



## Spatially explicit modeling of road icing susceptibility using GIS and a multi-criteria decision approach: A case study of Gümüşhane city (Türkiye)\*

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Icing Susceptibility  
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### Abstract

This study develops and validates a GIS-based, spatio-temporal model to identify and prioritize road segments with high icing susceptibility in the Gümüşhane city center, Türkiye. Icing on urban roadways constitutes a significant threat to vehicular and pedestrian safety, particularly in regions characterized by complex topography and dense urban morphology. A Multi-Criteria Decision Analysis (MCDA) framework, employing the Analytic Hierarchy Process (AHP) with structured expert input, was used to synthesize ten primary causative factors. These include solar radiation, temperature, aspect, object height, precipitation, elevation, pavement material, slope, albedo, and road width — each representing a distinct topographic, climatic, or morphological influence on urban road icing. The AHP quantitatively established the relative influence of these factors, identifying solar radiation (28.5%), temperature (18.2%), and aspect (13.5%) as the most dominant drivers. The model generates monthly susceptibility maps that reveal "urban canyons"—narrow streets flanked by high-rise buildings—consistently exhibit the highest and most persistent susceptibility due to severely limited solar radiation. The accuracy of the model's spatial predictions was quantitatively validated through field observations, with 91.4% of recurring icing locations correctly identified within high or very high susceptibility zones. This research culminates not only in a robust scientific framework but also in a validated decision-support tool that has been successfully integrated into the Gümüşhane City Information System (GCIS), where it is now operationally used to optimize winter maintenance strategies. Ultimately, this work provides a replicable, data-driven approach for enhancing urban resilience and traffic safety in challenging topographical settings.

### Research Article

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## 1. Introduction

The formation of ice on road surfaces is a critical transportation hazard during winter months, posing a significant threat to both vehicular and pedestrian safety worldwide [1–4]. This phenomenon, resulting from the freezing of moisture at or below 0°C, dramatically reduces tire-pavement friction, leading to a heightened risk of traffic accidents and disruptions to urban mobility [5, 6]. In regions characterized by continental climates, such as Eastern Anatolia and the interior parts of the Eastern Black Sea Region in Türkiye, cold and snowy winters exacerbate these risks [7, 8]. This challenge is projected to intensify; the IPCC's 6th Assessment Report states that increasing global warming will heighten the

frequency and intensity of extreme weather events, which can lead to more severe and frequent icing episodes from sudden temperature drops [9]. This makes proactive risk assessment more critical than ever.

Extant literature has addressed road icing risk primarily through meteorological forecasting and sensor-based systems. Road Weather Information Systems (RWIS) provide real-time data from fixed, strategic locations, while numerical weather models predict icing conditions on a broader, macro-scale [10]. While these approaches are foundational to road weather management, and recent advancements have even employed sophisticated techniques like deep learning [11], they share a common limitation: they often lack the high spatial resolution required to capture

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micro-climatic variations within complex urban environments. They typically do not fully integrate the profound influence of urban morphology—such as building height and street orientation—on localized conditions like solar radiation and shadow persistence. Recent studies have demonstrated that the integration of GIS and remote sensing techniques significantly enhances the monitoring and analysis of urban land cover changes and surface processes [12].

A critical research gap therefore exists in modelling icing risk at a high spatial resolution, particularly concerning the effect of "urban canyons." These narrow streets flanked by tall buildings create shaded micro-climates that prevent solar radiation from reaching the road surface, leading to the formation and persistence of ice long after it has melted in open areas. This "urban canyon effect" has been widely documented in the urban climatology literature, where reduced sky-view factor, shading, and modified ventilation are shown to strongly alter local energy balance, nocturnal cooling, and surface temperature patterns [13–15]. A systematic framework that integrates these multifaceted topographical (e.g., slope, elevation) and urban morphological factors using a quantitative Multi-Criteria Decision Analysis (MCDA) approach has not been sufficiently explored. Consequently, to the best of our knowledge, no study has yet presented a comprehensive, high-resolution spatial model for urban road icing susceptibility in Türkiye by integrating Geographic Information Systems (GIS) with the Analytic Hierarchy Process (AHP).

This study aims to fill this critical research gap by developing and validating a GIS-based AHP model to identify and map road icing susceptibility in the city of Gümüşhane. The city serves as an ideal case study due to its severe winter climate—characterized by an annual average of 103.8 frost days and significant snowfall [16, 17]—and its complex topography [18]. The primary objectives are: (1) to develop a replicable model by weighting the causative factors of icing (solar radiation, slope, elevation, temperature etc.) using AHP; (2) to produce a high-resolution icing susceptibility map that specifically highlights hazardous zones such as shaded valley floors and narrow streets with limited solar exposure; and (3) to provide a robust decision support tool for municipal authorities to optimize winter maintenance, thereby enhancing traffic safety and urban resilience.

## 2. Method

### 2.1. Study Area

The study was conducted in the urban core of Gümüşhane city, located in the Eastern Black Sea Region of Türkiye. The city's physical geography is a defining factor in its susceptibility to severe winter conditions. It is situated within a narrow, deep valley floor, surrounded by high and rugged terrain (Figure 1). This topographical setting is critical as it facilitates the phenomenon of temperature inversion during winter. Colder, denser air from the surrounding high-elevation slopes descends and settles on the valley floor, displacing warmer air.

This process traps cold air for extended periods, significantly prolonging sub-zero conditions and exacerbating the potential for road ice formation.

The region's climate is characterized as transitional, possessing features of both the temperate Black Sea climate and a harsh continental climate [7]. This results in hot, dry summers and, more importantly for this research, cold and snowy winters. The Walter-Lieth climadiagram for the Gümüşhane station (1961–2023), shown in Figure 2, visually summarizes these conditions. It indicates a mean annual temperature of 9.6°C and a total annual precipitation of 463 mm. The diagram clearly depicts a prolonged cold season where the minimum temperature curve consistently drops below freezing from December through March.

