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A geometric solar radiation model with applications in agriculture and forestry

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Abstract

Incoming solar radiation (insolation) is fundamental to most physical and biophysical processes because of its role in energy and water balance. We calculated insolation maps from digital elevation models, using an insolation model that accounts for atmospheric conditions, elevation, surface orientation, and influences of surrounding topography. Herein, we focus on the application of this insolation model for spatial interpolation of soil temperature measurements over complex topography at landscape scales. Existing interpolation techniques generally apply only at continental or broad regional scales and do not capture the high variation of finer scales. In our field study in the vicinity of the Rocky Mountain Biological Laboratory, average soil temperature was correlated with insolation and elevation. Whereas daily minimum temperature was negatively correlated with elevation ($r = -0.730$, $P < 0.05$), daily temperature change (maximum minus minimum) was positively correlated with daily insolation ($r = 0.504$, $P < 0.01$). We generated daily minimum and maximum soil temperature maps based on regression analyses. Residual variation was explained by factors such as vegetation cover. This application demonstrates the importance of characterizing spatial and temporal variation of insolation for studies of energy and water balance.

Keywords: Environmental modeling; Geographical information systems; GIS; Insolation; Solar radiation maps; Temperature maps

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1. Introduction

Insolation, through its influence on the energy and water balance at the earth's surface, affects such processes as air and soil heating, evapotranspiration, photosynthesis, winds, and snow melt (Geiger, 1965; Swift, 1976; Gates, 1980; Nikolov and Fox, 1994; Dubayah and Rich, 1995; Rich et al., 1995). Accurate insolation maps at landscape scales are needed for many applications in agriculture and forestry. At landscape scales, topography is the major factor modifying the distribution of insolation. Variability in elevation, surface orientation (slope and aspect), and obstruction by surrounding topographic features creates strong local gradients of insolation. For most geographical areas accurate insolation data are not available. Furthermore, simple interpolation and extrapolation of point measured insolation are not feasible because of high topographic heterogeneity. In contrast to the high-cost of building and maintaining insolation monitoring stations, spatially-based solar radiation models provide a cost-efficient means for characterizing the spatial and temporal variation of insolation. The SolarFlux model (Hetrick et al., 1993a,b; Rich et al., 1995; Rich and Fu, 2000a) and other similar models (Kumar et al., 1997) simulate the influence of shadow patterns on direct insolation at discrete intervals through time. These models were developed for the ARC/INFO GIS platform (ESRI, Redlands, CA), and have been widely used by researchers of diverse fields. But these models are limited by the computation speed of Arc Macro Language, simplistic diffuse calculations, and availability only for use with high-cost GIS software. A new generation model is needed to provide better accuracy, faster speed, more rigorous diffuse calculations, improved flexibility, and broad availability.

At landscape and local scales, temperature patterns are strongly influenced by fine-scale insolation variation and microsite factors (vegetation, soil properties, wind). Innumerable researchers have observed high temperature variation in areas of high topographic relief. For example, Holch (1931) found that maximum air temperatures were from 0.5 to 5 °C higher on south versus north-facing slopes. Cottle (1932), in his study of vegetation in the mountains of Big Bend County, Texas, found that soil temperatures at 6 cm below the surface were about 5–10 °C higher on south-facing versus north-facing slopes. Wilson (1970) documented air temperature differences (mean weekly maximum) of 5 °C in spring and 1.8 °C in summer for north versus south-facing slopes in forested areas of Mont St. Hilaire, Quebec. Temperature differences for bare ground areas were even larger. More recently, Dixon (1986) in his study of plant distributions in the Rocky Mountains, found that soil temperatures were typically 0.4–12.1 °C warmer than ambient air temperature, and both air and soil temperature vary significantly with topographic position.

