TOPOGRAPHIC EFFECTS ON THE SPATIAL AND TEMPORAL PATTERNS OF SNOW TEMPERATURE GRADIENTS IN A MOUNTAIN SNOWPACK

by

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ABSTRACT

The objective of this study was to investigate the importance of topography in controlling the geographic patterns of deep snow temperature gradients within a seasonal snowpack. Demonstration of the relative importance of topography in influencing spatial snowpack temperature gradients could aid future modeling of snow layer development and behavior, with benefits for avalanche and snowmelt modeling. This spatial, or geographic, analysis of the relationship of snow temperature gradient patterns to topography utilized landscape-scale modeling in an attempt to identify responses in complex, mountainous terrain.

During the snow season of 2001-2002, 30 temperature profiles were sampled on each of nine sample days. Profiles were collected using a portable snow temperature profile probe. These data were used to calculate temperature gradients for each profile. Topographic attributes were derived from a digital elevation model using a geographic information system. Linear regression models were used to quantify the relationships between the topographic variables and snow temperature gradient patterns in the spatially distributed dataset, and to demonstrate the relative importance of the terrain variables in determining spatial patterns of temperature gradients. Analysis showed a complex pattern of relationships between temperature gradients and the static topographic variables. A qualitative assessment of weather variables recorded onsite suggested the utility of using more dynamic variables such as weather data in future modeling efforts.

INTRODUCTION

Snow temperature is a dominant variable in many physical processes in a seasonal snowpack. The snow temperature through the depth or profile of the snowpack reveals much about both the physical state of the snowpack and its likely future behavior. Temperature gradient-driven metamorphic processes within a cold snowpack can stabilize or weaken individual layers, and hence determine the likelihood of avalanche activity. The temperature stratigraphy of the snowpack directly influences a mountain watershed's hydrology, and affects the ability of the snowpack to buffer extreme melt events. The spatial geography of snow temperature gradients therefore influences snowmelt patterns through controls on snow layer texture (Blöschl et al, 1991), and influences avalanche hazard through the development of weak layers at many levels in the snowpack (Armstrong, 1976; McClung and Schaerer, 1993; Clarke and McClung, 1999). This project measured spatial variation in snow temperature gradients, and explored regression relationships between these gradients and the topographic attributes of the terrain in which they were measured.

Spatial and temporal variation in snow properties, including temperature gradients, present significant challenges for operational modeling of and research into snowcover processes such as avalanche forecasting and snowmelt prediction. Often the variation observed is recognized, but is not addressed explicitly; rather the observer or modeler relies on their experience to assess the representativity of a measurement or the applicability of a model. The problems caused by this variation have often been avoided by observing snow phenomena on scales where the variability is relatively small or quantifiable, such as an entire mountain range (Armstrong and Armstrong, 1987) or the individual snow crystal (Colbeck, 1982; Miller, 2002). However, most modeling efforts and operational forecasting function on scales intermediate to those above. Variation in snow properties between adjacent slopes, or within a single basin or watershed often provides the crux of the analysis (Blöschl et al., 1991; Birkeland et al. 1995; Cline et al., 1997; Landry 2002).

Topography exerts a significant control on spatial and temporal variation in snow temperature patterns (McClung and Schaerer, 1993; Gerrard, 1990). The amount of solar radiation incident on a snow surface varies with slope aspect, and will vary within a given aspect as a function of slope angle. Elevation influences the amount of snowfall through both orographic effects and the ambient air temperature, influenced by the environmental lapse rate (Armstrong and Williams, 1986). Topographic profile and planform curvature are other measures of topography that could prove important, as they describe the relative "sharpness" or exposure of the terrain. Vegetation and ground surface material may also have significant effects on snow temperature and snow temperature gradients.

Solar input and air temperature are directly related to snowpack temperature (Gray and Male, 1981). Both duration and intensity of sun exposure, as well as air temperature, increase from the winter solstice until the summer solstice. Additionally, as the melt season approaches and snow temperatures continue to increase, temperature gradients within the snowpack tend to decrease (McClung and Schaerer, 1993). Therefore, snow temperature gradients show a relationship to date of season.

An exploration of the relationship of snow temperature patterns to topography, utilizing spatial analysis and landscape-scale modeling, can potentially explain temperature variability in complex terrain. Quantification of the relationship between temperature gradients and topography could aid in explaining some of the variation observed in snow properties. Ferguson (1999) suggested that Geographic Information System (GIS) analysis of digital terrain data be used to establish a topographic attributes-based modeling approach for snowmelt prediction. Specifically, Ferguson (1999, p. 220) suggested "clear possibilities of using GIS tools and gridded Digital Elevation Model (DEM) data to set up zonal models distributed not just by elevation but also slope aspect and other topographic controls of snow accumulation and snowmelt."

Knowledge of the relative importance of topographic factors in influencing snowpack temperature gradient patterns through space and time could aid in development and refinement of snowmelt and avalanche forecasting models. If snow temperature gradients do indeed exhibit a significant correlation to topographic attributes, the result would support the conventional beliefs about terrain influence on snow temperatures. An assessment of the spatial variability of snow properties (i.e. temperature) as a function of terrain variables could also help link the spatial resolution of a theoretical (physical) model with the predictive ability of an operational, empirical model for snowmelt or avalanche prediction, combining process representation with reasonable data requirements.

RESEARCH HYPOTHESES

The objective of this project was to observe variations in snow temperature gradients within a mountain basin, and to use topographic variables in an attempt to explain that variation. Specifically, this project tests the following hypotheses based on previous literature:

1. Snow profile temperature gradients will show a significant correlation to the topography. The largest temperature gradients will be observed on highest elevation, north-facing slopes, while the smallest temperature gradients will be found on south-facing slopes at all elevations.
2. The magnitude of snow profile temperature gradients will show a significant correlation to the date within an individual snow season. The largest snow temperature gradient values will occur early in the snow season and will decrease towards late season.

Hypothesis #1 is based on the atmospheric lapse rate, which predicts the occurrence of lower air temperatures at higher elevations, which would affect snow surface temperatures at these locations. It is also based on the differences in solar input among differing aspects.

Hypothesis #2 relies upon the general increase in air temperature throughout the season, as well as an increase in snow depth. These two factors combine to produce lower temperature gradients, as the temperature difference between the ground surface and air is distributed over a deeper snow cover.

LITERATURE REVIEW

This review is an examination of previous research concerning snow temperature gradients and associated applications. Previous investigators (e.g. Akitaya, 1974; Colbeck, 1982) have established that temperature gradients are a driving force controlling dry snow metamorphism, with important ramifications for avalanche hazard via the development of weak layers, and for meltwater drainage, by influencing snow texture (Kattelmann, 1984). Other research (e.g. Armstrong, 1985; Birkeland, 1998) has shown that diurnal fluctuations in near-surface snow temperatures produce large temperature gradients over small changes in depth. Spatial variability in snow temperature gradients has been linked to topographic variables (Dexter, 1986), and requires a consideration of the scale of observation relative to the scale(s) upon which the temperature gradients change (Blöschl, 1999). It is in the context of these issues that this project was designed to explore the topographic influence on the spatial variability in snow temperature gradients.

Temperature Gradients and Dry Snow Metamorphism

Temperature gradients in a snowpack generally result from a temperature differential between the air and the ground surface. Ground temperatures are typically at or near 0°C in midlatitude mountain environments where permanent snow or ice is not present (McClung and Schaerer, 1993). Winter air temperatures in this environment often drop below 0°C, creating a temperature gradient within the snowpack, between the ground and air. The magnitude of this gradient also depends upon the thickness of the snow cover and the character of the snow layers contained within. Local variations in topography, vegetation, or surface roughness (i.e. the presence of boulders or rocky outcrops) can affect the flow of heat energy through the snowpack and thereby affect snow temperatures and temperature gradients (Dexter, 1986; McClung and Schaerer. 1993; Aarons et al., 1998).

Snow temperature gradients can be measured in different ways, depending on the purpose in studying them. Often, for coarse-scale spatial or temporal assessment, a gradient over the full snow depth is determined from a measured air temperature and an assumption that the ground temperature is 0°C. This type of measurement is often used for characterization of snow climate effects (Armstrong and Armstrong, 1987; Mock and Kay, 1992; McClung and Schaerer, 1993). When studies call for the interpretation or prediction of snow crystal metamorphism, a smaller-scale gradient, usually on the order of a 5 to 10cm interval, is commonly used (McClung and Schaerer, 1993). Temperature gradients near the snow surface can be many times greater than are commonly found deeper in the snowpack (Birkeland, 1998). To measure near-surface temperature gradients, sensors may be arrayed over intervals smaller than a centimeter (Birkeland et al., 1998).

The magnitude of a temperature gradient within a snow layer directly affects the magnitude of the vapor pressure gradient within that layer, and consequently the rate and type of snow crystal metamorphism (Armstrong, 1985; Dexter, 1986). It has been found to be the controlling factor in dry snow metamorphism (McClung and Schaerer, 1993).

Large temperature gradients produce rapid crystal growth and the associated "kinetic" or "faceted" forms, while slower growth rates stem from smaller temperature gradients and tend to produce rounded, well-bonded snow grains (McClung and Schaerer, 1993). Armstrong, (1977) found that a temperature gradient of 10 °C/m produced a sufficient vapor pressure gradient to produce faceted crystals, given the conditions of his study in the San Juan Mountains in Colorado, and this is often cited as the boundary between faceting and rounding growth rate regimes. Other factors, such as snow temperature and density, also have a strong effect on snow metamorphism; however, the magnitude of the temperature gradient remains the most critical influence (Miller, 2002).

A conventional assumption holds that the highest temperature gradients are found on high elevation, north-facing (Northern Hemisphere), shaded slopes, where there is less solar input than sun-exposed slopes, and colder air temperatures due to the standard atmospheric lapse rate (Dexter, 1986; McClung and Schaerer, 1993). LaChapelle and Armstrong (1977), however, found that various combinations of air temperature and snow depth resulted in similar temperature gradients on north-facing and south-facing aspects, at similar elevations. Dexter (1986) observed highest temperature gradients at lower elevations on south-facing slopes, which he attributed to the shallower snow depths at those locations. Other factors, such as areas of increased heat flow or conduction from the ground surface, can influence the distribution of temperature gradients on a scale smaller than an entire slope (McClung and Schaerer, 1993; Tremper, 1995; Aarons et al., 1998). Snow temperatures and temperature gradients are also influenced by forest canopy cover, which limits incoming shortwave radiation traps outgoing longwave radiation, dependent on the density of the canopy (McClung and Schaerer, 1993).

Diurnal Temperature Fluctuations

The daily cycle of air temperatures produces fluctuations in snow temperatures, the magnitude of which diminishes with increasing depth in the snowpack (McClung and Schaerer, 1993). Snow depths greater than about 30 cm show little to no diurnal snow temperature change, due to the insulating capacity of the overlying snow (Armstrong, 1985). The near surface, diurnal temperature fluctuations are capable of producing large or extreme temperature gradients over small distances, driving rapid faceted crystal growth (Birkeland, 1998). These faceted crystals, if buried by subsequent snowfall, can form persistent weak layers leading to increased avalanche hazard (Birkeland et al., 1998). Warm air temperatures can form melt-freeze layers at or near the surface, affecting crystal growth (Birkeland, 1998) and later influencing meltwater runoff (Marsh and Woo, 1984a; Kattelmann and Dozier, 1999).

Fukuzawa and Akitaya (1993) examined growth of near-surface faceted crystals, and found that strong temperature gradients in the 100-300 °C/m range drive the rapid crystal growth. Meteorological conditions leading to these extreme gradients were also examined, with results indicating the largest temperature gradients were associated with clear-sky conditions permitting the escape of longwave radiation from the snow surface.

The formation of a layer of near-surface facets and nearby avalanche activity was documented by Birkeland et al. (1998). They measured temperature gradients greater than 200 °C/m in the top 5 cm of the snowpack. Gradients 15-20 cm below the surface were considerably weaker. The faceted layer created by these gradients was observed to exist over a wide geographic area (on the order of 50 km). Avalanche activity on the faceted crystals was reported at various elevations and on all aspects, implying that the conditions that created this weak layer were not differentiated by topographic influences.

Hardy et al. (2000) reported observations of near-surface faceted crystals in a high elevation, tropical climate. They attributed the crystal development to unique energy balance conditions in that environment, consisting of high solar input at high elevation, low albedo snow cover, and rapid longwave cooling associated with the thin atmosphere at high altitude.

Snowmelt Processes and Wet Snow Metamorphism

Snowmelt processes, like temperature gradients and dry snow processes, have been shown to be related to the nature of the topography involved (Coughlan and Running, 1997; Carey and Woo, 1998). While melt processes are not directly temperature gradient dependent (except on the microscale), the previous temperature profile history of the snowpack combines with terrain controls to affect snow texture, and, therefore, influence spatial melt patterns (Kattelmann, 1984).

Isothermal snow is defined as snow at a temperature of 0°C in equilibrium with free, liquid water (Marsh and Woo, 1984; McClung and Schaerer, 1993). An isothermal snowpack (or any part of a given snowpack deemed isothermal) is 0°C throughout, has free water at all depths, and contributes to the snowmelt hydrograph of its given basin

(Michaels, 1983). A snowpack becomes isothermal differentially; therefore, isothermal, or ripe, snow can exist without having an entirely ripe snow*pack*.

An isothermal snowpack is the result of melt metamorphism, also called *maturing* (Colbeck, 1977), *aging*, or *ripening*. This process is initiated by the introduction of liquid water into the snowpack (either from snowmelt or rainfall), which can be distributed to the full-depth of the snowpack by the propagation of water through pore spaces and along strata within the snow structure (Kattelmann and Dozier, 1999). The movement of water within the snowpack is largely controlled by the relative texture of different snow layers (Kattelmann, 1984). Large-grained snow, like that which has been influenced by a large temperature gradient, exerts less capillary pressure on meltwater than does smaller-grained snow. At layer boundaries where small-grained snow overlies large-grained snow, meltwater may be impounded in the small-grained snow and move laterally until a suitable penetration location (i.e. smaller grains or a previously established meltwater channel) allows the water to progress downward through the snow strata. Therefore, the spatial patterns of snow temperature gradients during the winter, by exerting a control on the snow texture, can have an effect on ripening and melt runoff patterns in the subsequent melt season.

Snowpack ripening has been shown to depend on aspect, by Carey and Woo (1998). In a study in the Canadian subarctic, they found a time difference in snow ripening of 10 days between north- and south-facing slopes, and attributed this largely to differences in solar radiation receipt on these slopes.

Snow depth and snowmelt are known to vary with elevation, an effect addressed in all snowmelt models (Ferguson, 1999). In a study of snow depletion date (the date at which the snowcover is entirely melted at a given site), Coughlan and Running (1997) found a codependency on site orientation (aspect) and elevation. Furthermore, their results showed that vegetation cover was more important than aspect as a snowmelt variable, due to the vegetation effects on shortwave energy input. Snow depletion and snowpack ripening were found to share common variables, such as vegetation cover (leaf-area index) elevation, and aspect (Coughlan and Running, 1997; Carey and Woo, 1998).

The presence of vegetation above the snowcover can distort or mute topographic snowmelt effects. Coughlan and Running (1997) determined that a leaf-area index variable was the most important variable for modeling snow accumulation and melt at higher elevations. Furthermore, the type of vegetative cover is important if its effect on snow temperature and melt patterns is to be determined. Gary and Coltharp (1967) found that a spruce-fir forest type held snow 4-5 weeks longer than other tree and grassland cover types. They also noted large differences in snow depletion date based on aspect.

Hardy et al. (1990), studying logging effects, and Skidmore et al. (1994), studying fire effects, reported that snow accumulation decreased as canopy density increased, for their studies in southwest Montana. Additionally, they related canopy density to snow ablation, with high canopy densities correlating to low ablation rates, and the highest ablation rates occurring in low canopy density areas.

Avalanche Forecasting and Snowmelt Modeling

Computer-based avalanche forecasting models vary in their approach to the problem of accurate forecasting, due to the scale of forecast required and the type of data available for input. Several tools attempt to model the evolution of the snowpack structure, using high-resolution meteorologic data, such as CROCUS (Durand, et al., 1999) and SNOWPACK (Lehning et al., 1999). Temperature and temperature gradient data are critical to these models, which attempt to predict the formation of different snow crystal types in the snowpack. Since these models operate on the point scale, some estimation of temperature gradients based on terrain relationships is needed if this data is to be available for applying the models at a regional scale.

Judson et al. (1980) included a temperature gradient parameter in their "process-oriented" avalanche danger model. It was implemented in order to simulate the development of faceted crystals. The thickness of the faceted layer was then factored into the overall avalanche danger assessment.

In response to concerns about the extreme heterogeneity that troubles energy-balance snowmelt models, alternatives to purely physically based models have been proposed (Andersson, 1992; Ferguson, 1999). A combination of measured snow variables and inclusion of topographic parameters, such as aspect, as modifications to existing conceptual models could prove effective in simulating melt patterns. According to Andersson (1992), future model development should strike a balance between conceptual and physically based models, utilizing simple inputs and implicit variable representation while working at relatively high spatial and temporal resolutions.

Ferguson (1999) recommended incorporating multiple topographic variables such as elevation and aspect to enhance conceptually based models.

The ability to predict snowmelt response (including ripening patterns) depends on the understanding of the relative importance of melt-controlling variables, particularly those related to topography (Michaels, 1983). The scale used must have a sampling grid or mosaic of a size small enough to detect changes due to topographic influence. Variability of snowpack attributes such as density, grain types, porosity, and finger flow paths within grid elements must be implicit in the size of mosaic chosen (Blöschl, 1991). Field measurements should include multiple elevations, slopes and aspects, and be designed to statistically represent grid size (Blöschl et al, 1991). A model of this type could find application in many aspects of study and development in mountainous regions, "including ski development, avalanche forecasting, montane ecology and climate change" (Ferguson, 1999, p.220).

Spatial Variability

Spatial variability in the seasonal snow cover's many properties and scales has been noted. Dexter (1986) tested the observations of previous researchers involving elevational and aspect controls on depth, snow-water equivalent (SWE), temperature, temperature gradient, and density. During one field season in the Colorado Front Range, Dexter noted that high elevation, north-facing slopes remained coldest for the duration of the season. The steepest temperature gradients occurred in the early portion of the snow season, during cold air and shallow snow conditions. For the majority of the season, the low elevations held the steepest temperature gradients, likely due to shallower snow depths at these locations.

