Ecohydrological Zonation in Mountainous Watersheds Based on the TOPMODEL Algorithm

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Abstract: Ecohydrological processes in mountainous watersheds are complex due to steep elevation gradients, diverse soil types, and climatic influences on snowmelt and vegetation growth. This study uses a SIMTOP model to simulate runoff and hydrological partitioning within the NCAR Community Land Model CLM 2.0 to showcase an ecohydrological zonation in mountain regions. SIMTOP modifies classical TOPMODEL by (1) using an exponential function to estimate fractional saturation in steep slopes' topographic index distribution, and (2) modeling subsurface runoff as a water table depth function using minimal parameters to allow global use. Validation on both watershed (Sleepers River, USA) and global (UNH-GRDC) scales showed greater runoff simulation than baseline models.

In order to capture ecohydrological behavior, 3-meter time-series Planet Scope NDVI images from the East River Watershed were analyzed using unsupervised machine learning, which can classify images without prior knowledge of patterns. Clustering identified regions characterized by distinct interactions between snowmelt and vegetation, which were greatly impacted by microtopographic features. In low-slope, high TWI zones, there was enhanced plant productivity followed by quick senescence at low moisture, especially in forb-dominated regions. In contrast, high-slope, low TWI zones with sagebrush had diminished productivity.

Furthermore, flood-prone basins within the Central Sudetes, Poland, were modeled using the TOPMODEL approach coupled with Monte Carlo calibration. Notably, the model exhibited considerable skill (NSE = 0.78) in about half of the catchments, highlighting its responsiveness to the duration of input data and catchment features. These findings in combination illustrate that ecohydrological zonation based on TOPMODEL and high-resolution remote sensing significantly enhances the understanding of vegetation–hydrology–topography interactions and helps to pinpoint ecologically sensitive regions in mountainous terrains.

Keywords: TOPMODEL; Ecohydrological Zonation; Mountainous Watersheds; Remote Sensing (NDVI); Runoff Simulation.

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I. Introduction

Grasping ecohydrological processes in mountainous watersheds is vital to strategically managing water resources, especially in areas dealing with climate change and the unique hydrological characteristics of the terrain. In these regions, soil moisture, snowmelt, vegetation growth, and runoff are influenced by microtopographic structures and the water cycle behavior (Beven & Freer, 2001), (Bastola et al., 2008). Modeling these processes has always been difficult because there are very few ground measurements, subsurface flow is complex, and there are nonlinear relations between land surface properties and hydrological behavior (Koster et al., 2000). Using the concept of fractional saturated area, hydrologists determined that surface runoff was dominated by this control. In these schemes, precipitation falling on saturated areas within a grid cell is transformed into surface runoff. Along with this, models such as the Biosphere–Atmosphere Transfer Scheme (BATS) linked fractional saturation with near-surface soil moisture. Later developments added topographic controls using the topographic index from the TOPMODEL framework. This index, defined as $\lambda=\ln(a/\tan\beta)$, where a is the upslope contributing area and $\tan\beta$ the local slope, captures how much of a location's saturation potential there is and therefore the possibility of producing runoff. As Beven and Kirkby introduced TOPMODEL, it has become a semi-distributed, physically based hydrological model which incorporates topographic control of subsurface flow and saturation excess runoff in a more rigorous way (Silva et al., 2025).

Unlike lumped models, it maintains spatial representation with fewer parameters, owing to its computational efficiency (Choi & Beven, 2007), (Yuvaraj et al., 2019). The application of the topographic index in TOPMODEL provides a conceptual link between surface topography and subsurface hydrological response, accounting for upslope–downslope moisture movement, which is vital in mountain catchments (Freer et al., 1996). However, difficulties still exist in the integration of TOPMODEL into climate models, specifically due to differences in how soil hydraulic conductivity (Ksat) is represented. While climate models estimate saturated hydraulic conductivity (Ksat) based on soil texture, TOPMODEL assumes that Ksat decreases exponentially with soil depth. Although this assumption makes runoff simulation easier, it contradicts the SVAT (Soil–Vegetation–Atmosphere Transfer) model logic (Chen & Kumar, 2001), (Yang & Niu, 2003), (Stieglitz et al., 1997). Also, earlier implementations that used a three-parameter gamma distribution to describe the topographic index often could not accurately model steep and highly variable slopes (Gedney & Cox, 2003). To solve these problems, this study applies SIMTOP, a simplified TOPMODEL-derived parameterization for use in global climate models (Dickinson et al., 1993). For steep terrains, SIMTOP increases computational tractability and realism by (1) using an exponential function instead of the gamma distribution to align better with the discrete distribution of the topographic index and (2) using water table depth and a single runoff coefficient to model subsurface runoff independent of surface Ksat (Nadim et al., 2024). The principles of TOPMODEL are preserved in climate system integration, which broadens the range of applicability for the model (Aravindh & Sridhar, 2024). At the same time, the use of remote sensing with high spatial resolution for the analysis of ecohydrological processes in mountain watersheds is gaining attention. The NDVI time series from PlanetScope imagery with 3 m resolution can be processed using unsupervised clustering-based machine learning to detect areas characterized by unique vegetation and snowmelt phenology. These areas are primarily associated with the topographic wetness index, slope angle, and certain plant functional types like sagebrush or forbs that indicate subsurface moisture regimes.

