Topographic analysis supported by a knowledge graph: A case of ridge landscape recognition

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Abstract

The intrinsic connections between geographical elements are important for uncovering hidden geo-scientific laws. However, current research on terrain and landform analysis mainly focuses on the landscapes themselves, with insufficient attention to the connections between them. Therefore, this study proposes a knowledge graph approach based on geographical units (TUKG). Specifically, fi-ne-grained geographical units are extracted based on three types of data: remote sensing images, DEM, and contour lines. These units serve as entity nodes in the TUKG and are described by their slope and aspect. Additionally, point-based and line-based connections between geographical units are proposed based on spatial topological relationships, serving as connections between entity nodes in the TUKG. Finally, inference rules for ridge landscape problems are extracted from typical cases of ridge land-scapes to support reasoning in the TUKG. Experimental results conducted in the Yarlung Zangbo Grand Canyon in southwest China demonstrate that the TUKG can accurately infer ridge landscapes and has the potential to identify more complex terrain landscapes.

1. Introduction

In geographical research, while studying geographical elements, attention is also given to their intrinsic connections, aiming to uncover hidden patterns. Despite the importance of these connections in geographical research, current data processing tends to prioritize individual elements over their relationships (Murdoch, 2005). Terrain and landforms are crucial components of the Earth's surface, with their formation, evolution, and underlying mechanisms holding significant importance for geographic and environmental studies (Ma, 2022; Xu et al., 1993; Zhou et al., 2021) . However, current terrain studies often focus on extracting individual features while overlooking their intrinsic connections, hindering precise descriptions of terrain structures and mechanisms.

Knowledge graphs , as advanced tools for relationship inference and knowledge discovery, have been introduced into geographical research (Deng et al., 2021; Fensel et al., 2020; Mai et al., 2020; Zheng et al., 2022; Zhou et al., 2021). For instance, Zhang et al. (2020) integrated spatiotemporal features with knowledge graph techniques, proposing a method for constructing a geographical knowledge graph that considers spatiotemporal characteristics. Jiang et al. (2018) addressed the issue of data heterogeneity in geoscientific research, proposing a technique for constructing large-scale geoscientific knowledge graphs based on heterogeneous data sources. Additionally, there are emergency knowledge graphs for specific tasks such as natural disaster response (Ge et al., 2022) and crowdsourced geographical knowledge graphs like the GeoNames Ontology (Yang et al., 2018) and the OSM (OpenStreetMap) Semantic Network (Ballatore et al., 2013). While significant progress has been made in theoretical methods and construction processes of geoscientific knowledge graphs, there is still some way to go before their practical application.

Against this backdrop, this study focuses on terrain as a key natural geographical element. Leveraging the holistic, relational, and structural characteristics exhibited by various terrain units within landscapes, a knowledge graph of terrain structural units is constructed, with a specific application in ridge landscape inference. This research aims to enhance the accuracy of terrain analysis and improve the inference capabilities of terrain analysis techniques.

2. Method

2.1 Framework

The knowledge graph of terrain units (TUKG) represents terrain-related knowledge in a graphical format. In this graph, entity nodes ***E*** correspond to terrain structural units, attribute ***A*** of the entity nodes represents the terrain features of the units, and relations ***R*** between entity nodes represent the relationships between terrain units. Therefore, the knowledge graph of terrain units can be denoted as **G**={***E***, ***R***, ***A***}.

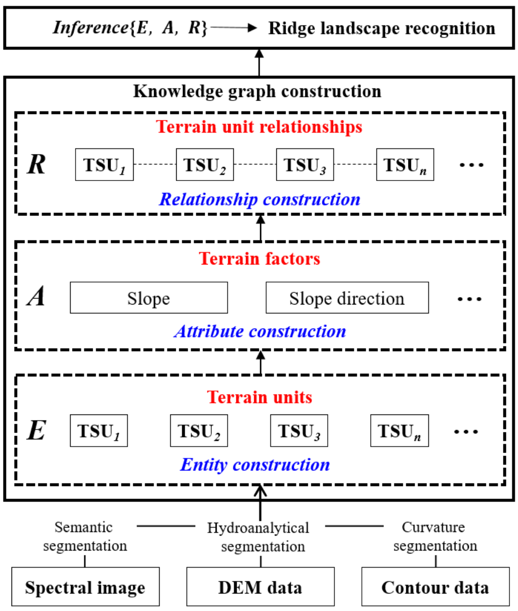


Figure 1. Topographic-unit-based knowledge graph construction and its task reasoning