Birkeland et al. (1995) examined spatial variation in snow resistance on single slopes. They found that while snow depth and average temperature gradient were important in determining snow resistance, these variables were in turn controlled by complex relationships with wind, vegetation, and microtopography.

Variability in SWE was shown to change with elevation (Ingersoll et al., 1996), with high elevation sites showing dramatically more spatial variation than lower, forested sites. Based on their results, they suggest dividing the basin into zones of similar terrain, thereby enabling different sampling schemes based on the anticipated level of variation in the snowcover for each zone.

Elder et al. (1998) used a regression tree analysis to estimate the spatial variability of SWE in an alpine basin. They found deepest snowpacks on high elevation, north-facing slopes. Additionally, sites receiving highest net radiation input had lower snow depths. They also found a slope threshold at around 37° that separated higher and lower accumulation zones.

Conway and Wilbour (1999) addressed temporal variation in snow stability with their stability index model by including the rate of snow accumulation. It was recognized, however, that complex interactions between wind and topography made accurate accumulation predictions difficult.

Birkeland (2001) considered spatial variation in snow stability over the mesoscale, comparing terrain, snowpack, strength, and stability data. Results were mixed, showing different relationships between sampling days, which was attributed to differing weather patterns. Observed spatial patterns at the regional scale were confounded by microscale variations in snowcover properties, attributed to terrain fluctuations. However, some generalizations were possible, indicating a differing degree of predictability based on the appropriate scale of observation.

The research cited above represents most of the efforts addressing spatial variation in various snow properties. In all cases, relationship with or dependence on topography was addressed or noted. While Dexter (1986) is the only study specifically addressing temperature gradients, it can be inferred that since topographic effects are important influences on the spatial variation in snow properties, spatial patterns of snow temperature gradients must also be influenced by topography to some degree.

Scale Issues

Issues of scale are inherent in studying snow processes. Small areas studied in detail may exhibit extreme heterogeneity, while larger areas studied in less detail may allow for identification of patterns and homogeneity (Blöschl, 1999). A more accurate understanding of the processes of interest, however, would integrate several scales of observation, including the linkages between the scales (Hägeli and McClung, 2000). To study the geography of snowpack temperature gradients within a given basin, the scale of observation must be of sufficient detail or resolution to measure differences in inputs (i.e. elevation, aspect, slope, or snow depth) yet of low enough resolution to exclude microscale effects such as grain size and type differences, small variations in water flow paths, density horizons, and differences in porosity. In other words, topographic effects must be addressed explicitly, while heterogeneity in the microscale must be implicit in the size of the observational unit chosen (Blöschl et al, 1991).

The relationship between microscale snow structure, macroscale climatic factors, and mesoscale avalanche formation has been examined (Armstrong, 1977; Jamieson and Johnston, 2001). They observed the importance of including microscale snow information in response to observations of nonlinear interactions between weather patterns and avalanche formation, with the size of avalanche showing little correlation to the size of precipitation event.

Temperature gradient data is categorized as Class II (snowpack) data, of intermediate level entropy between Class III (meteorologic data) and Class I (snow stability data) (McClung and Schaerer, 1993). Therefore, temperature gradient data, which are point data, could only be applied at one scale of observation and analysis (the scale at which they are measured) unless a scaling factor is applied (Blöschl, 1999; Hägeli and McClung, 2000). Topographic data, however, spans several scale orders, and thus holds potential as a scaling factor, if a relationship between temperature gradients and topography can be known.

METHODS

In order to assess spatial variability in snow temperature gradients, some measure of that variability had to be obtained. This required a study site with a wide variety of potential sample locations, as well as easy, consistent access. Additionally, a method of sampling was needed that enabled rapid data collection and portability of measuring devices from site to site. Once the spatial dataset was obtained, correlation and regression procedures were applied. Finally, weather data collected within the study area were qualitatively analyzed to explain some of the regression relationships developed.

Study Area

The study area used for this project is a mountain basin referred to as Wolverine Basin, in the Bridger Mountains of southwest Montana (Figure 1). The basin is located roughly one kilometer north of Bridger Bowl Ski Area, 15 miles north of Bozeman. This study area was chosen for several reasons, but of first consideration was ease and safety of access. The Bridger Bowl Ski Patrol provided ski lift access and authorized crossing the northern ski area boundary. This accessibility facilitated installation of the weather instrumentation, promoted safety for the data collectors, and allowed a higher frequency of collection dates than would be possible with a more remote site. Second, the study area provided a variety of slopes, aspects, and elevations as required for this project. Third, other researchers were using this area and adjacent sites, providing both a margin of safety as well as opportunities for collaboration in data collection efforts.

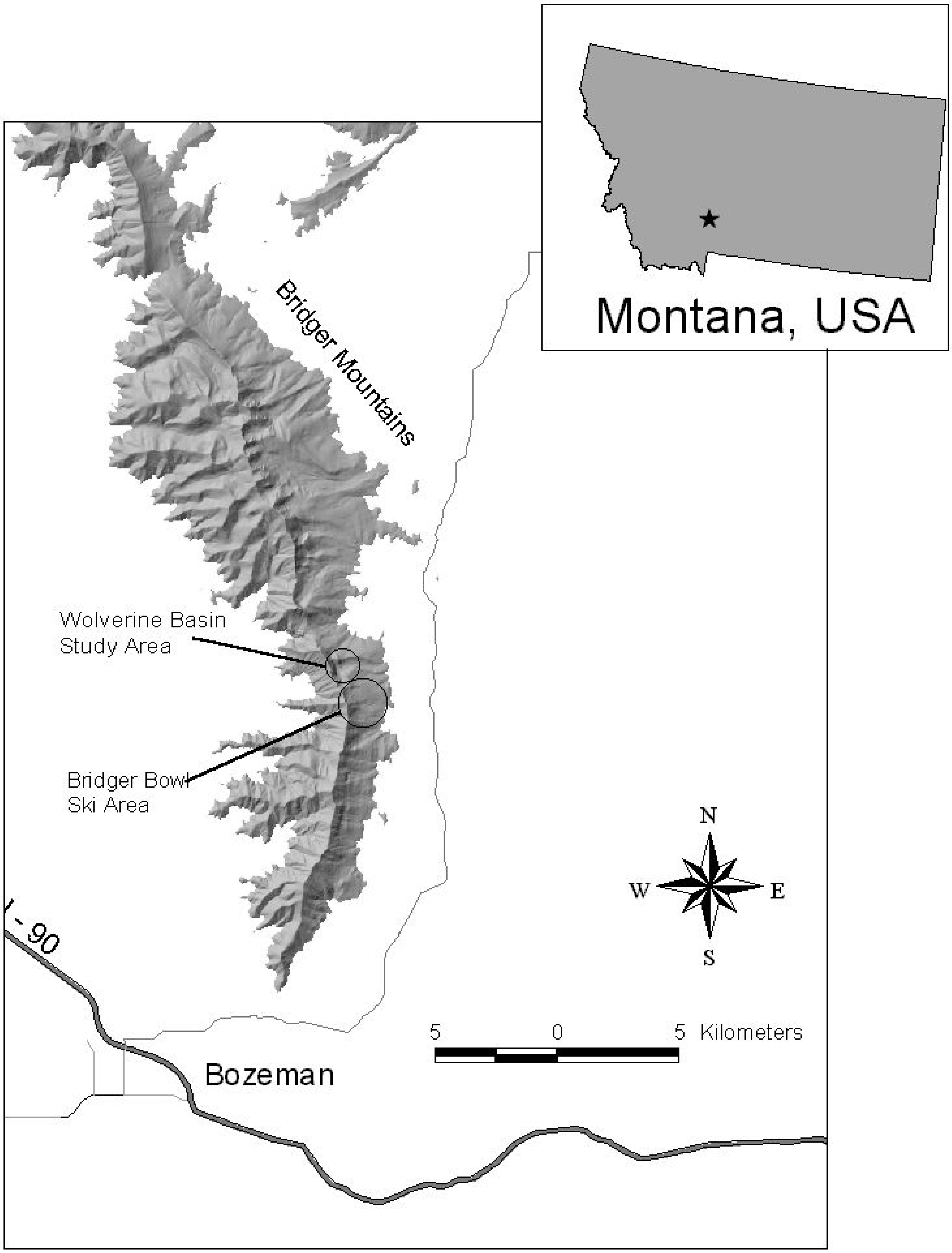

Figure 1: Wolverine Basin, in the Bridger Mountain Range, Southwest Montana, USA.

The Bridger Mountains are in an intermountain snow climate (Mock and Birkeland, 2000), often exhibiting characteristics of both continental and maritime snow climates. Lowest air temperatures generally occur December through February, and maximum precipitation and snowfall typically occur in February and March (Table 1).

Table 1: Bridger Bowl Ski Area weather data summary, 1968-1995 (WAN, 1995)

	Maximum Daily Air Temperature (°C)	Minimum Daily Air Temperature (°C)	Average Daily Air Temperature (°C)	Average Monthly Snowfall (m)	Average Monthly Precipitation (mm)
November	0.0	-7.4	-3.8	1.22	107.4
December	-4.9	-19.1	-12.0	2.68	168.3
January	-3.2	-10.9	-7.1	2.88	178.9
February	-1.1	-10.0	-5.7	2.99	204.6
March	1.5	-7.9	-3.2	3.50	252.9
Total				13.26	912.1

Instrumentation

Probe Design

I designed the Snow Temperature Profile Probe (STPP) to enable rapid sampling of a large number of temperature profiles with minimal site disturbance. A direct digital interface was desired to speed up sampling and to ease data transfer and processing. The final design was lightweight and field portable, and was interfaced with a handheld, personal computer.

The probe was 2.3 m long, constructed of clear polycarbonate plastic, with an aluminum cutting tip for snowpack penetration. Direct-to-digital temperature-sensing chips (Dallas Semiconductor DS18s20) extend through the plastic at 10cm intervals, beginning at 10cm from the ground surface, and continuing up the probe to 2 meters from the cutting tip. The interior of the probe was filled with white foam beads, in order to insulate each sensor from internal temperature conduction by minimizing air circulation and solar input. The chips were wired to a processing unit (Spiderplant Corp., Waltham, MA), which communicates directly with the handheld PC.

Computer Interface

The temperature sensor processing unit required a serial port interface (RS-232) to communicate with any platform compatible with that protocol. For the purposes of this project, I chose a Compaq iPAQ 3650 for field use due to its size and programming versatility. I designed a program in Visual Basic for Applications in MS Excel (Microsoft Corp., Seattle, WA) to communicate with the probe device. The program prompted the user for manually measured variables, including site number, snow depth, snow surface temperature, air temperature, and any additional comments. It then commanded the probe unit to sense temperatures, read data from the probe, and wrote the data to a text file. The data text file was then available to import into a spreadsheet for data processing.

Probe Testing and Calibration

The accuracy of the probe was critical to the interpretation and analysis of the field data. To this end, it was necessary to calibrate the probe sensors in two respects: accuracy of the measured temperatures and time required for equilibration. The measurement accuracy had a direct effect on the reliability of the field data, while the equilibration time was necessary for development of the sampling routine.

The STPP was calibrated in an ice bath at 0°C. This was accomplished by the construction of a shallow trough made of PVC drainpipe. The trough was filled with ice water, measured with dial-stem and digital thermometers to be at or very near 0°C. While the trough was being filled, the probe was allowed to equalize to the ambient air temperature outdoors, approximately -3°C. The probe temperatures were continuously logged during equilibration and testing.

Once the trough was filled and the probe equalized to air temperature, the probe was inserted in the trough, with the individual sensors immersed in the ice bath. The insertion time was noted. The probe was allowed to remain in the bath for a full 20 minutes.

I analyzed the log file for equilibration temperatures and time to equilibration. The final, stable temperatures were noted, so that they may be used to adjust the readings from the field datasets. It was determined that the sensors equilibrated to within 0.1°C of the final stabilization temperature within 3 minutes of immersion (Figure 2).

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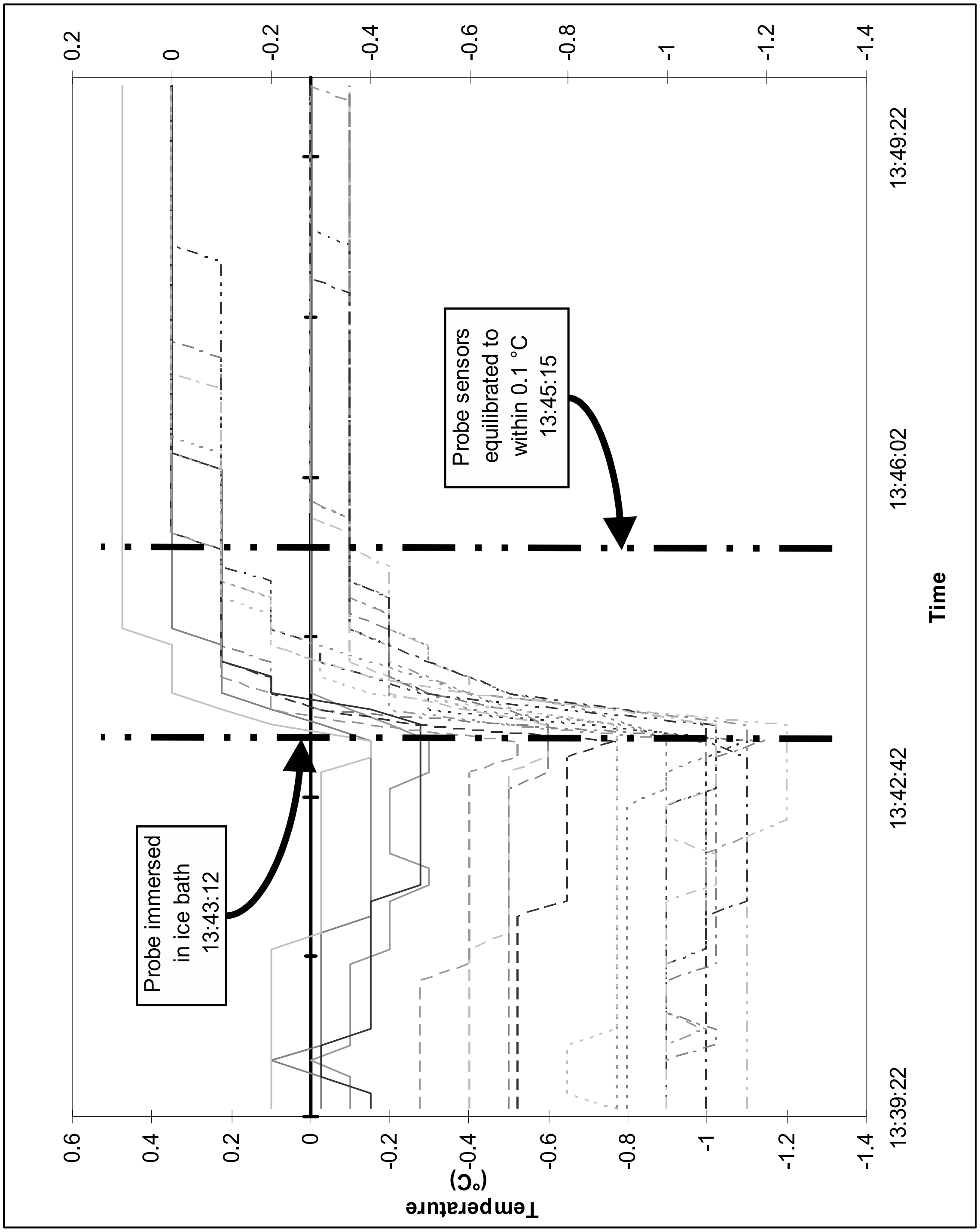

Figure 2: Temperature Probe calibration data. Each plot line represents a single temperature sensor.

Use of the Probe

The point sampling routine using the STPP was as follows: First, the probe was inserted into the snowpack perpendicular to the snow surface. It was inserted in this manner in order to permit sampling of a full profile over the widest possible range of snow depths, as well as to sample temperatures along the shortest path to air. Second, while the probe sensors were equilibrating, the user entered manual measurements of snow depth, snow surface temperature, and air temperature. Once sufficient time had elapsed for sensor equilibration, the computer was instructed to log the probe data. The entire routine required about 3-5 minutes to complete for each individual measurement site.

Weather Instrumentation

The weather station used in this project was located in the center of Wolverine Basin, in a low-angle (ca. 2° SE) clearing at an elevation of 2240 meters. This site has been used for weather data collection in the past (Lundy et al, 2000).

The weather station measured wind speed, snow surface temperature, snow depth, reflected shortwave radiation, and a full-depth snow temperature profile. The data was logged using a Campbell Scientific CR10X Datalogger (Campbell Scientific Corp., Logan, UT). The station collected data at 5-minute intervals, and output averages once per hour. This sampling rate effectively covered the sample dates of this study, enabling an analysis of weather phenomena as related to snow temperature gradients.

Field Data Collection

Sampling Design

Of concern in the design of a sampling routine was the number and location of sampling points, frequency of repetition, order and efficiency of collection, and safety of field personnel. These issues were addressed in the design phase of the project.

A large sample size representing a variety of topographic variables was desired for statistical purposes, as indicated by the results of a pilot study. Additionally, the sample point distribution needed to approximate the distribution of available sites in the field area. This was assessed by comparing the distribution of terrain characteristics in the set of sample points to the distribution of terrain characteristics in the basin.

Safety was of primary concern in the sampling design, as there were numerous avalanche slopes within the study area. Sites which had slope values over 30 degrees or those which possessed a high exposure to avalanche danger (e.g. in a confined runout path) were omitted from sample consideration.

