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Developing a LiDAR-Based Geospatial Digital Twin Framework for Sustainable Tourism Planning in Mountain Ski Resorts: The Davraz Ski Resort Case

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Abstract

Sustainable planning of mountain ski resorts requires high-resolution terrain information and an explicit account of visitor-oriented landscape accessibility. This study develops and evaluates an update-ready LiDAR-based geospatial Digital Twin prototype for the Davraz Ski Resort (Türkiye). The term prototype is used deliberately: the empirical implementation represents a single survey epoch and a reproducible analytical workflow, rather than a continuously synchronized or bidirectionally coupled operational Digital Twin. UAV-LiDAR data were acquired on 17 June 2025 with a DJI Matrice 350 RTK platform and Zenmuse L2 sensor at $100\,m$ above ground level over $681.013\,ha$. LiDAR-derived terrain layers (elevation, slope, aspect, mean curvature, and Terrain Ruggedness Index) were reclassified to ordinal suitability scores and integrated by weighted linear combination to produce the Ski Slope Suitability Index (SSI; weights $0.40, 0.25, 0.15, 0.10$, and 0.10, respectively). A cumulative viewshed derived from the Digital Surface Model provided the visibility-frequency proxy termed the Visual Landscape Quality Index ($VLQI$) and the baseline Sustainable Tourism Planning Index (STPI) was calculated as $0.60 \times SSI + 0.40 \times VLQI$. The SSI identified 43.33% of the area as highly or very highly suitable; 8.43% had high or very high visual exposure; and 34.17% had high or very high STPI values. Descriptive spatial validation against 14 existing pistes showed that 13 pistes (92.9%) had mean SSI values in the Moderate or High classes. This correspondence supports planning relevance but is not independent predictive validation. Because independent elevation checkpoints, visitor-perception data and multi-temporal or real-time inputs were unavailable in the submitted dataset, the outputs should be interpreted as screening-level evidence. The principal contribution is therefore a transparent geospatial data-flow, index-integration, and update logic that can form the static baseline of a future operational Digital Twin.

Keywords: UAV-LiDAR; Geospatial Digital Twin Prototype; Ski Slope Suitability; Cumulative Viewshed; Spatial Concordance Validation; Sustainable Tourism Planning.

1. INTRODUCTION

Mountainous regions are among the most important destinations in the global tourism industry due to their outstanding natural landscapes, recreational opportunities, and significant contributions to regional economies. In particular, ski resorts constitute a fundamental component of winter tourism by supporting regional development, creating employment opportunities, and diversifying local economic activities. However, the long-term sustainability of ski resorts is increasingly threatened by climate change–induced snow variability, growing visitor pressure, land-use change, and environmental degradation. Recent studies emphasize that the sustainability of ski destinations should be evaluated not only from an economic perspective but also in terms of environmental integrity, resource efficiency, and social sustainability (Deng et al., 2019; Kiashemshaki et al., 2026; Li et al., 2025). Consequently, there is an increasing demand for integrated, data-driven decision-support systems capable of supporting sustainable planning and management of mountain tourism destinations.

Topography represents one of the most influential factors governing the planning and sustainable management of ski resorts. Terrain characteristics such as slope, aspect, elevation, surface morphology, and visual landscape quality directly affect ski-run design, skier safety, snow retention, visitor experience, and infrastructure planning (Akın & Erdoğan, 2017; Deng et al., 2019). Therefore, spatial analyses play a critical role not only in evaluating existing ski facilities but also in developing future planning scenarios. Although Geographic Information Systems (GIS) combined with multi-criteria decision-making (MCDM) approaches have substantially improved ski suitability assessments, most existing studies rely on static datasets and remain insufficient for representing the dynamic and complex nature of mountain tourism systems (Aksoy, 2024; Bağcı et al., 2022; Naumoski et al., 2019). Moreover, there is a growing need for integrated spatial frameworks capable of simultaneously evaluating environmental conditions, operational performance, and visitor experience.

In response to these challenges, unmanned aerial vehicle (UAV)-based LiDAR technology has emerged as a transformative tool for acquiring high-resolution spatial data. UAV-LiDAR systems enable highly accurate terrain modelling by penetrating dense vegetation through multiple-return laser measurements and generating centimeter-level Digital Elevation Models (DEMs). These capabilities make LiDAR particularly suitable for mountainous environments characterized by steep slopes and limited accessibility (Acharya et al., 2021; Choi et al., 2023). Compared with conventional photogrammetric techniques, UAV-LiDAR provides more reliable and consistent topographic information in complex terrain (Tamimi & Toth, 2024). High-density point clouds further facilitate the generation of Digital Surface Models (DSMs), three-dimensional terrain representations, and detailed geomorphological analyses that support snow monitoring, terrain characterization, natural hazard assessment, and environmental change detection (Candan & Kaçar, 2023; Giordan et al., 2020; Harder et al., 2020). Consequently, UAV-LiDAR has become an increasingly valuable data source for mountain tourism research and ski resort planning.

Parallel to these advances in spatial data acquisition, Digital Twin (DT) technology has emerged as a next-generation framework for creating dynamic virtual representations of physical systems. Initially developed for manufacturing and smart-city applications, Digital Twins have rapidly expanded into infrastructure management, natural resource planning, disaster risk management, and tourism (Aslan, 2024; Florido-Benítez, 2024). By integrating spatial and temporal information obtained from the physical environment into a continuously updatable virtual environment, Digital Twins enable scenario simulation, system performance assessment, and predictive decision-making (Rahmadian et al., 2023; Türkan & Yılmaz, 2025). Recent tourism studies have highlighted their considerable potential for visitor flow modelling, infrastructure management, environmental monitoring, and sustainable destination governance (de Almeida et al., 2025; Karaca & Özkan Önem, 2023; Keertana & Vijay Vishnu Kumar, 2025). Nevertheless, applications of Digital Twin technology specifically targeting mountain tourism and ski resort planning remain scarce.

Previous studies on ski resorts have primarily focused on individual aspects such as ski-run suitability, snow-cover modelling, avalanche susceptibility, or destination management (Akın & Erdoğan, 2017; Deng et al., 2019). Although Digital Twin applications in tourism have expanded considerably in recent years, most have concentrated on smart destination management, visitor experience, and digital governance (de Almeida et al., 2025; Florido-Benítez, 2024; Rahmadian et al., 2023). In contrast, studies integrating high-resolution UAV-LiDAR-derived Digital Twins with spatial decision-support systems for sustainable ski resort planning remain extremely limited (Kourtit et al., 2025; Martins et al., 2025). In particular, comprehensive frameworks that simultaneously evaluate ski-run suitability, visual landscape quality, and spatial planning components are still lacking (Reveiu, 2025; Zhang, 2023). This gap highlights the need for next-generation Digital Twin–based planning frameworks capable

of representing complex mountain tourism systems using high-resolution geospatial data while directly supporting sustainable spatial planning and management (Gjura et al., 2026; Tan & Cheng, 2024).

Accordingly, this study aims to develop a UAV-LiDAR-based geospatial Digital Twin prototype for the Davraz Ski Resort and to test its usefulness as a transparent spatial decision-support workflow. The specific objectives are to: (i) formalize the flow from raw point clouds to co-registered terrain, visibility, and planning layers; (ii) define the scoring, weighting, integration, and classification rules used for SSI, $VLQI$, and STPI; (iii) assess descriptive spatial concordance between model outputs and the 14 existing pistes; and (iv) state the update mechanism, validation boundary, and variables required to progress from the present single-epoch prototype to an operational Digital Twin. The study therefore claims an update-ready geospatial Digital Twin framework, not real-time synchronization or autonomous simulation.

2. MATERIALS AND METHODS

2.1.Study Area

This study was conducted at the Davraz Ski Resort, located in the Lakes Region of the Mediterranean Region, southwestern Türkiye. The study area is situated on the Kulovası Plateau, approximately 26 km southeast of Isparta city center, on the northern slope of Mount Davraz. The highest point within the study area is Ulparçukuru Peak ($2{,}635\ m\ a.s.l.$), while skiing activities are concentrated between 1,650 and 2,344 m above sea level. Owing to its high topographic diversity, favorable snow conditions, and well-developed winter tourism infrastructure, Davraz is recognized as one of Türkiye's major ski destinations (Anonymous, 2025; Isparta Valiliği, 2025) (Figure 1).

