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Understanding the Role of Climate and Watershed Properties in Rain-on-Snow Runoff Using XGBoost-SHAP Interpretable Machine Learning

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Abstract

Rain-on-snow (ROS) events significantly impact hydrological processes in temperate regions, yet their seasonal drivers remain poorly understood particularly in low elevation and low-gradient catchments. This study leverages interpretable machine learning (XGBoost-SHAP) to analyze meteorological and watershed controls on ROS runoff across the Great Lakes Basin region. ROS events were defined as days with concurrent rainfall ≥1 mm and snow water equivalent ≥1 mm. The models demonstrated acceptable predictive accuracy, with winter achieving higher performance (R^2 = 0.65, Nash-Sutcliffe = 0.59) than spring (R^2 = 0.56, Nash-Sutcliffe = 0.49), indicating greater predictability during colder months. Our results reveal distinct seasonal controls on ROS runoff generation. Winter runoff is predominantly governed by climatic factors—rainfall, air temperature, and their interactions—with soil permeability and slope orientation playing secondary roles. In contrast, spring runoff shows increased sensitivity to land cover characteristics, particularly agricultural and shrub cover, as vegetation-driven processes become more influential. Snow depth effects shift from predominantly negative in winter, where snow acts as storage, to positive contributions in spring at shallow to moderate depths. ROS runoff responded positively to air temperatures exceeding approximately 2.5°C in both winter and spring, as warmer conditions promoted snowpack melting. Land cover influences on ROS runoff differ by vegetation type and season. Agricultural areas consistently increase runoff in both seasons due to limited infiltration, whereas shrub-dominated regions exhibit stronger runoff enhancement in spring, likely driven by shifts in snow accumulation and distribution. The seasonal shift in dominant controls underscores the importance of accounting for land–climate interactions in predicting ROS runoff under future climate scenarios. These insights are essential for improving flood forecasting, managing water resources, and developing adaptive strategies.

Keywords: rain-on-snow, interpretable machine learning, XGBoost, SHAP

1. Introduction

Rain-on-snow (ROS) events, where rain falls on existing snowpack, are a critical hydrological phenomenon ROS events are increasingly recognized as significant factors influencing water resources. These events can lead to rapid snowmelt, increased runoff, and subsequent changes in water quality. ROS events can have both positive and negative impacts on groundwater recharge. On one hand, ROS events can enhance groundwater recharge by increasing the amount of water available for infiltration, particularly in regions where the snowpack acts as a natural reservoir (Barnhart et al., 2016; Hyman-Rabeler and Loheide, 2022; Trubilowicz and Moore, 2017). On the other hand, midwinter melt events followed by freezeback can reduce groundwater recharge by increasing soil water content and leaving the ground exposed to subsequent cold periods, which can lead to frozen ground and reduced infiltration (Hyman-Rabeler and Loheide, 2022). ROS events are critical for understanding freshwater ecosystems, particularly in forested and agricultural regions. These events can lead to rapid snowmelt combined with rainfall leading to high runoff, which in turn affects water quality by mobilizing nutrients, sediments, and organic matter into surface waters (Hensley et al., 2022; Eimers et al.2007; Casson et al., 2010). These events can lead to the mobilization of nitrogen (N) and phosphorus (P), which are essential nutrients but can cause eutrophication when present in excess. Studies have shown that ROS events contribute a substantial proportion of annual and seasonal nutrient export, particularly in forested catchments (Crossman et al., 2016; Casson et al., 2010, 2014).

In the Great Lakes region and the eastern U.S., where ROS frequently contribute to rapid snowmelt, high runoff, and flooding (Surfleet and Tullos, 2013; Grote, 2020), ROS events are particularly common in late winter and early spring when warm, moist air masses from the Gulf of Mexico and Atlantic Ocean interact with persistent snowpack (Cohen et al., 2015; Jeong and Sushama, 2018). Studies indicate that ROS events in this region vary in frequency and intensity due to factors such as elevation, proximity to the Great Lakes (which enhance lake-effect snowfall), and synoptic-scale atmospheric patterns (Grote, 2020; Wachowicz et al., 2019). For instance, the Appalachian regions of Pennsylvania and New York experience more frequent ROS-induced flooding due to orographic precipitation and deep snowpack (Grote, 2020), while the Midwest sees variability linked to fluctuating winter temperatures and snow cover duration (Cohen et al., 2015). The frequency and intensity of ROS events are influenced by climate change, with warmer winters and altered precipitation patterns exacerbating their occurrence (Seybold et al., 2022; Myers et al., 2023). Climate projections indicate that ROS events may become more frequent, driven by increased rainfall occurrence but reduced intensity due to declining snowpack and diminished melt contributions (Jeong and Sushama, 2018; Surfleet and Tullos, 2013). In the Great Lakes Basin, ROS snowmelt in warmer, southern subbasins are projected to decrease by approximately 30% by the mid-21st century, while colder, northern subbasins will experience less than a 5% reduction (Myers et al., 2023)