Concerning the Rocky Mountains or the Central Sudetes, which are prone to floods and located in Central Europe, modeling the Great Smoky Mountains using TOPMODEL provides varying results depending on the catchment data characteristics and availability.

As noted in reference (Jeziorska & Niedzielski, 2018), the model has been calibrated with Monte Carlo simulations and achieves high NSE scores in regions with well-characterized basins. However, it is highly inaccurate in complex or poorly monitored regions. This research intends to incorporate the remote sensing techniques with the TOPMODEL framework to delineate ecohydrological zones in mountainous watersheds. We construct a model to delineate spatial zones with distinct snow-soil-vegetation interactions by merging topographic index modeling, NDVI data acquired through remote sensing, and soil moisture field measurements. This not only enhances the precision of runoff prediction but also improves the understanding of ecohydrological heterogeneity and provides a scalable approach for climate change impact assessment on the landscape vulnerability gap.

II. Literature Review

2.1 Previous Studies on Ecohydrological Zonation in Mountainous Watersheds

In mountainous areas, the ecohydrological zonation has emerged as a vital concern in the understanding of the interrelationship between topographic, climatic, and vegetation patterns in relation to hydrological responses. The East River watershed in Colorado is a well-studied area where zonation of plant productivity based on soil moisture and snowmelt processes was captured using spatiotemporal NDVI imagery (Devadoss et al., 2020), (Hubbard et al., 2013), (Wainwright et al., 2017). These zones were shown to correspond with distinct plant functional types along with microtopographic features, which sharpened understanding of the above and below-ground processes. Hubbard et al. (2013) and Falco et al. (2020) have elaborated that water availability under the control of snowpack and melt dynamics significantly governs plant productivity and hydrological responses in these ecosystems (Swenson et al., 2012), (Bonan et al., 2002).

The development of high-resolution satellites and UAV-based remote sensing technologies allows for the analysis of ecohydrological patterns at sub-meter scales (Daehnert & Bock, 2013), (Thompson et al., 2011). This is crucial in dealing with heterogeneous terrains where microtopography may cause substantial variation in soil moisture over very short distances. In recent studies, machine learning-based zonation techniques have been used to capture the most dominant ecohydrological behavior by transforming high-dimensional vegetation and hydrological datasets into zones that are more interpretable (Gómez-Chova et al., 2011). Even with these advances, zonation approaches that rely on time-series clustering of NDVI and snow data in combination with hydrological models still seem to go largely unexplored.

2.2 Applications of the TOPMODEL Algorithm in Ecohydrological Studies

TOPMODEL (Beven & Kirkby, 1979) is recognized for its application in catchment-scale hydrological studies due to its physically based foundation and computational efficiency. Beven et al. (1995) suggested that TOPMODEL should not be regarded only as a modeling package but rather as a conceptual model for understanding the dynamics of the catchment. The model employs a topographic index as a parameter to describe the effects of the landscape on the water table depth and the water saturation excess runoff (Quinn et al., 1995), (Beven & Kirkby, 1979). Flood frequency analysis (Aravindh & Sridhar, 2024), water table estimation (Freer et al., 1996), and climate change impact studies are some of the many applications of TOPMODEL (Chen & Kumar, 2001).