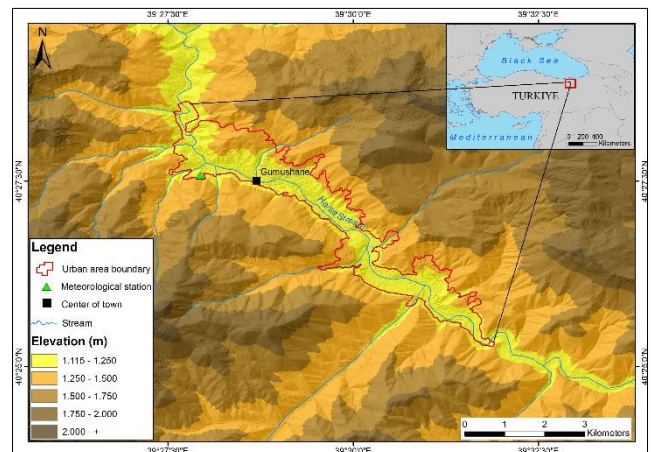


**Figure 1.** Location map of the city of Gümüşhane.

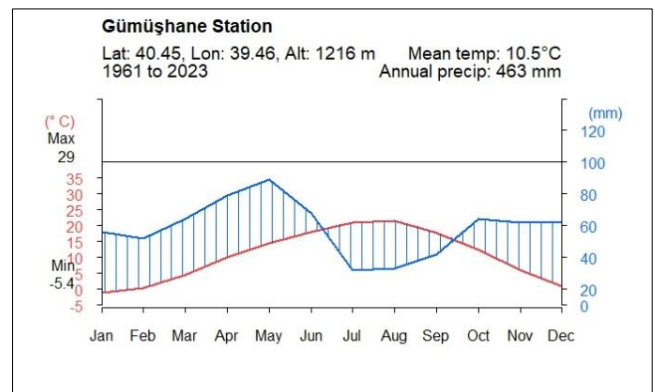


**Figure 2.** Climadiagram of the Gümüşhane station (1961–2023).

The severity of the winter season, which forms the basis of this study, is further quantified in Figure 3. This chart illustrates the monthly distribution of frosty and snowy days based on long-term averages. Gümüşhane experiences an annual total of 103.8 frosty days, with the highest concentrations occurring in January, February, and December. These same months also account for the majority of the 34.26 average annual snowfall days. The frequent co-occurrence of sub-zero temperatures (frosty days) and precipitation (snowfall) creates ideal and recurring conditions for ice accretion on road surfaces.

The persistence of these winter conditions is highlighted by the long-term snow depth records from 1965 to 2024 (Figure 4). The data reveals a significant mean snow depth of 134.7 cm. This substantial and

consistent snow cover acts as a continuous source of meltwater during brief thawing periods, which subsequently refreezes as temperatures drop, a key mechanism in the formation of hazardous "hidden ice." The combination of this unique valley topography, frequent frost and snow events, and persistent snow cover makes Gümüşhane an ideal "natural laboratory" for developing and validating a high-resolution road icing susceptibility model.

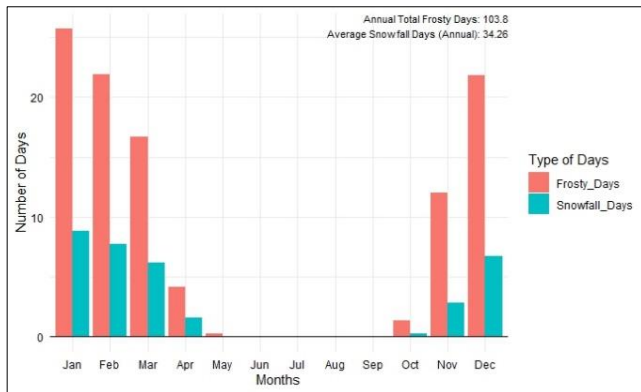


**Figure 3.** Monthly average number of frosty days and snowfall days for Gümüşhane station (1961-2024).

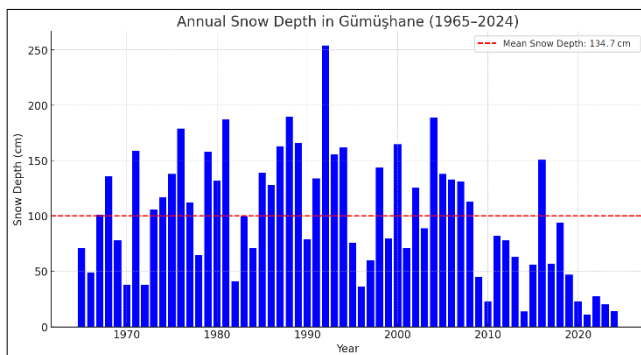


**Figure 4.** Annual mean snow depth for Gümüşhane station (1965-2024).

In addition to long-term snow depth and frost records, the satellite-based MODIS snow cover dataset (2000–2024) provides further insights into the persistence and variability of snow cover in the study area. Figure 5 presents the average monthly snow cover percentage in Gümüşhane, which clearly indicates that the snow season is concentrated between December and March, peaking in January (23.1%) and February (19.7%). This pattern corresponds well with the high frequency of frosty and snowy days (Figure 3), emphasizing the critical winter months for road icing susceptibility.

Furthermore, the temporal trend analysis of snow cover (Figure 6) reveals a slight but consistent decrease over the 24-year period (slope =  $-0.0142$ ). This declining tendency in snow cover percentage is of particular importance for understanding long-term climate variability in the region. Reduced snow persistence not only alters hydrological regimes but may also influence the frequency and severity of road icing events by changing the timing and duration of freeze-thaw cycles.

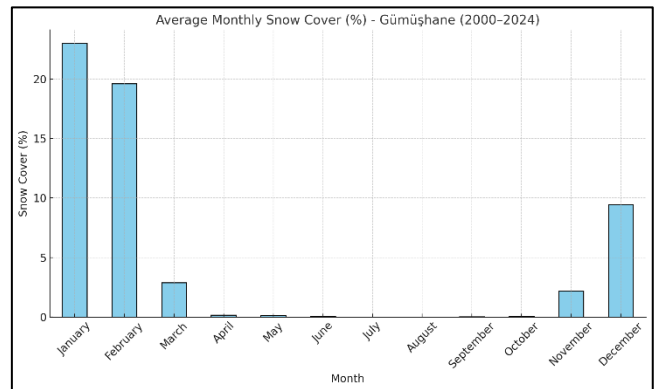


**Figure 5.** Average monthly snow cover percentage in Gümüşhane (2000-2024).

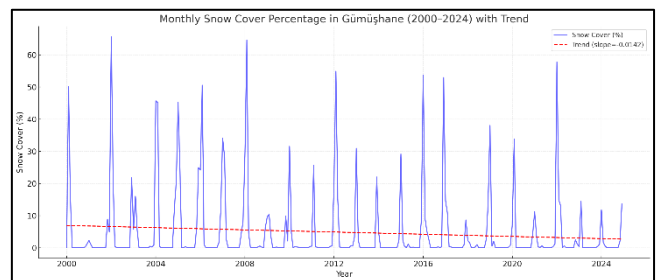


**Figure 6.** Monthly snow cover percentage with long-term trend for Gümüşhane (2000-2024).

## 2.2. Data acquisition and processing

The development of the road icing susceptibility model is predicated on the rigorous integration of multi-source geospatial and climatological datasets with varying spatial and temporal resolutions. To ensure geometric consistency and positional accuracy throughout the analysis, all spatial data layers were projected to the WGS 1984 UTM Zone 37N coordinate system and resampled to a common spatial resolution of 5 meters, congruent with the foundational elevation model. Data processing, derivation, and analysis were performed using an integrated workflow combining ArcGIS 10.7 for geospatial analysis and the Google Earth Engine (GEE), a cloud-based platform leveraged for its computational efficiency in processing large-scale satellite and climate datasets [19–24].