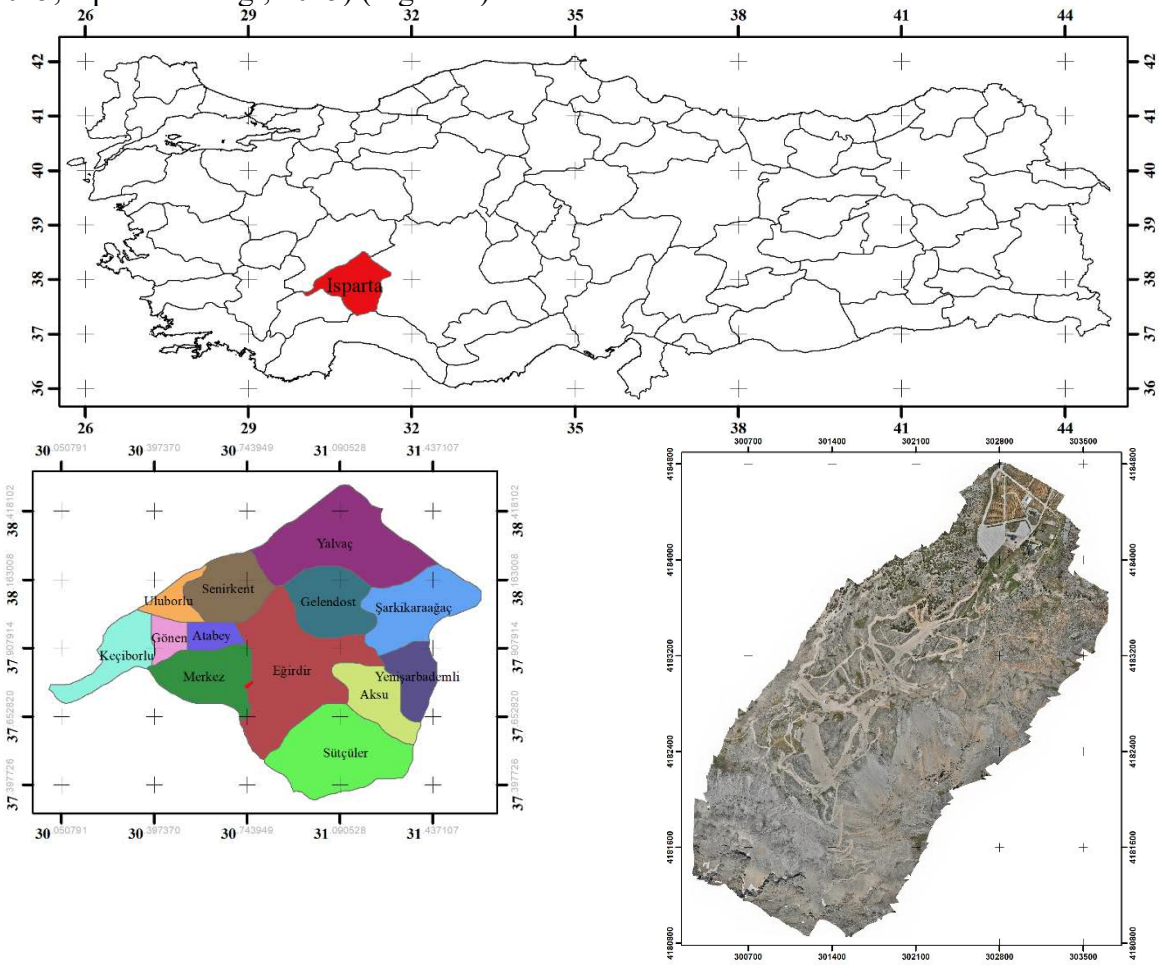


Figure 1. Location of the study area.

The ski resort covers approximately $681.013\ ha$ and has an average elevation of nearly $2{,}000\ m$ above sea level**.** Its high-altitude setting provides favorable climatic conditions for winter tourism, with the ski season generally extending from December to May, depending on annual meteorological conditions. Snow depth typically ranges between 0.5 and 2.5 m throughout the season. The resort currently comprises 14 ski slopes with varying difficulty levels, supported by a modern lift system including a gondola, chairlifts, and surface lifts, providing the infrastructure required for year-round recreational development (Anonymous, 2025). These characteristics highlight the resort's significant potential for sustainable mountain tourism.

The northern slopes of Mount Davraz combine large elevation gradients, heterogeneous slopes, and complex terrain morphology, making the site suitable for testing terrain-suitability and visibility-screening methods. The coexistence of 14 operational pistes also permits a descriptive comparison between modelled values and an established resort layout. Davraz was therefore selected to develop and evaluate the single-epoch geospatial Digital Twin prototype; the site selection does not, by itself, constitute model validation.

2.2.UAV-LiDAR Data Acquisition and Processing

The LiDAR survey was conducted on 17 June 2025 using a DJI Zenmuse L2 airborne laser scanner mounted on a DJI Matrice 350 RTK UAV. The survey covered $681.013\ ha$ and was flown at $100\ m$ above ground level. Real-Time Kinematic (RTK) corrections during acquisition were provided by a DJI D-RTK 2 High Precision GNSS Mobile Station.

Raw observations were processed in DJI Terra and exported as georeferenced LAS/LAZ point clouds. The classified cloud was used to derive a bare-earth Digital Elevation Model (DEM), a first-surface Digital Surface Model (DSM), an intensity raster, and an RGB orthophoto; the products were then imported into ArcGIS Pro for terrain derivation, cumulative viewshed analysis, zonal statistics, and map algebra. For cell-by-cell integration, the analytical rasters were processed on a common spatial framework with consistent extent, alignment, snap raster, and NoData handling. Figure 2 summarizes this processing chain.

The acquisition configuration therefore comprised the DJI Matrice 350 RTK–Zenmuse L2 system, with the aircraft RTK solution referenced to the DJI D-RTK 2 mobile station.

Within the implemented workflow, DJI Terra processing produced the classified georeferenced point cloud used for bare-earth DEM and first-surface DSM generation; the resulting products were subsequently analysed in ArcGIS Pro.

Independent ground checkpoints were not available in the manuscript dataset; therefore, project-specific vertical bias, mean absolute error (MAE), vertical root mean square error ($RMSE_z$), and 95% vertical accuracy were not estimated. Manufacturer specifications were not used as substitutes for empirical survey accuracy.

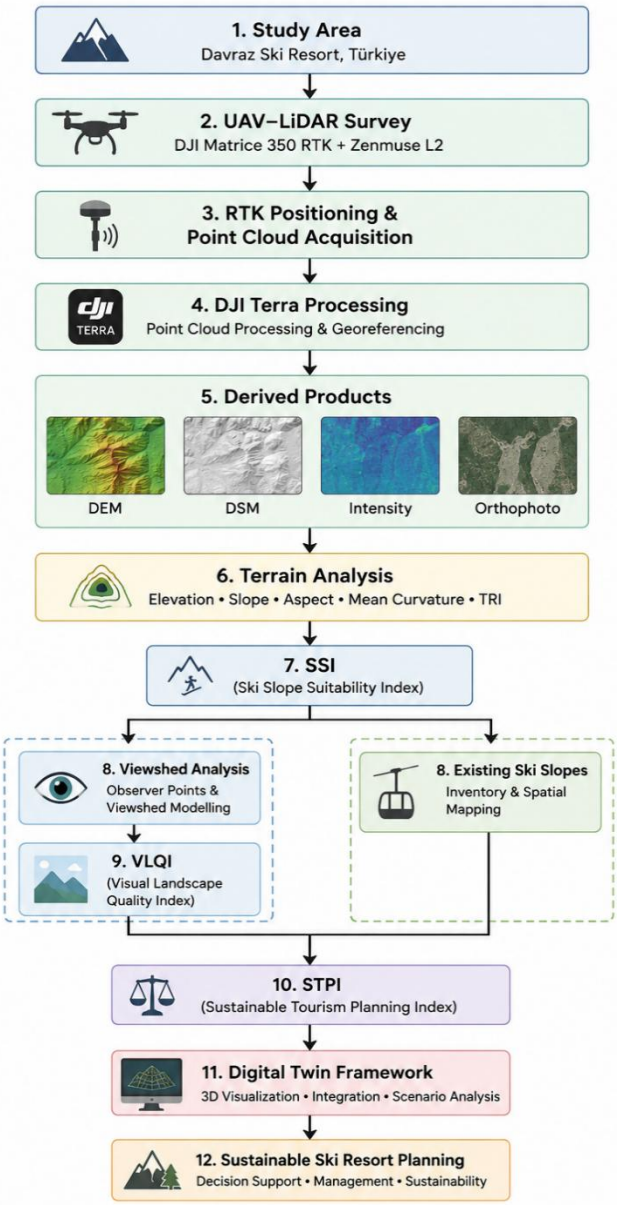


Figure 2. Operational data flow from UAV-LiDAR acquisition to the single-epoch geospatial Digital Twin prototype.

UAV-LiDAR is well suited to detailed three-dimensional mapping in steep, difficult-to-access terrain and provides the physical data foundation used in this study. RTK-supported acquisition and dense point clouds can improve terrain representation, but the accuracy of the Davraz products cannot be inferred from the sensor type alone. Project-specific point density, classification quality, raster resolution, and independent checkpoint statistics are required before the DEM or DSM can be described as accuracy-validated.

Reproducibility boundary. Only acquisition and processing parameters documented in the archived project record are reported. Unavailable mission parameters (including flight speed, strip overlap, scan pattern, return mode, and point rate), point-cloud density metrics, classification and filtering settings, DEM/DSM interpolation settings, software versions, and independent checkpoint statistics were not reconstructed from manufacturer defaults or assumed retrospectively. The study is therefore reproducible at the level of the documented geospatial transformation and index-integration workflow, whereas exact replication of the original LiDAR acquisition and terrain-product accuracy assessment would require the missing project metadata.

2.3.Development of the LiDAR-Based Geospatial Digital Twin Prototype

For this study, the physical entity is the 681.013 ha Davraz Ski Resort terrain and piste system, while the virtual representation comprises timestamped LiDAR point clouds, terrain/surface rasters, piste vectors, analytical indices, and map-based planning outputs. Current Digital Twin definitions require synchronization between the physical entity and its virtual representation at a stated frequency and fidelity; a non-synchronized model used to test future integration is more accurately described as a Digital Twin prototype (Digital Twin Consortium, n.d.). Because only one LiDAR epoch ($t_0 = 17\ June\ 2025$) was available, the implemented product is therefore classified here as a single-epoch, update-ready geospatial Digital Twin prototype rather than a live Digital Twin system.

The reproducible architecture contains five connected layers. Equation (1) The source layer stores the timestamped LAS/LAZ cloud, RGB imagery, RTK trajectory information, and the existing-piste vectors. Equation (2) The processing layer classifies the point cloud and produces spatially aligned DEM, DSM, intensity, and orthophoto products. Equation (3) The analytical layer derives elevation, slope, aspect, mean curvature, and TRI from the DEM and binary visibility rasters from the DSM. Equation (4) The integration layer applies the stated scoring functions, weights, and class breaks to generate SSI, $CVI/VLQI$, and STPI. Equation (5) The output layer stores maps, class areas, and piste-level zonal statistics. Thus, data move in one direction from a dated physical survey to traceable spatial outputs; a new survey epoch replaces the source package and triggers the same processing graph rather than requiring a new conceptual model (Figure 3).

