Multi-scale comparison of Topographic Wetness Index for Soil Erosion Assessment

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Abstract

Soil erosion remains a complex environmental phenomenon with broad implications for ecosystem stability and land management. The topographic wetness index (TWI), a commonly employed indicator in hydrological and geomorphological modeling, plays a crucial role in understanding how moisture distribution influences erosion potential. Despite its widespread use, TWI's theoretical grounding in multi-scale erosion assessment remains underexplored. Existing literature tends to focus on empirical applications at isolated spatial scales, often overlooking scale-sensitive behaviors and theoretical consistency. This study develops a conceptual framework for understanding the scale dependency of TWI in soil erosion modeling. It explores the assumptions underpinning TWI, its mathematical structure, and its interaction with scale-related processes by interacting with theoretical perspectives from geomorphology, hydrology, and spatial analysis. The study proposes a theoretical model for evaluating TWI's suitability across scales, identifying key factors that influence its performance. This framework aims to inform more robust and theoretically grounded applications of TWI in soil erosion assessment, paving the way for improved model transferability and sustainable land management practices.

Keywords: Soil erosion; Topographic wetness index; Theoretical framework; Spatial scale theory; Erosion modeling; Geospatial indicators.

1. Introduction

Soil erosion keeps drawing attention from researchers and policymakers because it removes fertile material, lowers agricultural production, and brings sediment to rivers and reservoirs (Owens, 2020; Rashmi et al., 2022). Global reports indicate that almost half of arable land now shows some degree of surface degradation, and the tendency is especially strong on steep slopes with intense rainfall (Prăvălie et al., 2021; Gomiero, 2016). Management plans often rely on models that estimate where erosion is most severe, and many of these models include terrain-based indicators for water concentration (Fenta et al., 2016; Diwediga et al., 2018). Among such indicators, the topographic wetness index (TWI) appears frequently. The index, first proposed inside hydrological flow accumulation studies, combines upslope contributing area and local slope to estimate potential water content in each cell of a digital elevation model. Larger TWI values point to wetter zones, while lower values mark drier ridges. Erosion studies adopt TWI because soil detachment and transport are sensitive to moisture, and moisture itself follows terrain form. However, the theory behind TWI comes from assumptions valid at one mapping scale, and researchers seldom test whether the same relation holds when resolution or extent changes. Scale in spatial analysis refers to resolution, extent, and zoning. Resolution describes the size of the grid cell or polygon, extent indicates the total area studied, and zoning notes how boundaries are drawn. Previous studies have warned that changing any of these three elements can modify statistical relations. When TWI is calculated on fine grids, upslope area, and slope reflect microtopography. When it is calculated on coarse grids, these terms smooth small ridges and gullies, so the index can hide fine erosion processes. Fu et al. (2006) designed a multi-scale soil loss evaluation index and concluded that indicator response differed across nested catchments. Lesschen et al. (2009) made similar remarks in a semi-arid basin while combining connectivity rules with a multi-scale approach. These findings indicate that scale effects influence TWI as well, yet a formal theory remains missing.

Several studies already applied TWI or related topographic variables at various scales. Xiong et al. (2021) tested the relationship between vegetation index and terrain attributes, including TWI, in a small watershed with a 5-m resolution. Deng et al. (2007) and Yu et al. (2015) also compared terrain complexity measures across scales. León (2005) already called for scale-aware erosion assessment in the Andes, but the concept did not grow into a formal model. Doumit (2024) later surveyed multi-scale approaches in terrain analysis, confirming that scale theory often stays detached from indicator design. However, currently, no accepted framework explains how TWI should behave when resolution, extent, or zoning changes. The absence limits model transferability across regions and hampers the comparison of results produced with different data sources. Without a clear conceptual base, practitioners can misread wetness patterns and thus misplace conservation efforts. This study aims to build a theoretical framework that clarifies the relation between TWI and spatial scale in soil erosion assessment. It brings together existing theories from geomorphology, hydrology, spatial science, and GIScience, then outlines a model that explains the scale dependency of TWI and gives guidance for future empirical work.

2. Method

2.1 Theoretical Background

The topographic wetness index (TWI) is typically defined as a natural logarithm that tempers extreme values, so the index follows a semi-normal distribution in many landscapes. The formula for TWI arises from the steady-state topographic model of Beven and Kirkby, which assumes uniform precipitation, homogeneous soil, and equilibrium between inflow and outflow at each point.

$$TWI = In\left(\frac{A}{\tan\beta}\right) \tag{1}$$

where A is the upslope contributing area per unit contour length; β is the local slope.

