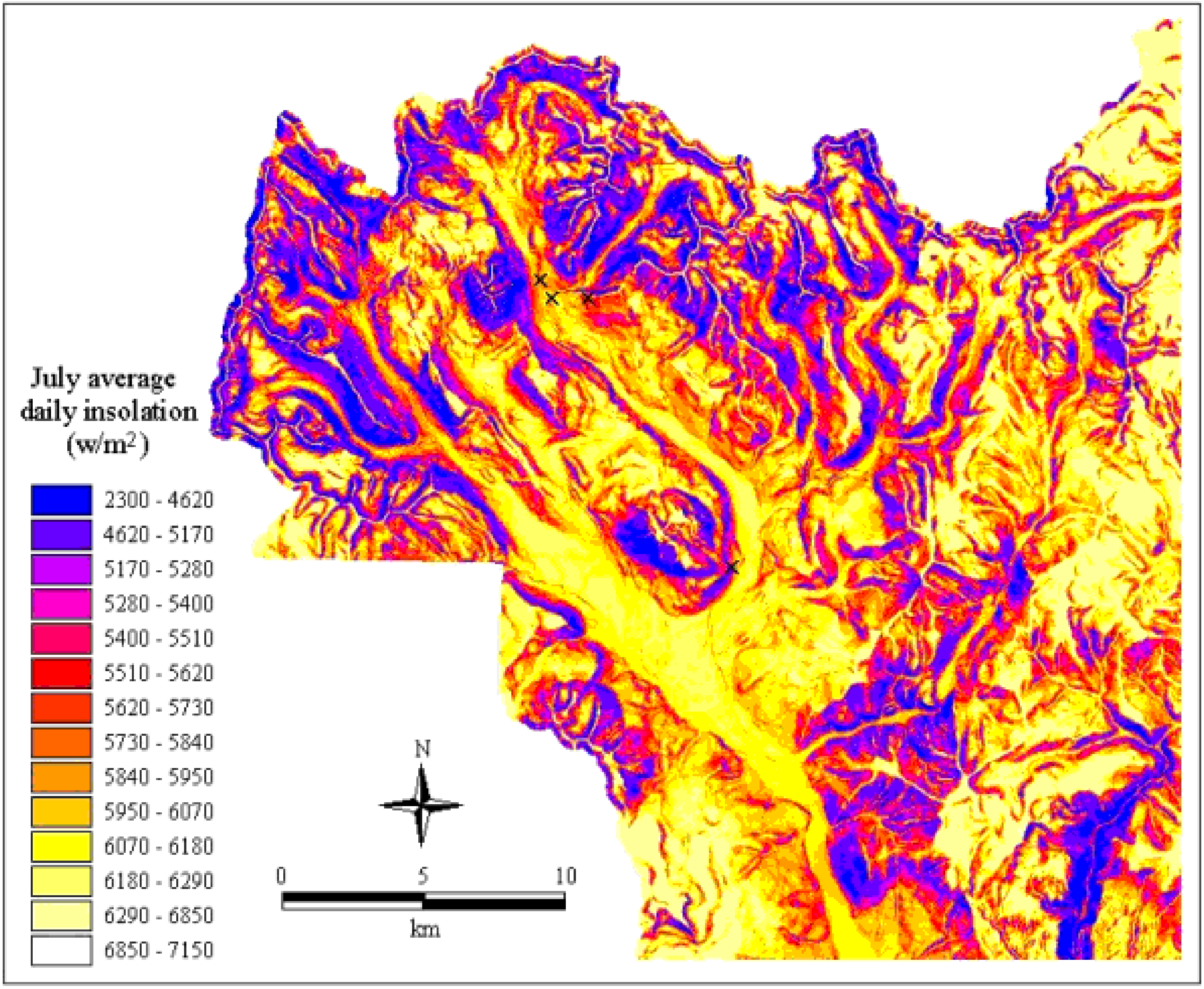

Figure 1. Daily global insolation during July for the RMBL study site.