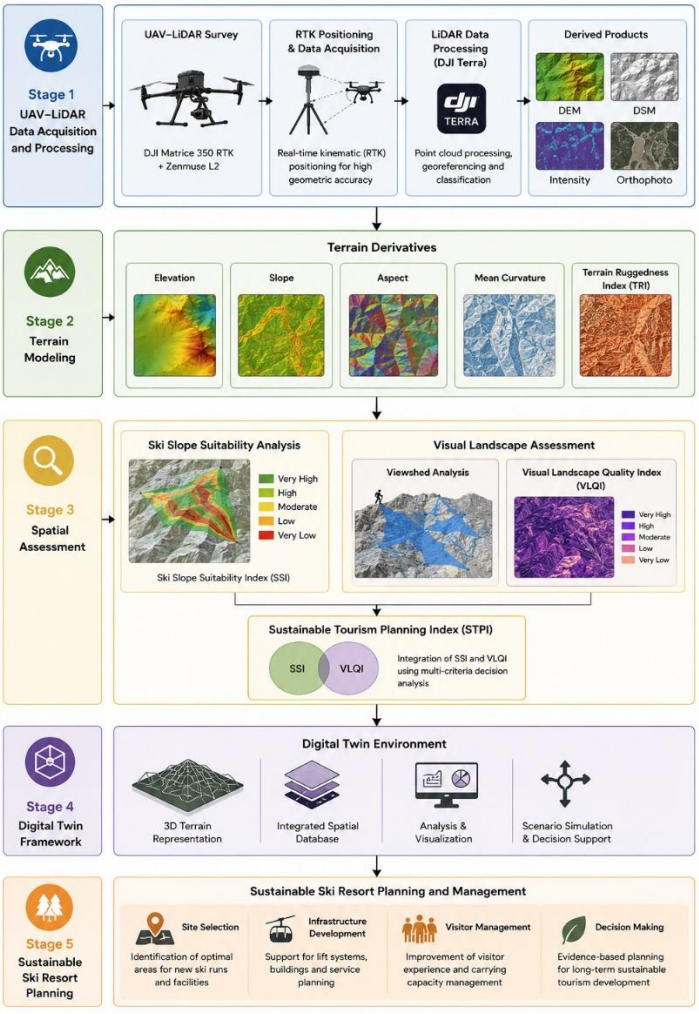


Figure 3. Computational architecture of the single-epoch UAV-LiDAR-based geospatial Digital Twin prototype, showing source data, terrain/surface models, analytical modules, index integration, and planning outputs.

For a survey epoch t and a scenario parameter set s the implemented prototype is formally represented as Equation (1)

$$DTp(t,s) = \{D(t), T(t), SSI(t,s), VLQI(t,s), STPI(t,s), OTS(t,s)\} \quad (1)$$

where $D(t)$ is the dated source-data package; $T(t)$ is the set of co-registered terrain and surface layers; s contains criterion scores, weights, class breaks, and optional constraint layers; $SSI(t,s)$, $VLQI(t,s)$, and $STPI(t,s)$ are cell-level analytical states; and $OTS(t,s)$ contains maps, area summaries, and piste-level statistics. Scenario evaluation is implemented by changing s and rerunning the same map-algebra chain. The present paper reports only the baseline scenario s_0; it does not report real-time ingestion, automated two-way control, or multi-temporal forecasting.

The workflow and outputs associated with each stage are summarized in Table 1.

Table 1. Workflow and outputs of the proposed UAV-LiDAR-based Digital Twin framework.

Stage	Input Data	Main Process	Output
Stage 1. UAV-LiDAR Data Acquisition	UAV-LiDAR observations	RTK-supported data acquisition and preprocessing	Georeferenced LAS/LAZ point cloud
Stage 2. Terrain Modelling	LiDAR point cloud	Generation of DEM, DSM, Intensity raster, and RGB orthophoto	Terrain datasets
Stage 3. Terrain Analysis	DEM	Derivation of Elevation, Slope (%), Aspect, Mean Curvature, and TRI	Topographic variables
Stage 4. Spatial Assessment	Topographic variables	SSI modelling, cumulative Viewshed Analysis, and $VLQI$ calculation	Spatial suitability layers
Stage 5. Digital Twin Integration	SSI and $VLQI$	Baseline STPI generation and versioned geospatial prototype integration	Single-epoch integrated planning layer
Stage 6. Sustainable Tourism Planning	Digital Twin model	Baseline decision support and parameterized what-if reruns	Screening scenarios and update pathway

The prototype differs from a conventional stand-alone map by explicitly linking a dated physical survey, a reproducible transformation graph, scenario parameters, and updateable outputs. Nevertheless, it remains static at t_0. Operational deployment would require: (i) a defined acquisition interval or event trigger; (ii) automated quality checks and versioned ingestion of new LiDAR, snow, weather, ecological, and infrastructure data; (iii) change detection between t and $t+1$; and (iv) an interactive interface that reruns scenarios and records model versions. These are specified as the update pathway, not claimed as functions already demonstrated in this case study.

2.4.Terrain Analysis and Derivation of Topographic Variables

Terrain analyses were performed in ArcGIS Pro using the LiDAR-derived DEM. Five variables were retained: elevation, slope, aspect, mean curvature, and Terrain Ruggedness Index (TRI). Slope represents skiability and engineering difficulty; aspect and elevation serve as topographic proxies for solar exposure and relative snow persistence; mean curvature represents local concavity/convexity and corridor continuity; and TRI represents neighbourhood-scale roughness. The selection was deliberately restricted to variables derivable from the single summer LiDAR survey so that the topographic component could be reproduced from one internally consistent dataset (Akın & Erdoğan, 2017; Deng et al., 2019; Riley et al., 1999; Wilson & Gallant, 2000).

Scope of excluded variables. Snow depth and duration, avalanche susceptibility, wind exposure, ecological sensitivity, soil stability, land ownership, infrastructure cost, visitor demand, and climate variability are relevant to operational ski-resort sustainability but were not measured by the available single-epoch dataset. They were therefore not used as hidden or qualitative criteria

in SSI or STPI. The reported STPI is a topography-visibility screening index, not a comprehensive measure of environmental, social, and economic sustainability. In a future operational Digital Twin, these variables should enter either as exclusionary constraint masks (for example, avalanche or protected-habitat zones) or as additional standardized criteria with independently justified weights.

Elevation was used to characterize the topographic structure of the study area and identify elevation zones. In mountainous environments, elevation strongly influences air temperature, snow persistence, and local microclimatic conditions, making it one of the most important factors affecting the spatial suitability of ski resorts.

Slope was calculated from the LiDAR-derived DEM using the Slope tool in ArcGIS Pro and expressed as percentage slope (%)**.** Percentage slope was preferred because it is directly comparable with international ski slope design guidelines and engineering standards. Slope is widely regarded as the primary terrain variable controlling ski-run difficulty, operational safety, and engineering feasibility.

Aspect was derived to characterize the orientation of terrain surfaces. Aspect influences incoming solar radiation, snow accumulation, snow persistence, and local microclimatic conditions. In the Northern Hemisphere, north- and northeast-facing slopes generally retain snow cover for longer periods owing to reduced solar exposure, making them particularly suitable for winter recreation (Deng et al., 2019).

Mean Curvature was generated from the LiDAR-derived DEM using the Surface Parameters tool in ArcGIS Pro. Mean Curvature describes the local morphology of the terrain by distinguishing concave, convex, and near-planar surfaces. Negative values indicate concave landforms, positive values indicate convex terrain, and values close to zero represent relatively planar surfaces. This variable was incorporated to characterize terrain continuity, drainage behaviour, and the spatial continuity of potential ski corridors (Florinsky, 2012; Wilson & Gallant, 2000).

Terrain heterogeneity was quantified using the Terrain Ruggedness Index (TRI), which measures elevation differences between a central cell and its surrounding neighbourhood (Riley et al., 1999). Higher TRI values indicate increasingly rugged and heterogeneous terrain conditions. TRI was calculated according to Equation (2)

$$TRI = \sqrt{\sum_{i=1}^{8} (z_i - z_c)^2} \quad (2)$$

where z_c is the elevation of the central cell and z_i is the elevation of each of its eight neighbours. The raw TRI was subsequently transformed to a $0 - 1$ range using min-max normalization, Equation (3):

$$TRI_n(x) = [TRI_{raw}(x) - TRI_{raw,min}(x) / [TRI_{raw,max} - TRI_{raw,min}] \quad (3)$$

Only the normalized TRI layer was reclassified for SSI.

The derived terrain variables served as the primary inputs for subsequent ski slope suitability assessment**,** visual landscape analysis, and the development of the UAV-LiDAR-based Digital Twin framework. Their characteristics and relevance to sustainable ski resort planning are summarized in Table 2.

Table 2. Topographic variables derived from the UAV-LiDAR-based Digital Elevation Model.

Variable	Unit	Description	Relevance to ski resort planning
Elevation	m	Surface altitude above sea level	Terrain zoning and snow-retention potential
Slope	%	Terrain steepness derived from the DEM	Ski-run difficulty, safety, and engineering suitability

Variable	Unit	Description	Relevance to ski resort planning
Aspect	°	Terrain orientation relative to north	Snow persistence, solar radiation, and microclimate
Mean Curvature	m^{-1}	Local terrain morphology (concave, convex, planar)	Surface continuity, drainage characteristics, and ski corridor alignment
Terrain Ruggedness Index (TRI)	$Dimensionless$	Terrain heterogeneity based on neighbourhood elevation differences	Terrain complexity and identification of unsuitable areas

2.5.Ski Slope Suitability Assessment

Ski slope suitability was evaluated at the common raster-cell resolution using five DEM-derived criteria: elevation, slope, aspect, mean curvature, and TRI. For each cell x, the raw value $r_i(x)$ was converted to an ordinal suitability score $X_i(x)$ in $\{1, 2, 3, 4, 5\}$ according to Table 3. Aspect and slope used rule-based intervals, whereas elevation, absolute mean curvature, and TRI used data-dependent Jenks intervals. The analysis therefore combines externally reasoned score direction with study-area-specific class limits.