ROS events often result in rapid increases in river discharge due to the combined effects of rainfall and snowmelt. The magnitude of ROS runoff depends on the meteorological variables such as the intensity and duration of rainfall, air temperature and condition of the snowpack (Kroczynski, 2003; Maclean et al., 1995; Yang et al., 2023). For instance, in mountainous regions like the Sierra Nevada, the cold content of the existing snowpack influences how watersheds respond hydrologically to extreme ROS events (Katz et al., 2023). Similarly, in coastal mountain regions, high-elevation rainfall during ROS events can lead to enhanced runoff due to the contribution of snowmelt (Trubilowicz, 2015).

In addition, the magnitude of ROS runoff is also influenced by watershed characteristics, including slope, forest cover, soil permeability, and aspect. Steeper slopes accelerate runoff by reducing infiltration time, leading to faster peak discharges (Pomeroy et al., 2012). Forest cover modulates snowmelt rates by intercepting rainfall and reducing wind-driven snow redistribution, while also influencing energy fluxes through canopy shading, longwave radiation, and reduced turbulence (Storck et al., 2002; Winkler et al., 2005). Similarly, agricultural catchments with impermeable soils and reduced infiltration capacity may experience higher runoff responses during ROS events (Aygün et al., 2022). Catchment size and drainage network characteristics also influence ROS runoff generation. Smaller catchments tend to respond more rapidly to ROS events, with shorter lag times between rainfall and runoff. For example, in the Sierra Nevada, small headwater catchments exhibited rapid runoff responses during ROS events due to their steep terrain and well-developed drainage networks (Haleakala et al., 2022). In contrast, larger catchments may exhibit more attenuated runoff responses due to the greater opportunity for water to infiltrate or be stored in the landscape (Barnhart et al., 2020).

Most existing studies on snowmelt and runoff have focused on mountainous regions, where elevation and terrain dominate hydrologic responses (Pomeroy et al., 2012; Pradhanang et al., 2013). Here, we examine how climate variables (rainfall, temperature, and snow depth) and watershed properties influence rain-on-snow runoff in low-elevation, low-gradient catchments across the U.S. Great Lakes basin, where ROS events are frequent but remain understudied (Surfleet and Tullos, 2013; Jeong and Sushama, 2018). We examine how land cover modifies the effects of precipitation and temperature on ROS runoff variability. We also assess how this modulation changes from winter to spring, as shifts in snowpack and canopy conditions may alter the relative importance of land cover versus climate controls (McNamara et al., 2005; Brandt et al., 2022).

2. Data and Methods

2.1 Study Area

The study focuses on the US Midwest region, encompassing eight U.S. states: Wisconsin, Minnesota, Illinois, Michigan, Indiana, Ohio, Pennsylvania, and New York, and the Canadian province of Ontario (Figure 1). This region is characterized by its proximity to the Great Lakes, which significantly influence local climate patterns, including snowfall and temperature regimes (Grote, 2020). The area experiences frequent rain-on-snow (ROS) events, particularly during late winter and early spring, when warm, moist air masses from the Gulf of Mexico and Atlantic Ocean interact with existing snowpack (Suriano, 2022; Grote, 2020; Cohen et al., 2015; Hao et al., 2025). The terrain varies from flat plains in the Midwest to more rugged topography in the Appalachian regions of Pennsylvania and New York, which can exacerbate runoff and flooding during ROS events (Grote, 2020). The Great Lakes also contribute to lake-effect snow, further complicating snowpack dynamics and runoff processes (Surfleet and Tullos, 2013). This region's hydrology is critical for water resource management, flood forecasting, and understanding climate change impacts on winter precipitation and snowmelt patterns (Jeong and Sushama, 2018; Myers et al. 2021, 2023).