Figure 1 illustrates the construction of TUKG and its inference tasks. Firstly, terrain units are constructed based on three types of data: remote sensing imagery, digital elevation models, and contour lines. These terrain units are used as entity nodes in the knowledge graph. Secondly, terrain features such as slope and slope length are extracted from the terrain units and serve as attribute descriptions for the entity nodes. Finally, the topological relationships between terrain units are used to establish connections between the entity nodes. By completing these three steps, the construction of TUKG is achieved, and it can be applied to various terrain analysis tasks by designing relevant inference rules.

2.2 Construction of Entity Nodes in TUKG

In this study, terrain units are defined as the smallest geographic units representing a single terrain feature, such as hillslopes or plains. Terrain units are used as the entity nodes in TUKG. Due to the complexity of terrain structures, extracting effective terrain information from a single type of sensor data is quite challenging. This study proposes a method that integrates remote sensing spectral imagery, digital elevation models (DEM), and contour line data to extract terrain units. As depicted in Figure 2, the process begins with semantic segmentation of remote sensing spectral imagery to extract valley and water body regions (Figure 2(b)). Next, the DEM is cropped using the obtained valley and water body regions to acquire DEM data within mountainous areas, addressing issues where flat areas may cause hydrological analysis methods based on DEM to generate small or unreasonable polygons. Subsequently, hydrological analysis is conducted on the cropped DEM (Figure 2(c)) to extract watershed regions (Figure 2(d)), which serve as primary terrain units (Figure 2(e)). Finally, to ensure consistency in the terrain features encompassed by terrain units, a curvature segmentation process is performed on the primary terrain units using contour lines to obtain refined terrain units (Figure 2(f)) (Jones, 1998). Based on these operations, refined terrain units are proposed as entity nodes in TUKG. Additionally, for the attribute descriptions of entity nodes, this study utilizes slope and aspect features of terrain units.

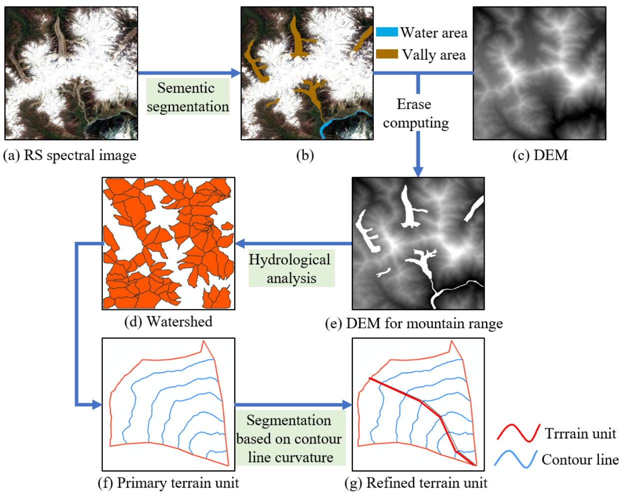


Figure 2 Construction of terrain units using as TUKD entity node

2.3 Construction of Entity Node Relationships in TUKG

The relationships between terrain structural units primarily rely on spatial topological relationships, which constitute a crucial aspect of geospatial research with numerous established methodologies (Theobald, 2001; Yu et al., 2016). This study employs two categories of topological relationships. The first category distinguishes the degree of contact, known as adjacency relationships. It requires setting a threshold ε to differentiate between adjacency at points (when the contact length is less than ε) (see Figure 3(a)) and adjacency along lines (see Figure 3(b)). The second category examines the three-dimensional spatial relationships between terrain structural units, specifically slope aspect relationships. This involves calculating the projection direction of their normal vector onto the base, determining whether the slopes are facing each other (see Figure 3(b)) or in opposite directions (see Figure 3(d)).