To make the implemented baseline reproducible, Table 3 now reports the numerical break values retained for elevation (m), absolute mean curvature ($|MC|, m^{-1}$), and normalized TRI $(0 - 1)$. The displayed limits are rounded only for presentation; the raster calculations used the stored cell values.

Among the selected variables, Slope was considered the most influential criterion because it directly determines ski-run difficulty, operational safety, and construction feasibility. Consequently, slope received the highest weighting (40%) in the suitability model. Slope classes were established according to internationally recognized ski slope design recommendations and adapted to the geomorphological characteristics of the Davraz Ski Resort. Areas with slopes between $25 - 40\%$ were considered optimal for ski slope development, whereas gentler ($< 25\%$) and steeper ($> 40\%$) terrain received lower suitability scores.

Aspect was incorporated because of its influence on incoming solar radiation, snow persistence, and local microclimatic conditions. North- and northeast-facing slopes received the highest suitability scores owing to their greater snow-retention potential. Elevation was included to represent variations in snow reliability and local climatic conditions, while Mean Curvature was used to characterize terrain continuity and local surface morphology. Areas with near-planar terrain were considered more suitable for ski corridor development than highly concave or convex surfaces. Terrain Ruggedness Index (TRI) was incorporated to quantify terrain heterogeneity, with lower ruggedness values representing more favourable conditions for ski infrastructure development.

The standardized score $X_i(x)$ equals the Table 3 score assigned to the interval containing $r_i(x)$. SSI was then calculated for every valid raster cell by weighted linear combination. The criterion weights sum to 1.00 and the theoretical SSI range is $1 - 5$. Cells outside the common analysis mask were assigned NoData and were excluded from class-area calculations. Because Jenks limits are dataset-dependent, the resulting SSI categories are interpreted as case-specific rather than universal thresholds Equation (4):

$$SSI(x) = 0.40\,Xslope(x) + 0.25\,Xaspect(x) + 0.15\,Xelevation(x) + 0.10\,Xcurvature(x) + 0.10\,XTRI(x) \quad (4)$$

The weights represent literature-informed analyst assumptions: slope received the largest weight because it directly constrains skiability and engineering feasibility; aspect and elevation represent snow-retention proxies; and curvature and TRI refine corridor continuity and terrain roughness (Akın & Erdoğan, 2017; Malczewski, 1999, 2006). No formal expert panel, pairwise-

comparison matrix, consistency ratio, or empirical weight optimization was conducted. Accordingly, the weights should be interpreted as the baseline scenario s0 rather than universal coefficients.

Continuous suitability values were subsequently classified into five categories (Very Low, Low, Moderate, High, and Very High) using the Jenks Natural Breaks classification method, which minimizes within-class variance while maximizing between-class differences. The resulting suitability map was used as the primary topographic input for subsequent Digital Twin analyses and for evaluating existing ski slopes as well as identifying potential areas for future ski slope development. The parameters used in the suitability assessment are summarized in Table 3**.**

The criterion scores and weights reported in Table 3 define the baseline scenario. They were informed by the cited literature and analyst judgement; no formal expert panel, AHP pairwise-comparison matrix, or empirical weight optimization was used.

A formal weight-sensitivity analysis was not performed. Consequently, no claim is made that SSI class areas, piste rankings, or STPI outcomes are stable under perturbation of the baseline weights. The reported statistics apply only to the baseline scenario s0; robustness to alternative weight structures remains an explicit validation requirement for future implementations.

Table 3. Parameters used for ski slope suitability assessment within the LiDAR-based digital twin framework.

Parameter	Class / Category	Range / Condition	Score
Slope (%)	Gentle terrain	$0 - 25$	2
	Optimum ski terrain	$25 - 40$	5
	Steep terrain	> 40	3
Aspect	North–Northeast	$337.5 - 67.5°$	5
	East–Northwest	$67.5 - 112.5°;\ 292.5 - 337.5°$	4
	West	$247.5 - 292.5°$	3
	Southeast–Southwest	$112.5 - 157.5°;\ 202.5 - 247.5°$	2
	South	$157.5 - 202.5°$	1
Elevation	Very low	$1647.45 - 1784.29$	2
	Low	$> 1784.29 - 1934.02$	3
	Moderate	$> 1934.02 - 2099.00$	4
	High	$> 2099.00 - 2306.81$	5
	Very high	$> 2306.81 - 2580.99$	1
Mean Curvature	Near-planar	$\lvert MC \rvert \leq 0.0427$	5
	Slight curvature	$0.0427 < \lvert MC \rvert \leq 0.0978$	4
	Moderate curvature	$0.0978 < \lvert MC \rvert \leq 0.1692$	3
	High curvature	$0.1692 < \lvert MC \rvert \leq 0.2744$	2
	Extreme curvature	$0.2744 < \lvert MC \rvert \leq 2.6600$	1
Terrain Ruggedness Index (TRI)	Very low ruggedness	$0.00 - 0.40$	5
	Low ruggedness	$> 0.40 - 0.47$	4
	Moderate ruggedness	$> 0.47 - 0.51$	3
	High ruggedness	$> 0.51 - 0.58$	2
	Very high ruggedness	$> 0.58 - 1.00$	1

Note: The scores and weights define the implemented baseline model. Slope and aspect use explicit rule-based intervals; elevation, absolute mean curvature, normalized TRI, and the final SSI use study-area-specific Jenks Natural Breaks. MC denotes mean curvature. Elevation limits are reported to 0.01 m, |MC| limits to 0.0001 m^{-1}, and normalized TRI limits to 0.01. In each interval after the first, the lower bound is exclusive and the upper bound is inclusive. The weighting scheme is literature-informed and analyst-defined, not AHP-derived or statistically calibrated.

2.6.Cumulative Visual Exposure Assessment (workflow label: $VLQI$)

Visual assessment was operationalized strictly as cumulative visual exposure. The acronym $VLQI$ is retained to maintain consistency with the established workflow and result tables, but in this study it is an operational visibility-frequency proxy: it quantifies how often each cell is visible from the selected observer set. It does not measure scenic beauty, visitor preference, landscape character, or aesthetic quality. Accordingly, references to "quality" are interpreted only in this restricted spatial-visibility sense rather than as a psychophysical or preference-based landscape-quality construct (Bishop, 2003; Daniel, 2001; Inglis et al., 2022).

The analysis used the LiDAR-derived DSM as the obstruction surface in ArcGIS Pro. For each observer j, the viewshed analysis produced a binary raster $V_j(x)$, where 1 indicates an unobstructed line of sight from observer j to cell x and 0 indicates non-visibility. All output rasters were aligned to the DSM grid and summed cell by cell. Because observer geometry and line-of-sight settings influence the resulting visibility pattern, the output is interpreted as a case-specific cumulative-visibility surface.

Observer candidates were selected from four planning-relevant location types: existing pistes, lift stations, summit areas, and recreational viewpoints. Equal weight was applied to every observer in the baseline CVI; no observer received a higher scenic or visitation weight, and the observer set was not calibrated against measured visitor frequency. Consequently, the output represents visibility frequency relative to the selected observer sample and is sensitive to its number and spatial distribution.

The viewshed output was used only as a relative visibility-frequency measure within the common DSM grid and was not treated as a universally transferable representation of visual quality.

The Cumulative Visibility Index CVI was calculated for every cell as Equation (5)

$$CVI(x) = sum[j = 1..m]\, Vj(x), with\, Vj(x) \text{ in } (0,1) \quad (5)$$

where m is the number of observers used in the analysis and $CVI(x)$ ranges theoretically from 0 to m. A value of 0 means that cell x is not visible from any selected observer; larger values indicate visibility from more observer locations.

$CVI = 0$ cells were retained as $VLQI(x) = 0$ to preserve the distinction between no visibility and low positive visibility. Positive CVI values were classified by Jenks Natural Breaks and assigned ordinal $VLQI$ scores from 1 (very low positive exposure) to 5 (very high exposure). Thus, $VLQI$ has an implemented range of $0 - 5$. The resulting $VLQI$ is interpreted as a case-specific visual-accessibility proxy rather than as a validated measure of aesthetic quality.

No independent field-verified scenic-viewpoint ratings, expert landscape assessments, geotagged visitor-photograph dataset, or visitor survey was available. $VLQI$ was therefore not treated as a validated aesthetic-quality measure (Table 4).

Table 4. Variables used in the Visual Landscape Quality Assessment.

Variable	Description	Role in , $VLQI$
DSM	Digital Surface Model	Surface representation for visibility analysis
Observation Points	Ski slopes, lift stations, summit areas, and recreational viewpoints	Viewpoint definition
Cumulative Viewshed	Visibility frequency from multiple viewpoints	Visual accessibility assessment
Cumulative Visibility Index (CVI)	Sum of visibility values	Visual landscape quality calculation
Jenks Natural Breaks	Natural breaks classification	$VLQI$ classification

2.7.Topography-Visibility Planning Integration (workflow label: STPI)

The final integration combines terrain suitability and cumulative visual exposure into a two-component screening layer. The acronym STPI is retained as the workflow label for its intended planning application, but the implemented index is not a comprehensive sustainability metric. It excludes ecological, avalanche, snow, climate, economic, social, and stakeholder criteria;

therefore, STPI should be read as a topography-visibility planning screen that identifies locations for subsequent multi-domain assessment, not as evidence of sustainability in itself.