2.2. Data

We defined rain-on-snow (ROS) events as days meeting two concurrent conditions: (1) liquid precipitation (rainfall) $\geq$ 1 mm, and (2) snow water equivalent (SWE) $\geq$ 1 mm on the ground (Jeong et al. 2014; Myers et al. 2023). Rainfall was partitioned from total precipitation when daily average air temperature exceeded 0°C, following standard hydrometeorological practice (Marks et al., 2013). ROS-induced runoff (Qr_ros) was quantified as the difference between discharge on the ROS-day and baseline discharge (taken as the discharge one day prior to the ROS event onset), isolating the ROS contribution to streamflow (Berghuijs et al., 2016). Only ROS events that generated measurable runoff increases (Qr_ros > 0) were retained for analysis, ensuring focus on hydrologically significant events (Pradhanang et al., 2013).

Daily discharge data were obtained from the HYSETS database (Arsenault et al., 2020), which compiles quality-controlled streamflow records from the United States Geological Survey (USGS) National Water Information System (NWIS) (USGS, 2023) and the Environment and Climate Change Canada (ECCC) Water Survey Canada (WSC) National Water Data Archive (HYDAT) (ECCC, 2023). Precipitation (mm/day) and maximum/minimum air temperature (°C) were also sourced from HYSETS, which integrates multiple data products including station observations, gridded datasets, and reanalysis data (e.g., ERA5-Land). Snow water equivalent (SWE; mm) was derived from the ERA5-Land reanalysis (Muñoz-Sabater et al., 2021), a high-resolution (9 km) global dataset for snowpack dynamics. Watershed properties (e.g., elevation, slope, land cover) were extracted from HYSETS, which incorporates physiographic data from the North American Land Change Monitoring System (NALCMS, 2010) and digital elevation models. To ensure data quality and representativeness, we selected watersheds with: (1) ≥2 years of complete daily records (2000-2023) without missing values, (2) ≥10% forest cover, and (3) drainage areas between 10 and 1,000 km². All variables were spatially averaged at the watershed scale.

2.3 Meteorological and watershed controls on rain-on-snow (ROS) runoff

To investigate the factors influencing rain-on-snow (ROS) runoff variability, we employed an explainable machine learning approach using Extreme Gradient Boosting (XGBoost) combined with Shapley Additive Explanations (SHAP). XGBoost is a powerful tree-based algorithm that excels in handling nonlinear relationships and complex interactions in ecological and hydrological datasets (Chen and Guestrin, 2016; Lundberg et al., 2020). We trained separate XGBoost models for winter and spring seasons, to predict ROS runoff using predictors including rainfall, temperature, forest cover, and watershed properties (e.g., slope, forest cover, soil permeability, soil porosity, and aspect). The model hyperparameters were optimized using Bayesian optimization with k-fold cross-validation. Physical relationships between predictors and hydrological response were preserved by incorporating monotonicity constraints during the optimization process. The model enforced positive monotonic constraints on features where higher values are physically expected to increase runoff: slope (steeper terrain enhances flow), urban (impervious surfaces reduce infiltration), rainfall (greater precipitation amplifies runoff), and temperature (warmer conditions accelerate snowmelt). Conversely, negative constraints were applied where higher values suppress runoff: north_aspect (reduced solar exposure suppress melt), soil_perm (higher permeability promotes infiltration), and soil_porosity (greater pore space increases water retention). These constraints ensured the model's behavior aligned with hydrological principles. The model incorporated several key feature interactions to capture nonlinear hydrological processes: rain_temp (rainfall × temperature) to account for rain-on-snow events, forest_temp (forest cover × temperature) and forest_wind (forest cover × wind speed) to modulate melt dynamics under canopy effects, aspect_temp (north/east aspect × temperature) to represent slope-dependent solar radiation impacts, and temp_snow (temperature × snow depth) to capture melt-rate sensitivity to snowpack conditions. These interactions were included alongside base features to better represent complex watershed responses.