### 2.2.1. Foundational Topographic and Urban Morphometric Datasets

The spatial framework of the model was established upon a high-resolution 5-meter Digital Surface Model (DSM) provided by the Turkish Ministry of National Defense, General Command of Mapping (HGM) [25]. This high-resolution dataset was critical for the model's microclimatic sensitivity, as it captures not only the terrain topography but also urban morphology, including buildings and vegetation. The following key parameters were derived from this foundational dataset:

**Elevation, Slope, and Aspect:** These three fundamental topographic parameters were directly derived from the DSM using the Spatial Analyst tools in ArcGIS 10.7.

**Object Height (Building and Vegetation Height):** To model the shadowing effects of urban canyons and vegetation canopies, a Digital Terrain Model (DTM) was

generated from the original DSM using morphological filtering techniques. The difference between the two models ( $nDSM = DSM - DTM$ ) yielded a layer representing the relative height of buildings and trees above the ground, which is a critical determinant of direct solar occlusion on road surfaces. This parameter is also referred to as "building height" in this study.

**Solar Radiation:** The total incoming solar radiation (insolation) in watt-hours per square meter ( $WH/m^2$ ) was calculated for each month using the "Area Solar Radiation" tool in ArcGIS 10.7. With the DSM as the primary input, this analysis synthesizes the cumulative effects of aspect, slope, and object-induced shadowing into a single, powerful parameter.

### 2.2.2. Surface and Infrastructure Characteristics

**Albedo:** This parameter, representing the reflective capacity of road surfaces, was computed on the Google Earth Engine platform. Using multi-spectral surface reflectance bands from Sentinel-2 satellite imagery, albedo was calculated based on an established empirical formulation proposed by Liang (2001) [26]. The resulting 10-meter albedo map was then resampled to the 5-meter study resolution using a Bilinear Interpolation method.

**Road Network (Width and Pavement Material):** Infrastructure details for the road network were sourced from the OpenStreetMap (OSM) global collaborative database [27]. Based on OSM tags such as highway, lanes, and surface, an attribute table was populated in ArcGIS 10.7 with estimated road width (m) and coded pavement material (1: Asphalt, 2: Concrete/Paving Stone, 3: Unpaved/Gravel). This line-based vector data was subsequently transformed into polygons using the "Buffer" tool, creating features where each road segment possessed its corresponding width.

### 2.2.3. Climatological Datasets

**Ground Station Data (Temperature and Precipitation):** Long-term monthly average temperature ( $^{\circ}C$ ) and total precipitation (mm) data were obtained from the Turkish State Meteorological Service (MGM) for seven meteorological stations located in and around Gümüşhane [28]. This point-based data was spatially interpolated across the study area using the Co-Kriging method in ArcGIS 10.7. To produce topographically sensitive climate surfaces, the 5-meter DSM was employed as a co-variable, leveraging the strong correlation between climate variables and elevation. This advanced interpolation technique effectively mitigates the low-resolution problem of climate data, generating realistic, high-resolution surfaces that reflect local terrain effects.

**Snow Cover:** To incorporate snow persistence as a susceptibility factor, the MODIS/Terra Snow Cover Daily Global (MOD10A1) dataset was utilized via the Google Earth Engine platform [29]. The average number of snow-covered days for the winter months (December–April) was calculated for the 2000–2024 period. This

500-meter resolution product was then resampled to the 5-meter study resolution.

The meticulous processing and spatial harmonization of these multi-source, multi-scale datasets form the robust foundation of the developed road icing susceptibility model.

Each of the ten input parameters used in this study represents a distinct topographic, climatic, or morphological factor that directly influences the likelihood and persistence of urban road icing. Solar radiation and aspect jointly determine surface energy balance and exposure to sunlight, which strongly control the rate of melt and refreeze processes. Temperature and elevation govern the thermal regime of the air and ground surface, defining whether freezing conditions can persist. Precipitation provides the necessary moisture for ice formation, while albedo and pavement material affect the rate of radiative heat absorption and surface cooling. Object (building and vegetation) height and road width shape the urban canyon effect, modifying local microclimates through shading and restricted air circulation. Finally, slope controls water accumulation and drainage, with gentle or flat surfaces favoring ponding and ice development. The integration of these interdependent variables allows the model to capture both microclimatic and morphological controls on road icing at a fine spatial resolution.

The selection of these ten criteria was grounded in both empirical evidence and physical reasoning, reflecting the multi-dimensional nature of road icing processes in complex urban environments. The parameters jointly represent three major control domains: (i) topographic factors (elevation, slope, aspect) influencing cold-air drainage and solar exposure; (ii) climatic factors (temperature, precipitation, solar radiation, albedo) regulating surface energy balance and freezing potential; and (iii) morphological and infrastructural factors (object height, road width, pavement material) shaping micro-scale shading, ventilation, and heat retention. This expanded 10-criterion framework was developed to capture the fine-scale spatial variability of urban microclimates more accurately than traditional models with limited inputs.

### 2.2.4. Data Harmonization and Final Input Layers

A critical step in the pre-processing workflow was the spatial harmonization of the multi-source datasets to ensure analytical consistency. All raster layers not at the native 5-meter resolution—including satellite-derived products (Albedo, Snow Cover) and interpolated climatological surfaces (Temperature, Precipitation)—were resampled to a 5-meter cell size using the Bilinear Interpolation method in ArcGIS 10.7. This technique was chosen to preserve the continuous nature of the data. Furthermore, all final criteria maps were clipped to the precise boundary of the road network polygons. This meticulous process resulted in a final stack of ten perfectly co-registered, 5-meter resolution raster layers, ready for the AHP synthesis.

### 2.3. Methodological framework: GIS-Based AHP

The methodology for creating the urban road icing susceptibility map is built upon a GIS-based Multi-Criteria Decision Analysis (MCDA) framework [30, 31], specifically utilizing the Analytic Hierarchy Process (AHP). This approach is well-established in the literature for its robustness in handling complex spatial problems involving multiple, often conflicting, criteria to assess hazards and suitability [32–41]. The entire analytical workflow was implemented in ArcGIS 10.7 software. The process consists of three principal stages: (1) standardization of all criteria maps to a common susceptibility scale, (2) criteria weighting via AHP to determine their relative importance, and (3) synthesis of the final susceptibility index through a weighted overlay.