The sampling route (Figure 3) was designed for once weekly repetition. Data from all sample points was collected each field day. This approach attempted to maintain a continuity of data collection throughout the season as well as sample the full range of topographic variables on a single day. Thirty points were selected in the effort to balance all of the above factors, and their positions were recorded by a differentially corrected Global Positioning System (GPS) unit. Topographic attributes for the sample points (Table 2) were calculated from a USGS 30m DEM, using ArcView GIS software with the Spatial Analyst extension (ESRI, Redlands, CA). *Profile* was the profile curvature, or

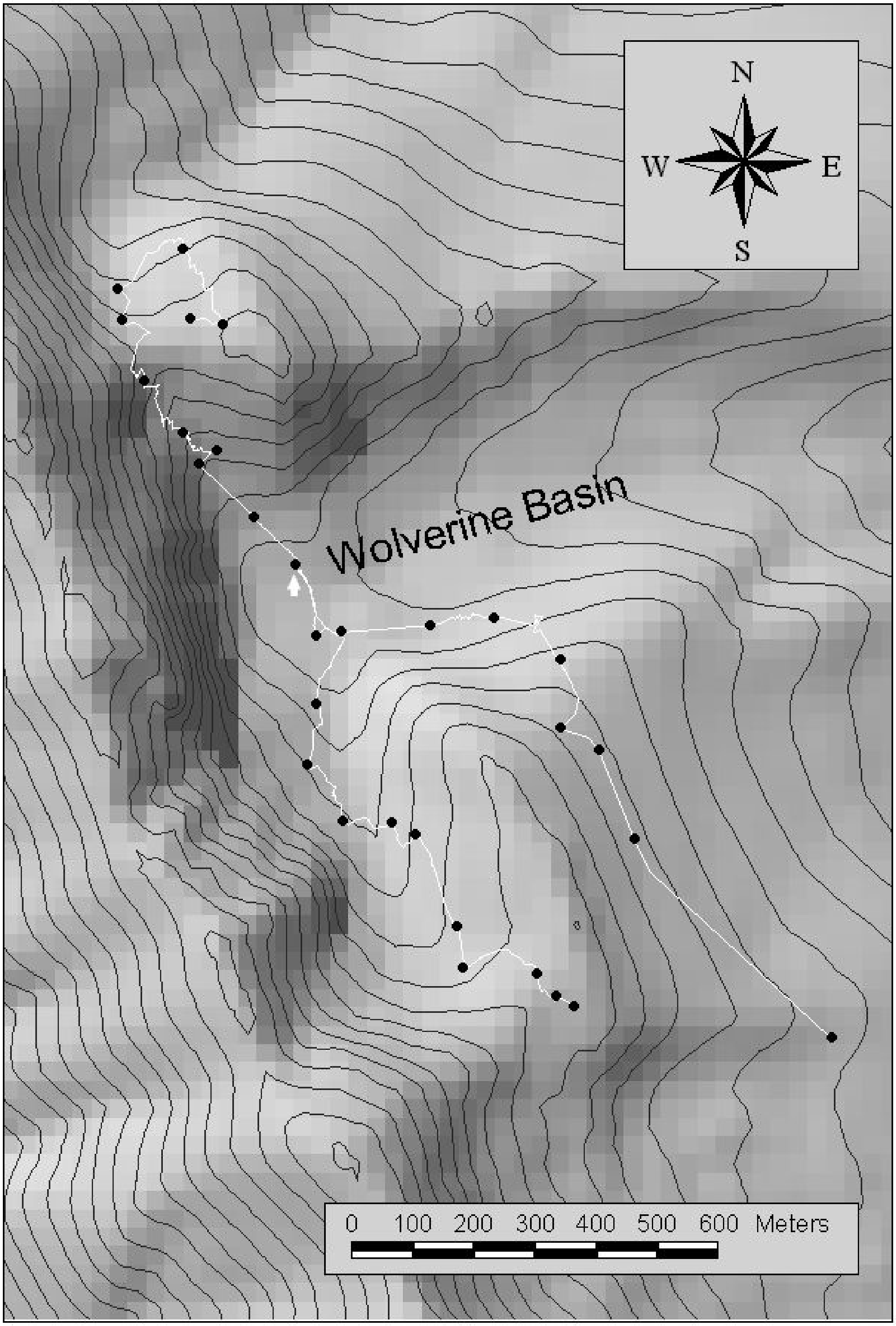

Figure 3: Study area and sample route. Black dots represent sample point locations.

rate of change in *Slope*, showing the terrain "sharpness" in the vertical dimension. *Planform* was the planform curvature, or rate of change in *Aspect*, showing the exposure of a site in planform. *Aspect* was also divided into sine, cosine, and degrees from north. These aspect derivatives potentially aided in interpretation of the regression models. The existence of Aspect in a regression would suggest its importance, but due to the circular nature of aspect data, it was difficult to interpret in a linear relationship. Degrees from north or cosine of aspect were more easily interpreted when utilized in a linear regression relationship.

Interaction variables are two variables serving to amplify the effects of each other. Regression models in which an interaction variable was included represented a sampling day where the influence of terrain variables was more complex than a simple linear combination of variable effects.

Canopy densities were collected manually, using a spherical densiometer (Forest Densiometers). A percentage value for open canopy was used in order to facilitate interpretation of the canopy/solar interaction variable in the analysis. Cumulative global solar radiation input was the modeled cumulative sum of direct and reflected shortwave solar input for each grid element, for the interval beginning on 11/28/01 and ending the day before each sample day. This parameter was modeled from the DEM using the Solar Analyst extension for ArcView (HEMI, Los Alamos, NM).

Data Analysis

Diurnal fluctuations in air temperature influenced shallow snow temperatures, and these changes were unavoidable in the temperature profiles sampled, due to the full day period required to collect a full dataset. To eliminate this effect, only temperatures deeper than 30cm were used for temperature gradient calculations, as temperatures deeper than 30cm below the snow surface generally show little daily fluctuation (Armstrong, 1985; Birkeland et al., 1998). Temperature gradients were calculated for each 10cm interval measured, and average (*AvgTG*) and maximum (*MaxTG*) 10cm gradients were calculated for each profile.

A temperature gradient for the bottom 10cm interval was initially calculated using an assumed ground temperature of 0°C (the STTP does not record ground temperatures). However, preliminary assessment of the temperature data showed some significant outliers, all due to the gradient calculated for the 0 – 10cm interval. Field investigation of one of these locations revealed a ground temperature much lower than the assumed 0°C. In light of this evidence, I removed the assumed ground temperatures from all profiles. Thus, the temperature intervals considered in this study are between 10cm above the ground surface and 30cm below the snow surface. This constraint on usable temperature readings could have had an important effect especially in the early season datasets, where shallow snow depths limited the available data to a few intervals or none at all for some profiles.

Regression Modeling

Model Development

Predictor variables (Table 2) used in the development of the regression models were tested for correlation using a correlation matrix (Table 3). Only variables that exhibited a low correlation (Pearson Correlation Coefficient < 0.5) were used in the same regression model. Pairwise scatter plots of individual predictor variables versus each response variable were examined to look for possible necessary transformations.

Table 2: Topographic attributes of the sample points: Variable codes, variable descriptions, and summary statistics. N = 30.

Variable	Description	Minimum	Maximum	Mean
Elevation	Elevation (m)	2230	2400	2318
Slope	Slope angle (degrees)	4	39	20.18
Profile	Profile curvature (Rate of change in Slope)	0	22	9.16
Aspect	Aspect (degrees)	2	354	169.3
Planform	Planform curvature (Rate of change in Aspect)	1	80	42.25
DfN	Degrees from north (degrees)	2	172	67.19
Sine	Sine of aspect	-0.99	0.96	-0.11
Cosine	Cosine of aspect	-0.98	0.99	-0.05
SlpSine	Slope X sine aspect	-36.03	20.24	-3.75
SlpCos	Slope X cosine aspect	-23.88	33.63	-0.70
SlpDfN	Slope X degrees from north	34	4472	1351
OCanopy	Open forest canopy (%)	0	57.1	10.58
Solar	Cumulative global solar input (Wm^{-2})	4084	241341	45050
CanSolar	OCanopy X Solar	2356	240617	40832

Table 3: Correlation matrix of Pearson's correlation coefficients for predictor variables. Bold values indicate coefficients of 0.5 or greater. N = 30.

	Elevation	Slope	Profile	Planform	Aspect	DfN	Sine	Cosine	SlpSine	SlpCos	SlpDfN	OCanopy	Solar	CanSolar	Date
Elevation	1	0.19	0.22	-0.07	0.20	0.02	-0.25	0.16	-0.21	0.25	0.08	0.16	0.03	0.04	-0.02
Slope		1	0.58	-0.22	-0.31	-0.01	-0.26	0.05	-0.33	0.23	**0.57**	-0.01	-0.03	-0.04	0.00
Profile			1	0.27	-0.23	-0.19	-0.30	0.27	-0.42	0.47	0.14	0.08	-0.05	-0.04	-0.01
Planform				1	-0.14	-0.31	**0.51**	0.15	0.40	0.09	-0.28	-0.16	-0.05	-0.07	-0.01
Aspect					1	-0.04	-0.22	0.24	-0.13	0.14	-0.16	**-0.51**	0.00	-0.05	0.00
DfN						1	-0.21	-0.15	-0.15	-0.02	**0.74**	0.26	0.21	0.24	-0.01
Sine							1	-0.20	**0.93**	-0.27	-0.27	-0.09	-0.02	-0.03	-0.01
Cosine								1	-0.29	**0.91**	0.01	-0.04	-0.03	-0.03	0.00
SlpSine									1	-0.38	-0.31	-0.10	-0.01	-0.02	0.00
SlpCos										1	0.15	0.00	0.01	0.01	0.00
SlpDfN											1	0.14	0.16	0.17	0.00
OCanopy												1	0.09	0.20	0.00
Solar													1	**0.99**	**0.89**
CanSolar														1	**0.85**
Date															1

Stepwise, least-squares regression was used to build the regression models. Regressions were built for pooled data, as well as for each sample day, using *AvgTG* and *MaxTG* as the response variables. A p-value of 0.15 was required for inclusion of a variable, in order to compensate for the small size of the dataset. Although this sacrificed confidence in the predictive ability of the models, it increased freedom in exploration of the variable relationships to the response.

Sample Point Time Series Grouping

Time series plots of MaxTG and AvgTG for each individual sample point were created, in an effort to explore for more relationships. Each plot contained up to nine values measured at that sample location on subsequent sampling days. The patterns of the time series graphs were compared, and groups of plots were constructed based on the shapes of the graphs. The groups of plots were then mapped in order to observe any potential spatial clustering in the groups. The terrain data for each sample point was examined to see if any of the predictor variables exhibited values common to all points in the group. This analysis provided the opportunity to find general geographic patterns, such as locational bias within the basin, or sites oriented preferentially to a particular storm direction, that might not be exposed by the regression analysis.

Evaluation of Weather Parameters

Four-day moving averages of weather parameters (air temperature, snow surface temperature, snow depth, and reflected shortwave) recorded at the weather station in the study area, were used to explore relationships between weather events and average and maximum temperature gradients measured at the weather station. The four-day moving averages were chosen to represent a cumulative effect of weather factors on the snowpack, as short interval fluctuations can be effectively buffered by the insulating capacities of the snowpack (Armstrong and Williams, 1986). The daily upper quartile of reflected shortwave radiation (the 75th percentile of all reflected shortwave measurements for each day) was used to represent maximum solar input. While not a direct measure of incoming solar radiation, short-term fluctuations were taken to represent intervals of cloudy and non-cloudy periods. Qualitative correlations aided explanation of the individual regression relationships derived for each dataset.

RESULTS AND DISCUSSION

The correlation and regression results showed significant correlations of temperature gradients with topographic variables, supporting Hypothesis #1. The date of season was also significantly correlated to the pooled average temperature gradient data, supporting Hypothesis #2. However, the regression relationships developed did not explain the majority of the variability in either the average or maximum temperature gradient data. A qualitative assessment of weather and snow temperature data collected at the Wolverine Basin weather station was revealing of potential dynamic weather controls on snow temperature gradients that could explain more of the variability observed in the data.

Weather Context of Sample Days

Sample days 1-4 were in the early part of the season, when snow depths were less than 1 meter (Figure 4). In these conditions, the average and maximum deep temperature gradients show strong sensitivity to air or snow surface temperature. Later in the season, when snow depths were greater, fluctuations in average temperature gradient at the weather station were more muted, despite large variation in air temperatures, which suggests a decreased sensitivity to air temperature. In addition, in the latter part of the season, fluctuations in the maximum deep temperature gradients seem to show increased sensitivity following periods of settlement (decreasing snow depth).

A general increase in reflected shortwave energy was seen as the season progresses, as expected with an increase in sun angle and day length (Figure 5). More solar input would serve to increase snow temperatures, and reduce average temperature gradients, as was evidenced by the general decrease in the average temperature gradients at the weather station throughout the season.

Pairwise Variable Correlations

The results of the pairwise variable correlations for *AvgTG* and *MaxTG* show a few significant relationships and some pattern in the type of predictors that were significant as the season progresses (Tables 4 and 5). Both research hypotheses were supported by the correlations observed.

Pooled Data

In the pooled *AvgTG* data, temperature gradients were negatively correlated to solar and date variables, suggesting that temperature gradients generally decreased throughout the season and with greater solar input. This agreed with previous literature (Dexter, 1986). Notably, the elevation and aspect variables showed no significant correlation to the pooled average deep temperature gradients, as noted previously by Dexter, (1986) and McClung and Schaerer (1993). The pooled *MaxTG* data shows no significant correlations, suggesting perhaps that the controlling mechanisms for maximum deep temperature gradients operate on a time scale shorter than the season of

Table 4: Pairwise Pearson correlation coefficients for Average deep temperature gradient (AvgTG). Bold values indicate significant correlations

Response		Slope		Aspect					Interactions			Solar/Vegetation			
	Elevation	Slope	Profile	Planform	Aspect	DfN	Sine	Cosine	SlpSine	SlpCos	SlpDfN	OCanopy	Solar	CanSolar	Date
Pooled Data															
All Days	-0.08	-0.10	-0.07	-0.03	0.06	-0.03	0.00	0.02	0.02	0.01	-0.08	-0.06	**-0.48**	**-0.47**	**-0.56**
p-value	*0.19*	*0.11*	*0.27*	*0.59*	*0.33*	*0.69*	*0.97*	*0.80*	*0.76*	*0.84*	*0.21*	*0.35*	*0.00*	*0.00*	*0.00*
By Sample Day															
12/4/01	-0.26	**-0.59**	**-0.47**	0.05	-0.05	0.26	0.27	-0.10	0.30	-0.08	-0.07	-0.10	0.33	0.29	0.00
p-value	*0.30*	*0.01*	*0.05*	*0.84*	*0.86*	*0.30*	*0.27*	*0.68*	*0.23*	*0.74*	*0.78*	*0.70*	*0.18*	*0.24*	*1.00*
12/9/01	-0.22	-0.04	0.02	-0.03	0.19	-0.23	-0.01	0.05	-0.11	0.04	-0.10	-0.08	0.06	0.00	0.00
p-value	*0.32*	*0.84*	*0.93*	*0.90*	*0.41*	*0.30*	*0.95*	*0.82*	*0.64*	*0.85*	*0.67*	*0.72*	*0.79*	*1.00*	*1.00*
12/20/02	-0.17	-0.21	-0.34	-0.27	0.30	**0.52**	-0.25	-0.02	-0.16	-0.07	0.33	-0.20	0.16	0.11	0.00
p-value	*0.44*	*0.33*	*0.10*	*0.21*	*0.16*	*0.01*	*0.23*	*0.92*	*0.46*	*0.74*	*0.11*	*0.36*	*0.44*	*0.62*	*1.00*
1/2/02	-0.18	-0.13	0.04	0.02	0.31	0.28	-0.09	0.30	-0.04	0.23	0.25	0.02	**0.45**	**0.40**	0.00
p-value	*0.37*	*0.53*	*0.84*	*0.91*	*0.12*	*0.16*	*0.65*	*0.13*	*0.85*	*0.25*	*0.20*	*0.91*	*0.02*	*0.04*	*1.00*
1/7/02	0.22	-0.29	-0.17	-0.08	-0.03	0.25	-0.17	-0.18	-0.06	-0.12	-0.03	**0.37**	0.32	**0.37**	0.00
p-value	*0.24*	*0.13*	*0.38*	*0.69*	*0.88*	*0.19*	*0.38*	*0.35*	*0.76*	*0.53*	*0.86*	*0.05*	*0.09*	*0.05*	*1.00*
1/14/02	0.15	**-0.44**	-0.15	0.01	**0.38**	-0.14	-0.02	0.09	0.13	-0.04	**-0.35**	-0.09	0.03	-0.01	0.00
p-value	*0.44*	*0.02*	*0.44*	*0.97*	*0.04*	*0.46*	*0.94*	*0.66*	*0.50*	*0.85*	*0.06*	*0.63*	*0.88*	*0.97*	*1.00*
2/4/02	-0.11	-0.05	-0.16	-0.05	0.28	-0.21	-0.02	**0.47**	0.00	**0.39**	-0.18	**-0.46**	**-0.43**	**-0.50**	0.00
p-value	*0.56*	*0.79*	*0.41*	*0.78*	*0.14*	*0.28*	*0.90*	*0.01*	*0.99*	*0.04*	*0.35*	*0.01*	*0.02*	*0.01*	*1.00*
3/8/02	-0.08	0.12	-0.01	0.03	0.08	-0.07	0.08	-0.05	0.13	0.04	-0.01	**-0.38**	-0.29	**-0.37**	0.00
p-value	*0.68*	*0.53*	*0.96*	*0.89*	*0.68*	*0.73*	*0.68*	*0.81*	*0.50*	*0.84*	*0.95*	*0.04*	*0.12*	*0.05*	*1.00*
4/1/02	-0.16	0.01	0.16	0.03	-0.20	-0.16	0.07	-0.29	0.09	-0.13	-0.21	0.06	-0.07	-0.02	0.00
p-value	*0.40*	*0.96*	*0.41*	*0.87*	*0.29*	*0.42*	*0.70*	*0.12*	*0.65*	*0.50*	*0.27*	*0.77*	*0.74*	*0.91*	*1.00*

Table 5: Pairwise Pearson Correlation coefficients for maximum deep temperature gradient (MaxTG). Bold values indicate significant correlations.