To interpret the contributions of each predictor, we used SHAP analysis, which shows the local and global importance of features by decomposing model predictions into additive effects (Lundberg and Lee, 2017). This approach aligns with recent ecological studies leveraging SHAP to disentangle driver interactions (Wang et al., 2022; Giardina et al., 2024). All analyses were conducted in R using the xgboost(Just et al. 2019) and SHAPforxgboost (Liu et al., 2023) R packages.

To assess the performance of our XGBoost models in predicting rain-on-snow (ROS) runoff, we employed three widely used evaluation metrics: the Root Mean Square Error (RMSE), coefficient of determination (R^2), and Nash-Sutcliffe Efficiency (NSE). RMSE quantifies the average magnitude of prediction errors in the original units (mm/day), with lower values indicating better model accuracy (Willmott and Matsuura, 2005). R^2 measures the proportion of variance in observed runoff explained by the model, ranging from 0 (no predictive power) to 1 (perfect fit) (Chicco et al., 2021). The NSE evaluates hydrological model performance by normalizing prediction errors against the variance of observed data, where values >0 indicate model skill exceeding the mean benchmark (Nash and Sutcliffe, 1970). These metrics were calculated for both training and validation datasets to assess potential overfitting, following best practices in hydrological machine learning (Addor et al., 2018; Knoll et al., 2019).

3. Results and Discussion

3.1 Performance of the XGBoost Model in Predicting Rain-on-Snow Runoff

The performance of the XGBoost model in predicting rain-on-snow (ROS) runoff for winter and spring seasons is summarized in Table 1. The XGBoost model exhibits distinct seasonal performance in predicting runoff from rain-on-snow events across the US Great Lakes region. For winter, the model achieves moderate predictive accuracy with a test R^2 of 0.65, RMSE of 4.21, and Nash-Sutcliffe efficiency of 0.59, supported by a strong Spearman correlation (0.74). In spring, the model shows slightly lower explanatory power (test R^2 = 0.56, Nash-Sutcliffe = 0.49) but demonstrates improved generalization, as evidenced by a test RMSE (3.61) slightly lower than training (3.44). The winter model's higher R^2 and Nash-Sutcliffe values suggest that runoff processes during colder months may be more predictable, possibly due to more stable snowpack dynamics. In contrast, spring runoff, influenced by rapid snowmelt and variable land-surface interactions, presents greater complexity, leading to reduced predictive performance. Consistent Spearman correlations (winter: 0.74; spring: 0.67) indicate that the model reliably ranks ROS events within both seasons. These differences highlight the importance of accounting for seasonal variability in hydrological modeling.

The model demonstrated acceptable predictive accuracy for both seasons, with winter (test R^2 = 0.65, Nash-Sutcliffe = 0.59) outperforming spring (test R^2 = 0.56, Nash-Sutcliffe = 0.49), suggesting greater predictability of ROS runoff processes during colder months. This aligns with findings from similar hydrological studies in snow-dominated regions, where winter ROS runoff is often more stable due to consistent snowpack dynamics, while spring runoff exhibits higher variability from rapid melt and heterogeneous land interactions (Pradhanang et al., 2013; Freudiger et al., 2014). However, temperature-driven snowmelt studies suggest spring snowmelt becomes more predictable as temperatures consistently exceed freezing, leading to uniform melt rates and higher model accuracy in spring compared to that in winter months (Lundquist et al., 2009; Þorsteinsson, 2015).

Both winter and spring XGBoost models in this study struggled with very low runoff values, as evidenced by extremely high MAPE (Mean Absolute Percentage Error) values (300-400%), highlighting the challenges of modeling near zero-inflated hydrological data even with transformation techniques (Seybold et al., 2023; Yu et al., 2024). Machine learning models, despite their flexibility, often fail to capture the physical constraints governing minimal runoff generation (e.g., infiltration capacity, residual storage), a weakness also observed in process-based models (Addor and Melsen, 2019). Recent work suggests that hybrid approaches or censored regression techniques may improve low-flow predictions (Feng et al., 2023).