Characterization of temperature for a study area typically relies upon a series of measurements at discrete locations. Weather stations are sparsely distributed. For example, Gunnison County, Colorado, an area with complex terrain, has about 40 official weather stations (including snowtel stations) within a 125 km by 125 km area (approximately one station per 400 km^2). Microclimate within such a vast area cannot be represented by measurements at only one location. Furthermore, these weather stations are not spatially representative, but rather biased in flat, open locations near areas with high human population. Spatial interpolation of these sparse measurements into a continuous surface is difficult. Researchers have used diverse statistical and geostatistical models to generate surface temperature from point sampling locations. The simplest technique uses the nearest measurements and can not capture temperature variation in complex topography. Another simple technique in widespread use examines a set of aspect, slope, and elevation groups, and assumes that temperatures within a group are similar (Daubenmire, 1956; Ayyad and Dix, 1964; Dixon, 1986). This method may treat very different landscape positions in similar ways because it neglects differences in sky obstruction by surrounding topographic features. In addition, categories are not continuous and subtle differences between surface orientation are neglected. Trend surfaces, inverse distance weighted interpolation, thin plate spline, and ANUSPLIN (Hutchinson, 1991) all have been used to interpolate temperature measurements over global, continental, and broad regional scales (Collins and Bolstad, 1996; Kesteven and Hutchinson, 1996). These models, however, assume the underlying surface is smooth and lack a mechanism for use in mountain regions with complex topography. Kriging and surface interpolations of the MT-CLIM model (Hungerford et al., 1989; Running and Thornton, 1996) and PRISM (Daly et al., 1994) can use correlated variables for creating surfaces, but they have not been used at landscape scales due to the lack of high-resolution insolation data. Remote sensing of surface temperature appears to be a promising technology, however, slope and aspect variations in mountainous regions lead to difficulties of data interpretation (Lipton, 1992). Ideally, microclimate factors would be modeled using mechanistic models of energy and water balance. These models can achieve excellent accuracy, but use large numbers of parameters that are not available for most studies. The problem of interpolating or extrapolating site-specific measurements, including temperature, to obtain landscape scale estimates remains a challenge (Burrough and McDonnell, 1998; Rich and Fu, 2000b).

The goal of this research is to construct high spatial resolution temperature maps based on a few measurements using high spatial resolution insolation maps. Insolation has a direct effect on temperature by adding energy that heats the ground surface. Successful spatial interpolators should not neglect this underlying physical process. We expect these insolation maps will be highly valuable in spatial interpolation and extrapolation of temperature measurements over complex topography.

Herein, we calculate temperature maps for a topographically diverse study area based on an insolation-modified adiabatic temperature model. First, we construct insolation maps, accounting for major topographic influences, in particular elevation, surface orientation, and sky obstruction by surrounding topographic features. Next, we construct temperature maps, using a simple adiabatic model to calculate minimum temperatures, and the insolation map to estimate daily heating for each landscape location. Then, we compare results from the insolation-modified temperature model with field measurements of soil temperature. Finally, we consider the value and limitations of this topoclimatic approach.

2. Materials and methods

2.1. Study area

This study was conducted in the vicinity of Rocky Mountain Biological Laboratory (RMBL), Gunnison County, Colorado, USA (Fig. 1). The study area is approximately 300 km^2, and has dramatic topographic variation, with elevation ranging from 2500 to 4300 m. We obtained USGS 7.5′/30 m resolution digital elevation models (DEMs) that cover the entire area. These DEMs serve as a primary data layer for constructing soil temperature maps. We obtained weather station data from the National Water and Climate Center.

2.2. Field measurements of temperature

In August of 1998, we buried eleven Hobo soil temperature sensors at 20-cm depth (Onset Computer Corporation, Bourne, Massachusetts) for a series of locations selected to represent a full range of aspects, slopes, and upward-looking viewsheds. Exact locations of the sensors were surveyed using a differential corrected global positioning system (Trimble Pathfinder) (Fig. 1). Temperature was logged hourly. Time of hourly readings was converted to local solar time for analyses. In June 1999, the sensors were dug up and sensor readings were downloaded. Of the 11 sensors, 3 were dug up by animals, and 1 had a bad connection. The analysis presented here uses measurements for the 7 functioning sensors (Table 1) between 10 August 1998 and 17 June 1999.