		Slope		Aspect					Interactions			Solar/Vegetation			
Response	Elevation	Slope	Profile	Planform	Aspect	DfN	Sine	Cosine	SlpSine	SlpCos	SlpDfN	OCanopy	Solar	CanSolar	Date
Pooled Data															
All Days	-0.09	-0.02	0.00	0.02	-0.10	-0.09	0.06	-0.06	0.08	-0.04	-0.10	-0.03	-0.06	-0.07	-0.01
p-value	*0.18*	*0.76*	*0.95*	*0.79*	*0.11*	*0.18*	*0.29*	*0.33*	*0.24*	*0.51*	*0.11*	*0.59*	*0.34*	*0.30*	*0.84*
By Sample Day															
12/4/01	-0.26	-0.28	-0.15	0.19	**-0.48**	-0.08	0.34	-0.01	0.29	-0.06	-0.18	0.13	0.06	0.08	0.00
p-value	*0.29*	*0.25*	*0.54*	*0.44*	*0.04*	*0.75*	*0.16*	*0.95*	*0.24*	*0.79*	*0.46*	*0.60*	*0.82*	*0.75*	*1.00*
12/9/01	-0.24	-0.31	-0.22	0.04	-0.02	-0.12	0.16	-0.23	0.05	-0.32	-0.27	0.21	-0.18	-0.10	0.00
p-value	*0.28*	*0.15*	*0.32*	*0.87*	*0.93*	*0.59*	*0.46*	*0.30*	*0.84*	*0.15*	*0.23*	*0.34*	*0.41*	*0.65*	*1.00*
12/20/01	-0.01	0.07	0.00	-0.26	0.23	0.29	-0.20	-0.16	-0.11	-0.09	0.17	**-0.59**	-0.15	-0.25	0.00
p-value	*0.96*	*0.74*	*0.99*	*0.20*	*0.29*	*0.18*	*0.34*	*0.45*	*0.61*	*0.66*	*0.41*	*0.00*	*0.46*	*0.25*	*1.00*
1/2/02	**-0.46**	-0.22	0.01	-0.02	-0.04	0.18	0.01	0.20	0.07	0.14	0.03	0.21	0.11	0.15	0.00
p-value	*0.01*	*0.26*	*0.95*	*0.93*	*0.82*	*0.36*	*0.96*	*0.31*	*0.74*	*0.50*	*0.89*	*0.29*	*0.59*	*0.46*	*1.00*
1/7/02	0.05	0.14	-0.03	-0.11	-0.26	-0.05	-0.14	-0.33	-0.10	-0.32	0.02	0.10	-0.10	-0.08	0.00
p-value	*0.80*	*0.44*	*0.87*	*0.55*	*0.17*	*0.81*	*0.46*	*0.07*	*0.59*	*0.09*	*0.93*	*0.61*	*0.61*	*0.70*	*1.00*
1/14/02	0.13	-0.11	0.04	-0.02	-0.06	0.09	-0.06	-0.10	-0.05	-0.01	-0.06	-0.05	0.08	0.05	0.00
p-value	*0.49*	*0.57*	*0.84*	*0.92*	*0.76*	*0.66*	*0.77*	*0.61*	*0.78*	*0.96*	*0.75*	*0.78*	*0.69*	*0.80*	*1.00*
2/4/02	0.22	0.08	0.08	0.10	-0.09	-0.34	0.07	0.04	0.13	0.11	-0.34	-0.12	**-0.41**	**-0.39**	0.00
p-value	*0.25*	*0.66*	*0.68*	*0.61*	*0.63*	*0.06*	*0.73*	*0.83*	*0.51*	*0.58*	*0.07*	*0.52*	*0.03*	*0.04*	*1.00*
3/8/02	-0.19	0.14	0.05	0.15	0.02	-0.20	0.21	0.09	0.22	0.09	0.00	-0.33	-0.24	-0.32	0.00
p-value	*0.33*	*0.47*	*0.81*	*0.44*	*0.92*	*0.29*	*0.26*	*0.63*	*0.25*	*0.64*	*1.00*	*0.08*	*0.21*	*0.09*	*1.00*
4/1/02	-0.29	-0.09	0.03	0.00	-0.33	-0.13	0.23	-0.33	0.22	-0.21	-0.23	0.18	-0.06	0.02	0.00
p-value	*0.12*	*0.65*	*0.89*	*1.00*	*0.08*	*0.49*	*0.23*	*0.07*	*0.26*	*0.27*	*0.23*	*0.35*	*0.77*	*0.90*	*1.00*

observation for this study, and that none of the predictors examined here were important in that relationship.

Individual Sample Days

The individual sample days showed a more complex response. For the *AvgTG* correlations, *Solar, OCanopy,* and *CanSolar* variables seemed to gain importance as the season progresses, though they were absent on 1/14 and 4/1. Their absence from these two sample days might be due to the preceding period of higher air temperatures in each case, which would have decreased the influence of solar and canopy effects. *Elevation* showed no significant correlation in any of the datasets, likely due to the relatively narrow range of elevations sampled (2230-2400m). *AvgTG* was negatively correlated to *Slope* and *Profile* on 12/4 and *Slope* was again correlated on 1/14, but *Slope* and *Profile* were otherwise uncorrelated. The aspect and interaction variables likewise showed infrequent correlations, although on 1/14 larger temperature gradients were observed on south and west aspects. These results insinuate that other, non-terrain factors should be examined in addition to the terrain factors included here.

Of all nine individual sample days, *MaxTG* was significantly correlated in only five instances, spread over four different days. Aspect was negatively correlated on 12/4, showing the smallest *MaxTG* values on south-facing and west-facing slopes. On 12/20, MaxTG was negatively correlated to *OCanopy*, indicating that maximum gradients decrease with increasing canopy cover. *Elevation* was negatively correlated on 1/2, pointing to lower temperature gradients at higher elevations. Negative correlations also exist with *Solar* and *CanSolar* on 2/4, indicating that solar input resulting from lower canopy density reduces the temperature gradient. Maximum gradients on that day were lowest at locations with high solar input and low canopy cover, while largest maximum gradients were observed in areas with forest cover and less solar input, where lowest air temperatures would be expected.

Regression Modeling

The results of the stepwise, least squares, multiple regressions were generally similar to the correlation results above. However, linear combinations of multiple terrain variables showed more significant relationships to the temperature gradient data than did the individual correlations (Tables 6 and 7).

Pooled Data

For the pooled *AvgTG* data, a significant regression was generated for using *Slope* and *Date* (R^2 = 0.32). *Date* had a negative coefficient, showing a decrease in average deep temperature gradients as the season progressed, supporting Hypothesis #2. This was confirmed as well by the average temperature gradient data collected at the weather station in Wolverine Basin. The negative coefficient of *Slope* was interesting, as it indicated that average deep temperature gradients decrease with increasing slope. This result perhaps indicates that cold air was pooling in the bottom of the basin, where the majority of the low slope sites were located.

Table 6: Standardized partial regression coefficients for average deep temperature gradients (AvgTG).

Response	R^2	Elevation	Slope: Slope	Slope: Profile	Aspect: Planform	Aspect: Aspect	Aspect: DfN	Aspect: Sine	Aspect: Cosine	Interactions: SlpSine	Interactions: SlpCos	Interactions: SlpDfN	Solar/Vegetation: OCanopy	Solar/Vegetation: Solar	Solar/Vegetation: CanSolar	Date
Pooled Data																
All Days	0.32		-0.10													-0.56
p-value			*0.06*													*0.00*
By Sample Day																
12/4/01	0.35		-0.59													
p-value			*0.01*													
12/9/01	N/R															
p-value																
12/20/01	0.39						0.86								-0.49	
p-value							*0.00*								*0.05*	
1/2/02	0.53	-0.45				0.34			0.31					0.56		
p-value		*0.01*				*0.04*			*0.06*					*0.00*		
1/7/02	0.14														0.37	
p-value															*0.05*	
1/14/02	0.26		-0.36			0.27										
p-value			*0.05*			*0.14*										
2/4/02	0.62			-0.51							0.65				-0.56	
p-value				*0.00*							*0.00*				*0.00*	
3/8/02	0.15												-0.38			
p-value													*0.04*			
4/1/02	0.09								-0.29							
p-value									*0.12*							

Table 7: Standardized partial regression coefficients for maximum deep temperature gradients (MaxTG).

Response	R^2	Elevation	Slope: Slope	Slope: Profile	Aspect: Planform	Aspect: Aspect	Aspect: DfN	Aspect: Sine	Aspect: Cosine	Interactions: SlpSine	Interactions: SlpCos	Interactions: SlpDfN	Solar/Vegetation: OCanopy	Solar/Vegetation: Solar	Solar/Vegetation: CanSolar	Date
Pooled Data																
All Days	0.02					-0.12						-0.12				
p-value						*0.08*						*0.07*				
By Sample Day																
12/4/01	0.37		-0.38			-0.55										
p-value			*0.09*			*0.02*										
12/9/01	0.10										-0.32					
p-value											*0.15*					
12/20/01	0.68						0.68		-0.32				-0.61	-0.43		
p-value							*0.00*		*0.03*				*0.00*	*0.05*		
1/2/02	0.39	-0.60							0.31						0.31	
p-value		*0.00*							*0.07*						*0.08*	
1/7/02	0.11								-0.33							
p-value									*0.08*							
1/14/02	N/R															
p-value																
2/4/02	0.25	0.29												-0.46		
p-value		*0.10*												*0.01*		
3/8/02	0.11												-0.32			
p-value													*0.08*			
4/1/02	0.11								-0.34							
p-value									*0.07*							

The regression relationship obtained for the pooled *MaxTG* data has poor explanatory capability (R^2 of 0.02), indicating that spatial patterns of *MaxTG* change on a time scale shorter than that spanning the data collection season. This was reinforced by the notable exclusion of the *Date* variable from the pooled regression. A look at the weather station data (Figure 2, page 41) shows that the maximum temperature gradient varies about a mean of 0.73 °C/cm, with no decline in the mean during the measurement period. While the variability about the mean through the season was of interest for the individual sample day regressions, the seasonal trend of the maximum temperature gradients was important for the analysis of the pooled data. Since the trend in the maximum temperature gradient data was nearly flat over the entire data collection period, no relationship was evident in the regression. If data had been collected past the isothermal date, a falloff in *MaxTG* would likely be evident, and perhaps a significant relationship with *Date* would have been observed.

It appears, however, that aspect-related variables and canopy density do have some relationship to the spatial variability of maximum deep temperature gradients on the seasonal scale, as evidenced by the inclusion of *Aspect* and *SlpDfN* in the pooled regression model. Aspect provides a significant energy balance control on snow temperatures, while the interaction term indicates that the smallest maximum gradients were found on low-angle, south-facing slopes. This is in direct contrast to the results of the pooled *AvgTG* regression, indicating that the patterns of the maximum temperature gradients do not necessarily reflect the patterns of the average gradients over the course of the entire season.

Individual Sample Days

Separate regression models for each sample day varied in their ability to explain variability in *AvgTG*, with R^2 values between 0.0 (no models created) and 0.62. The pattern of included variables showed no discernable trend according to time of season. Furthermore, coefficients of variables included in several models often were of opposite sign on different sample days, indicating that the relationships between temperature gradient and terrain vary through the season, perhaps under the influence of more dynamic factors.

Elevation was notably absent from the majority of models, likely due to the limited range of elevations represented. *AvgTG* exhibits a strong negative dependency on *Slope* on 12/4 and on 1/14, indicating highest average temperature gradients on lower-angle slopes. This could be due to sampling bias related to the relative topographic position of low-angle slopes in the study area, most of which are located on areas exposed to wind with low snow accumulation, or in the bottom of the basin where cold air would subside and pool during calm conditions.

Aspect variables were difficult to assess, as the circular nature of the data makes interpretation in a linear relationship difficult. However, the significant correlations with *Aspect* on 1/2 and 1/14 were meaningful in that they demonstrate some degree of temperature gradient dependency on aspect. *Cosine* was represented in regressions for 1/2 and 4/1, *DfN* was included on 12/20, and *Sine* was not present in any regressions, demonstrating that average temperature gradients were sensitive to the north/south orientation of a site, represented by *DfN* and *Cosine*, but not the east/west orientation represented by *Sine.* The coefficient of *Cosine* changed sign from positive on 1/2 to negative on 4/1, indicating that maximum average gradients were found on north-facing slopes on 1/2, and on south-facing slopes on 4/1. This is potentially explained by the difference in air temperatures leading up to each of these sample days, as the four-day moving average of air temperature on 1/2 was much lower than that on 4/1.

Solar and vegetation variables were important throughout the season, but in different capacities as represented by the signs of the coefficients. The inclusion of *CanSolar* in three different regressions was interesting, as it highlights the combined influence of solar input and canopy cover. The coefficient on 1/7 was positive, while the other two on 12/20 and 2/4 were negative, which indicates that the nature of the relationship changes during the season, and suggests that controlling factors other than terrain parameters have an influence.

The *MaxTG* regressions for individual datasets showed fluctuation throughout the season, with no discernable progression through types of variables or in the strength of individual variable relationships. R^2 values ranged from 0 to 0.68; thus even the best regression leaves approximately one-third of the variability in the data unexplained. *Elevation* and *Cosine* were included in several models, but not always with the same sign for the coefficients. This would seem to indicate that the terrain variable in these instances, while an important influence, has a different effect on the snow temperature gradients depending on the behavior of other controlling factors. Variables such as *OCanopy*, *Solar*, *Slope* and *Aspect* have the same coefficient sign for all regressions in which they were included, perhaps showing that these variables have a similar effect on snow temperature gradients in each case, independent of any non-terrain controlling factors. The presence of *Cosine* and absence of *Sine* in the regressions insinuates that maximum gradients were more sensitive to the north/south orientation of the sample site than the east/west orientation, as was also the case with the average temperature gradient data. This suggests that maximum temperature gradients are influenced by the larger difference in solar input between north and south-facing slopes, as opposed to the moderate differences in solar input between east-facing and west-facing slopes. Solar and vegetation variables were also frequently important, with negative coefficients indicating that smallest maximum gradients were associated with the largest potential solar input and with increased canopy cover.

In summary, the regression results were generally similar to the correlation results, but the *combined* effects of the terrain variables were more significant than were the individual, pairwise correlation relationships. This is the case for many multivariate relationships with snowpack and snow stability parameters, as found by Birkeland (2001). For example, some variables that do not show strong correlation to *AvgTG* individually were significant in a predictive regression model when included with other variables (e.g. *Slope*). This implies that the common practice of separating terrain components to relate them to snow parameters is perhaps not valid in all circumstances, because in reality the temperature-terrain relationship exhibits much complexity.

Separate regression models for each dataset and both response variables varied in their ability to explain variability in the response, with R^2 values between 0 (no significant models created) and 0.68. The pattern of significant variables showed no seasonal trend. The results implied that the *Elevation*, *Slope*, *Aspect*, *Cosine*, *Solar*, and

OCanopy variables, while important to the spatial variability of temperature gradients as evidenced by the regression models, could only explain a portion of the overall variability in the spatial patterns of snow temperature gradients. Furthermore, coefficients of variables included in several models often were of opposite sign on different days. This would suggest that terrain factors are too static to account for the variability in the temperature gradient data, and that more dynamic factors, such as weather variables, have a significant influence on the spatial patterns of deep snow temperature gradients.

Sample Point Time Series Groupings

The time series plots for each sample point were revealing of different seasonal trends throughout the basin, and provided a valuable perspective from which to examine the dataset (Appendix B). The maps of sample point groupings showed no pronounced geographic pattern for the *MaxTG* response, but did display some aspect-dependency for the *AvgTG* data (Figures 4 and 5). For each of the response variables (*MaxTG* and *AvgTG*), there was a group of points that exhibited a general pattern that showed no correlation to any of the predictor variables (Group 1 for each response). These groups had no common predictor variable values, but did show a similar time series pattern, suggesting that the pattern was derived from basin-wide processes, such as weather patterns. The other groups constructed were all very small in number, containing only 3 to 6 points. Therefore, though some potential correlations were observed, qualitative conclusions drawn from these groups must be viewed with caution.

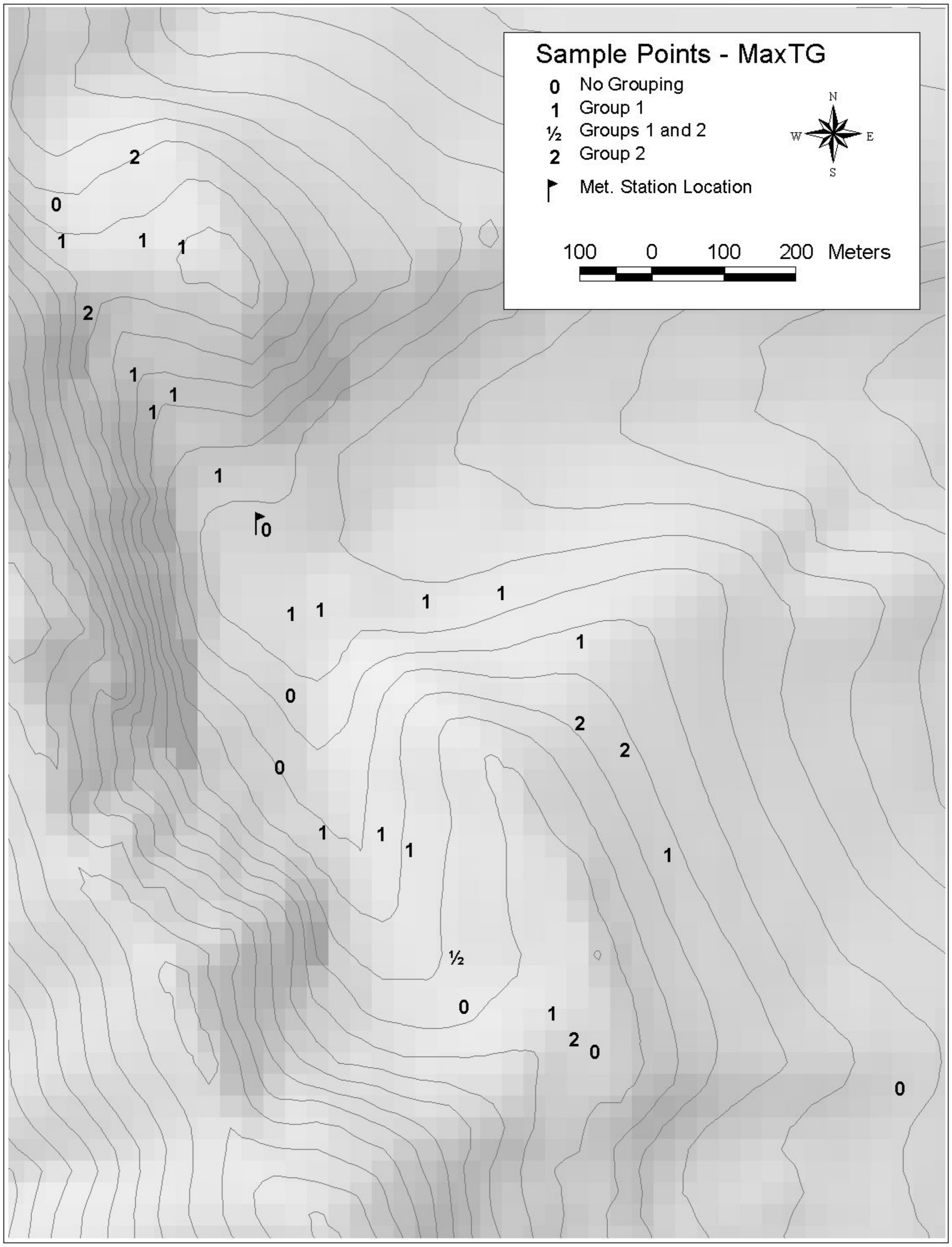

Figure 4: Map of sample point time series groupings for average temperature gradient response.