The baseline scenario assigned 60% weight to SSI and 40% to $VLQI$ because terrain is treated as the primary physical constraint and cumulative visibility as a secondary visitor-experience proxy. SSI ranges from 1 to 5, whereas $VLQI$ ranges from 0 to 5 because zero visibility was retained. The implemented STPI therefore has a theoretical range of $0.60 - 5.00$, not $1 - 5$. The $0.60/0.40$ split is an analyst-defined scenario parameter and was not empirically optimized Equation (6):

$$STPI(x \mid s_0) = 0.60\, SSI(x) + 0.40\, VLQI(x) \quad (6)$$

where x is a valid raster cell and s0 denotes the reported baseline parameter set. For an alternative scenario s, the two weights may be changed subject to $wSSI + wVLQI = 1$; additional constraint layers must be documented and the entire raster calculation rerun.

Continuous STPI values were classified into Very Low, Low, Moderate, High, and Very High classes using Jenks Natural Breaks. Because this data-dependent method minimizes within-class variation for the Davraz dataset, the resulting categories are case-specific and should not be transferred unchanged to other resorts.

The five-category STPI classification was used to summarize the baseline Davraz scenario; interpretation was based on relative cell ordering and class-area distributions rather than on universal threshold values.

Within the prototype, a scenario is a recorded parameter set containing the SSI criterion weights, SSI/VLQI/STPI class breaks, observer configuration, SSI-to- $VLQI$ integration weights, and any constraint masks. Parameterized scenario evaluation consists of rerunning the deterministic map-algebra chain and comparing class area, corridor continuity, and piste-level statistics. Only the baseline scenario s0 is reported in the present results; interactive scenario switching, temporal forecasting, and real-time simulation are part of the proposed update pathway rather than demonstrated capabilities.

Internal checks verified that the criterion weights summed to 1.00, analytical layers shared a common mask, and the class areas for SSI, VLQI, and STPI each summed to the 681.013 ha analysis extent. Descriptive external concordance was evaluated by overlaying the 14 existing piste centrelines and extracting minimum, maximum, and mean SSI, VLQI, and STPI values with zonal statistics. Piste location was not used to calculate SSI, although piste-related locations contributed to the observer-candidate pool for VLQI.

This validation is intentionally bounded. Existing pistes provide a plausibility benchmark for terrain suitability but are not independent ground truth and may reflect historical engineering, ownership, or operational decisions absent from the model. No independent terrain checkpoints were available in the manuscript dataset to validate DEM accuracy; no visitor survey or scenic-rating dataset was available to validate VLQI; and no independent sustainability outcome was available to validate STPI. The terms correspondence and concordance are therefore used instead of predictive accuracy.

3. RESULTS

3.1.LiDAR-Derived Topographic Characteristics

The LiDAR-derived topographic variables, including Elevation, Slope, Aspect, Mean Curvature, and Terrain Ruggedness Index (TRI), are presented in Figure 4, while their descriptive statistics are summarized in Table 5. These variables constitute the primary topographic layers of the proposed UAV-LiDAR-based Digital Twin framework and provide the basis for the subsequent ski slope suitability, visual landscape quality, and sustainable tourism planning analyses.

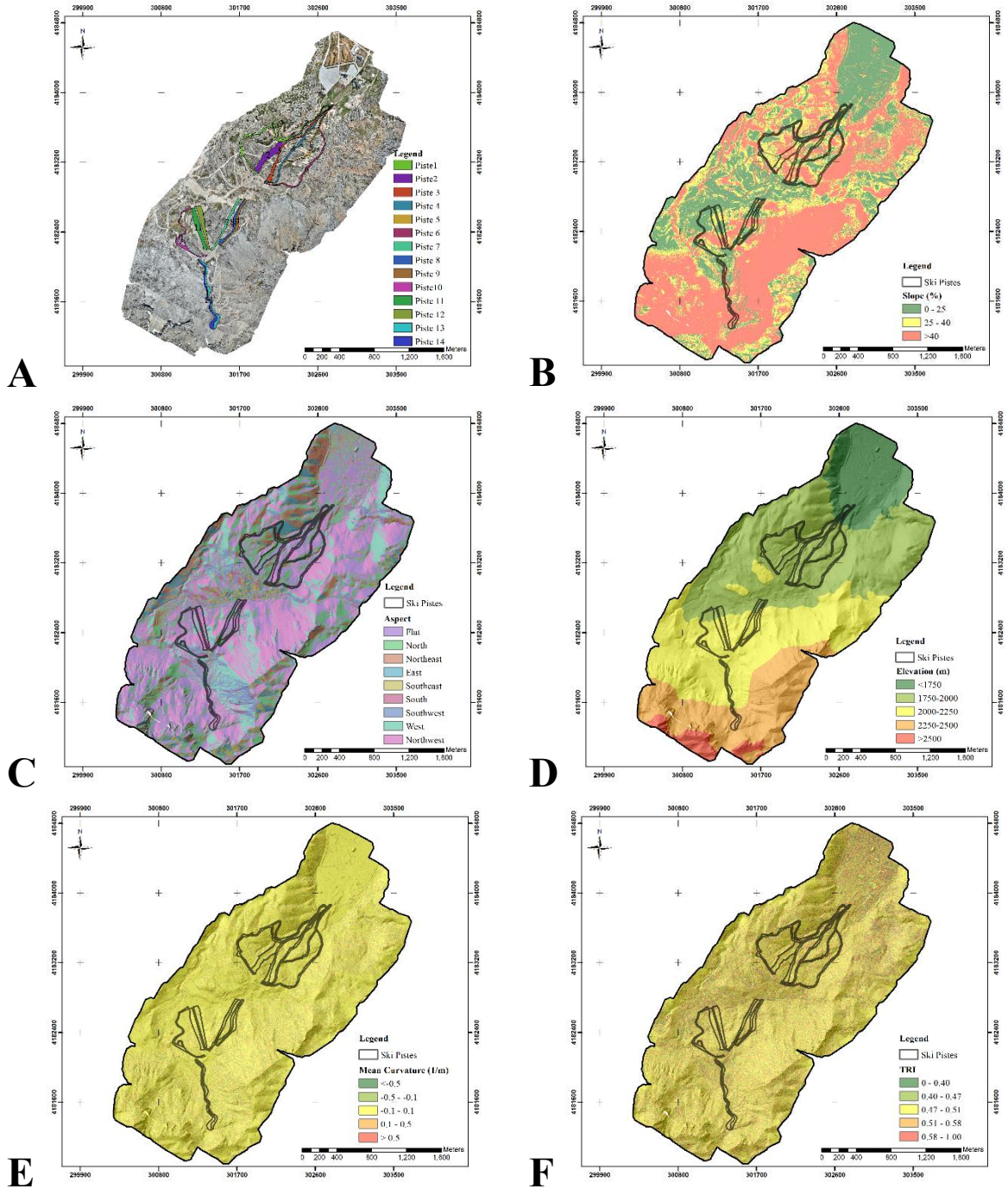


Figure 4. LiDAR-derived topographic variables used in the single-epoch geospatial Digital Twin prototype: (A) RGB orthophoto, (B) Slope (%), (C) Aspect (degrees), (D) Elevation (m), (E) Mean Curvature m^{-1} and (F) Terrain Ruggedness Index (TRI).

Slope values ranged from 0% to 5906.24%, with a mean of 42.91% and a standard deviation of 36.16% (Table 5). The extreme maximum is not a physically representative ski-run gradient; it most likely occurs at near-vertical surface discontinuities and/or local gridding artefacts. It is reported for transparency but should not be interpreted as skiable terrain. Accordingly, SSI interpretations are treated as screening-level evidence, and no accuracy claim is made for anomalous terrain cells.

Aspect values ranged from $-1°$ to $360°$, where $-1°$ represents flat terrain automatically assigned by ArcGIS Pro. The spatial distribution of aspect (Figure 4C) demonstrates

considerable directional variability across the study area, resulting in diverse terrain orientations.

Aspect values ranged from $-1° \; to \; 360°$, where $-1°$ represents flat terrain automatically assigned by ArcGIS Pro. The spatial distribution of aspect (Figure 4C) demonstrates considerable directional variability across the study area, resulting in diverse terrain orientations.

Elevation ranged from $1647.56\,m$ to $2580.99\,m$, with a mean elevation of $2032.11\,m$ and a standard deviation of $233.53\,m$ (Table 5). The approximately $933\,m$ elevation difference reflects pronounced vertical variability throughout the Davraz Ski Resort. As shown in Figure 4D, the highest elevations are concentrated around the summit region of Mount Davraz, whereas lower elevations occur mainly around the existing ski infrastructure.

Mean Curvature values varied between $-1.867\,m^{-1}$ and $2.660\;m^{-1}$, with a mean value close to zero $(0.0003\,m^{-1})$ and a standard deviation of $0.106\,m^{-1}$ Negative values represent concave landforms, whereas positive values indicate convex terrain. The near-zero mean value suggests a balanced spatial distribution of ridges, valleys, and transitional slope forms throughout the study area (Figure 4E).

The normalized Terrain Ruggedness Index (TRI) ranged from 0.00 to 1.00, with a mean value of 0.50 and a standard deviation of 0.054. Higher TRI values were primarily concentrated in rocky outcrops and highly dissected terrain, whereas relatively smooth surfaces exhibited lower TRI values (Figure 4F).

Overall, the LiDAR-derived terrain variables reveal considerable geomorphological variability within the Davraz Ski Resort and provide a high-resolution representation of the study area's topographic structure. These terrain layers constitute the primary input datasets for the subsequent Ski Slope Suitability Index (SSI), Visual Landscape Quality Index (VLQI), and Sustainable Tourism Planning Index (STPI) analyses developed within the proposed UAV-LiDAR-based Digital Twin framework.