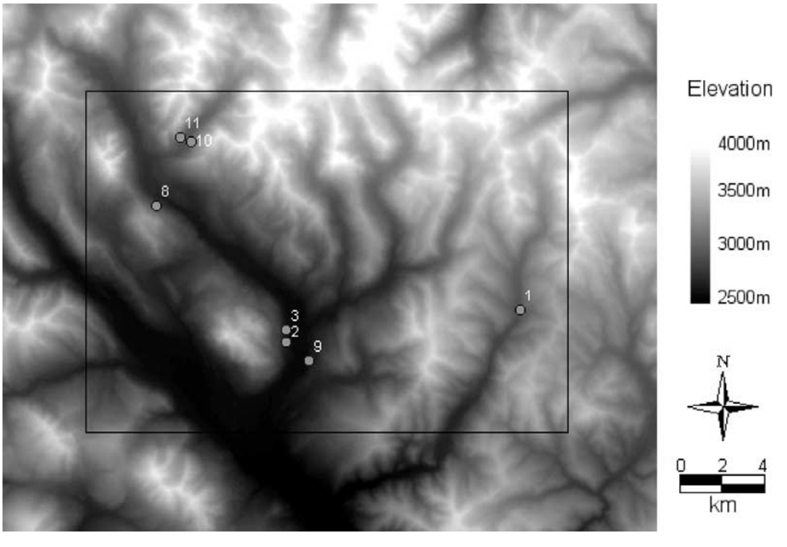

Fig. 1. Locations of soil temperature sensors shown on the DEM for the immediate vicinity of RMBL. Circles indicate sensors used in our analysis ($n = 7$).

Table 1
Topographic positions of the soil temperature sensors

Sensor ID	Elevation (m)	Slope (°)	Aspect (°)
1	3078	24	255
2	2782	23	81
3	2758	19	94
8	3002	27	34
9	2767	11	276
10	3117	15	280
11	3119	31	131

2.3. Insolation and temperature maps

For insolation calculations, we developed the TopoView model, which calculates insolation maps, including both direct and diffuse solar radiation, from DEMs. We ported the model as the Solar Analyst, an ArcView GIS extension (ESRI), which provides an expanded user interface and calculation capabilities. The theory and algorithms of TopoView and the Solar Analyst are described in detail by Fu and Rich (1999a,b), http://www.hemisoft.com). In essence, these programs use an algorithm developed by Rich et al. (1994) that generates upward-looking viewsheds based on DEMs, and uses these viewsheds to calculate incoming direct and diffuse radiation from each sky direction.

For most statistical analysis, seven samples would be an insufficient sample size. But in reality, weather stations are much more sparsely distributed, and most do not record soil temperature. Many landscape scale studies (covering several 100 km^2) have even fewer soil temperature measurements available. This study adds a physical process component, the insolation submodel, to the statistical analysis of the field measurements. This hybrid approach is based on an understanding of the insolation heating effects.

We used the Solar Analyst to calculate the insolation for the study area. Since daily sky conditions (e.g. random clouds) are not available, we used transmittivity and diffuse proportion parameters for average sky conditions of the study area during late summer. The resultant insolation integrates over both sunny and cloudy days, and which average the influence of clouds over time. The 30-m DEM covering the study area and its surroundings was used as input. Insolation was calculated for 1 month (10 August 1998 to 9 September 1998) and divided by 31 days to determine average daily insolation.

The daily soil temperature measurements for the same time period were also averaged to calculate daily maximums, minimums, and ranges (maximums minus minimum). Then we examined correlations of each measure of soil temperature with elevation and insolation. We tested the statistical significances of these correlations using t-tests. Where significant correlations were obtained, separate regressions where formulated to predict soil temperature as a function of elevation and insolation. Finally, we generated soil temperature surfaces over the entire field study area based on these regressions.

3. Results

During most of the period for which temperature measurements were available, the seven sampling locations had very different temperature regimes. Only during November, when snow started to accumulate, and during late March and early April, when snow started to melt, did most locations have similar temperatures, all fluctuating near 0 °C. During the winter, temperatures of sensors at different locations ranged from −0.2 to −7.5 °C. This variation was related to differences of snow accumulation and snow depth, with the lowest temperatures associated with less snow cover. Both late summer (August–September) and late spring (May–June) showed high variation between sensors (Fig. 2). Average daily pattern for late summer shows that the daily minimum temperatures were quite similar (2 °C range) and the daily maximum temperatures were very different (10 °C range).