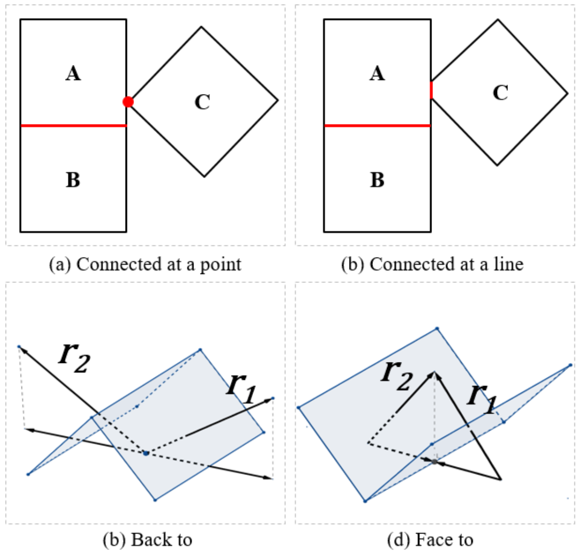


Figure 3 Construction of relationship among TUKG entities based on 2D and 3D topological relation-ships of terrain units respectively

2.4 Terrain Landscape Inference

Terrain landscape analysis based on TUKG relies on the graph rules of terrain landscapes (see Figure 4). Firstly, typical terrain landscapes are geometrically analyzed. Then, graph rules tailored to specific terrain landscapes are established based on the geometric feature combination patterns of terrain units, namely the inference rules composed of terrain features, terrain unit relationships, and inference predicates. Finally, TUKG inference for terrain landscape analysis is conducted based on these graph rules.

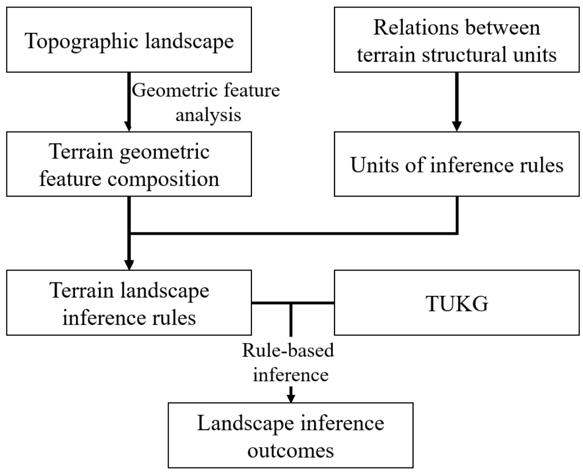


Figure 4 Terrain landscape inference process based on TUKG

Before specifying the inference rules based on the landscape pattern recognition inference framework (see Figure 4), it is necessary to establish the inference rule units expressed in first-order predicate form based on the relationship between terrain structural units. This can be done by integrating the supplementary information on spatial adjacency relationships between opposing elements in Section 2.3 of this paper and transforming it into inference rule units, as shown in Table 1.

Relation	Specific meaning	First-order predicate expression
Connect at a point	The terrain units (i.e., entity nodes) A and B are adjacent, with the adjacent area being a point feature.	ECatPoint(A,B)
Connect at a line	The terrain units A and B are adjacent, with the adjacent area being a line feature.	ECatLine(A,B)
Back to	The normal vectors of terrain unit A and terrain unit B are opposite in direction when projected onto the plane.	BackTo(A,B)
Face to	The normal vectors of terrain unit A and terrain unit B have opposite directions when projected onto the ground plane.	FaceTo(A,B)

Table 1 The formal expression of first-order predicates for the inference rule unit, where A and B correspond to the geospatial units in Figure 3

3. Experiments

This study selected the Yarlung Zangbo Grand Canyon in southwest China as the experimental area. The region is located between 94.68°E and 95.52°E, and 29.10°N to 29.98°N. It features significant terrain variations and complex terrain structures, including numerous mountainous landscapes. The experimental data consisted of remote sensing images and a DEM provided by the Geographic Spatial Data Cloud (Figure 4(a) and (b)). The extraction of terrain units was conducted using remote sensing image classification tools and hydrological analysis tools provided by ArcGIS. A total of 2434 terrain structural units were extracted within the experimental area (Figure 4(c)), and the relationships between terrain units were stored in a Neo4j database. The TUKG (Figure 4(d)) was constructed using the method described in Section 2.3.