Table 5. Descriptive statistics of the LiDAR-derived topographic variables.

Variable	Unit	Minimum	Maximum	Mean	SD
Elevation	m	1647.56	2580.99	2032.11	233.53
Slope	%	0.00	5906.24	42.91	36.16
Aspect	°	−1.00	360.00	174.46	133.45
Mean Curvature	m^{-1}	−1.867	2.660	0.0003	0.106
Terrain Ruggedness Index (TRI)	*Dimensionless*	0.00	1.00	0.50	0.054

3.2.Ski Slope Suitability Assessment

The spatial distribution of the Ski Slope Suitability Index (SSI) generated using the Weighted Linear Combination (WLC) approach is presented in Figure 5, while the spatial extent of each suitability class is summarized in Table 6. The results reveal pronounced spatial variability in terrain suitability across the Davraz Ski Resort.

The class-area calculations and the percentages reported in Table 6 use the same $681.013\;ha$ valid-cell analysis extent, ensuring consistency between the tabulated and narrative results.

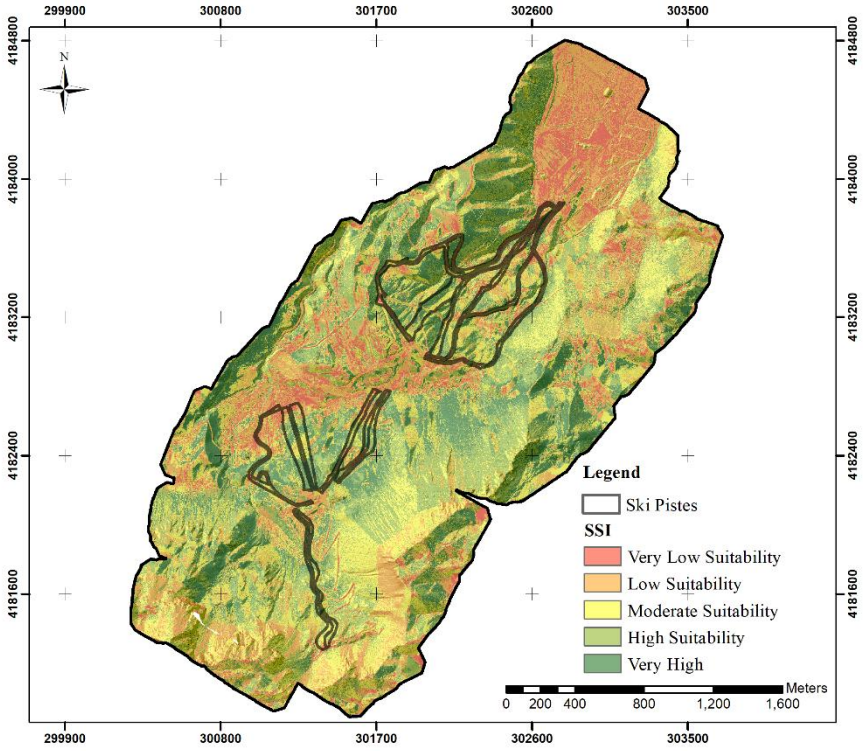


Figure 5. Spatial distribution of SSI under the baseline parameter set, derived from weighted integration of the five LiDAR-based terrain variables.

The Very High Suitability class covers 122.766 ha (18.03%) of the study area, whereas the High Suitability class occupies 172.318 ha (25.30%) (Table 6). Collectively, these two classes represent 43.33% of the total study area, indicating that nearly half of the terrain exhibits favourable topographic conditions for ski slope development. As illustrated in Figure 5**,** high-suitability areas form relatively continuous spatial corridors concentrated along the central mountainous zone rather than isolated patches, reflecting consistent terrain conditions across these sectors.

The Moderate Suitability class represents the largest category, occupying 177.386 ha (26.05%) of the study area. These areas exhibit intermediate topographic characteristics and form transitional zones between highly suitable and unsuitable terrain. In contrast, the Low Suitability and Very Low Suitability classes cover 149.200 ha (21.91%) and 59.344 ha (8.71%), respectively. These classes are predominantly associated with steep rocky slopes, highly rugged terrain, and topographically fragmented areas distributed mainly around the peripheral parts of the study area.

Table 6. Spatial distribution of Ski Slope Suitability Index (SSI) classes within the 681.013 ha common analysis mask.

SSI Class	Area (ha)	Percentage (%)
Very Low Suitability	59.344	8.714
Low Suitability	149.200	21.908
Moderate Suitability	177.386	26.047
High Suitability	172.318	25.303
Very High Suitability	122.766	18.027
Total	**681.013**	**100.000**

For descriptive spatial validation, mean SSI values were extracted for the 14 existing pistes (Table 7). Values ranged from 2.712 to 3.569, with a mean across piste-level means of 3.168.

Piste 11 had the highest mean SSI (3.569), followed by Piste 2 (3.482), Piste 12 (3.400), and Piste 8 (3.373); Piste 1 had the lowest mean (2.712).

Thirteen of the 14 pistes (92.9%) had mean SSI values in the Moderate or High classes: four were High, nine were Moderate, and one was Low. For context, 69.38% of the full study area was mapped as Moderate, High, or Very High. The greater proportion among piste-level means is consistent with historical placement on comparatively suitable terrain. This result is evidence of descriptive spatial concordance, not an independent estimate of classification accuracy, because piste positions reflect past planning decisions and the comparison uses corridor means rather than cell-level presence/absence testing.

Table 7. Topographic suitability characteristics of existing ski slopes based on the proposed Ski Slope Suitability Index (SSI).

Rank	Piste	Length (m)	Min SSI	Max SSI	Mean SSI	Suitability Class	Relative Performance
1	Piste 11	628	1.40	4.65	3.569	High	Excellent
2	Piste 2	1462	1.25	4.60	3.482	High	Excellent
3	Piste 12	400	1.50	4.75	3.400	High	Excellent
4	Piste 8	1600	1.70	5.00	3.373	High	Very Good
5	Piste 9	1876	1.60	4.65	3.339	Moderate	Very Good
6	Piste 14	2166	1.40	4.65	3.308	Moderate	Very Good
7	Piste 13	1082	1.10	4.65	3.270	Moderate	Good
8	Piste 3	511	1.25	4.60	3.165	Moderate	Good
9	Piste 4	300	1.35	4.60	3.012	Moderate	Moderate
10	Piste 6	1475	1.35	4.60	3.005	Moderate	Moderate
11	Piste 7	1264	1.50	5.00	2.962	Moderate	Moderate
12	Piste 5	200	1.35	4.60	2.881	Moderate	Moderate
13	Piste 10	680	1.50	4.75	2.879	Moderate	Moderate
14	Piste 1	496	1.35	4.70	2.712	Low	Low

The SSI map is the terrain-screening component of the single-epoch geospatial prototype. It was subsequently combined with the visibility-frequency proxy (VLQI) to form the baseline STPI; neither integration step converts the model into a complete sustainability assessment.

3.3.Visual Landscape Quality Assessment

The spatial distribution of the Visual Landscape Quality Index (VLQI) derived from cumulative viewshed analysis is presented in Figure 6, while the corresponding area statistics are summarized in Table 8. The results indicate considerable spatial variability in visual accessibility across the Davraz Ski Resort.

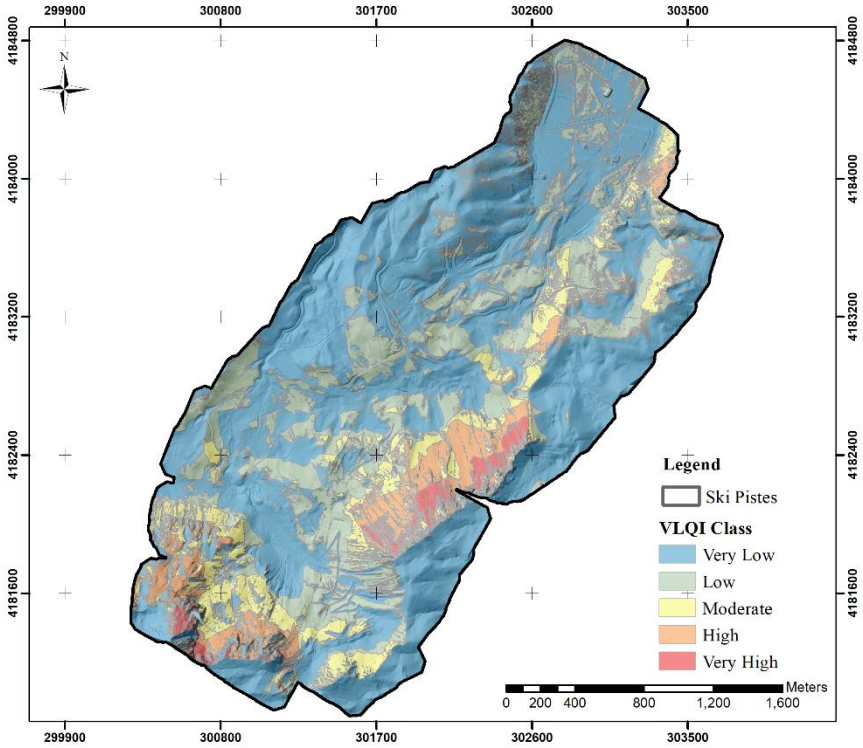


Figure 6. Spatial distribution of the visibility-frequency proxy termed VLQI, derived from cumulative viewshed analysis using the LiDAR-based DSM and the selected observer set.

The VLQI area summary shows that the class labelled Very Low occupies 392.219 ha (57.59%) and the Low class occupies 163.705 ha (24.04%) (Table 8). Together, these visibility-frequency classes account for 81.63% of the study area. Moderate, High, and Very High classes occupy 67.671 ha (9.94%), 43.855 ha (6.44%), and 13.563 ha (1.99%), respectively.