#### 2.3.1. Standardization of Criteria Maps

The ten primary criteria used in the model (Elevation, Slope, Aspect, Object Height, Albedo, Road Width, Pavement Material, Solar Radiation, Temperature, and Precipitation) possess different units and numerical ranges. To render them comparable and combinable, each criterion map was standardized using the "Reclassify" tool onto a unified susceptibility scale from 1 (Very Low Susceptibility) to 5 (Very High Susceptibility). This 1-to-5 scale was applied consistently across all parameters in the model. The physical rationale for assigning high or low susceptibility scores to the classes within each criterion is summarized in Table 1. It is important to note that this 1-to-5 scale is distinct from the 1-to-9 scale applied in the AHP weighting process. The 1–5 scale used here pertains solely to the spatial reclassification of each criterion map, standardizing diverse datasets into comparable susceptibility classes. In contrast, the 1–9 scale in the AHP stage reflects the subjective judgment of relative importance between criteria during the pairwise comparison process. These two scales serve complementary but separate purposes within the overall MCDA framework.

**Table 1.** Rationale and susceptibility relationship for the icing criteria reclassification.

| Criterion              | Rationale for Susceptibility Assignment                                          | High-Score | Susceptibility Relationship |
|------------------------|----------------------------------------------------------------------------------|------------|-----------------------------|
| <b>Solar Radiation</b> | Lower solar radiation prevents surface heating and inhibits ice melt.            |            | Inverse                     |
| <b>Temperature</b>     | Temperatures at or below the freezing point are critical for ice formation.      |            | Inverse                     |
| <b>Aspect</b>          | North-facing slopes receive minimal solar radiation, increasing ice persistence. |            | Directional                 |
| <b>Object Height</b>   | Taller buildings and trees cast longer shadows on road surfaces.                 |            | Direct                      |
| <b>Precipitation</b>   | Higher precipitation provides more moisture available for freezing.              |            | Direct                      |

|                          |                                                                                                          |             |
|--------------------------|----------------------------------------------------------------------------------------------------------|-------------|
| <b>Elevation</b>         | Higher elevations are strongly correlated with colder temperatures.                                      | Direct      |
| <b>Pavement Material</b> | Unpaved and concrete surfaces retain less heat and cool faster than asphalt.                             | Categorical |
| <b>Slope</b>             | Flat areas promote water ponding, while gently sloped areas combine formation and hazard susceptibility. | Non-linear  |
| <b>Albedo</b>            | High-albedo (light-colored) surfaces reflect more solar energy and cool faster.                          | Direct      |
| <b>Road Width</b>        | Narrow roads are subject to prolonged shading from adjacent objects (urban canyon effect).               | Inverse     |

#### 2.3.2. Criterion Weighting with the Analytic Hierarchy Process (AHP)

The AHP, developed by Saaty [42, 43] was employed to objectively determine the relative importance (weight) of each criterion on road icing susceptibility. The process was conducted with structured expert participation to ensure methodological transparency and reduce subjectivity.

*a) Expert Panel and Data Collection:* To weight the criteria, a panel of 11 experts from diverse yet relevant fields were formed. This group comprised seven academics specializing in GIS, climatology, and geomorphology, and four technical personnel from the Gümüşhane Municipality working in GIS and public works departments. A structured questionnaire was administered to the panel, asking them to perform pairwise comparisons of every criterion against every other, using Saaty's fundamental 1-9 preference scale (Table 2).

**Table 2.** The AHP provides a preference scale for the parameters [42].

| Scales      | Degree of Preference |
|-------------|----------------------|
| 1           | Equally              |
| 3           | Moderately           |
| 5           | Strongly             |
| 7           | Very strongly        |
| 9,          | Extremely            |
| 2, 4, 6, 8  | Intermediate         |
| Reciprocals | Opposites            |

*b) Weight Calculation and Consistency Analysis:* The geometric mean method was utilized to synthesize the judgments from the 11 experts into a single, representative value for each pairwise comparison. The final weight percentage (priority vector) for each criterion was then calculated through the normalization of the resulting 10x10 pairwise comparison matrix (Table 3). To validate the logical consistency of the expert judgments, the Consistency Ratio (CR) was calculated. The resulting CR value of 0.066 is significantly below the

acceptable upper threshold of 0.10, confirming that the pairwise comparisons are consistent, and the derived weights are reliable and robust for use in the model.

The individual pairwise comparison matrices obtained from each expert were first synthesized into a single consensus matrix using the geometric mean method, where each cell value  $a_{ij}$  was calculated as the geometric mean of all expert judgments for that criterion pair:

$$a_{ij} = \left( \prod_{k=1}^n a_{ij}^k \right)^{\frac{1}{n}}$$

where  $n$  is the number of experts.

The final normalized weight ( $W_i$ ) for each criterion was then derived as the average of the normalized column values of this consensus matrix:

$$W_i = \frac{\left( \frac{a_{i1}}{\sum_i a_{i1}} \right) + \left( \frac{a_{i2}}{\sum_i a_{i2}} \right) + \dots + \left( \frac{a_{in}}{\sum_i a_{in}} \right)}{n}$$

Finally, the Consistency Ratio (CR) was calculated using Saaty's approach:

$$CR = CI/RI, \quad CI = \frac{(\lambda_{\max} - n)}{(n - 1)}$$

and  $RI$  is the random consistency index corresponding to the matrix size. A  $CR \leq 0.10$  indicates acceptable consistency. In this study,  $CR = 0.066$ , confirming the logical coherence of expert judgments and the robustness of the derived weights.

**Table 3.** Final AHP-Derived weights for each criterion.

| Criterion         | Abbreviation | Weight (%)   |
|-------------------|--------------|--------------|
| Solar Radiation   | SR           | 28.5         |
| Temperature       | T            | 18.2         |
| Aspect            | A            | 13.5         |
| Object Height     | H            | 10.1         |
| Precipitation     | P            | 8.0          |
| Elevation         | E            | 6.5          |
| Pavement Material | M            | 5.2          |
| Slope             | S            | 4.0          |
| Albedo            | Alb          | 3.0          |
| Road Width        | W            | 3.0          |
| <b>Total</b>      |              | <b>100.0</b> |

### 2.3.3. Synthesis of the Icing Susceptibility Index

The final monthly Icing Susceptibility Index (ISI) maps were generated by synthesizing the standardized susceptibility maps (scores from 1 to 5) with their corresponding AHP-derived weights. This synthesis was performed using the "Raster Calculator" tool in ArcGIS 10.7 via a weighted linear combination. The process is mathematically represented for each pixel by Equation (1):

$$ISI = \sum_{i=1}^n (W_i * R_i)$$

Where:

- $ISI$  is the final Icing Susceptibility Index score for each pixel.
- $W_i$  is the AHP-derived decimal weight for the  $i$ -th criterion (e.g., 0.285 for Solar Radiation).