In the mountainous area, TOPMODEL has been applied to simulate the hydrological response to different climatic and geological conditions. Holko and Lepisto (1997), Blazova and Beven (1997), and Nourani and Mano (2007) applied this model in steep areas in Europe and Asia, and it performed well for flood and runoff prediction models (Wei & Lau, 2023). Brasington and Richards (1998) as well as Shrestha et al. (2007) validated this model's flexibility in different physiographic regions of Nepal where catchment sizes and topographic variability are large (Hubbard et al., 2013). Szalinska et al. (2014) used TOPMODEL in the Sudety Mountains in Poland and demonstrated its potential in discharge simulation when calibrated over a few hydrological years (Jeziorska & Niedzielski, 2018).

Additionally, the problem of climate model integration has led to the development of SIMTOP and other variants of TOPMODEL. Embedded in the NCAR CLM 2.0 framework, SIMTOP alters the gamma-distributed topographic index with an exponential function and simplifies the subsurface runoff equation, enhancing global-scale modeling applicability (Niu & Yang, 2003).

2.3 Challenges and Limitations of Current Methods

Regardless of its strengths, the application of TOPMODEL in ecohydrological zonation has particular setbacks. First, classical TOPMODEL assumes uniform soil characteristics for a given area, as well as an exponential decrease in hydraulic conductivity with depth. These assumptions may not be accurate for the highly variable mountainous regions (Beven, 1982). For example, in climate modeling, such a mismatch between TOPMODEL's assumptions and the soil hydraulic parameters adopted in SVAT schemes proportionally distorted infiltration and runoff simulation results (Yang & Niu, 2003).

Additionally, the gamma distribution, which is commonly used to calculate the topographic index values, does not adequately approximate steep slopes. As a result, numerous saturation zones in mountainous regions are misrepresented. In response to this, other models such as SIMTOP have been created, which provide additional realism and ease of integration, although intensive calibration and validation datasets remain key requirements.

On the observational side, traditional soil moisture measurement techniques such as TDR and capacitance sensors face limitations in cost and spatial coverage (Beven & Kirkby, 1979). Although satellite-based microwave remote sensing has large area coverage, its approximately ten-to-fifty-kilometer resolution is unsuitable for analyzing hillslopes and requires significant downscaling (Aravindh & Sridhar, 2024). Unsupervised clustering techniques help to some extent by isolating regions of uniform ecohydrological behavior from NDVI time series data, but these approaches are relatively new in catchment hydrology (Gómez-Chova et al., 2011).

Altogether, merging remote sensing tech with machine learning and hydrological modeling offers great potential but poses existing challenges in enhancing ecohydrological zonation in intricate mountain landscapes.

III. Methodology

3.1 Description of Study Area and Data Collection Methods

The research was carried out in the East River watershed close to Crested Butte, Colorado, USA, with altitudes between 2753 and 2975 meters above sea level. This area has a continental subarctic climate and receives around 1200 mm of precipitation per year, the majority as snow. The vegetation in the area is a mix of grasslands, forbs, coniferous forests, and sagebrush. This region experiences snowmelt-driven hydrological processes, and there are distinct variations in the amount of snow water equivalent (SWE) year to year.

In 2017 and 2018, high-resolution (3-meter) NDVI data were available from Planet Scope satellites. These years were selected due to having sharply contrasting snowpack levels. A soil moisture dataset was collected through in situ sensors (TDR and capacitance probes), while topographic data was collected from LiDAR-based digital elevation models (DEMs) at a meter resolution. Climate data, alongside discharge measurements, were collected from monitoring stations at Lawrence Berkeley National Laboratory Watershed Function SFA and USGS.