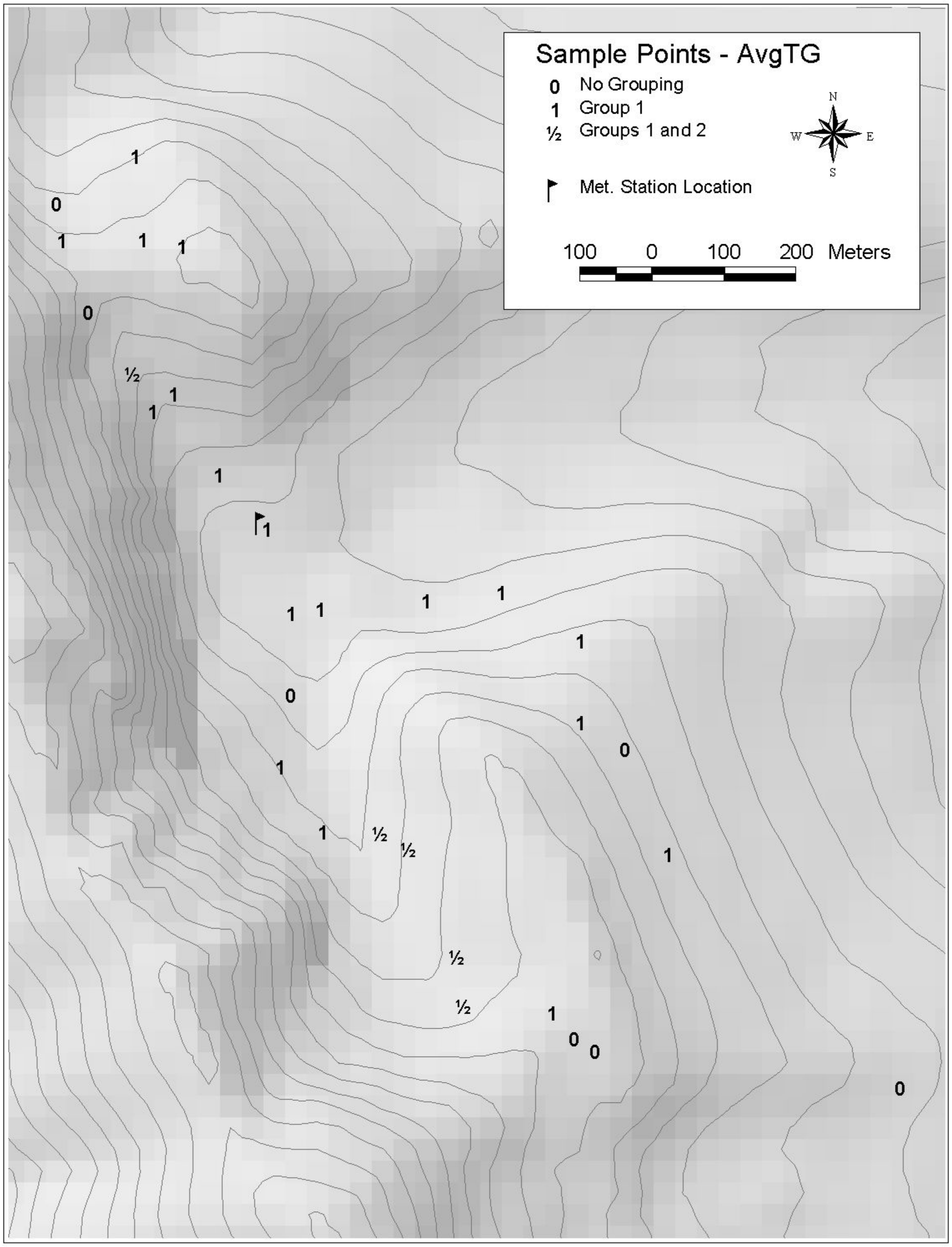

Figure 5: Map of sample point time series groupings for maximum temperature gradient response.

Group 2 for the *MaxTG* response, though showing similar low-variation patterns, did not seem to share any predictor variable characteristics. The predictors available in this study were not able to discriminate this group from the rest of the points in the sample set.

The sample points in Group 2 for the *AvgTG* response shared a west aspect component, as well as moderate profile curvature values. This suggested that the defining characteristic of the time-series graphs in this group, a sharp decrease at sample date 2, was correlated to west-facing slopes with low to moderate slope angle curvature. This feature could be related to afternoon sun exposure, or potentially to weather variable influence in the days prior to the collection of the second sample dataset.

The points in Group 3 of the *AvgTG* series were characterized by the lowest variability in all the *AvgTG* time series plots. The points in this group share a north aspect component, as well as low to moderate canopy coverage. This combination of variable values would minimize solar input and longwave radiation effects of the tree canopy. The north aspect at these sites would serve to keep the energy balance consistent throughout the season, relative to other topographic positions, explaining the low variability in the time series for these points.

The results of the point time series groupings indicate that, at least for the *AvgTG* response, discriminatory statistical techniques, such as cluster analysis or principle components analysis, could be useful, given a larger dataset. With the current dataset, the results lend qualitative support to Hypothesis 1, that some correlation exists between deep temperature gradients and topographic variables. The lack of variable patterns in the *MaxTG* groups suggests that other variable types, perhaps features local to the individual sample sites such as ground cover type or surface roughness, should be explored.

Weather Data

A qualitative assessment of weather data from the remote weather station in Wolverine Basin revealed relationships that aided in explaining the observed spatial variation in snow temperature gradients. Four-day moving averages of snow depth, air temperature, snow surface temperature, daily upper quartile of reflected shortwave radiation, the average deep temperature gradient, and the maximum deep temperature gradient, calculated from data measured at the weather station (Figure 6), reveal trends that offer clues as to why some topographic variables were important predictors on certain sample days and not on others. Weather variables are more dynamic than terrain variables, and as such may change in how they influence temperature gradients in different locations. For example, while aspect affects the solar radiation balance of a site, the orientation of that site with respect to an individual storm or wind event may have a variety of effects on snow accumulation and air temperatures, and hence the magnitude of temperature gradients at that site.

The fluctuations in model structure for *AvgTG* regressions on individual sample days were potentially explained by fluctuations in the measured weather parameters. For example, *Elevation* was included only in the regression on 1/2, during a period of low air temperatures and clear skies (as indicated by the relatively high reflected shortwave radiation), which would have served to enlarge differences in air temperature at different elevations. That same model included two aspect components (*Aspect* and *Cosine*) as well as *Solar*, which demonstrated the influence of the clear sky conditions on the temperature gradients. Periods of warm air temperatures, such as on 1/7, 1/14, and 4/1, seemed to coincide with poor regression results. Warm air, as from warm front advection, rather than solar gain, would have tended to affect the snowpack on all terrain configurations, and therefore a topography-based regression would be expected to perform poorly.

MaxTG generally shows stronger regression relationships in the early season datasets, likely due to the existence of larger temperature gradients in a shallow snowpack. The *MaxTG* regressions for 12/4, 12/9, 12/20, and 1/2 show significant relationships to slope, aspect, and elevation variables, indicating a notable dependency on terrain factors in the early season. Later datasets exhibit generally poor regression models for *MaxTG*, suggesting that terrain factors were inadequate to explain the spatial variability in the temperature gradients later in the snow season, or that maximum temperature gradients in the deeper snowpack of late season show less spatial variability.

A local maximum in reflected shortwave occurred on 1/2, which may explain the inclusion of *Solar* in the *AvgTG* regression model for that sample day. In contrast, the data from 3/8 and 4/1 coincided with local minima in the reflected shortwave curve, and therefore solar input was not affecting the snowpack to a large degree.

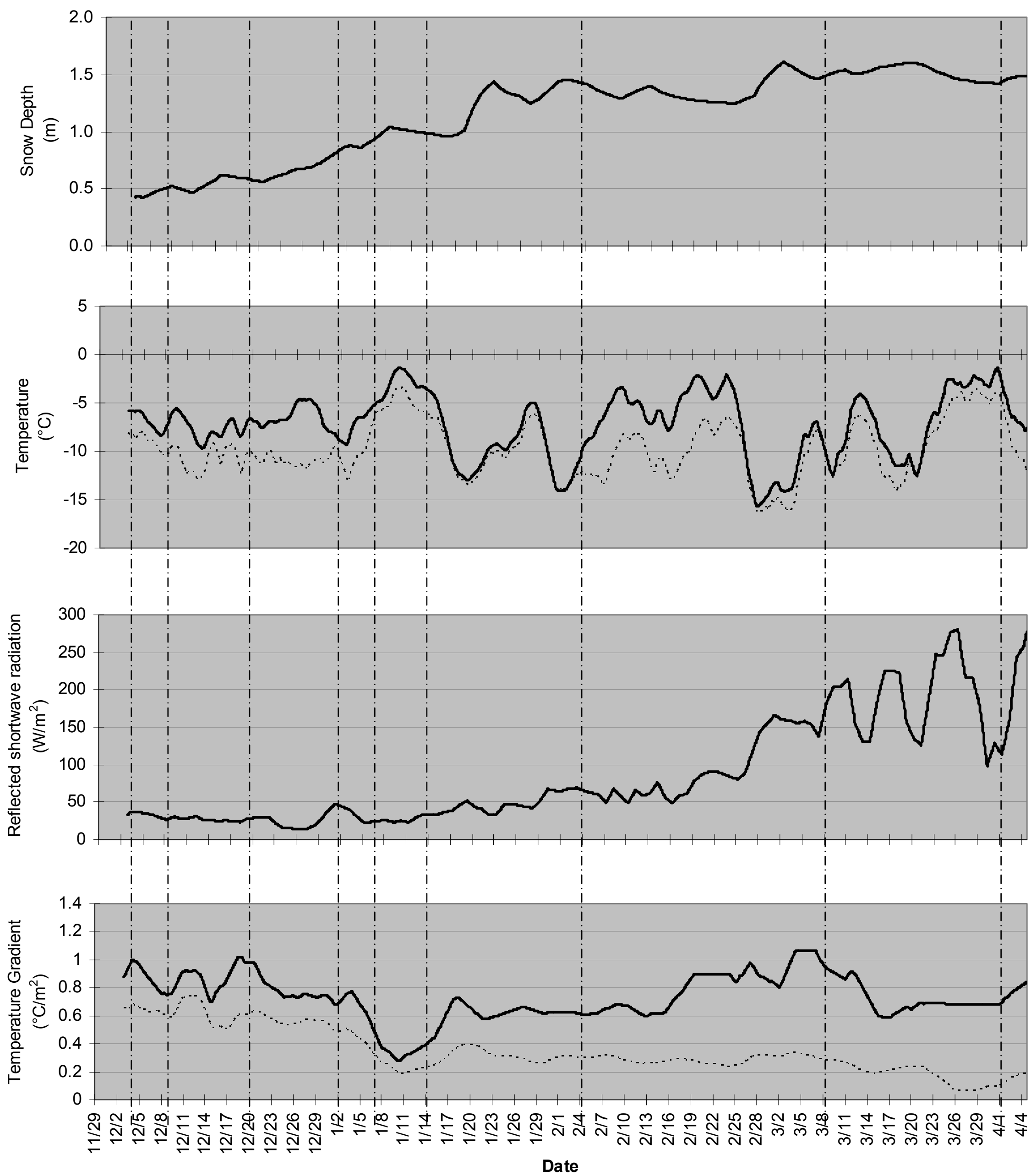

Figure 6: Time series graphs of weather variables measured in Wolverine Basin. Four-day moving averages of hourly output data are shown. Vertical dashed lines represent sample collection dates.

This may explain why *Solar* was not included in the *AvgTG* models for those datasets, and suggests that other variables such as air or snow surface temperature, which show marked fluctuation around these sample days, were responsible for the spatial patterns observed.

OCanopy and *Solar* were included in the *MaxTG* regression for 12/20, where a relative high in reflected shortwave radiation also occurred. The negative coefficients for these variables indicate that for that sample day, the maximum deep temperature gradients existed on slopes with high canopy cover and low solar input. However, *Solar* was again included in the regression on 2/4, where the shortwave data showed no particular deviation. Because this dataset also coincided with a previous period of low air temperatures, *Elevation*, with a positive coefficient, was included as a predictor in the regression, showing increasing temperature gradients with increasing elevation.

The weather data measured in Wolverine Basin did help in the interpretation of the regression models developed with terrain data. The regressions show that some static terrain parameters (e.g. aspect or canopy density) can in some cases represent the variability in the deep snow temperature gradients. In most cases, however, terrain parameters are not dynamic enough to account for variations in the weather variables. Weather is certainly affected by terrain, yet it would appear that terrain was not an adequate surrogate for atmospheric controls at the scale examined in this study.

Inclusion of weather parameters in the regression models, unfortunately, is limited by the non-spatial nature of the weather data. The weather data collected were not distributed spatially and as such represented a single point. Despite the high temporal resolution, these data only provided a qualitative explanation for the component of spatial temperature gradient variation not explained by terrain. An estimation of the spatial variation in time series of weather parameters could be useful in improving understanding of the relationship between terrain, weather, and snowpack temperature profiles.

CONCLUSIONS

This study explored the spatial variability of snow temperature gradients by examining their relationships with topography. Results show a significant correlation of temperature gradients with some topographic variables. The regression relationships developed did not completely explain the variability in the temperature gradient data, however. It is concluded that while the influences of terrain factors are important, more dynamic controls of snow temperature gradients, such as weather, must be assessed.

Temperature gradients showed a significant correlation to some of the topographic attributes of the measurement sites, supporting Hypothesis #1. However, neither the highest average nor maximum temperature gradients were always found on high-elevation, north-facing slopes, contrary to the specific assertions made in Hypothesis #1. A positive relationship with elevation only existed in one of three models that included elevation, indicating that in datasets where elevation was an important factor, highest temperature gradients were more commonly found at lower elevations. This is consistent with the results of Dexter (1986), where it was concluded that the lower snow accumulations at lower elevations contributed to higher temperature gradients at those sites.

Aspect variables showed inconsistent results, with a mixture of positive and negative coefficients, demonstrating that the highest gradients were not always found on the north-facing aspects. Planform curvature, or the "sharpness" of the terrain in planform, was insignificant in any of the correlation or regression relationships.

Slope variables, including slope angle and profile curvature, were occasionally important in several regression models, and always had a negative influence on temperature gradients. This showed the existence of higher temperature gradients on lower-angled terrain, or on smooth slopes that did not change steepness quickly. This result is counterintuitive, as one would expect higher snow accumulations on low-angled or smooth slopes, and a corresponding reduction in temperature gradients, as per Dexter's (1986) results. This could be an artifact of sampling bias, as higher-angle slopes were not sampled, and a full distribution of profile curvature was not obtained in the sample route. It could also be a result of cold air pooling in the bottom of the basin, where the lowest slope angles were found.

Solar and canopy cover variables proved to be very important in the regression models. They exhibited significant correlations with both maximum and average temperature gradients, and throughout the season. These results were consistent with previous studies referencing the effects of these variables on the energy balance of the snowpack (Gray and Male, 1981; McClung and Schaerer, 1993; Cline et al., 1998). The interaction of these two variables was interpreted as the modified level of potential solar input reaching the snow surface. Solar and canopy variables were included in many, but not all, models indicating that early in the season, or during periods of high cloud cover, the importance of these variables was overwhelmed by other influences, such as simple terrain effects or weather-related phenomena.

The overall results suggest that other factors influence snow temperature gradients more than does topography. For some days topographic variables are strongly related to the spatial pattern observed in the temperature gradients, while on other days the temperature gradient patterns are essentially independent of the terrain characteristics.

There was a definite decrease in temperature gradients later in the snow season. This supports Hypothesis #2. The trend was also seen in the snow temperature data recorded at the Wolverine Basin weather station, which shows a downward trend in the average deep temperature gradient throughout the season.

The pooled maximum deep temperature gradients data showed no relationship with date, however, suggesting that the maximum gradient in a temperature profile was more sensitive to factors that change on time scale shorter than the season. In fact, the maximum deep temperature gradients recorded at the weather station displayed an almost perfectly flat trend throughout the season. Had data been collected past the late season isothermal date, I perhaps would have observed a drop in maximum gradient as the isothermal date approached. In that case, a relationship between maximum temperature gradient and date could have been apparent.

Time-series plots of each response variable for each data collection point allowed the construction of point groups, based on the shape of the curves. Exploration of the predictor variables represented by these groups suggested that aspect was a useful discriminatory variable in dividing the dataset. Cluster analysis or principle components analysis would likely be useful if a larger dataset were available.

Qualitative interpretation of the weather parameters measured at the Wolverine Basin weather station provided some insight as to potential controlling factors that may aid in explaining the variability in the temperature gradient data left unexplained by the topographic variables. Air temperature and reflected shortwave radiation seemed particularly relevant, as fluctuations in these variables seemed to correlate with terrain, solar, and canopy variables in the regression models. Early season temperature gradients were particularly sensitive to changes in air temperature, as affected by the shallow snowcover during that period. This sensitivity appeared to decrease as the snow cover accumulates through the season.

Reflected shortwave radiation seemed to distinguish cloudy periods from clear periods. Regression models for days following periods of clear weather (i.e. high solar input) tended to include solar and canopy variables, whereas these variables were generally not included in models representing cloudy periods.