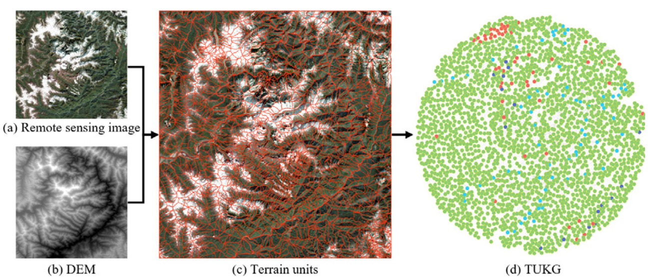


Figure 5 Visualization of terrain units and TUKG

3.1 Ridge Landscape Inference Based on TUKG

The ridge landscape, a prominent feature in mountainous terrain, consists of elevated sections resembling the ridges of a house, formed by the combination of terrain features with opposing slope directions, extending in a ridge-like pattern. Figure 5 illustrates the composition of ridge terrain units. The inference rules for ridge landscapes in TUKG can be summarized as follows (see Figure 6): (1) Identifying two slope surfaces with opposing slopes that are adjacent along a line as a ridge unit. (2) If the two terrain surfaces in a ridge unit are adjacent along a line to two terrain surfaces in another ridge unit, these two ridge units can be connected to form a ridge element. (3) Combining ridge elements pairwise based on shared ridge units to identify a complete ridge. Conducting retrieval in TUKG based on these rules enables ridge landscape inference.

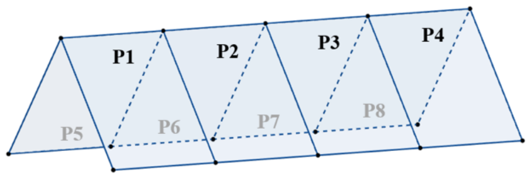


Figure 6 Geometric schematic of terrain units in a ridge landscape

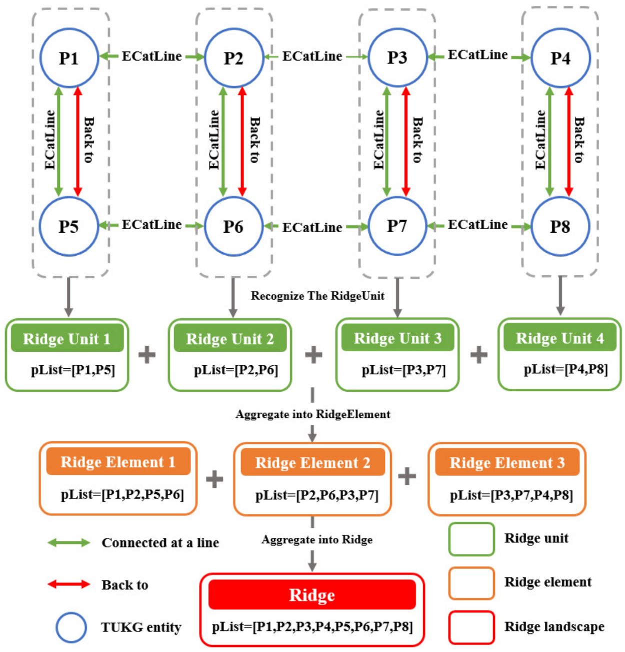


Figure 7 Schematic diagram of ridge landscape inference rules based on TUKG

Based on the previously defined inference rule unit, the first-order predicate logic representation of the ridge landscape inference process is as follows:

(1) $ECatLine(P1,P5) \wedge BackTo(P1,P5)$
$\rightarrow RidgeUnit(P1,P5)$

(2) $RidgeUnit(P1,P5) \wedge RidgeUnit(P2,P6)$
$\wedge ECatLine(P1,P2) \wedge ECatLine(P5,P6)$
$\rightarrow RidgeEle(RidgeUnit(P1,P5), RidgeUnit(P2,P6))$

$$
\begin{aligned}
\textbf{(3)}\ & RidgeEle\big(RidgeUnit(P1,P5), RidgeUnit(P2,P6)\big) \\
& \land RidgeEle\big(RidgeUnit(P2,P6), RidgeUnit(P3,P7)\big) \\
& \land RidgeEle\big(RidgeUnit(P3,P7), RidgeUnit(P4,P8)\big) \\
& \rightarrow Ridge(SetP)
\end{aligned}
$$

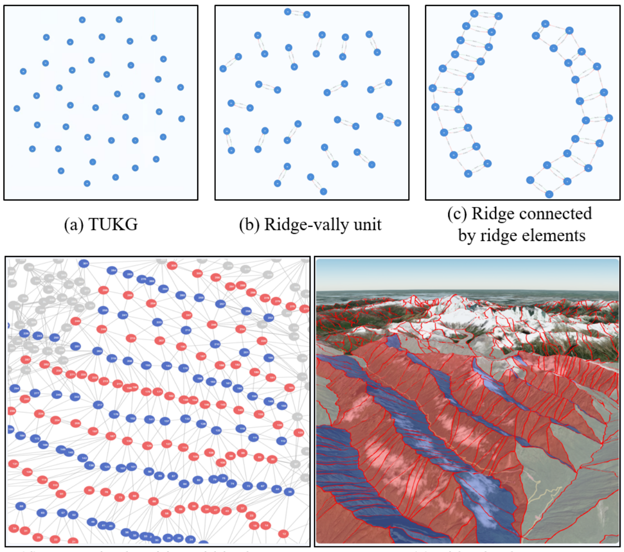
Where $\land$ = Merge operation
$\rightarrow$ = Inference operation
$RidgeEle$ = Ridge element
$SetP = \{P1, P2, P3, P4, P5, P6, P7, P8\}$

Based on the inference process of the ridge landscape abovementioned, the following rules for identifying ridge landscape patterns can be generalized:

$$
\begin{aligned}
Ridge(SetP) \leftarrow \bigvee_{(a,b,c,d)\in SetP} & \{RidgeEle(RidgeUnit(a,b), \\
& RidgeUnit(c,d)) \land ECatLine(a,b) \land ECatLine(a,c) \\
& \land ECatLine(a,d) \land ECatLine(c,d) \\
& \land BackTo(a,c) \land BackTo(a,d)\}
\end{aligned}
$$

3.2 Ridge Landscape Inference Results

The ridge inference rules from Figure 6 are applied to TUKG inference, and the TUKG query results are mapped to the terrain space (as shown in Figure 7(d)). First, the ridge units are identified (as shown in Figure 7 (b)). Then, based on the ridge units, the ridge elements adjacent along a line are recognized. Finally, ridge elements that are connected pairwise are merged (as shown in Figure 7(c)). As depicted in Figure 7 (c) and (d), the application of these geometric rules in TUKG accurately identifies the ridge landscape.



(a) TUKG (b) Ridge-vally unit (c) Ridge connected by ridge elements

(d) Recognized entities within the TUKG (e) Ridge landscape

Figure 8 Inference processes and results for ridge landscapes

4. Conclusions

This study utilizes knowledge graph technology to investigate the field of terrain, an important subject in physical geography. The research focuses on the construction of knowledge graph models for terrain units, knowledge extraction methods, and ridge landscape inference techniques. Through experimental verification, the proposed TUKG demonstrates accurate identification of large-scale ridge landscapes, indicating a potential for generalization to more complex terrain landscapes.

However, there are several areas that can be improved, including: (1) In the knowledge modeling of terrain structural units, this study only considers spatial morphology knowledge, neglecting important factors such as geological structures, rock properties, internal and external forces, human activities, and evolutionary time in terrain formation (Tucker and Hancock, 2010). Future research should enhance the knowledge of geomorphology to enrich the content of the knowledge graph. (2) Incorporating more types of terrain landscapes into the knowledge inference system and discussing different compositional patterns within the same type of terrain landscape. Overall, further advancements in these areas will contribute to the refinement and expansion of knowledge graph-based terrain research.

Acknowledgements

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