Insolation-modified temperature model

We calculated maps of air and soil temperature for the RMBL study site using an insolation-modified lapse rate model. This model accounts for local heating in proportion to insolation calculated based on elevation, surface orientation, and sky obstruction. Major findings include the following:

- **Daily hourly air temperature can be predicted using an insolation-modified lapse rate model.** The lapse rate model accounts for the adiabatic changes in air temperature with elevation; whereas insolation accounts for addition of energy by ground surface heating (r=0.75 between residual and insolation). Effects of air mixing are accounted for by using a focal mean function, wherein insolation values of adjacent locations (represented by cells in a raster map) are averaged.

- **Daily minimum soil temperature can be predicted from elevation based on a simple lapse rate model; whereas daily soil temperature increase (maximum minus minimum) can be predicted based on insolation-driven diurnal heating (figures 2 and 3).** Minimum temperature has a strong negative correlation with elevation (r=-0.89 at 12 cm depth and r=-0.71 at 25 cm between minimum temperature and elevation); whereas daily soil temperature increase has a significant positive correlation with insolation (r=0.96 at 12 cm and r=0.91 at 25 cm).

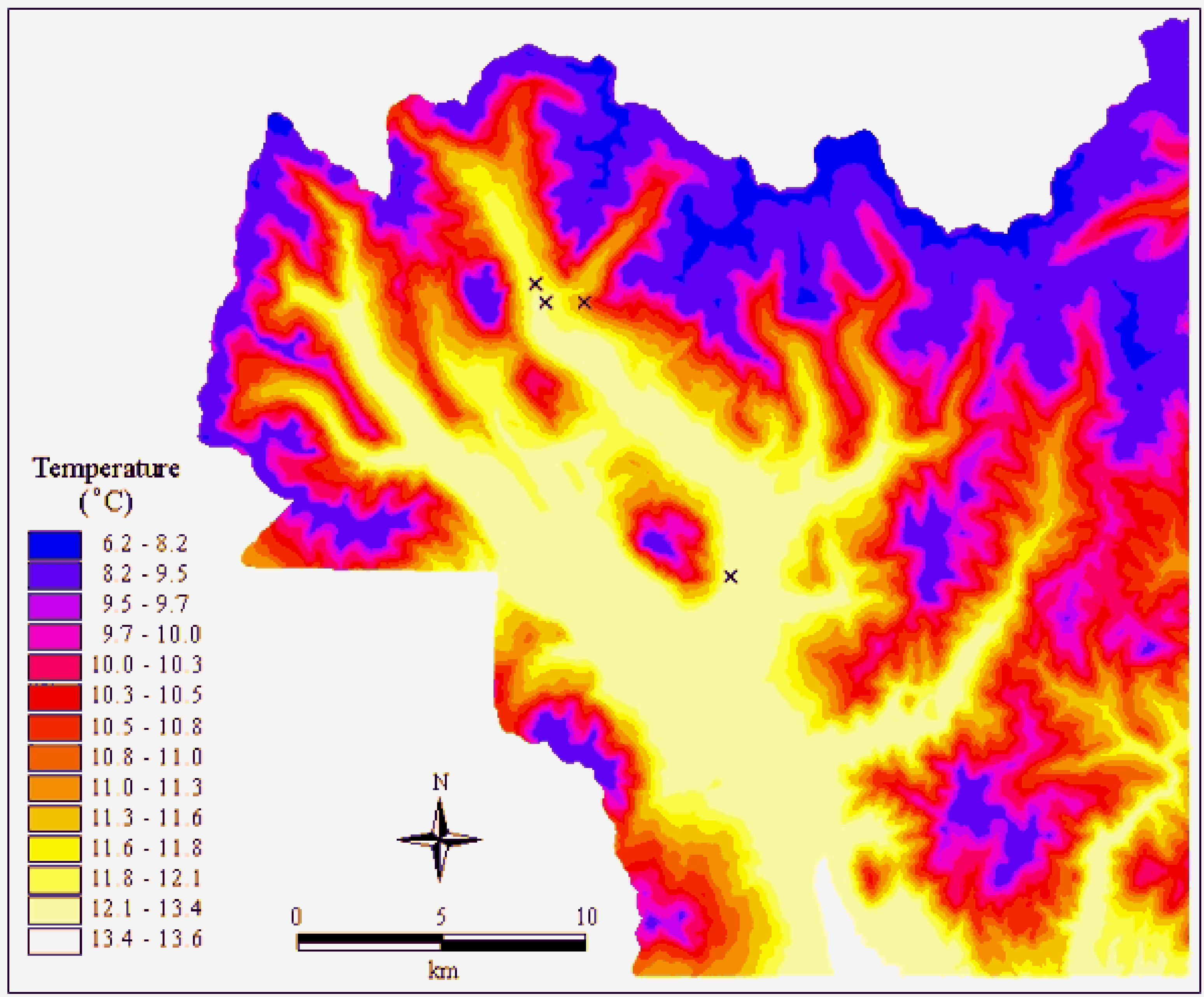

Figure 2. Daily minimum soil temperature (12 cm depth) during July for the RMBL study site.

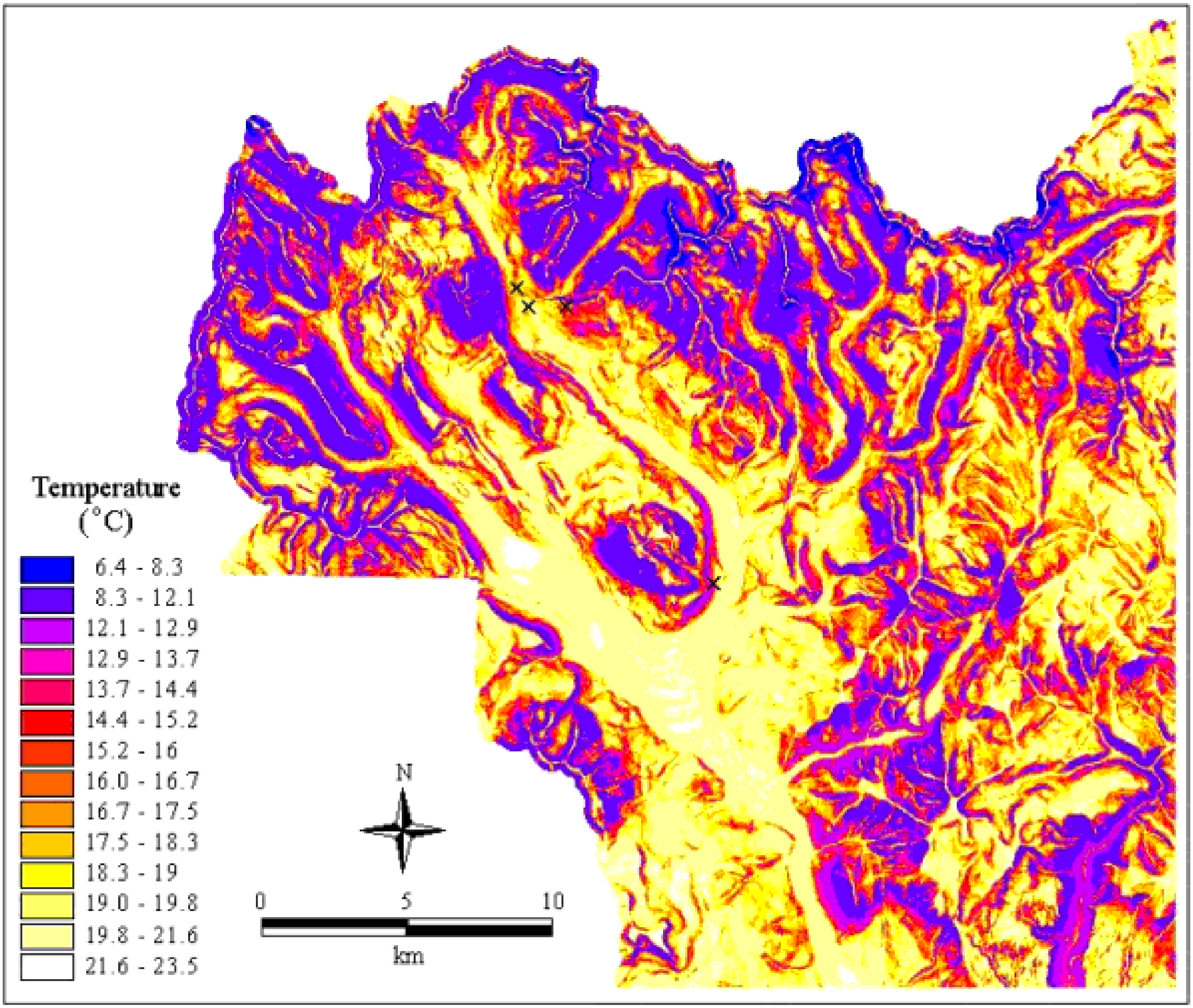

Figure 3. Daily maximum soil temperature (12 cm depth) during July for the RMBL study site.