3.2 ***Meteorological and watershed controls on rain-on-snow runoff***

The feature importance plots reveal both consistent and seasonally distinct drivers of Rain-on-Snow (ROS) runoff in the US Great Lakes Basin, with rainfall and its interaction with temperature (rain_temp) emerging as the dominant predictors across both winter and spring, underscoring the fundamental role of precipitation intensity and thermal conditions in melt dynamics. Slope ranks highly in both seasons, reflecting the universal importance of terrain steepness in runoff generation, while snow_depth maintains moderate influence, though its relative significance diminishes slightly in spring as snowpack depletes. However, key seasonal differences emerge in secondary drivers: winter runoff is strongly shaped by soil permeability (soil_perm) and north_aspect, highlighting the importance of subsurface drainage and solar exposure during colder months when frozen or saturated soils dominate hydrologic response. In contrast, spring runoff shows increased sensitivity to land cover, with crop and shrub gaining prominence, suggesting that surface characteristics and vegetation-driven processes (e.g., albedo, interception) become more influential as temperatures rise. The temperature-linked interactions (forest_temp, temp_snow) and static features like urban or east_aspect remain consistently low in importance across seasons, indicating their secondary role compared to climatic and broader landscape controls. Together, these patterns illustrate a winter system governed by rain-snow transitions and infiltration capacity, while spring behavior shifts toward land-cover-mediated surface flow, with both seasons sharing a foundational dependence on precipitation and temperature synergies.

During winter, ROS events are predominantly governed by climatic factors such as rainfall intensity, air temperature, and the thermal state of the snowpack, which collectively determine the extent of rainwater infiltration and subsequent runoff generation (Brandt et al., 2022; Bouchard et al., 2024). The high cold content of the snowpack and potential presence of frozen soils during this period limit infiltration, enhancing surface runoff. In contrast, spring ROS events occur when the snowpack is typically warmer and more isothermal, allowing for greater percolation of rainwater, while progressing soil thaw increases subsurface water transmission capacity. Consequently, both climatic drivers and land surface characteristics, such as vegetation cover become more influential in modulating ROS runoff (Juras et al. 2021; Jennings et al., 2017). In addition, during winter, when vegetation is largely dormant, its role in ROS processes is minimal (Musselman et al., 2008). However, with the onset of spring, increased vegetation activity begins to significantly influence ROS runoff through multiple mechanisms. Emerging foliage intercepts rainfall, reducing direct snowpack saturation and altering melt dynamics (Pomeroy et al. 2002). Additionally, active root water uptake through transpiration enhances soil storage capacity during spring, which modulates surface runoff generation (Winkler et al., 2005). These insights are crucial for refining models and developing targeted management strategies to address ROS runoff under changing climate scenarios.

Figure 3 show how meteorological, topographic, and land cover factors differentially influence ROS runoff across seasons. The SHAP values reveals the direction of these relationships between winter and spring. The SHAP summary plots provide insights into the nature of the impact of each feature on ROS runoff during winter and spring seasons. In both seasons, rainfall consistently exhibits a strong positive impact on ROS runoff, with higher rainfall values leading to increased runoff. The interaction term rain_temp also shows a predominantly positive influence, indicating that warmer temperatures during rainfall events enhance ROS runoff by promoting snowmelt and surface water generation.

The SHAP summary plots reveal distinct seasonal patterns in how crop, shrub, snow depth, and drainage area influence ROS runoff. In winter, higher snow depth generally has a negative effect on runoff, indicating that deeper snowpack initially absorbs or delays the release of meltwater, reducing immediate runoff generation. However, in spring, this relationship shifts, with moderate snow depths contributing positively to runoff.

Crop cover shows a consistently positive influence across both seasons, suggesting that agricultural land tends to enhance runoff potential, possibly due to reduced infiltration capacity and faster overland flow compared to natural vegetation. Shrub exhibits a stronger positive impact in spring, implying that shrub-dominated landscapes may promote runoff through mechanisms likely due to altered snow accumulation patterns (Würzer and Jonas, 2018). ROS runoff increases with increase in crop (agricultural) land fraction due to soil compaction and reduced infiltration capacity caused by agricultural practices. Compacted soils, particularly those with plough pans, have significantly lower porosity and hydraulic conductivity, leading to increased surface runoff (Burt and Slattery, 2006).