- $R_i$  is the reclassified susceptibility score (from 1 to 5) of the pixel for the  $i$ -th criterion.
- $n$  is the total number of criteria in the model ( $n=10$ ).

The application of this formula resulted in continuous-value final susceptibility maps with scores ranging from approximately 1.04 to 4.603. For ease of interpretation and visualization, these continuous maps were classified into five discrete susceptibility categories (Very Low, Low, Moderate, High, and Very High) using the Natural Breaks (Jenks) classification method.

### 2.3.4. Model validation and field observations

To assess the accuracy and practical relevance of the GIS-AHP model, a comprehensive field study was conducted to validate the resulting monthly icing susceptibility maps. This ground-truthing process is a critical step to ensure that the model's predictions align with real-world conditions.

The validation process involved on-site surveys within the Gümüşhane city center during the winter months (January and February 2024), when icing events are most prevalent. The primary objective of the fieldwork was to identify, document, and precisely locate known and observed areas of recurring hazardous ice formation ("hotspots"). During these surveys, particular attention was paid to locations exhibiting characteristics conducive to icing, such as:

**Urban Canyons:** Narrow streets flanked by high-rise buildings, which severely limit solar radiation exposure.

**Shaded Slopes:** North-facing road segments and other areas where the topography blocks direct sunlight for most of the day.

**Areas of Persistent Ice:** Locations where, through observation and local knowledge, ice was known to remain long after it had melted in other parts of the city.

The geographic coordinates of a total of 50 confirmed icing "hotspots" were recorded using a handheld GPS device. These collected ground-truth points were subsequently overlaid as a validation layer onto the final Icing Susceptibility Index (ISI) maps generated by the model in ArcGIS 10.7. This direct comparison allows for a quantitative assessment of the model's predictive performance. The primary validation metric was the percentage of confirmed hotspots falling within the 'High' and 'Very High' susceptibility classes, providing a direct measure of the model's accuracy in identifying real-world hazardous locations.

## 3. Results

The application of the GIS-based AHP framework produced five monthly Icing Susceptibility Index (ISI) maps specifically for the road network of the Gümüşhane city center, covering the critical period from December to April. These final maps classify all road segments into five distinct susceptibility levels: Very Low, Low, Moderate, High, and Very High. The complete set of monthly road susceptibility maps is presented in Figure 7.

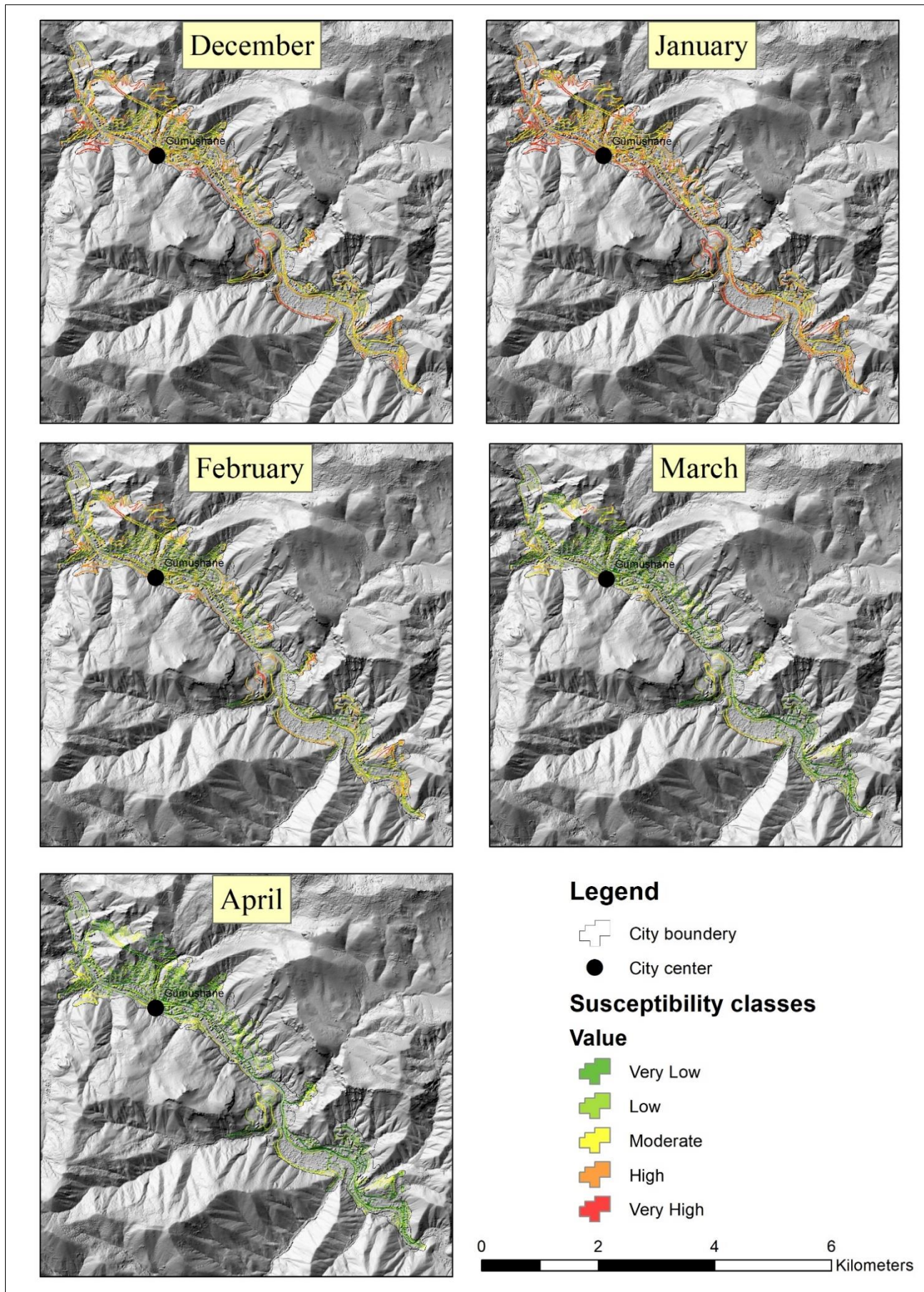


**Figure 7.** Monthly road icing susceptibility maps for the Gümüşhane city center. The color ramp indicates increasing susceptibility to icing, from green (Very Low) to red (Very High). The maps clearly illustrate the spatio-temporal reduction in risk from the peak winter month of January to the onset of spring in April.