When water inputs exceed soil storage, saturation occurs, and overland flow begins. Even though these assumptions seldom hold perfectly, TWI still captures the first-order control of terrain on moisture. Scale theory enters through both A and β. Contributing area depends on the delineation of flow paths, which in raster models is guided by cell size and flow-routing rule. The slope angle also changes with resolution because finer grids reveal short, steep facets that disappear after resampling. The MAUP explains that statistical aggregates vary when the unit size or boundary shifts, and TWI is an aggregate of slope and flow length over the upslope domain. Resolution effects often dominate at a local scale, while extent effects become more visible at regional mapping. Zoning is less discussed in erosion research, but catchment boundary choice can affect the value of A near watershed divides. Landscape hydrology provides further concepts. Connectivity theory states that water moves through a series of links and sinks, and the efficiency of those links depends on terrain roughness. A change in grid size alters link density, so the same physical surface yields different flow networks. Spatial science adds the idea of scale variance, meaning that a variable shows distinct behavior at different observational windows. High-variance clusters in TWI can fade into mean values when resolution decreases, making moist hollows appear less pronounced. GIScience also contributes. Digital elevation models come from multiple sources such as LiDAR, photogrammetry, and radar, each with its error structure. When researchers resample these models, they propagate error in nonlinear ways that feed into TWI. Metternicht et al. (2022) warned that free global DEMs vary in quality, which affects derived terrain attributes. Model sensitivity studies such as Vergopolan et al. (2022) revealed that soil moisture patterns display complex variability across scales. Finally, environmental modeling theory indicates that predictive performance hinges on scale match between process and data. If erosion occurs at the plot scale, then a coarse-resolution TWI cannot capture the triggering condition. When the objective is continental mapping, a fine-resolution model can consume significant computing power without improving accuracy. Therefore, the theoretical background calls for a framework that ties TWI to the appropriate scale of analysis.

2.2 Multi-scale Approaches in Environmental Modeling

The scale at which environmental data is analyzed plays a critical role in the accuracy of model predictions. In soil erosion assessments, scale-dependent factors such as topography, land cover, and soil properties can influence the results (Miller et al., 2015). Multi-scale analysis allows researchers to compare data at various spatial resolutions to understand how scale impacts model performance (Leempoel et al., 2015). In the context of soil erosion, multi-scale approaches are essential for addressing the varying dynamics of erosion processes at different spatial scales. For example, large-scale models can capture regional erosion trends but overlook fine-scale details such as micro-topography and vegetation cover, which are critical for accurate predictions at the plot level (Yu et al., 2015). In contrast, small-scale models may overemphasize local variations, leading to inaccurate regional predictions (Nelson et al., 2007). Recent studies have emphasized the importance of integrating multi-scale approaches in soil erosion modeling. For example, Deng et al. (2007) demonstrated that multi-scale linkages between topographic attributes and environmental variables can improve model accuracy. De Rosnay et al. (2009) conducted a multi-scale analysis of soil moisture measurements and found that integrating data from various scales can enhance the predictive power of hydrological models. Table 1 compares multi-scale approaches used in various environmental modeling studies.

Study	Scale(s) Analyzed	Key Findings
Yu et al. (2015)	Plot to Regional	Fine-scale data improves local accuracy but not regional.
Deng et al. (2007)	Multiple Scales	Multi-scale linkages between topography and vegetation enhance model accuracy.
Nelson et al. (2007)	Hillside Catchment	Multi-scale correlations reveal important topography-vegetation interactions.
Leempoel et al. (2015)	High Resolution	Very high-resolution DEMs are ecologically relevant.

Table 1. Comparison of Multi-scale Approaches Used in Environmental Modeling Studies.

3. Results

The framework begins with terrain input data. Digital elevation models enter the system together with metadata on resolution, vertical accuracy, and acquisition method. Error distribution is recorded because it affects downstream calculations. Thereafter, scale dependency analysis is conducted. The DEM is processed at a set of nested resolutions, for example, 5, 10, 30 m, and others. At each resolution, TWI is computed, and summary statistics such as mean, variance and semivariogram range are extracted. The comparison shows how TWI distribution shifts when cell size changes. The same step can be repeated for different extents to check the extent of the effect. The third component handles resolution harmonization. When additional variables such as rainfall or soil texture are used, they must be resampled to the same grid as TWI. The framework proposes an error-weighted resampling rule that gives more weight to high-quality data sources, reducing mismatch across layers.