The forest_wind interaction, which serves as a proxy for turbulence energy within forested areas, shows a positive contribution to ROS runoff, particularly during spring. This suggests that in the presence of forest cover, stronger winds enhance runoff generation, possibly by accelerating melt through microclimatic effects (Fuss et al., 2016). Soil frost in the forested catchments may alter the infiltration and flow of meltwater, enhancing the magnitude of runoff (Dwivedi et al., 2024; Jones and Pomeroy 2001). The forest_temp interaction, representing the influence of longwave radiation within forested canopies, exhibits a more nuanced pattern. During winter, this term tends to reduce ROS runoff, likely due to the insulating effect of dense canopy cover that limits snowmelt despite higher temperatures. However, in spring, the same interaction shifts toward a positive contribution, indicating that forest-modulated warming may enhance snowmelt and runoff. The forest canopy in snowy regions enhances longwave radiation transmission to the snowpack while reducing shortwave radiation due to shading (Essery et al., 2008).

3.3. Impact of air temperature and snow depth on rain-on-snow runoff generation

3.3.1 Air temperature

The partial dependence plots (figure 4) for ROS runoff in the winter and spring seasons illustrate the relationship between air temperature and its impact on runoff prediction, while also considering snow depth as a contributing factor. In the winter season plot, there is a clear positive trend in SHAP values (impact on runoff prediction) as air temperature increases from 0 to approximately 10°C. However, at air temperatures below approximately 2.5°C (on the X-axis), the SHAP values are negative. This observation indicates that very low temperatures suppress runoff generation because they prevent significant melting of the snowpack. In these cold conditions, even areas with deep snow (represented by darker colors in the color gradient) do not experience substantial runoff, as the snow remains frozen and does not contribute to liquid water flow. The negative SHAP values reflect the inhibitory effect of these low temperatures on runoff, emphasizing that such conditions reduce the likelihood or amount of runoff compared to higher temperatures. In spring, beyond approximately 5°C, SHAP values plateau and then decline, suggesting that higher temperatures may reduce runoff as snowpack becomes depleted or melting accelerates, promoting infiltration or evapotranspiration rather than surface runoff. However, at air temperatures below approximately 2.5°C, SHAP values are still negative, indicating that runoff is suppressed due to the lack of snowmelt. The transition to positive SHAP values occurs at around 2.5°C in both spring and winter, reflecting the threshold temperature at which melting begins to occur and runoff generation becomes more likely.

3.3.2 Snow depth (SWE)

The partial dependence plots for ROS runoff in the winter and spring seasons are shown in Figure 5. The x-axis represents snow depth (in millimeters, plotted on a log scale), while the y-axis shows the SHAP value, which quantifies the marginal effect of snow depth on the predicted runoff. In the winter season plot, SHAP values (impact on runoff prediction) are predominantly negative across most snow depth ranges. This indicates that, during winter, snow accumulation generally suppresses ROS runoff rather than enhancing it. At low snow depths (below approximately 10 mm), SHAP values remain negative, suggesting that shallow snowpacks do not contribute significantly to runoff. As snow depth increases from 5 mm to around 50–60 mm, SHAP values become slightly positive, implying that moderate snow depths have a positive effect on runoff generation. Beyond this range, SHAP values continue to decline, indicating that very deep snowpacks further suppress runoff. The color gradient representing total ROS rainfall shows that larger rain (darker colors) tends to mitigate the negative impact of snow depth on runoff, but at higher snowpack the overall trend remains negative. This suggests that during winter, snow acts more as a storage medium rather than a direct source of runoff due to the cold conditions inhibiting melting.

The spring season plot reveals a distinct pattern compared to winter. In spring, SHAP values become positive at relatively low snow depths, specifically, below approximately 5 mm, whereas in winter, SHAP values do not turn positive until snow depths reach around 10 mm. This suggests that even shallow snowpacks in spring can contribute positively to runoff prediction, likely due to the presence of warmer temperatures and increased melt potential. Additionally, the spring plot shows a more pronounced peak in SHAP values between 20–30 mm of snow depth, indicating that this range has the strongest positive influence on runoff generation. This enhanced response may be attributed to optimal conditions for snowmelt and rain infiltration, highlighting the seasonal differences in how snow depth influences ROS runoff processes. Beyond this point, SHAP values decline again as in winter, showing diminishing returns or suppression of runoff with very deep snowpacks. The color gradient for air temperature indicates that larger rainfall conditions (darker colors) play a less pronounced role in enhancing runoff compared to winter, reflecting the transition toward more dynamic melt processes typical of spring. The plots highlight the nuanced interaction between snow depth and runoff prediction, while snow depth generally suppresses runoff in winter due to cold conditions, it begins to play a more positive role in spring as temperatures rise.