If the spatial variability in the temperature gradient data was partially explained by the occurrence or convergence of weather events, the result would point to the complex dynamics of the seasonal snow system. Furthermore, it would appear that part of the variability could be explained by the relatively static (i.e. non-dynamic) terrain features, while the remainder must be attributed to dynamic, potentially non-linear interactions with the atmosphere. In this situation, modeling efforts that depend on only static parameters may be expected to fall short of explaining or predicting the true level of spatial variability in the snow cover.

The regression relationships developed here would have benefited from much larger datasets. It would be instructive to repeat the sampling using more data points. Perhaps two or three probe units and more personnel would facilitate this. More data would allow a greater range of each variable to be sampled, and would make the regressions more robust. Other variable interactions (such as slope and canopy, or elevation and slope) that were not used in this project could certainly be important for describing temperature gradient/terrain relationships, leaving room for future exploration.

It was assumed in the analysis methodology that the relationships between individual topographic variables and temperature gradients are linear. It may be that the relationships observed in this study were the best *linear* approximations of more complex interactions. Any future work on this subject would seem incomplete without some investigation of nonlinear interactions in this complex system. This effort would entail the exploration of more interaction variables, in addition to nonlinear regressions.

A quantitative analysis of contributing weather factors was beyond the scope of this study. However, future studies could be designed to integrate an analysis of weather parameters with the effects of topography. Measured weather parameters could be included as potential predictor variables. Using multiple-day moving averages of parameters such as air temperature or snow surface temperature would serve to include a "recent history" of the weather effects on the snowpack. It would also be particularly interesting to conduct the sampling days soon before or after dramatic weather changes, as well as bracketing periods of unchanging weather. This would help test the possibility that the variability in the data from certain sample days is dependent on the relatively static terrain variables, while on other days the variability is explained by the rapidly changing, dynamic weather factors.

Multiple weather stations would undoubtedly be useful, as spatial variability in measured weather parameters is perhaps even greater than that observed in the seasonal snowpack. The weather station used in this study was located on a flat, low-elevation site. Additional data from a higher elevation station could provide wind speeds and snow surface temperatures from a more exposed location. The comparison of data between the two stations would give some measure of the variation of air temperatures with elevation. This would assist in determining whether assumptions regarding the standard atmospheric lapse rate are reasonable for the local environment.

Measuring and analyzing the spatial variability in snow temperature gradients is a complex task that could benefit from the suggestions above. It is also a specifically geographic problem, which the geographer's toolbox can uniquely address through the issues of scale in space and time.

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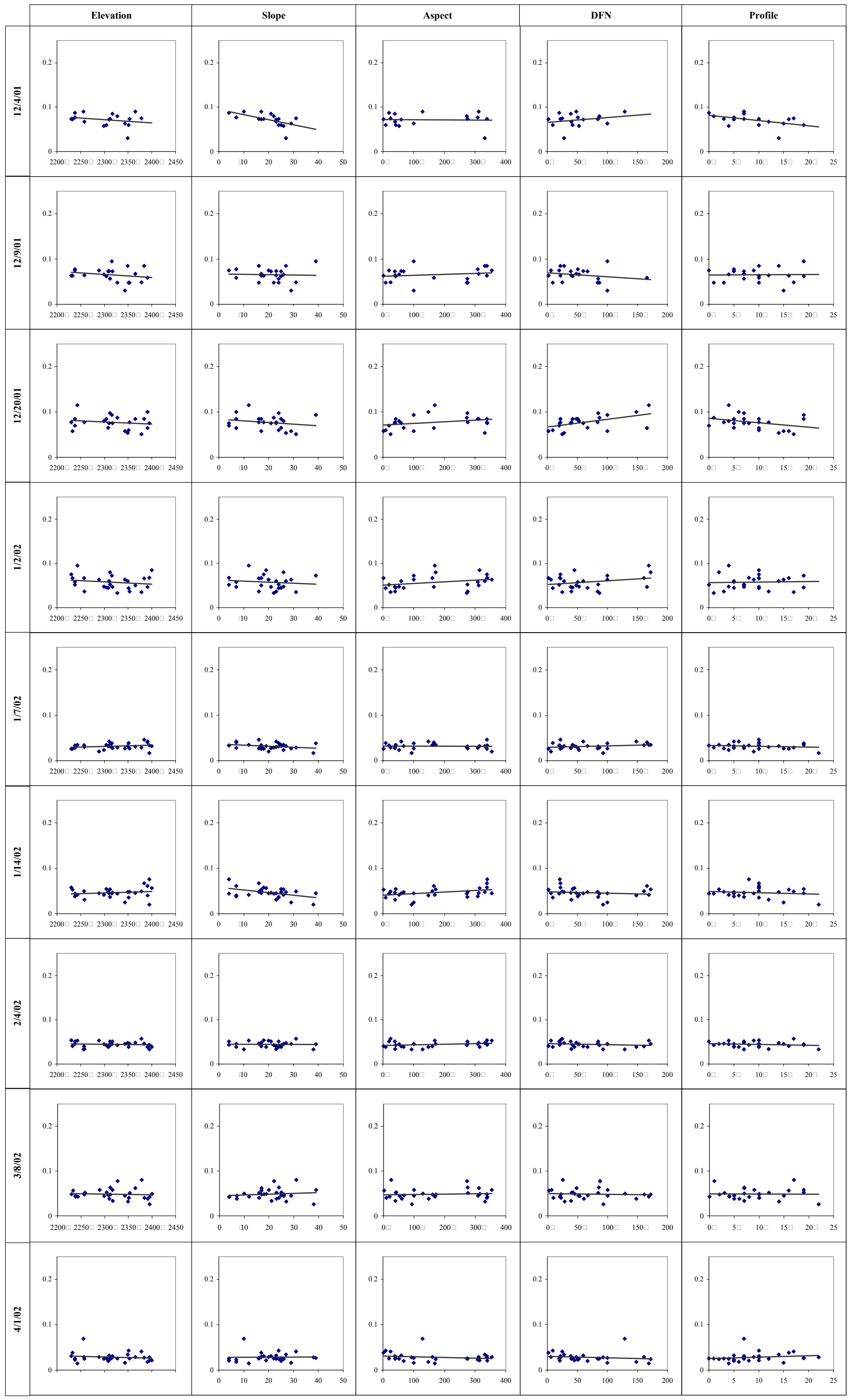
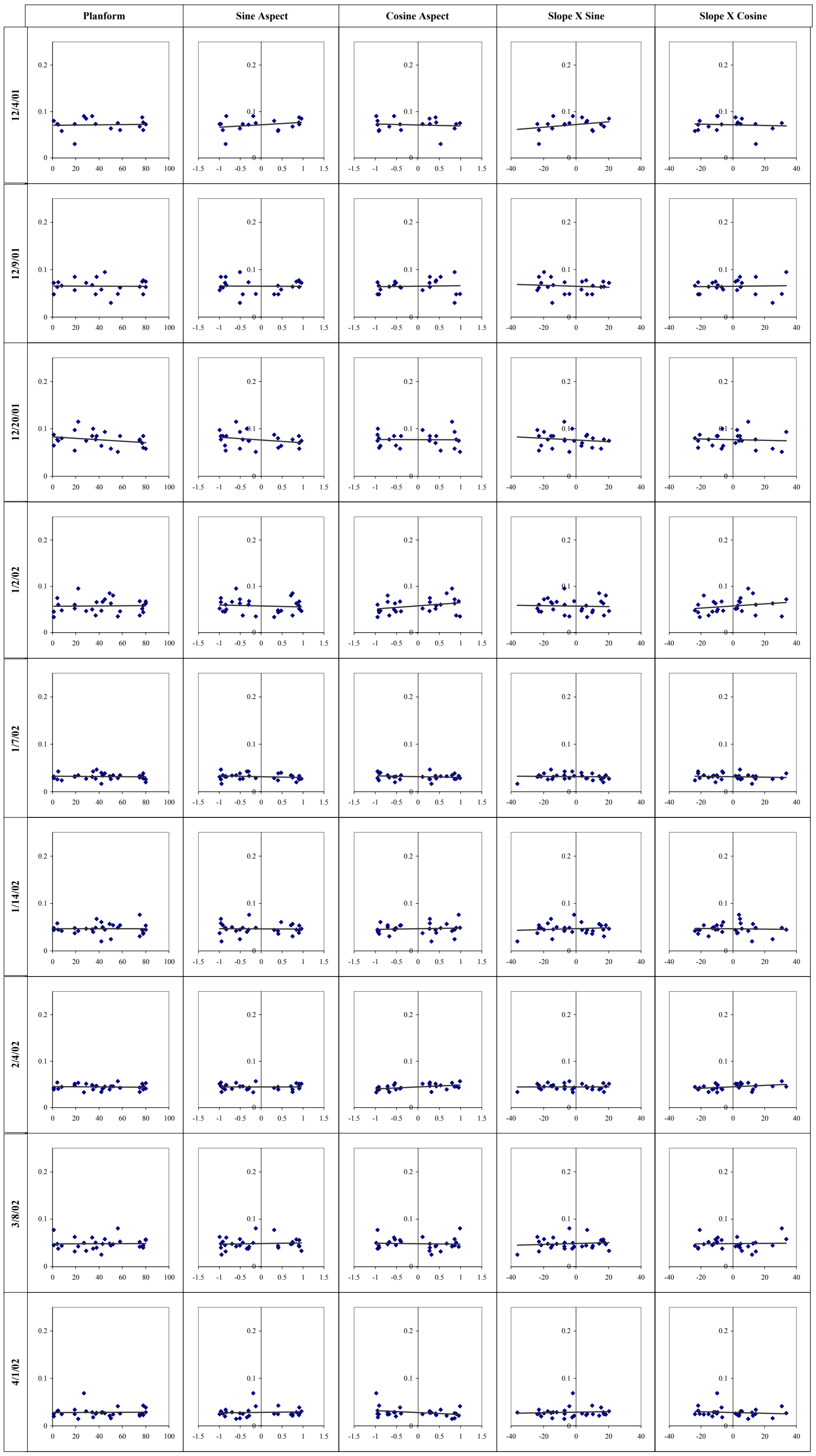
APPENDICES

APPENDIX A

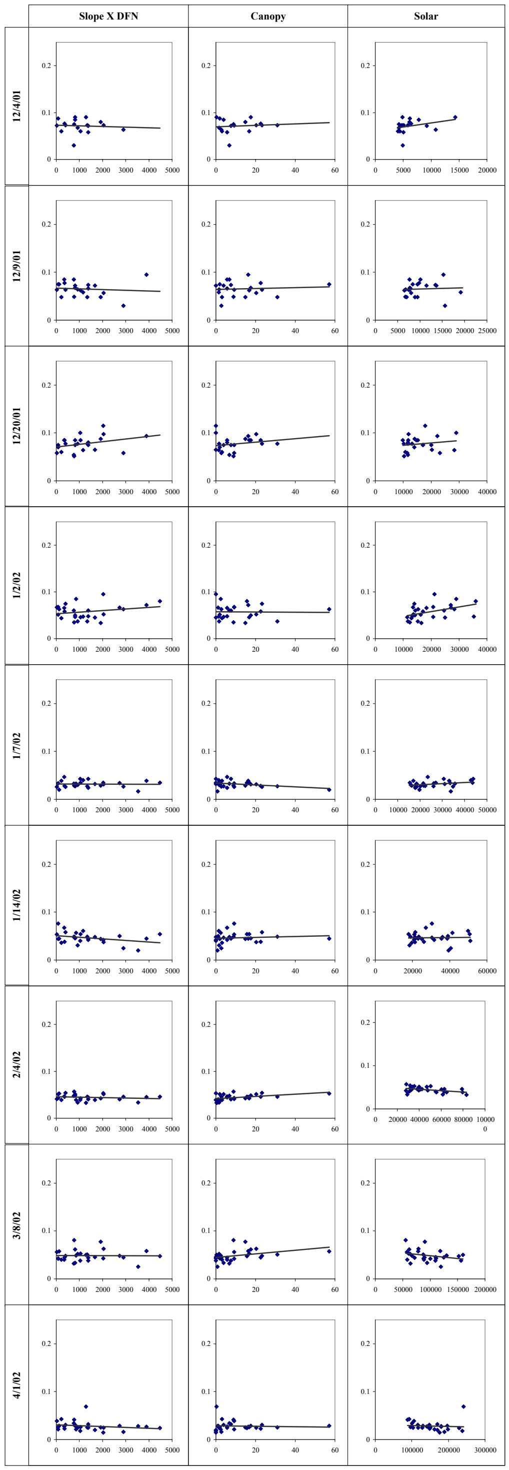
PAIRWISE SCATTER PLOTS



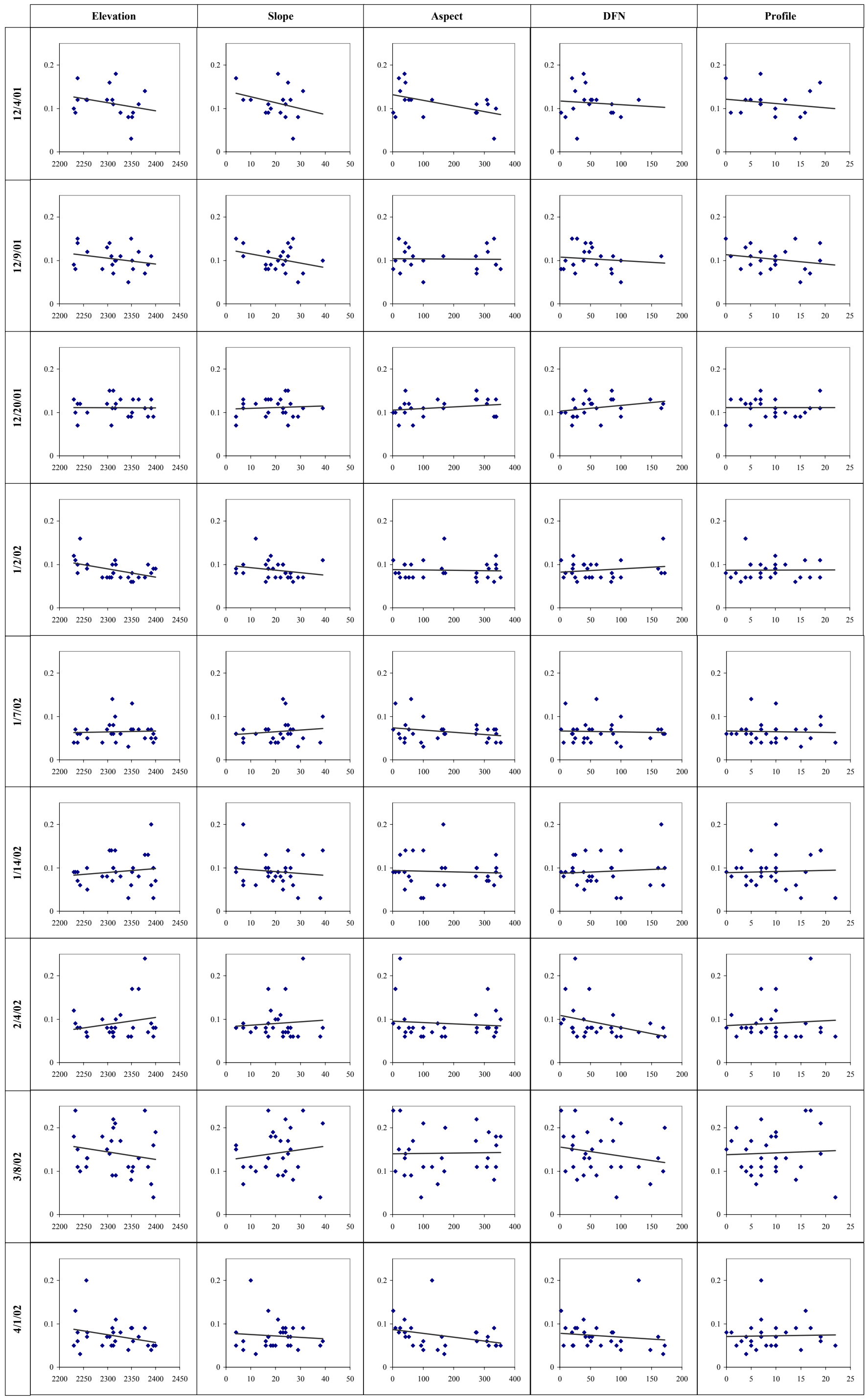
Average temperature gradient response, pairwise scatter plots, with linear best-fit.



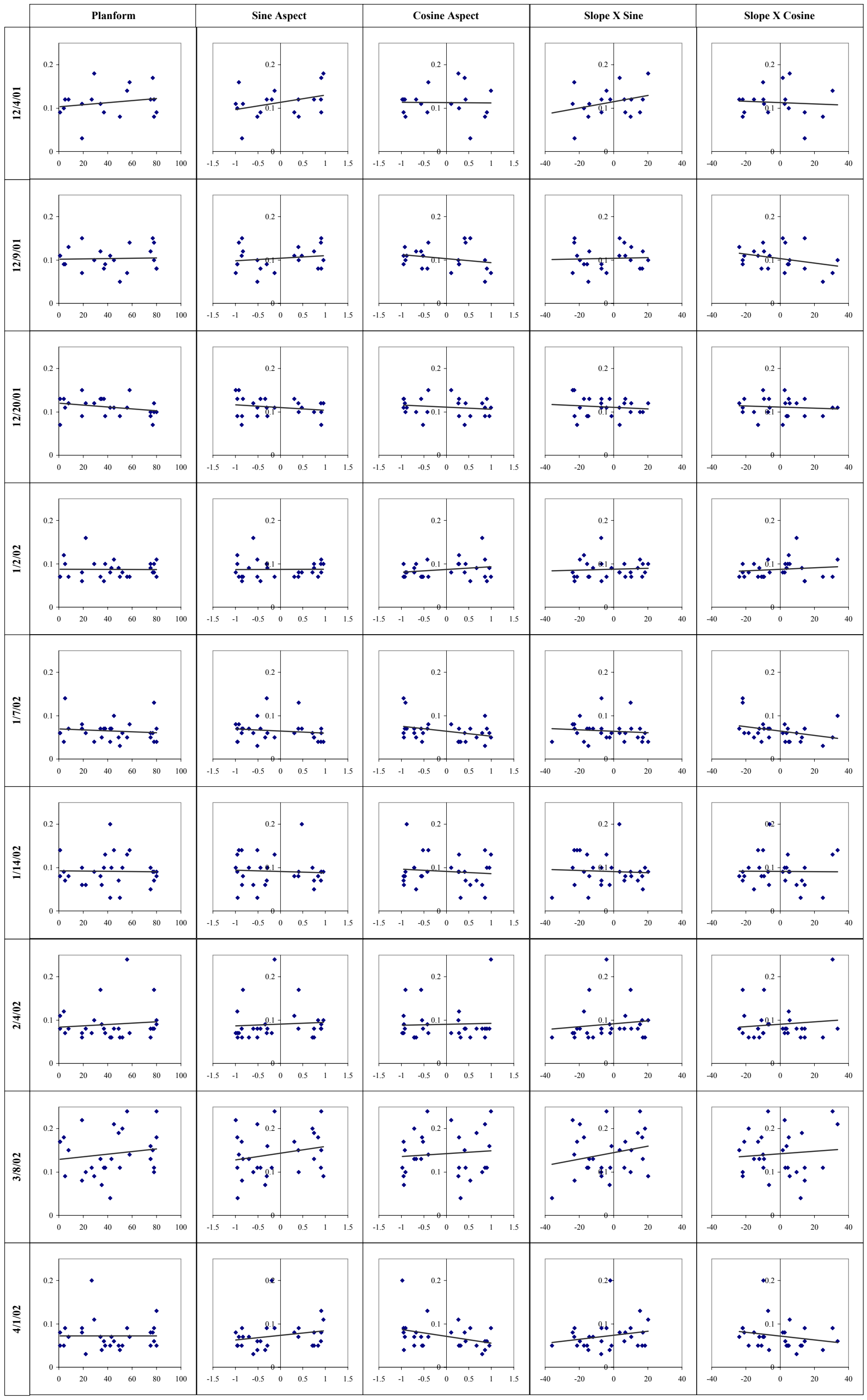
Average temperature gradient response, pairwise scatter plots, with linear best-fit.