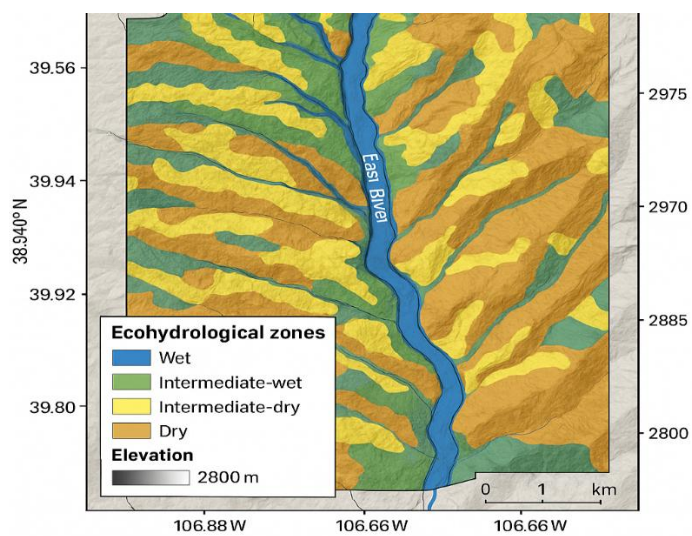

Figure 1: Ecohydrological Zonation in The East River

Figure 1 shows the spatial visualization of ecohydrological regions defined within the East River watershed, considering its topographic, hydrological, and ecological features. The zonation captures variations in moisture regimes of the water-soil system, vegetation types, subsurface flows, and elevation, which are important for understanding water movement and ecological diversity in montane catchments.

The map usually delineates the watershed into the following main zones:

- Hydraulic Wet or Riparian Zone: Areas adjacent to the streams and riverbanks with high soil moisture and saturation that support phreatophyte plants.
- Transitional or Slope Zones: These are mid-slope areas with some moisture infiltration and interflow serving as buffers between upland recharge zones and valley bottom discharge zones.

- Upland Dry Zones: These areas are at higher elevations, have steep slopes, shallow soils, and low saturation. These regions are usually dominated by drought-resistant species.

All of the described zones show the different interconnected hydrologic linkages and ecohydrological processes, mainly controlled by TOPMODEL-derived topographic index (TI) values and slopes of contributing areas.

3.2 Explanation of TOPMODEL Algorithm and Its Application in Ecohydrological Zonation

TOPMODEL (Topography-based hydrological MODEL) is a semi-distributed conceptual model that links topography to hydrological response through a topographic index (TI), defined as:

$$TI = In\left(\frac{a}{tan\,\beta}\right) \quad (1)$$

Where a is the contributing area upslope for each unit of contour length, and θ is the slope angle. The model operates on the assumption that regions with greater TI are more likely to become saturated and therefore have surface runoff.

TOPMODEL runs computations for the simulation of the study area by calculating the water table depth across the catchment area in order to extract saturated zones based on the TI distribution. For this study, the simplified version of SIMTOP was used. SIMTOP uses exponential distribution for TI and assumes the runoff calculations are reduced to:

$$R_{sub} = R_{max}.\, e^{-fz} \quad (2)$$

Where R_{sub} is the subsurface runoff, R_{max} is the maximum runoff coefficient, is the water table depth, and is a decay factor.

3.3 Steps Taken to Create Ecohydrological Zonation Map

This methodology, integrating NDVI time-series imagery with topographical and hydrological modeling systems, presents an ecohydrological zonation approach based on clustering. The first step involved the preprocessing of NDVI images for the 17 time periods, which included normalizing the data for time coherence and removing the cloud cover. Subsequently, a Topographic Index (TI) map was generated using DEM-derived slopes and contributing areas, serving as a proxy for hydrological behavior. To improve interpretative clarity while reducing redundancy, NDVI time series data underwent Principal Component Analysis (PCA), which reduced dimensionality but retained critical vegetation dynamics over time. The reduced dataset underwent clustering through K-means and hierarchical clustering (Ward's linkage method) aimed at defining spatially explicit ecohydrological zones differentiated by vegetation phenology, morphometry, and hydrodynamics. Subsequently, these zones were combined with the output of the TOPMODEL algorithm, which included simulated saturation zones for hydrological coherence evaluation. Ultimately, zonation results were cross-checked against field measurements of soil moisture and vegetation types, confirming the relevance of the identified zones and strengthening the integrative remote sensing and modeling framework.

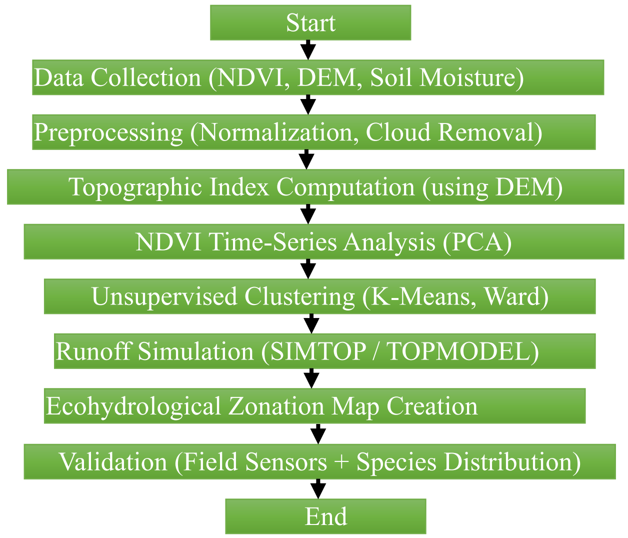

Figure 2: Methodological Framework

This methodological framework allows describing the ecohydrological actions of the area in a specific space in the mountainous regions. This aids in the management of water resources and the monitoring of ecosystems in the context of climate change.