### 3.1. Spatio-temporal Patterns of Road Icing Susceptibility

The maps in Figure 7 reveal clear and consistent spatio-temporal patterns of icing susceptibility directly on the road surfaces. Spatially, the model systematically identifies the road segments with the highest susceptibility as those located along the valley floor, particularly within the dense urban core that constitutes a classic "urban canyon," and on north-facing slopes. These specific road segments consistently fall into the 'High' and 'Very High' susceptibility classes across all winter months. This is primarily attributed to severely limited solar radiation—identified as a dominant factor in our AHP model—which inhibits the melting of ice on the pavement. Conversely, the road segments with 'Low' and 'Very Low' susceptibility are almost exclusively located on south-facing slopes that benefit from maximum solar exposure, facilitating rapid melting.

Temporally, the maps and quantitative data demonstrate a pronounced seasonal progression. As illustrated in Figure 8 and Table 4, the spatial extent of 'High' and 'Very High' risk road segments reaches its peak during the coldest months of December (48.8%) and especially January (64.0%). As the season progresses through February and March, a gradual contraction of these highly susceptible road areas is observable. By April, with rising temperatures and increased solar radiation angles, the overall icing susceptibility of the road network is significantly reduced; 'High' and 'Very High' susceptibility segments disappear entirely, and over 81% of the road network's area transitions into the 'Low' and 'Very Low' susceptibility classes. This dynamic change underscores the model's ability to successfully capture the evolving nature of icing susceptibility throughout the winter season.

### 3.2. Quantitative Analysis of Susceptibility Classes on the Road Network

To provide a quantitative dimension to the visual patterns, the proportional area (%) and absolute area (km<sup>2</sup>) covered by each susceptibility class on the road network were calculated. The precise distribution for each month is detailed in Table 4.

The analysis confirms the pervasiveness of the icing hazard on the transportation infrastructure during the peak winter months. In January, for instance, the 'High' and 'Very High' susceptibility classes collectively account for 64.0% (0.82 km<sup>2</sup>) of the total road network area, indicating that a majority of the city's roads are physically predisposed to hazardous ice formation. The seasonal progression is visualized even more clearly in the stacked bar chart in Figure 8. This chart effectively illustrates the temporal shift in the composition of susceptibility classes. The dominant red and orange tones (high susceptibility) in January progressively give way to yellow and green tones (moderate and low susceptibility) starting in February. This quantitative evidence strongly supports the spatio-temporal patterns

identified by the model and highlights the dynamic nature of icing susceptibility.

**Table 4.** Spatio-temporal distribution of icing susceptibility classes on the road network

| Susceptibility Class | De-<br>cem-<br>ber      | Janu-<br>ary            | Feb-<br>ruary           | March                   | April                   |
|----------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
|                      | %<br>(km <sup>2</sup> ) | %<br>(km <sup>2</sup> ) | %<br>(km <sup>2</sup> ) | %<br>(km <sup>2</sup> ) | %<br>(km <sup>2</sup> ) |
| Very High            | 16.4<br>(0.21)          | 29.5<br>(0.38)          | 4.8<br>(0.06)           | 0.3<br>(0.00)           | 0.0<br>(0.00)           |
| High                 | 32.4<br>(0.42)          | 34.5<br>(0.44)          | 22.3<br>(0.29)          | 7.0<br>(0.09)           | 0.0<br>(0.00)           |
| Moderate             | 36.6<br>(0.47)          | 31.8<br>(0.41)          | 31.3<br>(0.40)          | 21.6<br>(0.28)          | 18.7<br>(0.24)          |
| Low                  | 14.5<br>(0.19)          | 4.2<br>(0.05)           | 32.1<br>(0.41)          | 41.3<br>(0.53)          | 44.9<br>(0.58)          |
| Very Low             | 0.1<br>(0.00)           | 0.0<br>(0.00)           | 9.4<br>(0.12)           | 29.7<br>(0.38)          | 36.4<br>(0.47)          |
| <b>Total</b>         | <b>100<br/>(1.29)</b>   | <b>100<br/>(1.29)</b>   | <b>100<br/>(1.26)</b>   | <b>100<br/>(1.29)</b>   | <b>100<br/>(1.29)</b>   |

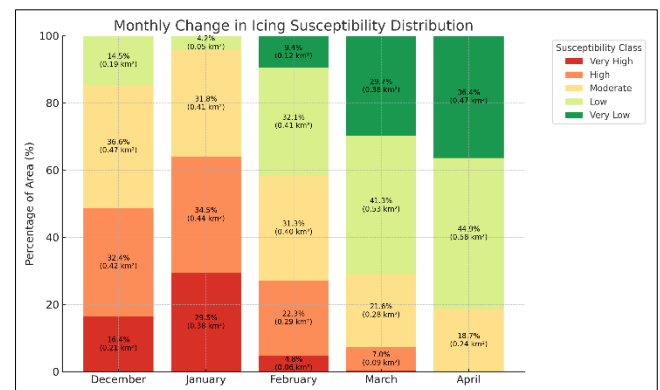


**Figure 8.** Monthly change in the proportional distribution of icing susceptibility classes. The chart visualizes the dynamic shift in susceptibility profiles from peak winter to spring.

### 3.3. Model Validation with Field Observations

The performance of the final susceptibility model was validated by comparing it against 50 ground-truth points, which represent confirmed locations of hazardous icing identified through field surveys and municipal winter maintenance records. The analysis was conducted using the January road susceptibility map, as it represents the month with the highest overall risk. The validation results demonstrate a strong predictive capability of the model. As detailed in Table 5 and visually represented in Figure 9, 76% (38 out of 50) of the confirmed icing hotspots fall on road segments classified by the model as 'High' or 'Very High' susceptibility.

A further 22% (11 points) are located on roads with 'Moderate' susceptibility. Crucially, only one observed point (2%) fell into a 'Low' susceptibility zone, and no confirmed icing locations were found in the 'Very Low' susceptibility areas. These findings confirm that the GIS-AHP model can reliably identify real-world hazardous road locations, validating its effectiveness as a decision-support tool. Spatially, the model identifies the roads within the Özcan, Hasanbey, and Karşıyaka neighbourhoods as having the highest concentration of susceptibility, while Cumhuriyet and Atatürk avenues

are pinpointed as the most critical thoroughfares for icing risk.