Element	Framework Component	Description

1	Terrain Input Characterization	Involves selecting the DEM with metadata on resolution, accuracy, and acquisition method. Accounts for error distribution in elevation data.
2	Scale Dependency Analysis	Computes TWI at multiple nested resolutions (5, 10, and 30 m). Compares summary statistics (mean, variance, semivariogram range) to reveal how TWI changes with scale.
3	Resolution Harmonization	Aligns other spatial datasets (rainfall and soil) with the DEM resolution using error-weighted resampling. Gives higher weight to data from accurate sources.
4	Moisture Dynamics Integration	Introduces a storage–release curve that links TWI classes to potential saturation time, using field or remote sensing soil moisture data where possible.
5	Scale Response Function	Establishes a piecewise linear function connecting TWI variance with erosion response. Shows how TWI effectiveness varies from fine to coarse scales.
6	Model Generalizability	Applies a similarity metric (terrain texture and rainfall seasonality) to transfer model coefficients across regions. Recalibrates if dissimilarity exceeds a threshold.

Table 2. Components of the proposed multi-scale TWI theoretical framework

The fourth element addresses moisture dynamics. Instead of assuming static conditions, the framework inserts a conceptual storage-release curve that links TWI classes to potential saturation time. The curve is parameterized from field or remote sensing soil moisture where available. This addition brings a temporal sense to the index without turning the model into a full hydrological simulation. A scale response function then joins TWI variance and erosion response. The function follows a piecewise linear form. For very fine resolution, erosion shows high spatial heterogeneity and TWI variance explains only part of the pattern because micro-roughness and vegetation cover also dominate. As resolution becomes moderate, TWI variance aligns better with measured soil loss, reaching a plateau. At a very coarse resolution, the relation weakens again because the upslope area smooths too much. The function is calibrated from empirical data where possible, but the concept itself is theoretical and guides expectation. Model generalizability forms the final block. The framework stores coefficients from the scale response function and uses them when transferring the model to another region. A similarity metric based on terrain texture and rainfall seasonality helps decide whether coefficients can be reused or need recalibration. Figure 1 illustrates these components and their links.

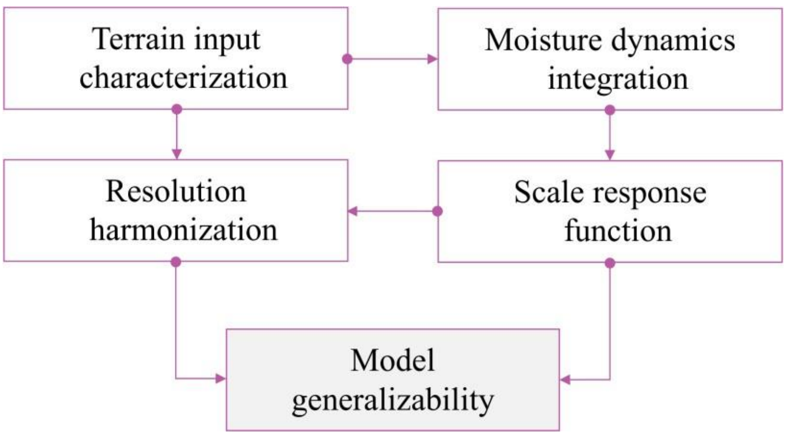

Figure 1. Conceptual diagram of the multi-scale TWI framework

The proposed framework stands on existing theory but adds a systematic way to study scale effects in TWI. It embeds scale in the workflow from the start, making it possible to anticipate how TWI values will shift and how erosion prediction can respond. The framework also answers the call for models that bridge microtopographic patterns and catchment responses. Through resolution analysis, the user can decide at which grid size the moisture pattern stabilizes relative to erosion data. In practice, the framework will run as follows. A researcher selects a DEM, records its properties, and sets a range of resolutions. TWI is calculated at each level, variance is plotted, and the scale response function is estimated. If the study aims at local conservation planning, the resolution where the function shows the strongest relation is chosen. If the goal is regional policy, a coarser resolution can be more efficient while still capturing the main trends. The conceptual storage-release curve extends the classic steady-state assumption. For instance, cells with TWI above one standard deviation from the mean can saturate within one rainfall event, while cells within half a deviation can need a week of cumulative rainfall. Such classification can guide early warning of runoff events. Resolution harmonization deals with the common situation where rainfall data come at 1-km grids, soil maps at 250-m polygons, and DEM at 30-m raster. The framework suggests resampling rainfall down to 30 m only after applying a correction based on orographic factors, thus avoiding artificial patterns. Generalizability uses a similarity index. If texture differs by less than a threshold, the same scale response coefficients can be applied; otherwise, a local adjustment is required. The proposed framework, while theoretical, creates a pathway for a systematic study of TWI across scales and should stimulate empirical validation. Figure 2 depicts a workflow for conducting TWI-based soil erosion modeling.