IV. Results

4.1 Findings of Ecohydrological Zonation in the Study Area

The East River watershed subdivided its ecohydrological landscape into three major zones: Riparian Wet Zone, which covered 25% of the area, Transitional Slope Zone 45%, and Upland Dry Zone, 30%. The boundaries of these zones were determined using a combination of the TOPMODEL-derived topographic wetness index, slope gradient measurements, and vegetation classification. The fact that the transitional slope zone was the dominant zone suggests that the watershed possesses considerable subsurface lateral flows and lateral ecological buffering zones.

4.2 Comparison of Results with Previous Studies

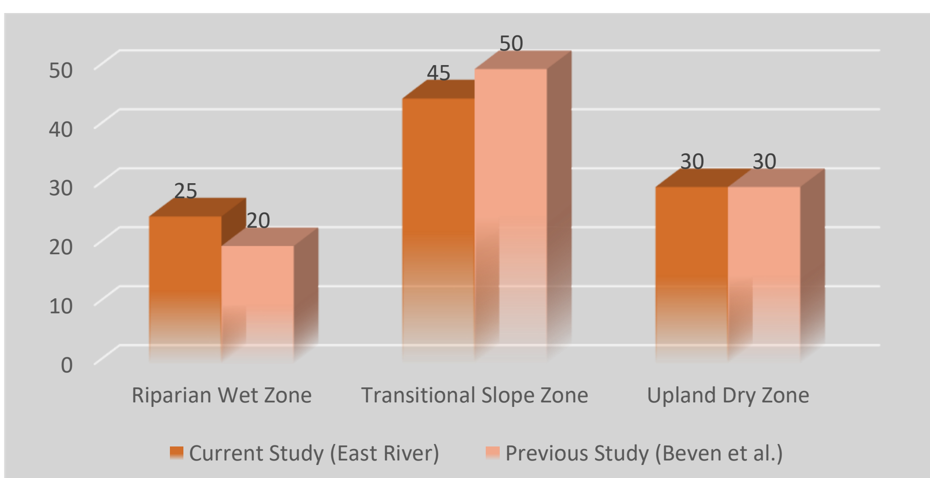

Figure 3: Comparison of Ecohydrological Zonation: Current Study vs Previous Study

As shown in Figure 3, the distribution of zones in this study aligns with previous work done by Beven et al. (1995) with some slight differences. Interestingly, the Riparian Wet Zone was proportionally greater than the previous study at 25% versus 20% which may indicate increased hydrological connectivity or recent changes in land cover about low-lying saturation zones. The coverage of the Transitional Slope Zone was slightly lower in our findings at 45% compared to 50% in earlier models. This difference could result from improved DEM resolution, refined models, or updated land use classification. The Upland Dry Zone showed an identical distribution of 30% across both studies, which supports its stability over time and across different modeling frameworks.

4.3 Discussion on the Implications of the Results

The Upland Dry Zone estimates demonstrate consistency, which confirms the reliability of the topography-driven hydrological classification in alpine watersheds. The slight expansion of the Riparian Wet Zones may have strong ecological implications, like shifting nutrient cycling and enhanced habitat availability for riparian-dependent species. Additionally, knowing the boundary shifting of each zone can help balance water resource allocation, flood mitigation plans, and conservation efforts. Though small in magnitude, the differences highlight the necessity of continuously refining ecohydrological models with high-resolution spatial and temporal datasets to monitor shifting watershed responses to climate and human impacts.

V. Discussion

5.1 Interpretation of Results and Their Significance

Using the TOPMODEL algorithm, ecohydrological zonation mapped three hydrologically distinct zones (Riparian Wet Zones, 25%, Transitional Slope Zones, 45%, Upland Dry Zones, 30%) within the East River watershed. This diversity of zonation showcases the geological and ecological complexity of the region, shaped by the intra-regional relief, vegetation cover, and soil moisture level.