While daily minimum temperature is significantly correlated with elevation (Table 2, $r = -0.730$, $P < 0.05$), it is not significantly correlated with insolation. The former can be explained by the adiabatic lapse rate, which causes predictably lower temperatures with increasing elevation. Daily maximum temperature has no significant correlations with insolation and elevation. Insolation is more strongly correlated with daily temperature range ($r = 0.504$, $P < 0.01$) than with maximum

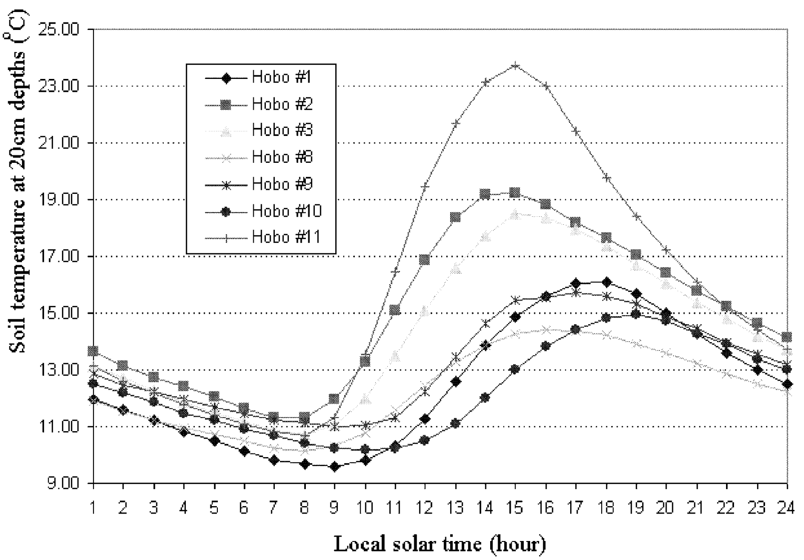

Fig. 2. Diurnal patterns of soil temperature for different spatial location during late summer (10 August 1998–9-September 1998, measurements averaged for each hourly time interval).

Table 2
Correlation coefficients of temperature with elevation and insolation (10 August 1998–9 September 1998), $N = 7$

	Max	Min	Average	Max−min
Elevation	0.041	−0.730	−0.21	0.183
Insolation	0.479	0.034	0.367	0.504

temperature. Heating during the day depends in large part upon differences of insolation to different sites.

Based on these relationships, linear regressions were calculated between daily minimum temperature and elevation (Eq. (1)), and between daily temperature range and daily insolation (Eq. (2)). These equations were applied to the field study area and maps of daily minimum and maximum temperature were generated (Fig. 3). The map predicts higher soil temperatures for lower elevation and south-facing slopes with high exposure, lower temperatures for north-facing slopes and other slopes with low exposure.

$$\text{Temperature}_{\text{min}} = -0.0025[\text{elevation}] + 17.90 \tag{1}$$

$$\text{Temperature}_{\text{max}} - \text{Temperature}_{\text{min}} = 0.003629[\text{insolation}] - 15.01 \tag{2}$$

4. Discussion

The results of this study are meaningful and reasonable. Minimum soil temperature generally follows a simple lapse rate model, wherein minimum

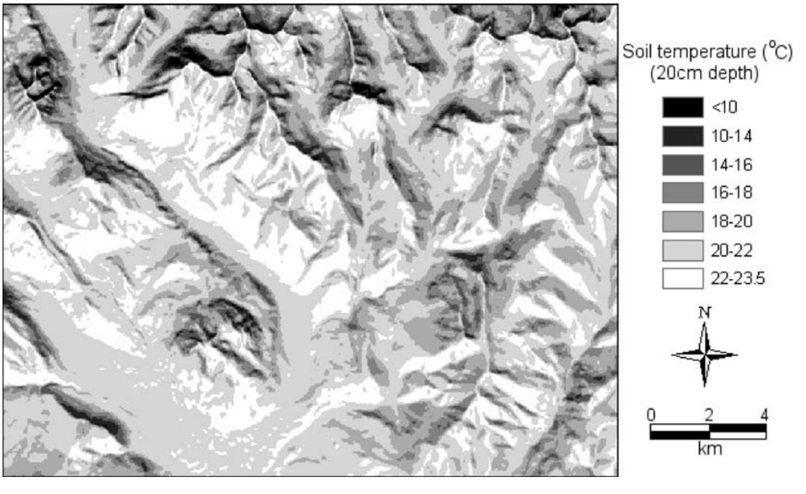

Fig. 3. Map of average daily maximum temperature for late summer (10 August 1998–9 September 1998).

temperature is inversely proportional to elevation. Maximum daily soil temperature is determined by heating during the day, and this is strongly influenced at the local insolation. Insolation proved to explain most of the variation in daily temperature increase. Adding an insolation term increased model accuracy especially for topographic positions that receive either very high or very low insolation.