4. Summary

This study investigated how climate variables (rainfall, temperature, snow depth) and watershed properties influence rain-on-snow runoff variability in the U.S. Great Lakes Basin, examining how land cover modifies the effects of precipitation and temperature on ROS runoff and how these relationships change seasonally from winter to spring. We employed an explainable machine learning approach using Extreme Gradient Boosting (XGBoost) combined with Shapley Additive Explanations (SHAP) to predict and interpret ROS runoff patterns across watersheds in eight U.S. states () and Ontario, Canada, using daily data from 2000-2023. The data were sourced from the HYSETS database and ERA5-Land reanalysis.

1. The XGBoost models demonstrated acceptable predictive accuracy with notable seasonal differences. The winter model achieved higher predictive performance ($R^2 = 0.65$, Nash-Sutcliffe = 0.59) compared to spring ($R^2 = 0.56$, Nash-Sutcliffe = 0.49), indicating greater predictability of ROS runoff processes during colder months when snowpack dynamics are more stable. Both models struggled with very low runoff values, highlighting the inherent challenges in modeling near-zero hydrological data even with advanced machine learning techniques.

2. During winter, runoff is predominantly governed by climatic factors including rainfall intensity, air temperature, and their interactions, with soil permeability and north-facing slopes playing important secondary roles. In contrast, spring ROS events show increased sensitivity to land cover characteristics, particularly crop and shrub cover, as vegetation-driven processes become more influential with rising temperatures.

3. Snow depth and temperature effects vary markedly between seasons. Snow depth effects shift from predominantly negative in winter, where snow acts as a storage medium, to positive contributions in spring at shallow to moderate depths as melting potential increases. Air temperature below approximately 2.5°C tend to suppress ROS runoff in both winter and spring seasons

4. Land cover effects on ROS runoff vary by vegetation type and season. Agricultural areas consistently enhance runoff across both seasons due to reduced infiltration capacity, while shrub-dominated landscapes show stronger positive effects in spring, likely through altered snow distribution patterns.

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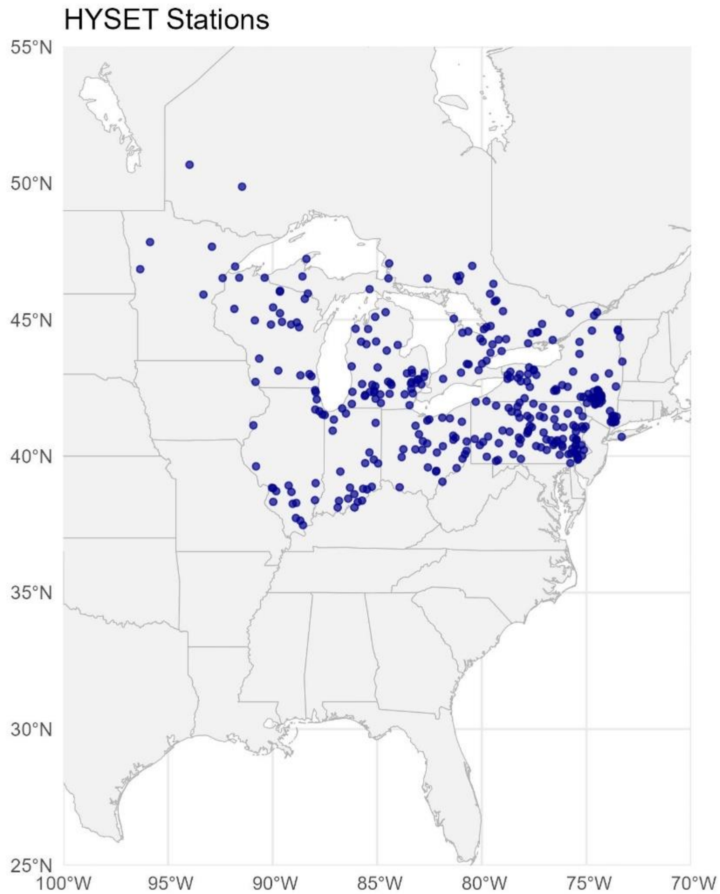

Figure 1. Distribution of HYSET catchments used in this study. Blue dots represent the streamflow gauge of the study catchments (n = 330) concentrated primarily within the Great Lakes basin and adjacent watersheds (eight US states and Ontario, Canada).