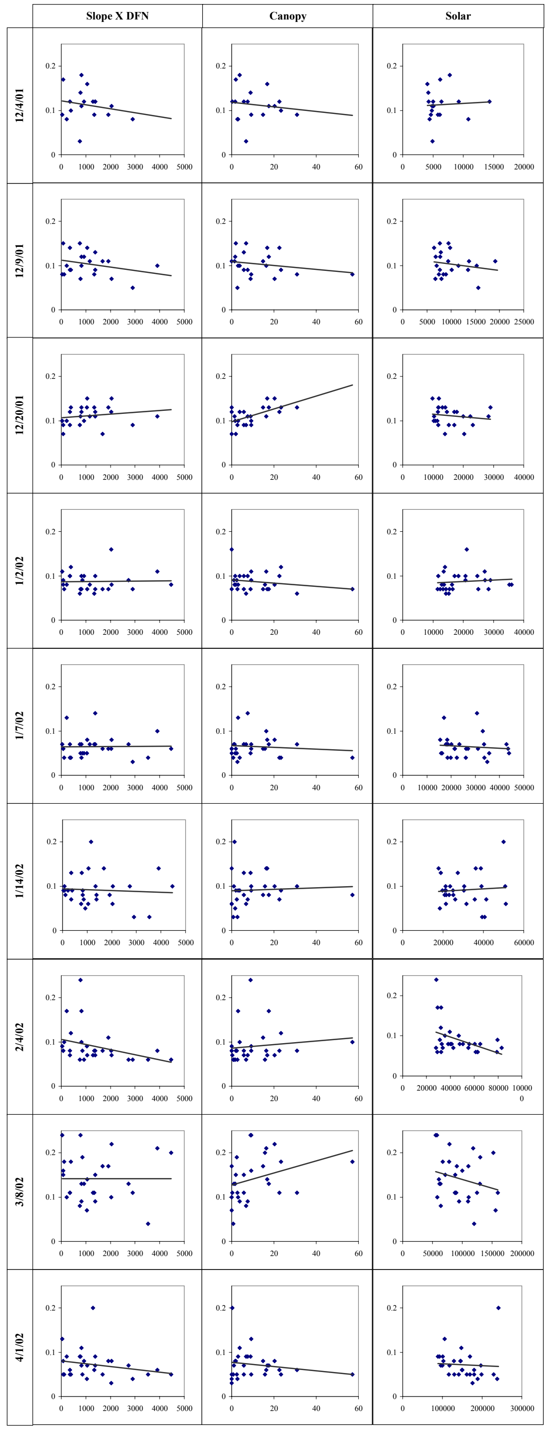
Average temperature gradient response, pairwise scatter plots, with linear best-fit.



Maximum temperature gradient response, pairwise scatter plots, with linear best-fit.



Maximum temperature gradient response, pairwise scatter plots, with linear best-fit.

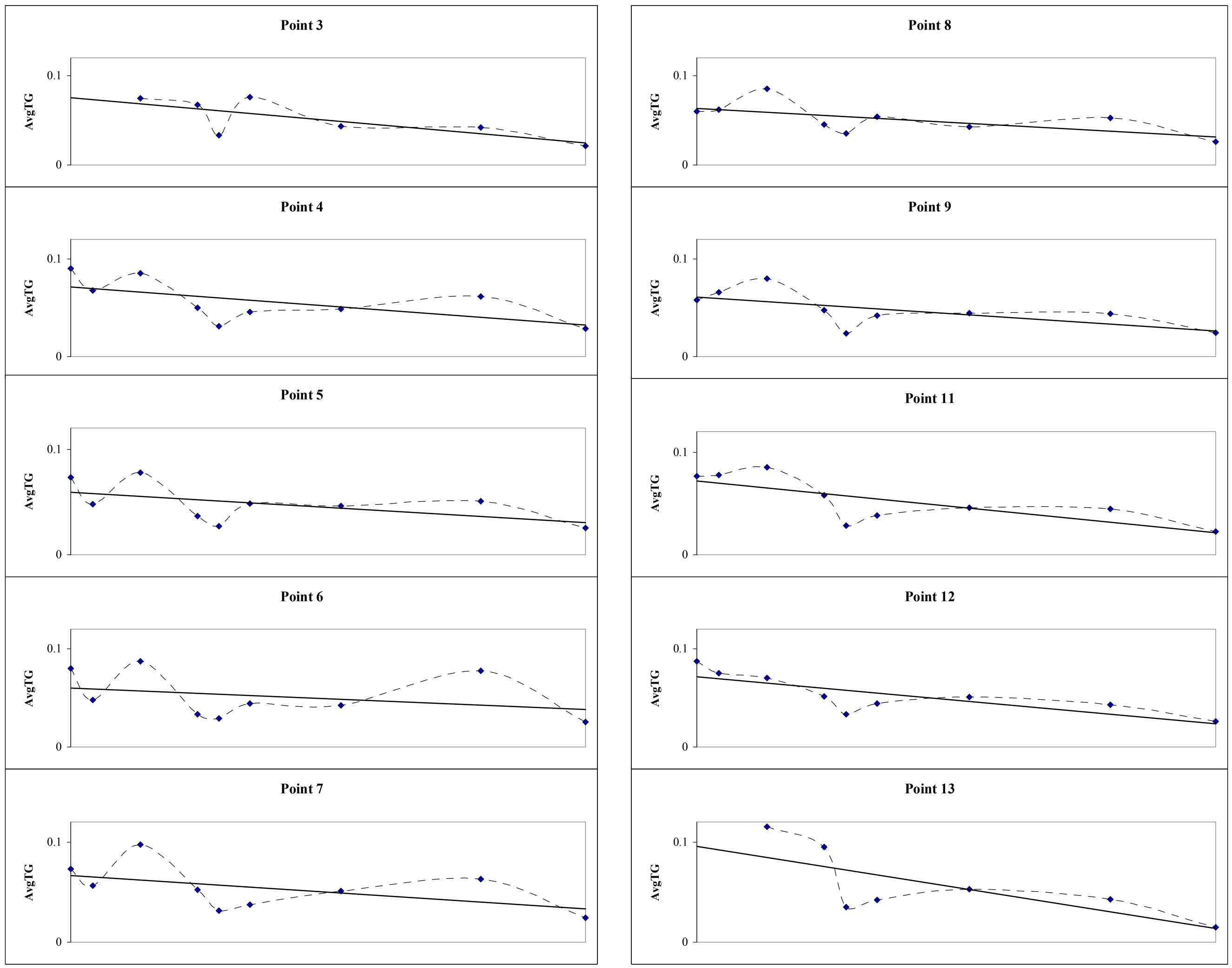


Maximum temperature gradient response, pairwise scatter plots, with linear best-fit.

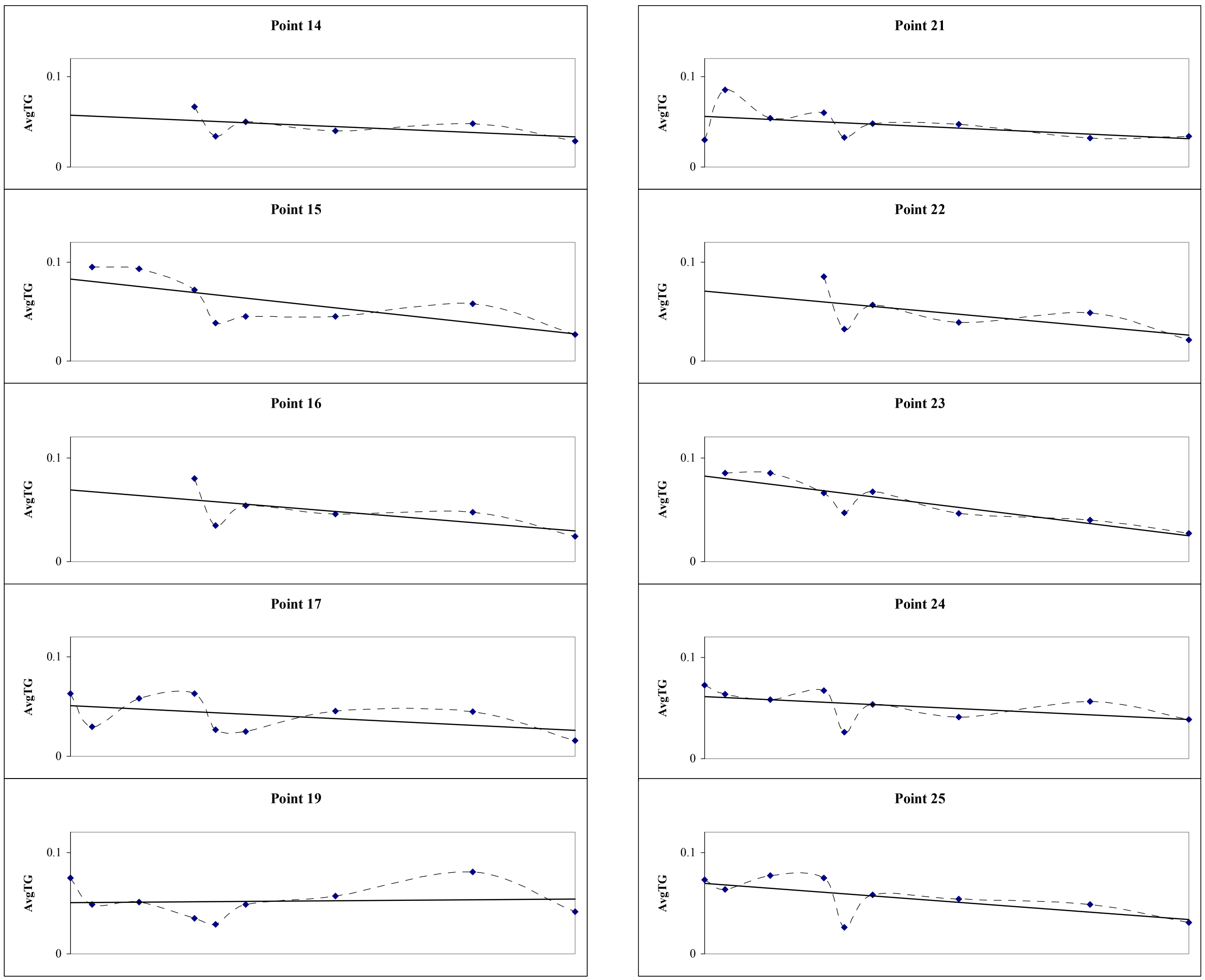
APPENDIX B

SAMPLE POINT TIME SERIES PLOTS

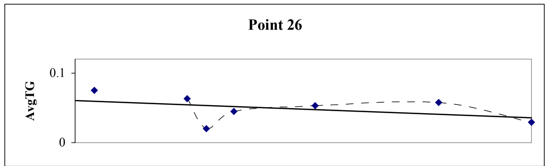
Average Temperature Gradients, Group 1

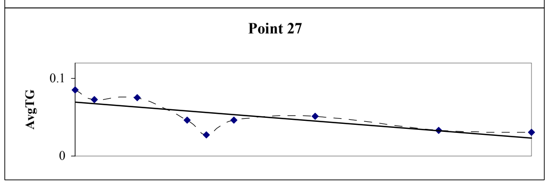


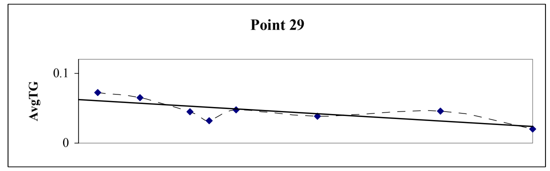
Average Temperature Gradients, Group 1, continued



Average Temperature Gradients, Group 1, continued



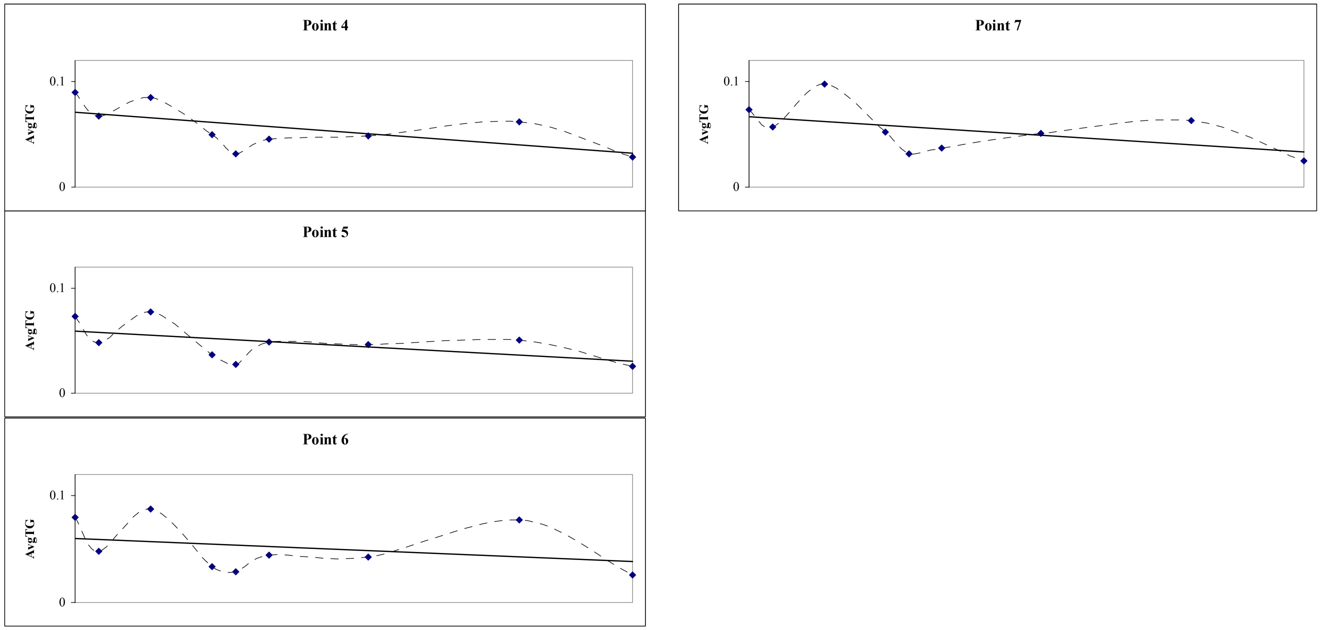




Average Temperature Gradients, Group 1, continued

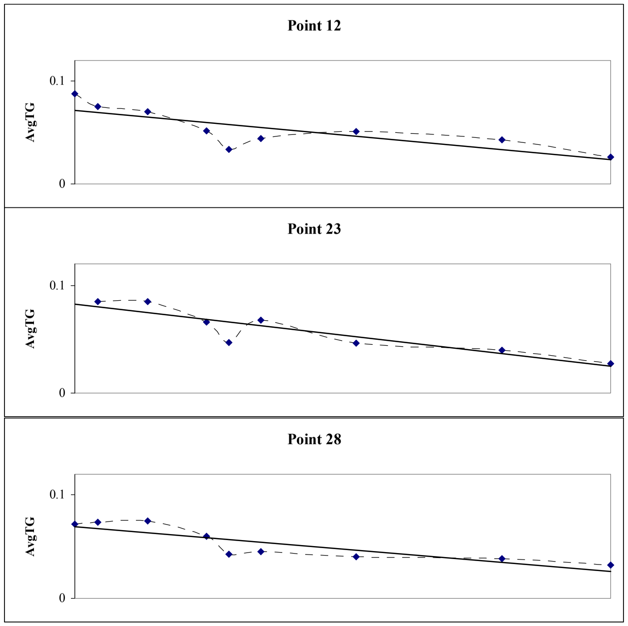
Point	Elevation	Slope	Aspect	DFN	Profile	Planform	Sine	Cosine	Slope X Sine	Slope X Cosine	Slope X DFN	Canopy	Aspect Class
3	2395	4	339	21	8	75	-0.288	0.958	-1.151	3.831	84	9.208	N
4	2365	17	312	48	7	34	-0.832	-0.555	-14.140	-9.436	816	17.604	NW
5	2353	16	276	84	3	37	-0.444	0.896	-7.105	14.336	1344	30.875	W
6	2327	22	273	87	1	1	0.313	-0.950	6.890	-20.893	1914	14.896	W
7	2312	24	275	85	7	19	-0.994	0.110	-23.853	2.650	2040	20.313	W
8	2304	25	42	42	19	58	-0.917	-0.400	-22.913	-10.000	1050	16.792	NE
9	2299	26	53	53	4	8	0.396	-0.918	10.294	-23.875	1378	5.688	NE
11	2238	7	309	51	5	78	0.902	0.432	6.313	3.025	357	22.479	NW
12	2238	4	20	20	0	77	0.913	0.408	3.652	1.632	80	1.896	N
13	2243	12	169	169	4	22	-0.602	0.798	-7.224	9.582	2028	0.000	S
14	2257	17	161	161	10	43	-0.702	-0.712	-11.941	-12.100	2737	1.083	S
15	2316	39	100	100	19	45	-0.506	0.862	-19.748	33.630	3900	16.250	E
16	2312	26	172	172	2	52	0.709	-0.706	18.425	-18.344	4472	15.708	S
17	2343	29	100	100	15	50	-0.506	0.862	-14.685	25.007	2900	2.708	E
19	2378	31	25	25	17	56	-0.132	0.991	-4.103	30.727	775	8.938	NE
21	2349	27	332	28	14	19	-0.846	0.533	-22.848	14.387	756	6.771	NW
22	2400	19	315	45	10	49	0.745	0.667	14.158	12.671	855	2.438	NW
23	2384	16	338	22	10	38	-0.961	0.275	-15.382	4.403	352	5.688	N
24	2233	17	2	2	16	80	0.909	-0.416	15.458	-7.074	34	9.208	N
25	2230	18	338	22	10	4	-0.961	0.275	-17.305	4.953	396	23.292	N
26	2289	20	354	6	9	80	0.841	-0.540	16.829	-10.807	120	57.146	N
27	2317	21	39	39	7	29	0.964	0.267	20.240	5.600	819	3.792	NE
29	2308	25	67	67	5	1	-0.856	-0.518	-21.388	-12.944	1675	0.000	NE