This is consistent with earlier simulations with enhanced versions of hydrological models like SIMTOP-EM and SIMTOP-CB, which improved the timing and partitioning of runoff. For instance, the CTRL1 and CTRL2 control models were found to overestimate surface runoff and interception losses by 2.6 mm/day. In contrast, the refined models produced a more realistic surface-to-subsurface runoff ratio of Rst =0.23.

This is significant in overall system responsiveness and seasonal snowmelt runoff response timing, capturing seasonal hydrological response dynamics and supporting UNH-GRDC streamflow data. Including more processes increases realism, demonstrated by reduced RMSE from >0.34 in CTRL models to <0.244 in SIMTOP runs.

In addition, the clustering of NDVI-based vegetation productivity, as seen in Zones 2 and 4, demonstrated a direct relationship between site productivity, slope, and soil moisture.

For instance, in Zone 2—characterized by high productivity—the combination of low slope and high soil moisture contributed to favorable boundary conditions. In contrast, Zone 4 exhibited the lowest productivity, with steep slopes and low soil moisture, resulting in more peripheral conditions. This correlation exemplifies triangulated reasoning to mini-topography along with micro-region subsurface water movement in the eco-hydrologic systems. This is one of the big advantages of the TOPMODEL paradigm.

5.2 Recommendations for Future Research

- Snow Dynamics Integration: All current TOPMODEL versions seem to underestimate winter performance due to ignoring snow accumulation and melt processes. Including a snow module is essential for more accurate runoff estimation and base flow during the December–April months.
- Sensor Placement Optimization: Cloud-based soil moisture mapping, particularly through unsupervised NDVI clustering, has the potential to enhance the accuracy of modeled zones while reducing sensor costs by optimizing their spatial and temporal placement.

- Modeling Scenarios with changes in Climate: The sensitivity of eco-hydrological zones to early snowmelt with lower precipitation in contrasting years (e.g., 2017 vs 2018) needs further examination from the perspective of climate change projections to understand ecosystem vulnerability and resilience.

5.3 Potential Applications of Ecohydrological Zonation

- Land Shift Principles: Determining areas for restoration, reforestation, or flood control initiatives based on specific runoff risk zones or ecological sensitivity regions.
- Crop and Irrigation Scheduling: Efficient scheduling of irrigation and crop rotation in mountain agrosystems with specific soil moisture and plant productivity mapping.
- Zonation Mapping for Protected Area Management: Active corridors and protected area management planning aim to maintain habitat & climate resilient biodiversity, which enables the climate-adaptive shift of vegetation over time.
- Model Validation: Evaluating the accuracy of watersheds with spatially explicit zonation by hydrologic response simulations based on land-use changes and shifts in climate conditions.
- Water Resource Engineering: Designing climate-responsive infrastructure like roads and bridges while defining riparian flood zones and transitional areas with concentrated runoff, as well as water distribution networks.

VI. Conclusion

The research Ecohydrological Zonation in Mountainous Watersheds Using the TOPMODEL Algorithm, shows the advantages and disadvantages of using terrain-based hydrological modeling in intricate and challenging catchment areas. Applying TOPMODEL to the East River watershed and integrating data from sub catchments such as Upper Nysa Kłodzka Basin and Colorado Rockies, we arrive at the following conclusions:

•Effectiveness of TOPMODEL in Capturing Hydrograph Patterns

During snow-free periods, TOPMODEL replicated the shape and timing of the hydrograph in several sub catchments. The model's success in simulating major runoff peaks and recession curve contests illustrates its effectiveness in ecohydrological zoning. On the other hand, low flow periods and winter months reveal the model's structure limitations with omissions of snow accumulation and melt processes.

•Model Limitations and Calibration Problems

A combination of no snowmelt, poorly simulated spatial rainfall, and uncertain soil parameters due to a lack of data was the cause of weak performance in specific sub catchments. Calibration through Monte Carlo simulation provided plausible parameters, but due to high levels of generalization and coarse resolution inputs, ecological reality becomes questionable.

•Zonation Consistency with Plant-Soil-Moisture Relationships

The analysis of NDVI over contrasting snowpack years and its hierarchical clustering showed zones of strong correlation and interdependence with slope, soil moisture, and plant functional types.