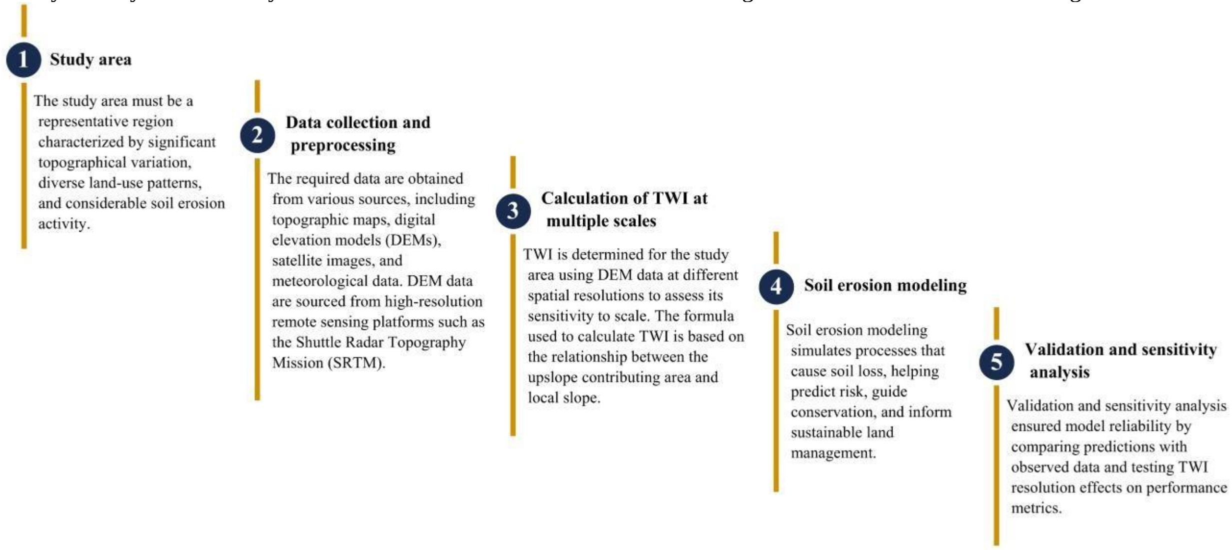

Figure 2: Workflow for performing a TWI-based soil erosion modeling.

4. Discussion

The framework provides several consequences for erosion modeling accuracy and practical decision-making. First, including scale dependency during the early stage helps avoid misinterpretation of wetness maps. When a user works with high-resolution LiDAR but intends to compare results with national studies based on 30-m grids, the framework signals the degree of comparability before field validation begins. Second, the storage-release curve tied to TWI classes adds temporal depth to what was often a static index. Land managers can now rank areas by wetness potential and by expected saturation time. Conservation measures such as buffer strips or contour hedgerows can then be timed to the rainfall season that produces the largest runoff. Third, resolution harmonization supports the integration of multi-source data. In regions where high-resolution rainfall is missing, the correction rule permits downscaling without creating spurious patterns. This feature is important for countries where data access remains limited. Fourth, the scale response function aids cost-effective modeling. Fine grids demand large computing resources. The function indicates the grid size where prediction skill no longer improves, so analysts can stop refining resolution beyond that point. Wang et al. (2024) showed that some landscape metrics peak in performance around 120 m, and the framework can detect similar plateaus for TWI. For land management policy, the framework encourages flexible mapping units. Conservation zones can be drawn at a coarse scale for budgeting yet refined locally where erosion risk concentrates. The similarity index guiding model transfer further reduces duplication of calibration work. Agencies can apply coefficients from one pilot basin to several nearby basins once similarity is confirmed. Finally, the framework raises transparent reporting. When studies document TWI variance at multiple scales, meta-analysis becomes feasible, and findings from Guo et al. (2021) and Fu et al. (2006) can be compared more directly. This transparency supports adaptive management, where models evolve with new data.

5. Conclusion

This study presents a theoretical framework that links the topographic wetness index to spatial scale in soil erosion assessment. A review of the literature exposes the lack of formal guidance on how TWI behaves when resolution, extent, or zoning change. The framework answers this gap by introducing terrain input characterization, scale dependency analysis, resolution harmonization, moisture dynamics, a scale response function, and model generalizability. Each component rests on concepts from geomorphology, hydrology, and spatial science. The inclusion of spatial scale theory strengthens TWI-based erosion modeling and permits more consistent comparison across studies. The framework can support empirical validation, guide data resolution choice, and inform land management planning at multiple levels. Future studies can test the storage-release curve against field moisture records and refine the similarity index for model transfer across contrasting environments.

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