Higher visibility-frequency scores occur mainly along elevated ridgelines, summit sectors, and cells visible from multiple observers (Figure 6). Lower scores occur mainly in incised valleys and enclosed terrain where surface obstruction limits line of sight. These spatial patterns describe visual exposure relative to the selected observer set, not perceived scenic quality.

Table 8. Spatial distribution of Visual Landscape Quality Index (VLQI) classes.

VLQI Class	Area (ha)	Percentage (%)
Very Low Visual Quality	392.219	57.593
Low Visual Quality	163.705	24.039
Moderate Visual Quality	67.671	9.937
High Visual Quality	43.855	6.440
Very High Visual Quality	13.563	1.992
Total	**681.013**	**100.000**

Mean VLQI exposure-proxy values were also extracted for the 14 operational pistes (Table 9). Values ranged from 0.622 to 2.025. Piste 14 had the highest mean (2.025), followed by Piste 13 (1.841) and Piste 9 (1.825); Piste 1 (0.622) and Piste 5 (0.908) had the lowest means. These are observer-sample-dependent visibility statistics.

The observed variation among ski slopes indicates considerable spatial differences in visual accessibility throughout the study area. Pistes located on elevated terrain and ridgeline environments generally exhibited higher VLQI values, whereas those situated within enclosed terrain or areas with limited visibility recorded comparatively lower values. Overall, the VLQI

results demonstrate a heterogeneous spatial distribution of visual accessibility across the existing ski resort.

Because no independent scenic-quality or visitor-preference observations were available, these results validate only the internal behaviour of the cumulative visibility calculation. They should not be interpreted as evidence that high VLQI cells are aesthetically preferred by visitors.

Table 9. Visual landscape quality characteristics of existing ski slopes ranked according to the mean Visual Landscape Quality Index (VLQI).

Rank	Piste	Length (m)	Min VLQI	Max VLQI	Mean VLQI
1	Piste 14	2166	0	5	2.025
2	Piste 13	1082	0	5	1.841
3	Piste 9	1876	0	5	1.825
4	Piste 8	1600	0	4	1.656
5	Piste 3	511	0	4	1.559
6	Piste 7	1264	0	4	1.479
7	Piste 4	300	0	4	1.315
8	Piste 12	400	0	3	1.313
9	Piste 2	1462	0	3	1.251
10	Piste 11	628	0	3	1.197
11	Piste 6	1475	0	4	1.192
12	Piste 10	680	0	4	1.182
13	Piste 5	200	0	4	0.908
14	Piste 1	496	0	4	0.622

VLQI supplies the cumulative-visibility component of the prototype. Its integration with SSI produces a two-component planning screen; it does not supply missing ecological, climatic, social, or economic sustainability evidence.

3.4.Sustainable Tourism Planning Index (STPI)

The spatial distribution of the Sustainable Tourism Planning Index (STPI), generated through the weighted integration of the Ski Slope Suitability Index (SSI) and the Visual Landscape Quality Index (VLQI), is presented in Figure 7, while the spatial distribution of the planning suitability classes is summarized in Table 10. The STPI represents the integrated planning layer of the proposed UAV-LiDAR-based Digital Twin framework.

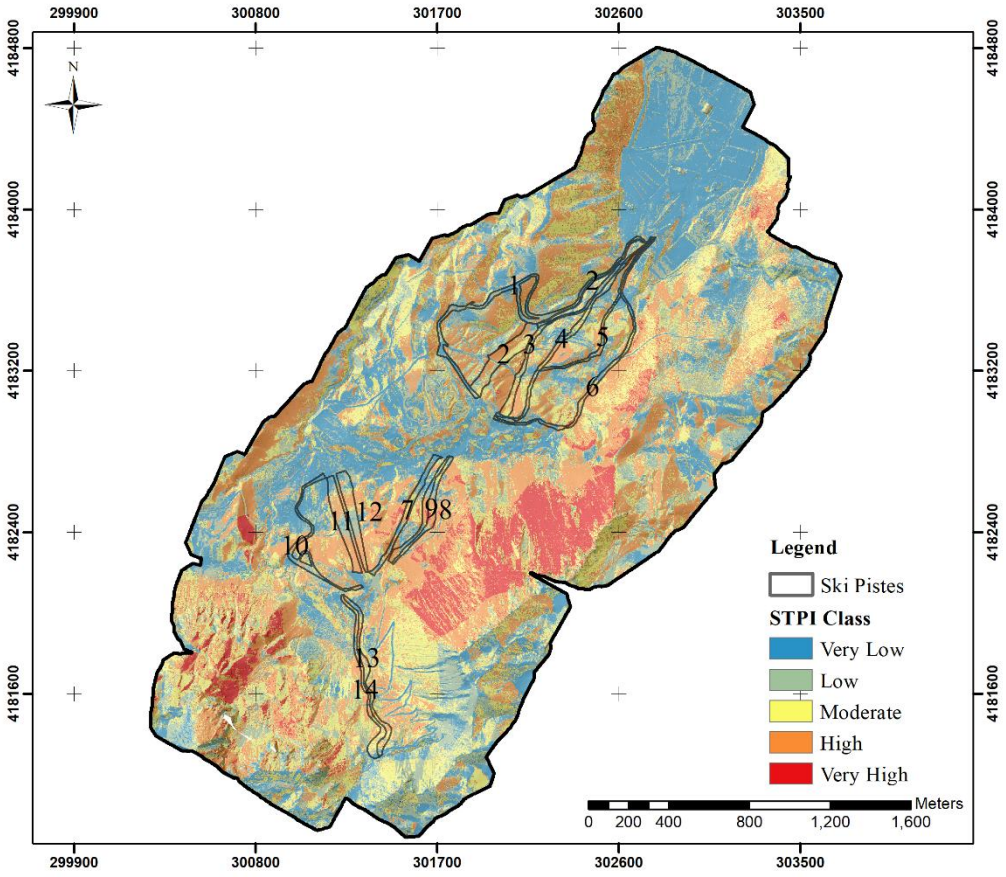


Figure 7. Spatial distribution of baseline STPI values calculated as;
$0.60 \times SSI + 0.40 \times VLQI$; this is a topography-visibility screening layer rather than a comprehensive sustainability metric.

According to the STPI results, the High Planning Suitability class occupies the largest proportion of the study area, covering 191.791 ha (28.16%). This is followed by the Moderate Planning Suitability class with 159.463 ha (23.42%) and the Very Low Planning Suitability class with 156.746 ha (23.02%) (Table 10). The Low Planning Suitability class covers 132.119 ha (19.40%), whereas the Very High Planning Suitability class occupies 40.893 ha (6.01%).

The combined High and Very High Planning Suitability classes account for 232.684 ha, representing 34.17% of the total study area. As illustrated in Figure 7**,** these areas are primarily distributed along continuous mountain corridors where favourable terrain conditions coincide with relatively high visual accessibility. In contrast, areas classified as Low and Very Low Planning Suitability are mainly concentrated in highly rugged terrain and topographically enclosed sectors exhibiting limited cumulative visibility.

Table 10. Spatial distribution of Sustainable Tourism Planning Index ($STPI$) classes.

STPI Class	Area (ha)	Percentage (%)
Very Low Planning Suitability	156.746	23.017
Low Planning Suitability	132.119	19.400
Moderate Planning Suitability	159.463	23.416
High Planning Suitability	191.791	28.163
Very High Planning Suitability	40.893	6.005
Total	**681.013**	**100.000**

Mean STPI values for the 14 operational pistes ranged from 1.88 to 2.86 (Table 11). Piste 11 had the highest mean value (2.86), followed by Piste 14 (2.80), Piste 2 (2.78), and Piste 12

(2.74); Piste 1 had the lowest mean (1.88). These values provide a descriptive ranking under the baseline $0.60/0.40$ scenario only.

The STPI ranking differs from the separate SSI and VLQI rankings because it combines terrain and visual exposure. However, no independent sustainability outcome was available for validation. The piste comparison is therefore used as a transparency check on the baseline scenario, not as proof that STPI predicts sustainable development.

Table 11. Sustainable tourism planning characteristics of existing ski slopes ranked according to the mean Sustainable Tourism Planning Index (STPI).

Rank	Piste	Length (m)	Min STPI	Max STPI	Mean STPI
1	Piste 11	628	1.0	3.8	2.86
2	Piste 14	2166	1.0	4.2	2.80
3	Piste 2	1462	1.0	3.8	2.78
4	Piste 12	400	1.0	3.8	2.74
5	Piste 9	1876	1.0	4.2	2.71
6	Piste 13	1082	1.0	4.2	2.71
7	Piste 8	1600	1.0	4.2	2.70
8	Piste 3	511	1.0	4.2	2.50
9	Piste 4	300	1.0	3.8	2.35
10	Piste 6	1475	1.0	4.2	2.31
11	Piste 7	1264	1.0	4.2	2.25
12	Piste 5	200	1.0	3.8	2.14
13	Piste 10	680	1.0	4.2	2.11
14	Piste 1	496	1.0	3.8	1.88

The STPI represents the final integrated planning layer of the proposed UAV-LiDAR-based Digital Twin framework and provides the basis for the interpretation of the relationships between terrain suitability, visual landscape quality, and sustainable tourism planning discussed in the following section.

4. DISCUSSION

This study presents a single-epoch UAV-LiDAR-based geospatial Digital Twin prototype that links terrain modelling, a terrain-suitability index, cumulative visual exposure, and a two-component planning index within one traceable workflow. Its novelty lies in the explicit data lineage and integration logic rather than in real-time synchronization. The implementation should therefore be compared with static GIS-MCDA workflows as an update-ready prototype and decision-support baseline, not described as a fully operational Digital Twin.