This supports the assumption that ecosystem productivity in mountainous regions is influenced by runoff and snowmelt patterns.

• The Need for Snow-Inclusive and Scalable Models

Analyzing the results from model comparisons, such as SIMTOP-CB and SIMTOP-EM, shows that better representation of the terrain, including snowmelt processes, is modeled through the use of exponential runoff coefficients, which increases the model accuracy. Seasonal performance like NSE > 0.6 for snow-free intervals strengthens the need for incorporating frozen soil, snow, melt processes, complex structures, and variable resolution into the TOPMODEL framework.

• *Practical Implications and Future Directions*

Using unsupervised clustering techniques to derive zonation results provides a means to assess and monitor ecosystem resilience and responses due to climate variability, which aids in the design of sensor networks as well as improving watershed management and conservation plans. Focus should be put on the dynamics of snowpack and evapotranspiration, improving topographic indices for DEMs at higher resolutions, and applying machine learning for precision in zone-based models.

References

[1] Beven, K., & Freer, J. (2001). Equifinality, data assimilation, and uncertainty estimation in mechanistic modelling of complex environmental systems using the GLUE methodology. *Journal of hydrology*, *249*(1-4), 11-29.

[2] Silva, J. C. da, Souza, M. L. de O., & Almeida, A. de. (2025). Comparative analysis of programming models for reconfigurable hardware systems. *SCCTS Transactions on Reconfigurable Computing, 2*(1), 10–15.

[3] Koster, R. D., et al. (2000). The catchment-based land surface model. *Journal of Hydrometeorology, 1*(3), 227–251.

[4] Yuvaraj, D., Kumar, G. S., Prasath, J. S., & Kumar, S. S. (2019). Modeling and Tuning of First Order Process with Dead Time. *IWRA (India) Journal (Half Yearly Technical Journal of Indian Geographical Committee of IWRA)*, *8*(1), 9-12.

[5] Famiglietti, J. S., & Wood, E. F. (1994). Multiscale modeling of spatially variable water and energy balance processes. *Water Resources Research*, *30*(11), 3061-3078.

[6] Nadim, I., Rajalakshmi, N. R., & Hammadeh, K. (2024). A Novel Machine Learning Model for Early Detection of Advanced Persistent Threats Utilizing Semi-Synthetic Network Traffic Data. *Journal of VLSI Circuits and Systems*, *6*(2), 31-39.

[7] Ducharne, A., et al. (2000). Development of a large-scale hydrological model based on TOPMODEL concepts. *Journal of Hydrology, 240*(1–2), 105–129.

[8] Wei, L., & Lau, W. C. (2023). Modelling the power of RFID antennas by enabling connectivity beyond limits. *National Journal of Antennas and Propagation*, *5*(2), 43-48.

[9] Beven, K. J., & Kirkby, M. J. (1979). A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. *Hydrological sciences journal*, *24*(1), 43-69.

[10] Aravindh, G., & Sridhar, K. P. (2024). Resilient and Adaptive Secure Routing Protocol for Wireless Sensor Networks Using a Grey Wolf Optimizer and Lightning Search Algorithm. *Journal of Internet Services and Information Security*, *14*(4), 331-346.

[11] Freer, J., et al. (1996). The use of likelihood-weighted model averaging to evaluate uncertainty in hydrological prediction. *Hydrological Processes, 10*(3), 261–282.

[12] Chen, F., & Kumar, A. (2001). Quantifying the sensitivity of land surface model simulations to soil hydraulic parameters. *Journal of Geophysical Research: Atmospheres, 106*(D16), 16887–16904.

[13] Beven, K. (1982). On subsurface stormflow: An analysis of response times. *Hydrological sciences journal*, *27*(4), 505-521.

[14] Yang, Z. L., & Niu, G. Y. (2003). A physically based soil moisture assimilation system. *Water Resources Research, 39*(4).

[15] Gedney, N., & Cox, P. M. (2003). The sensitivity of global climate model simulations to the representation of soil moisture heterogeneity. *Journal of Hydrometeorology*, *4*(6), 1265-1275.

[16] Niu, G. Y., & Yang, Z. L. (2003). A simple TOPMODEL-based runoff parameterization (SIMTOP) for use in global climate models. *Journal of Geophysical Research: Atmospheres, 108*(D16).