Average Temperature Gradients, Group 2



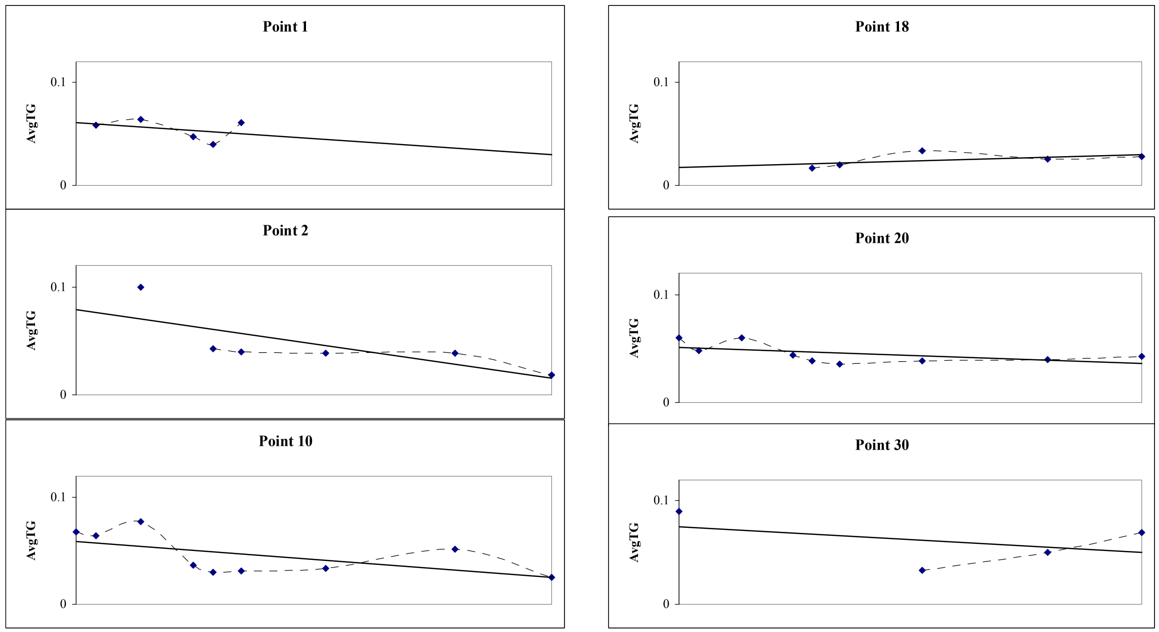
Point	Elevation	Slope	Aspect	DFN	Profile	Planform	Sine	Cosine	Slope X Sine	Slope X Cosine	Slope X DFN	Canopy	Aspect Class
4	2365	17	312	48	7	34	-0.832	-0.555	-14.140	-9.436	816	17.604	NW
5	2353	16	276	84	3	37	-0.444	0.896	-7.105	14.336	1344	30.875	W
6	2327	22	273	87	1	1	0.313	-0.950	6.890	-20.893	1914	14.896	W
7	2312	24	275	85	7	19	-0.994	0.110	-23.853	2.650	2040	20.313	W

Average Temperature Gradients, Group 3

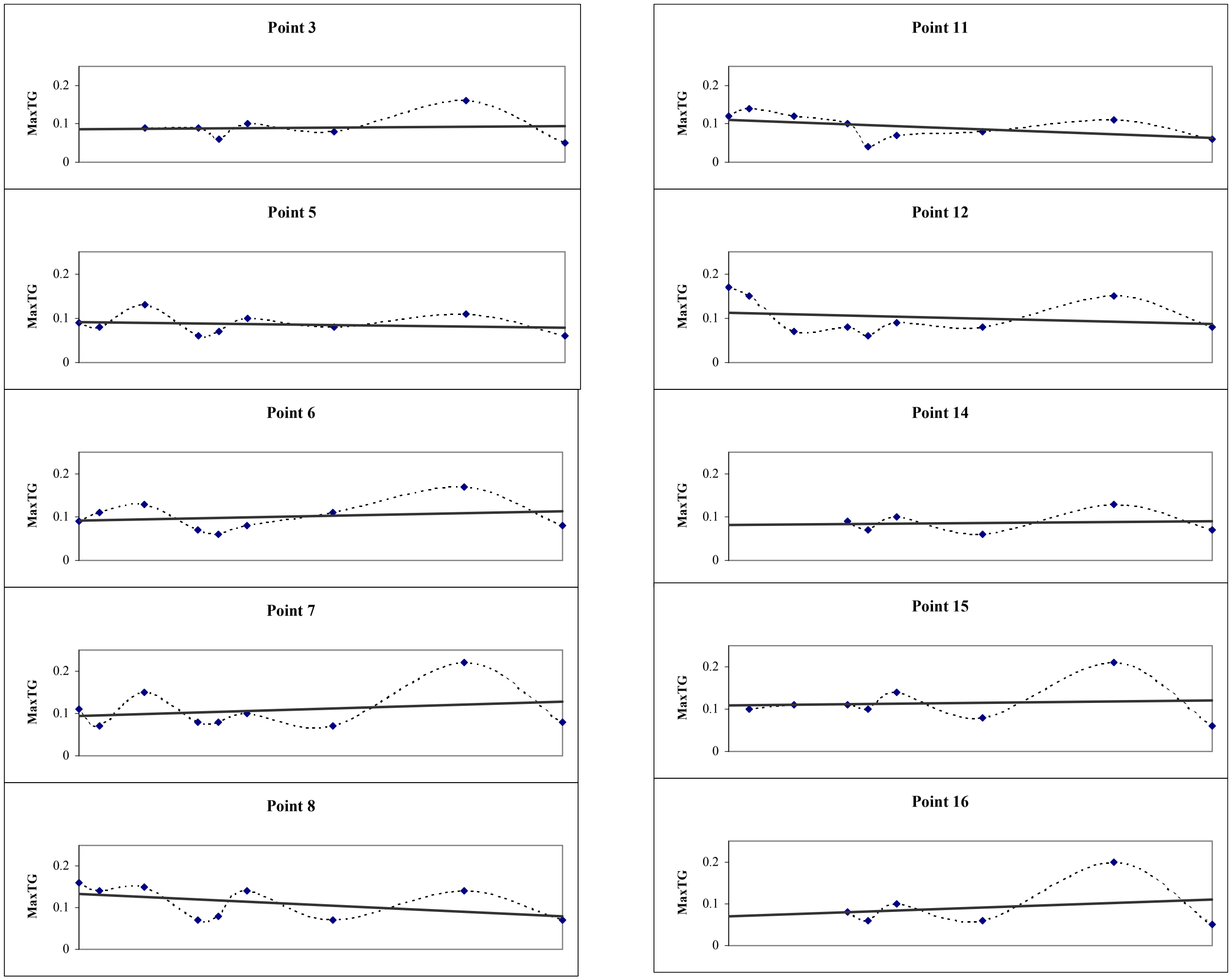


Point	Elevation	Slope	Aspect	DFN	Profile	Planform	Sine	Cosine	Slope X Sine	Slope X Cosine	Slope X DFN	Canopy	Aspect Class
12	2238	4	20	20	0	77	0.913	0.408	3.652	1.632	80	1.896	N
23	2384	16	338	22	10	38	-0.961	0.275	-15.382	4.403	352	5.688	N
28	2310	23	60	60	5	5	-0.305	-0.952	-7.011	-21.905	1380	7.583	NE

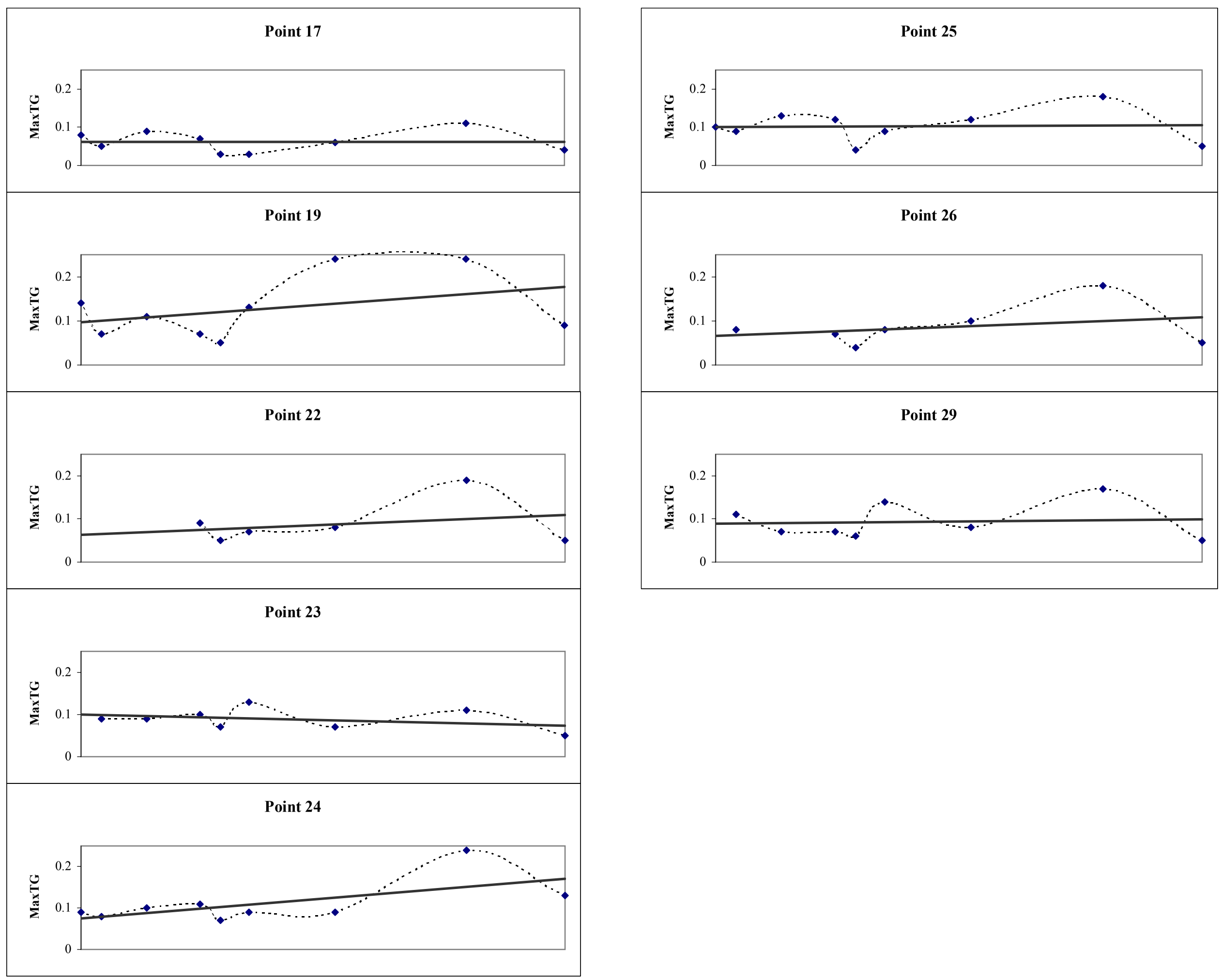
Average Temperature Gradients, Ungrouped Points



Maximum Temperature Gradients, Group 1



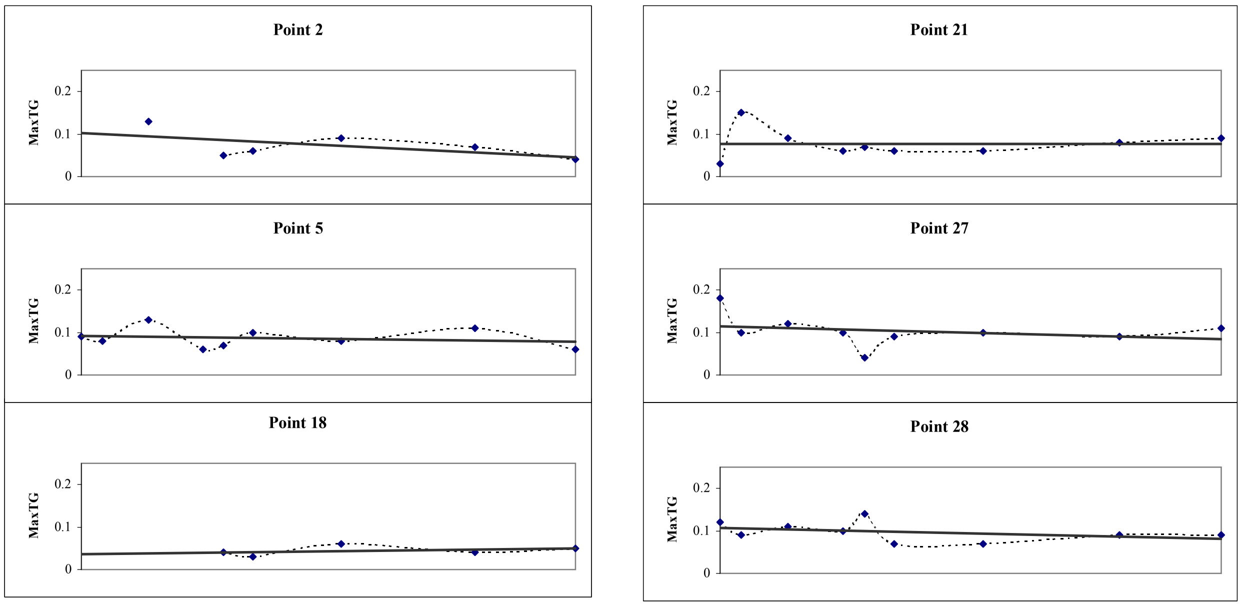
Maximum Temperature Gradients, Group 1, continued.



Maximum Temperature Gradients, Group 1, continued.

Point	Elevation	Slope	Aspect	DFN	Profile	Planform	Sine	Cosine	Slope X Sine	Slope X Cosine	Slope X DFN	Canopy	Aspect Class
3	2395	4	339	21	8	75	-0.288	0.958	-1.151	3.831	84	9.208	N
5	2353	16	276	84	3	37	-0.444	0.896	-7.105	14.336	1344	30.875	W
6	2327	22	273	87	1	1	0.313	-0.950	6.890	-20.893	1914	14.896	W
7	2312	24	275	85	7	19	-0.994	0.110	-23.853	2.650	2040	20.313	W
8	2304	25	42	42	19	58	-0.917	-0.400	-22.913	-10.000	1050	16.792	NE
11	2238	7	309	51	5	78	0.902	0.432	6.313	3.025	357	22.479	NW
12	2238	4	20	20	0	77	0.913	0.408	3.652	1.632	80	1.896	N
14	2257	17	161	161	10	43	-0.702	-0.712	-11.941	-12.100	2737	1.083	S
15	2316	39	100	100	19	45	-0.506	0.862	-19.748	33.630	3900	16.250	E
16	2312	26	172	172	2	52	0.709	-0.706	18.425	-18.344	4472	15.708	S
17	2343	29	100	100	15	50	-0.506	0.862	-14.685	25.007	2900	2.708	E
19	2378	31	25	25	17	56	-0.132	0.991	-4.103	30.727	775	8.938	NE
22	2400	19	315	45	10	49	0.745	0.667	14.158	12.671	855	2.438	NW
23	2384	16	338	22	10	38	-0.961	0.275	-15.382	4.403	352	5.688	N
24	2233	17	2	2	16	80	0.909	-0.416	15.458	-7.074	34	9.208	N
25	2230	18	338	22	10	4	-0.961	0.275	-17.305	4.953	396	23.292	N
26	2289	20	354	6	9	80	0.841	-0.540	16.829	-10.807	120	57.146	N
29	2308	25	67	67	5	1	-0.856	-0.518	-21.388	-12.944	1675	0.000	NE

Maximum Temperature Gradients, Group 2



Point	Elevation	Slope	Aspect	DFN	Profile	Planform	Sine	Cosine	Slope X Sine	Slope X Cosine	Slope X DFN	Canopy	Aspect Class
2	2391	7	148	148	6	35	-0.338	-0.941	-2.368	-6.587	1036	0.000	SE
5	2353	16	276	84	3	37	-0.444	0.896	-7.105	14.336	1344	30.875	W
18	2395	38	93	93	22	42	-0.948	0.317	-36.035	12.062	3534	0.813	E
21	2349	27	332	28	14	19	-0.846	0.533	-22.848	14.387	756	6.771	NW
27	2317	21	39	39	7	29	0.964	0.267	20.240	5.600	819	3.792	NE
28	2310	23	60	60	5	5	-0.305	-0.952	-7.011	-21.905	1380	7.583	NE

Maximum Temperature Gradients, ungrouped points.