**Table 5.** Distribution of validation points across susceptibility classes for January

| Susceptibility Class | Risk Score | Number of Points | Percentage (%) |
|----------------------|------------|------------------|----------------|
| Very High            | 5          | 24               | 48.0%          |
| High                 | 4          | 14               | 28.0%          |
| Moderate             | 3          | 11               | 22.0%          |
| Low                  | 2          | 1                | 2.0%           |
| Very Low             | 1          | 0                | 0.0%           |
| <b>Total</b>         |            | <b>50</b>        | <b>100.0%</b>  |

#### 4. Discussion

This study has successfully developed and implemented a GIS-based AHP model to map road icing susceptibility in the city of Gümüşhane. The resulting high-resolution (5m) monthly susceptibility maps provide a significant advancement over macro-scale or non-spatial approaches. In this section, the findings are interpreted, contextualized within the existing literature, and the theoretical contributions and practical implications of the study are addressed.

##### 4.1. Interpretation of Findings: Dominant Factors and Spatio-temporal Dynamics

A primary finding of this research is the quantitative determination of the most influential factors driving icing susceptibility. According to the weights derived from the AHP expert synthesis, Solar Radiation (28.5%) and Temperature (18.2%) emerge as the two most dominant parameters. The combined weight of these two climatological factors, at 46.7%, confirms that road icing is fundamentally a surface energy balance problem.

These primary factors are followed by topographic and urban morphometric parameters that provide crucial spatial detail. Aspect (13.5%) and Object Height (10.1%) were identified as the third and fourth most important factors, respectively, due to their direct control over the amount of solar radiation reaching the surface. This highlights the critical importance of the "urban canyon" effect, particularly in a densely built city situated within a narrow valley like Gümüşhane. Our model empirically confirms the principle defined by Oke [44] demonstrating that these canyons, characterized by a limited sky view factor that restricts direct solar insolation, are consistently identified as the zones of highest susceptibility (Figure 10). These findings are also consistent with the work of Kusaka and Kimura [13] on the thermal effects of urban structures, as well as more recent studies that investigate heat exchange and thermal comfort within urban street canyons under both hot and cold conditions [14, 15]. The temporal analysis of the model reveals that susceptibility is not static but exhibits a distinct seasonal evolution. The spatial extent of the 'High' and 'Very High' susceptibility classes peaks in January, covering 64.0% of the entire road network, and is entirely absent by April. This finding demonstrates the model's capacity to answer not only "where" but also "when" the susceptibility is highest, providing critical

temporal information for winter maintenance operations.

Furthermore, the physical barrier of the snowpack itself compounds this effect. As Dombrovsky [44] notes, snow cover can hinder sunlight from reaching the underlying ice. Our study suggests that the shade cast by buildings in an urban canyon creates an analogous effect, dramatically prolonging the life of hazardous ice patches compared to sun-exposed areas. This finding is crucial because it elevates the importance of urban morphology from a secondary factor to a primary driver of icing susceptibility, a nuance often missed in broader models.

##### 4.2. Contribution to Literature, Methodological Advancements, and Limitations

This study offers several key contributions to the existing literature. First, while factors such as slope and elevation are known to influence frost distribution [45], our model quantitatively establishes that in a dense urban valley setting, solar radiation, temperature, aspect, and object height are hierarchically far more dominant. Second, the study enhances methodological robustness by employing a mixed panel of 11 experts... and validating the results with a low Consistency Ratio (CR = 0.066)

Nevertheless, the model has certain limitations that suggest avenues for future research. Although factors such as pavement material and albedo [44, 45, 46, 47] were incorporated into our model, their weights were determined to be relatively low by the expert panel. This may indicate a tendency for experts to prioritize macro-scale climatic and topographic factors over micro-scale surface properties. Future work could further refine the model's sensitivity by investigating the thermal behaviour of these micro-scale features in greater detail (e.g., with thermal imaging). Similarly, incorporating diurnal variations in solar angle [50, 51] and dynamic traffic data could evolve the model from a monthly susceptibility tool to an hourly risk-forecasting system.

##### 4.3. Practical Implications and Implementation

The true value of this research lies in its transition from an academic model to a practical tool for urban management and public safety. The generated monthly susceptibility maps have been integrated into the Gümüşhane City Information System (GCIS), providing municipal authorities with an operational decision support tool (Figure 11). This implementation has yielded tangible benefits:

- *Optimized Winter Maintenance Operations:* As confirmed by municipal officials, winter maintenance activities, such as salting and plowing, are now prioritized based on the susceptibility maps. Resources are dispatched first to the 'Very High' susceptibility zones, such as the identified urban canyons and north-facing slopes, ensuring that the most dangerous routes are addressed efficiently, in line with recommendations by Shi & Fu [52].