Compared with conventional DEM-only assessments, the workflow adds mean curvature and TRI to elevation, slope, and aspect and links these terrain variables to a separate visibility-frequency layer. The benefit is analytical traceability: the influence of each source layer, score, and weight can be inspected and rerun. Claims about improved accuracy or robustness would require additional terrain-quality assessment, sensitivity analysis, and independent validation and are therefore not made here.

The topographic analyses further revealed that the Davraz Ski Resort possesses a well-balanced geomorphological structure capable of supporting ski slopes with varying levels of technical difficulty. Although elevation, slope, and aspect remain the primary determinants of ski resort planning, the results indicate that secondary terrain variables substantially improve the interpretation of mountain morphology. The near-zero mean curvature observed across the study area suggests a balanced distribution of concave and convex landforms, providing favourable conditions for surface continuity, natural drainage, and snow retention. Similarly, the predominance of moderate TRI values indicates that the terrain combines sufficient geomorphological diversity with engineering feasibility, creating favourable conditions for ski

infrastructure development. These observations are consistent with previous geomorphological studies highlighting the importance of terrain derivatives for representing landscape processes more effectively than conventional slope-based analyses alone (Florinsky, 2012; Li et al., 2025; Wilson & Gallant, 2000).

The Ski Slope Suitability Index (SSI) further demonstrated that favourable ski terrain is concentrated within distinct topographic corridors rather than being uniformly distributed throughout the study area. This spatial pattern indicates that ski slope suitability cannot be explained solely by slope gradients, but instead results from the interaction among elevation, aspect, terrain continuity, and geomorphological complexity. Similar conclusions have been reported in multi-criteria spatial suitability studies, which consistently demonstrate that integrating multiple terrain attributes produces more robust planning outcomes than single-criterion approaches (Geneletti, 2004; Malczewski, 1999, 2006; Saaty, 1982). In the case of Davraz, the volcanic geomorphology differs markedly from the glacial landscapes characteristic of many Alpine ski resorts, exhibiting more continuous ridgelines and moderate terrain ruggedness. These geomorphological characteristics likely contribute to the relatively continuous distribution of highly suitable ski corridors identified by the proposed model, suggesting that local terrain evolution should be considered when transferring ski slope suitability models to other mountain regions.

The piste overlay provides descriptive support for the SSI; 13 of 14 pistes (92.9%) had mean values in the Moderate or High classes. This concordance indicates that the model captures some terrain characteristics associated with the existing resort layout. It does not demonstrate predictive accuracy, because the pistes are not independent ground truth and their locations may also reflect access, construction history, ownership, snow management, and safety constraints not represented in SSI. Stronger validation would require independent suitable/unsuitable control corridors, field checkpoints, and out-of-sample testing.

An important contribution of the proposed SSI model lies in the incorporation of Mean Curvature and Terrain Ruggedness Index (TRI), demonstrating that ski slope suitability cannot be adequately explained using only conventional terrain variables such as slope and aspect. While slope determines the technical feasibility of ski slope construction, secondary terrain derivatives provide additional information regarding terrain continuity and geomorphological complexity. The results indicate that areas characterized by near-zero Mean Curvature generally exhibit higher suitability values, suggesting that balanced concave–convex terrain configurations favour continuous ski corridors through improved surface continuity, natural drainage, and snow retention. Similarly, the predominance of moderate TRI values within highly suitable areas indicates that excessive terrain ruggedness may constrain ski infrastructure development, whereas moderate geomorphological heterogeneity provides an appropriate balance between engineering feasibility and recreational diversity. These observations are consistent with recent LiDAR-based terrain modelling and geomorphological studies highlighting the importance of secondary terrain derivatives for improving the representation of mountain landscapes and supporting more reliable spatial planning (Choi et al., 2023; Florinsky, 2012; Giordan et al., 2018; Tamimi & Toth, 2024; Wilson & Gallant, 2000). By integrating these advanced terrain variables within a high-resolution UAV-LiDAR environment, the proposed framework captures landscape morphology more comprehensively than conventional DEM-based suitability models, thereby improving the robustness of sustainable ski resort planning.

The VLQI results show that terrain suitability and cumulative visual exposure do not necessarily coincide. However, cumulative viewshed frequency is a measure of visibility, not aesthetic quality. Until calibrated against independent scenic ratings, visitor surveys, or observed photo-taking behaviour, VLQI should be interpreted as a visual-accessibility proxy.

This narrower interpretation preserves the planning value of the viewshed analysis while avoiding unsupported claims about visitor preference or landscape beauty.

The SSI-VLQI integration makes an otherwise implicit planning trade-off explicit. The methodological contribution is not that weighted suitability analysis or viewshed modelling is individually novel; rather, it is their traceable and parameterized integration with dated UAV-LiDAR source data, explicit data lineage, scenario parameters, piste-level summaries, and a defined update pathway within one geospatial prototype. The resulting STPI values remain conditional on the selected inputs, observers, scores, weights, and class breaks.

The piste-level STPI comparison is likewise descriptive. The baseline index makes the trade-off between terrain suitability and visual exposure explicit, but the $0.60/0.40$ weights are analyst-defined and no independent sustainability outcome was available for calibration. Accordingly, the STPI map is most defensible as a screening layer for identifying locations that warrant subsequent avalanche, snow, ecological, engineering, economic, and stakeholder assessment.

The architecture may be transferred to other resorts, but its numerical parameters may not. A receiving site would require local source data, constraint layers, observer sampling, weight elicitation, threshold calibration, sensitivity testing, and external validation. Transferability therefore applies to the workflow structure rather than to the Davraz class breaks or weights.

The broader contribution is an update pathway. A future operational system could ingest repeated LiDAR surveys, snow and weather observations, infrastructure condition data, and ecological constraints; detect changes; and rerun recorded scenarios. None of these temporal or real-time functions was implemented in the present single-epoch case. Distinguishing demonstrated functions from future capabilities resolves the conceptual mismatch between a static GIS analysis and a synchronized Digital Twin system.

Climate change increases the importance of adding repeated snow, temperature, wind, and operational observations to future versions of the system. The current STPI cannot identify climate-resilient corridors because it contains no measured snow or climate variable. It can only indicate where the baseline terrain and visibility conditions justify more detailed climate, avalanche, ecological, and engineering assessment.

Several limitations directly bound the findings. First, the prototype uses one summer LiDAR epoch and has no continuous synchronization, temporal dynamics, or two-way interaction with the physical resort. Second, detailed mission and point-cloud processing parameters and independent checkpoint accuracy were not available in the manuscript dataset, limiting reproducibility and preventing project-specific DEM/DSM accuracy validation. Third, SSI and STPI weights were not derived from a formal expert-elicitation protocol or tested by sensitivity analysis. Fourth, VLQI measures cumulative visibility and lacks independent perceptual validation. Fifth, the STPI excludes snow-cover dynamics, avalanche risk, ecological sensitivity, climate variability, socioeconomic feasibility, and stakeholder preferences; it is therefore a topography-visibility screening index rather than a comprehensive sustainability metric. Finally, validation against existing pistes is descriptive and cannot substitute for independent ground truth or out-of-sample evaluation.

Within these limits, the workflow provides a transparent baseline for spatial screening at Davraz. Transfer to another resort requires local recalibration of scores, weights, observers, class breaks, and constraint layers, followed by independent accuracy, sensitivity, and stakeholder validation. The framework is structurally transferable; the numerical model is not assumed to be universally transferable.

The evidence therefore supports a cautious conclusion: high-resolution UAV-LiDAR can supply a detailed physical baseline, and explicit integration of terrain and visibility layers can improve the transparency of planning alternatives. It does not yet establish a real-time Digital Twin or a complete sustainability assessment.

5. CONCLUSIONS AND RECOMMENDATIONS

This study developed a single-epoch UAV-LiDAR-based geospatial Digital Twin prototype for the Davraz Ski Resort. The prototype links dated source data, terrain and surface models, explicit SSI and VLQI calculations, baseline STPI integration, and piste-level spatial summaries in a reproducible processing graph. It should be understood as the static, update-ready foundation of a future Digital Twin system rather than as a continuously synchronized implementation.

The baseline results identified 43.33% of the study area as High or Very High SSI, 8.43% as High or Very High VLQI, and 34.17% as High or Very High STPI. Thirteen of 14 existing pistes (92.9%) had mean SSI values in the Moderate or High classes, providing descriptive spatial concordance with the existing layout. Because the comparison is not independent and VLQI/STPI lack external outcome data, it supports plausibility rather than predictive accuracy.

The methodological contribution is the explicit separation of source data, transformation rules, scenario parameters, outputs, and update triggers. This structure allows future surveys or alternative weights to be processed through the same documented chain. It also makes clear which claims are demonstrated at t0 and which functions-real-time ingestion, change detection, interactive scenario switching, and forecasting-remain to be implemented.

Future work should retain complete survey and software metadata, quantify point-cloud and terrain-product accuracy using independent checkpoints, document observer geometry and viewshed settings, and archive numerical classification thresholds. Formal robustness analysis should perturb both the five SSI criterion weights and the SSI/VLQI integration weights and report the stability of class areas, cell rankings, and piste-level rankings. Future versions should also validate visual exposure against scenic ratings or visitor data and incorporate snow, avalanche, ecological, climatic, socioeconomic, and stakeholder layers.

Within these stated limitations, the framework offers a useful screening architecture for evidence-based mountain-resort planning. Its value lies in transparent, updateable spatial reasoning; its current outputs should not be treated as a complete sustainability assessment or as proof of a fully operational Digital Twin.

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Data Avaibility

The data supporting the findings of this study are available from the corresponding author upon reasonable request and will be shared when necessary for verification or scientific purposes.

Competing Interest

The authors declare that they have no competing interests.

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