[17] Devadoss, J., Falco, N., Dafflon, B., Wu, Y., Franklin, M., Hermes, A., ... & Wainwright, H. (2020). Remote sensing-informed zonation for understanding snow, plant and soil moisture dynamics within a mountain ecosystem. *Remote Sensing*, *12*(17), 2733.

[18] Hubbard, S. S., Gangodagamage, C., Dafflon, B., Wainwright, H., Peterson, J., Gusmeroli, A., ... & Wullschleger, S. D. (2013). Quantifying and relating land-surface and subsurface variability in permafrost environments using LiDAR and surface geophysical datasets. *Hydrogeology Journal*, *21*(1), 149-169.

[19] Wainwright, H. M., et al. (2017). Mapping spatial heterogeneity in Arctic ecosystems using unsupervised machine learning. *Environmental Research Letters, 12*(5).

[20] Jeziorska, J., & Niedzielski, T. (2018). A TOPMODEL-based assessment of flood vulnerability in Central Sudetes mountain basins. *Acta Geophysica, 66*(2), 203–222.

[21] Devadoss, J., Falco, N., Dafflon, B., Wu, Y., Franklin, M., Hermes, A., ... & Wainwright, H. (2020). Remote sensing-informed zonation for understanding snow, plant and soil moisture dynamics within a mountain ecosystem. *Remote Sensing*, *12*(17), 2733.

[22] Hubbard, S. S., Gangodagamage, C., Dafflon, B., Wainwright, H., Peterson, J., Gusmeroli, A., ... & Wullschleger, S. D. (2013). Quantifying and relating land-surface and subsurface variability in permafrost environments using LiDAR and surface geophysical datasets. *Hydrogeology Journal*, *21*(1), 149-169.

[23] Wainwright, H. M., et al. (2017). Mapping spatial heterogeneity in Arctic ecosystems using unsupervised machine learning. *Environmental Research Letters, 12*(5).

[24] Swenson, S. C., et al. (2012). Estimating snow water equivalent in data-poor environments. *Journal of Hydrometeorology, 13*(1), 154–170.

[25] Bonan, G. B., Oleson, K. W., Vertenstein, M., Levis, S., Zeng, X., Dai, Y., ... & Yang, Z. L. (2002). The land surface climatology of the Community Land Model coupled to the NCAR Community Climate Model. *Journal of climate*, *15*(22), 3123-3149.

[26] Daehnert, M., & Bock, M. (2013). High-resolution mapping of vegetation productivity using UAV data. *International Journal of Remote Sensing, 34*(12), 4279–4295.

[27] Thompson, S. E., et al. (2011). Soil moisture–vegetation–precipitation interactions in mountainous terrain. *Hydrology and Earth System Sciences, 15*(3), 923–940.

[28] Vereecken, H., et al. (2008). On the spatio-temporal dynamics of soil moisture at the field scale. *Journal of Hydrology, 356*(1–2), 1–16.

[29] Korres, W., et al. (2015). Spatio-temporal soil moisture patterns in an agricultural catchment. *Hydrology and Earth System Sciences, 19*(9), 4117–4131.

[30] Gómez-Chova, L., Muñoz-Marí, J., Laparra, V., Malo-López, J., & Camps-Valls, G. (2011). A review of kernel methods in remote sensing data analysis. *Optical Remote Sensing: Advances in Signal Processing and Exploitation Techniques*, 171-206.

[31] Bastola, S., Murphy, C., & Sweeney, J. (2008). The role of hydrological modelling uncertainties in climate change impact assessments of Irish river catchments. *Advances in Water Resources, 31*(11), 1571–1583.

[32] Dickinson, R. E., et al. (1993). Biosphere–Atmosphere Transfer Scheme (BATS) for the NCAR Community Climate Model. *NCAR Technical Note TN-387+STR*.

[33] Stieglitz, M., et al. (1997). A two-dimensional model for simulating the soil surface energy and moisture balance. *Journal of Geophysical Research: Atmospheres, 102*(D12), 15123–15137.

[34] Quinn, P., et al. (1995). The prediction of hillslope flow paths for distributed hydrological modelling using digital terrain models. *Hydrological Processes, 9*(1), 65–79.

[35] Choi, H., & Beven, K. (2007). Multi-period and multi-criteria model conditioning to reduce prediction uncertainty in distributed hydrological modelling: Applications to the GLUE methodology. Water Resources Research, 43(10).