The temperature model developed in this study has advantages and disadvantages. Soil temperature varies with topographic position in the landscape. Ideally, microclimate factors would be modeled using mechanistic models of energy and water balance. These models can achieve excellent accuracy, but use large numbers of parameters. By contrast, this study does not require large numbers of input parameters and is easy to use. The method can be widely applied in topographically diverse terrain. It is important to consider the limitations of this approach. In this study, hourly measurements for 1 month were summarized to minimize the problems with day-to-day variability. Thus this model is best at characterizing high spatial resolution patterns rather than high temporal resolution patterns.

The root mean square errors are 0.98 and 6.46 °C for Eqs. (1 and 2), respectively. The residual variation can be explained by various factors, including sensor placement, vegetation cover, and DEM quality:

(1) *Sensor placement:* The distances from sensors to ground surface varies with slope (Fig. 4). The larger the slope, the closer the direct line distance to the surface. This effect must be considered when examining soil conductivity. A simple linear correction increases the correlation coefficients between insolation and daily temperature range from 0.504 to 0.688.

(2) *Vegetation cover:* Crude categories of vegetation cover were recorded for each sensor location (bare, low, medium, high). Locations with positive residuals have low or no vegetation cover, while locations with negative residuals have high vegetation cover. More detailed analyses must include consideration of differences in vegetation cover. Vegetation influences various of the energy balance terms (latent energy, sensible heat, heating of soil surface...) depending upon such properties as evapotranspiration, amount of bare ground, and shadows cast by the canopy.

(3) *DEM quality:* High spatial resolution and high quality DEMs are needed to produce high-resolution temperature maps. In this analysis we used the USGS 30 m DEM, which is known to have many problems. This could result in errors in slope, aspect, and the derived viewshed, all of which can affect insolation calculations. We

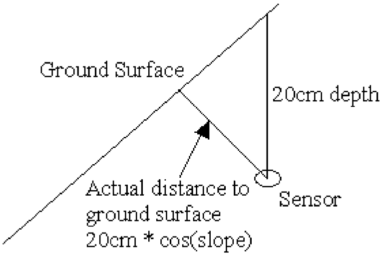

Fig. 4. Actual distance between sensor and ground surface on a slope.

noted differences between the DEM-derived and field measured slopes and aspects at the sensor locations. Using field measured slope and aspect improved the correlations between insolation and soil temperature by approximately 0.1.

(4) *Other factors:* Such factors as differences in air flow patterns, soil properties, soil moisture, and snow cover can all influence nearground energy balance. Cold air drainage, which can lead to temperature inversions, is not directly included in our temperature model, but is accounted for over time by a shallower observed temperature lapse rate than would otherwise be expected. During winter months, snow cover dominates and insolation does not significantly influence soil temperature regimes. Insolation is expected to influence snow melt patterns, but this relationship is complex, depending upon local snow accumulation and local energy balance.

The example of using insolation in temperature surface calculation is just one of many potential applications. Because solar radiation is the primary input for energy balance, and also the driving force for water balance, insolation is important for all of the physical and biological processes in agriculture and forestry. For example, soil moisture and air relative humidity are negatively related to insolation, while potential transpiration and evaporation are positively related to insolation. Insolation submodels would ideally be incorporated in models of forest and crop growth, productivity, crop zone planning, local-scale soil moisture and irrigation, non-source pollution, forest fire risk assessment, wildlife habitat, and biotic changes under different climate scenarios. In addition, the Solar Analyst can be applied in remote sensing for radiometric normalization of topographic influences; incorporation of a spectral model will improve performance for this purpose.

5. Conclusion

Soil temperature varies with topographic position in the landscape. In topographically diverse terrain, simple interpolation is not adequate for building high-resolution soil temperature maps. Mechanistic models require large numbers of parameters that are not generally available. For this study we developed an insolation-modified soil temperature model, which uses a geometric insolation submodel to improve soil temperature calculations. We generated 30-m resolution of insolation maps using the Solar Analyst, we then found the relations of soil temperature measurements with insolation and elevation. This model generated high spatial resolution representation of temperature regimes for the RMBL vicinity during snow-free periods, notably for the summer growing season. The model appears to provide reasonable accuracy, while requiring only a DEM and a few field measurements for input, however, further validation is needed. In this study insolation proved to be a critical factor for understand fine-scale patterns across the landscape. Similarly, other applications that involve energy or water balance, either directly or indirectly, could benefit from adding this insolation submodel.

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