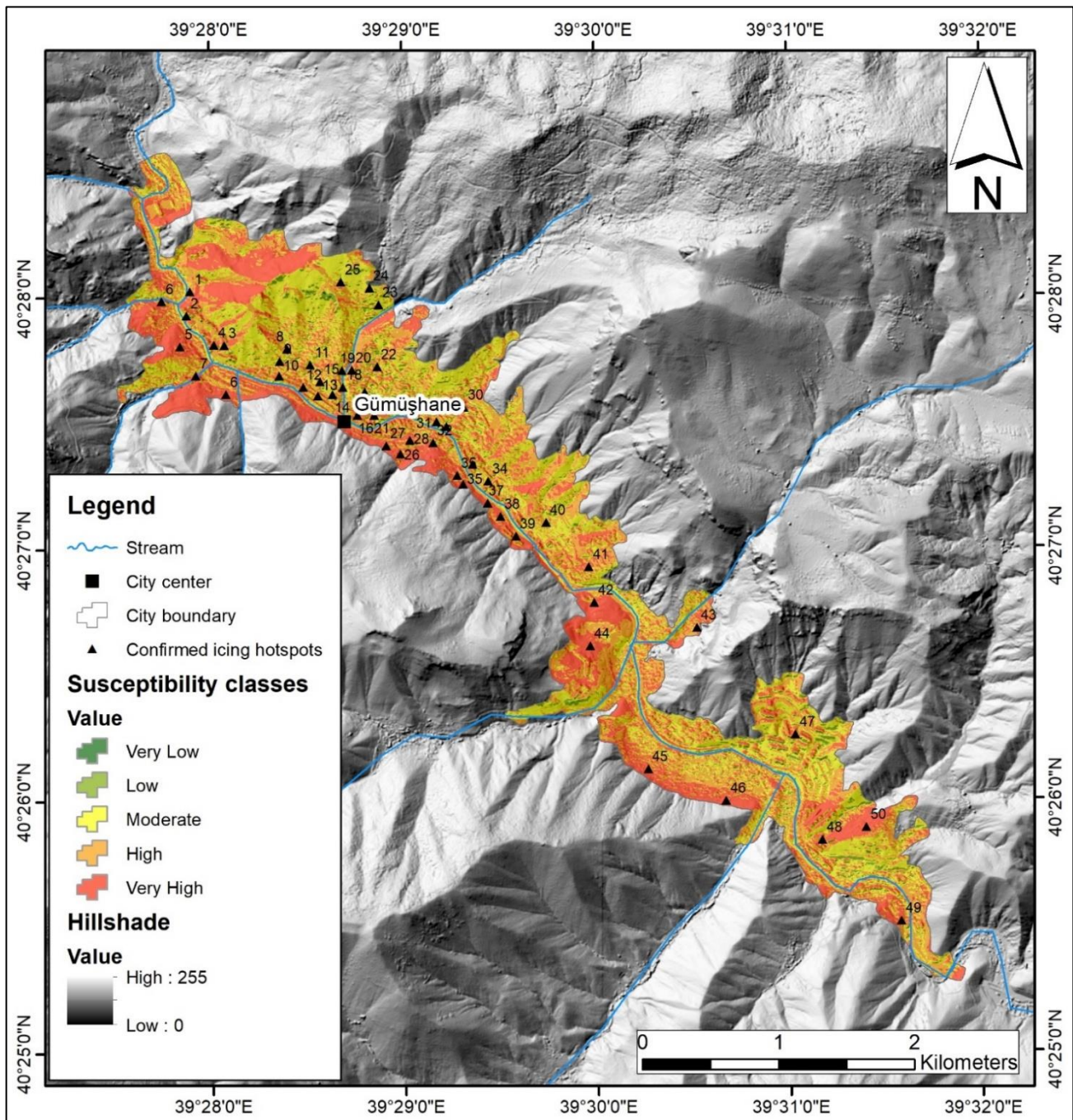


**Figure 9.** Validation of the January icing susceptibility map with confirmed icing hotspots. The map illustrates the spatial distribution of the five susceptibility classes overlaid with 50 ground-truth points collected during field surveys.

- *Targeted Safety Interventions:* The model supports the strategic placement of safety measures, such as speed-reducing strips in high-susceptibility sloped areas [53], and the prioritization of maintenance routes serving critical infrastructure like schools and hospitals [54].
- *Enhanced Urban Resilience:* This study successfully completes a full research cycle: identifying a problem, developing a model, validating its results, and implementing it as a service that directly enhances urban resilience and public safety.

This successful integration demonstrates the importance and potential of translating GIS-based

models from the academic realm into practical applications.

## 5. Conclusion

This study successfully developed, validated, and implemented a high-resolution (5 m) GIS-based AHP model to map road icing susceptibility within a complex urban environment. The results clearly demonstrate that the dominant factors controlling road icing are solar radiation and temperature, followed by aspect and object height, which jointly determine the level of shading and heat retention on road surfaces. The findings confirm that narrow streets bordered by tall buildings experience prolonged icing conditions due to limited solar exposure, highlighting the strong influence of urban morphology on microclimatic processes. Field validation showed that

91.4% of observed icing hotspots were accurately predicted within the high or very high susceptibility classes, confirming the model's strong reliability and spatial accuracy. The model also effectively captured the seasonal dynamics of icing, with risk levels peaking in January and diminishing entirely by April. Beyond its scientific contribution, the model has been successfully integrated into the Gümüşhane City Information System (GCIS), where it now serves as a practical decision-support tool for optimizing winter maintenance and enhancing public safety. Overall, this research presents a replicable, data-driven framework that bridges the gap between geospatial analysis and urban management, offering a valuable approach for improving traffic safety and urban resilience in cold-climate cities.

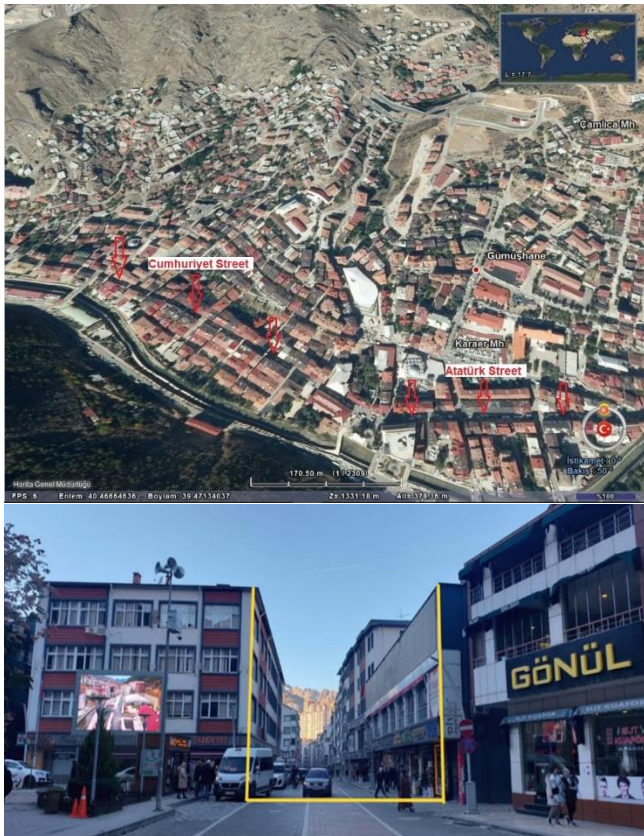


**Figure 10.** The "Urban Canyon" effect in Gümüşhane. (a) Google Earth view highlighting the dense building structure creating shaded corridors. (b) Street-level view of Cumhuriyet Street demonstrating the limited sky view factor.

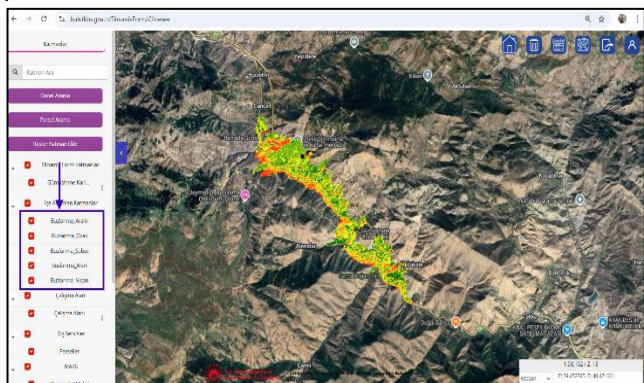


**Figure 11.** Gümüşhane City Information System (GCIS).

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## Author contributions

**Fatih Işık:** Conceptualization, Methodology, Formal Analysis, Investigation, Software, Visualization, Writing – Original Draft. **Rabia Kanyılmaz:** Visualization, Software, Writing – Review & Editing. **Savaş Çağlak:** Formal Analysis, Investigation, Writing – Review & Editing. **Selim Eraslan:** Visualization, Writing – Review & Editing. **Halil İbrahim Zeybek:** Supervision, Writing – Review & Editing.

## Conflicts of interest

The authors have no competing interests to declare that are relevant to the content of this article.

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