Some lessons

We have distilled various general lessons from our studies of topoclimatic modeling in the Rocky Mountains:

- **A combination of empirical and mechanistic approaches to topoclimatic modeling can yield the best results, given our current state of theory and available data.** Our predictions of temperature were accomplished using empirical lapse rates, modified by mechanistic calculation of insolation. In general, empirical approaches should be used when sufficient microclimate measurements are available, when our understanding of mechanism is not complete, and when mechanistic models require fine tuning. Mechanistic approaches depend upon sufficiently well-developed theoretical foundations and practicality of obtaining input parameters applicable to the entire landscape.

- **Topoclimatic models average out fine scale variation.** While they can produce satisfactory results for the landscape as a whole, caution must be used when applying results to particular locations.

- **Including an insolation submodel significantly improves predictions from topoclimatic models.** Insolation is especially important for processes involving input of sensible energy (e.g., air and soil temperature) and non-sensible energy (soil moisture balance).

- **Topoclimatic models often covary, but differ in linearity and dependence on local context.** For example, temperature models based on simple lapse rates linearly mirror DEMs, but do not depend upon surrounding topography; whereas, soil moisture models based upon accumulation and flow (Beven and Kirkby 1979) depend strongly upon surrounding topographic context; and geometric insolation models depend upon local topographic context, with non-radial symmetry, based upon directionality of the path of the sun.

- **Topoclimatic modeling approaches provide new opportunities for dynamical modeling of key habitat factors for terrestrial organisms.** Microclimate factors, such as temperature, potential evapotranspiration, and soil moisture, represent key abiotic factors influencing the distribution of organisms. Detailed knowledge of biotic distributions and physical requirements of organisms is generally lacking.

Future directions

Much work is still needed to build better topoclimatic models. In general, there is a need to increase the mechanistic content of topoclimatic modeling, while maintaining sufficient simplicity to make application practical. The following are major directions for future research:

- **Ecologists and environmental modelers should set a research agenda for topoclimatic modeling.** This could be accomplished via a focused workshop/symposium, and should include a comprehensive published review. Such a review would identify what work has been completed, evaluate the advantages of alternative approaches, and identify major research needs.

- **Topoclimatic models should incorporate more mechanistic components.** As modeling sophistication increases, we expect more mechanistic submodels to replace empirical submodels. In particular, energy and water balance modeling requires consideration of tradeoffs between accuracy and ability to obtain input parameters at landscape scales.

- **Topoclimatic models should be validated using systematic and rigorous approaches.** The availability of low-cost sensors and data loggers that can be distributed across the landscape presents new opportunities to provide key input data and to validate predictions. Comparisons of model performance can identify strengths, limitations, and directions for further research.

- **Sampling designs need to consider the full range of variation in the landscape.** New strategies are needed to ensure that field measurements adequately represent the full range of topographic positions in the landscape.

- **Much work is needed to understand links between microclimate and biology.** In essence, microclimate surfaces can be equated to potential habitat once sufficient knowledge is available concerning relations between the distributions of organisms and physical factors. Microclimate habitat models can describe changes in the extent and connectivity of potential habitat under different climate scenarios (Harte and Shaw 1995), and thereby serve as an important tool for basic ecological study, as well as for conservation management. Linking topoclimatic models to biology will remain a major frontier of research long into the future.

Conclusion

Topography is among the most powerful and accessible input parameters for environmental models. Topoclimatic models have the advantage that they use readily available topographic data to predict temporal and spatial patterns of climatic factors. Major challenges still remain to build better topoclimatic models, through advances in our understanding of physical processes and biology, as well as through improved sampling design.

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