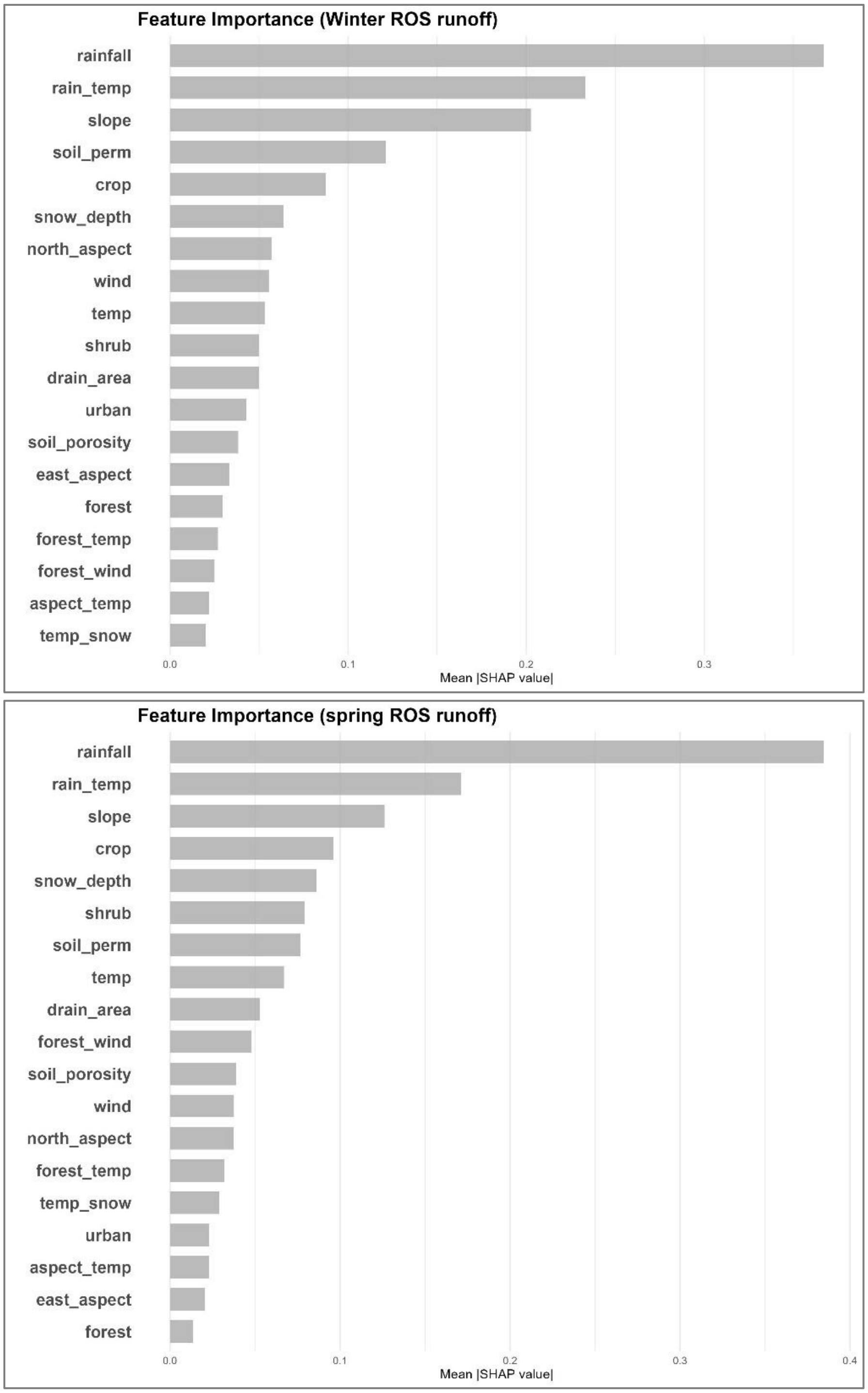

Figure 2. Relative importance of predictor variables in XGBoost models for rain-on-snow (ROS) runoff prediction during winter (top) and spring (bottom) seasons. Bars represent mean SHAP (SHapley Additive exPlanations) values indicating the average contribution of each feature to model predictions.

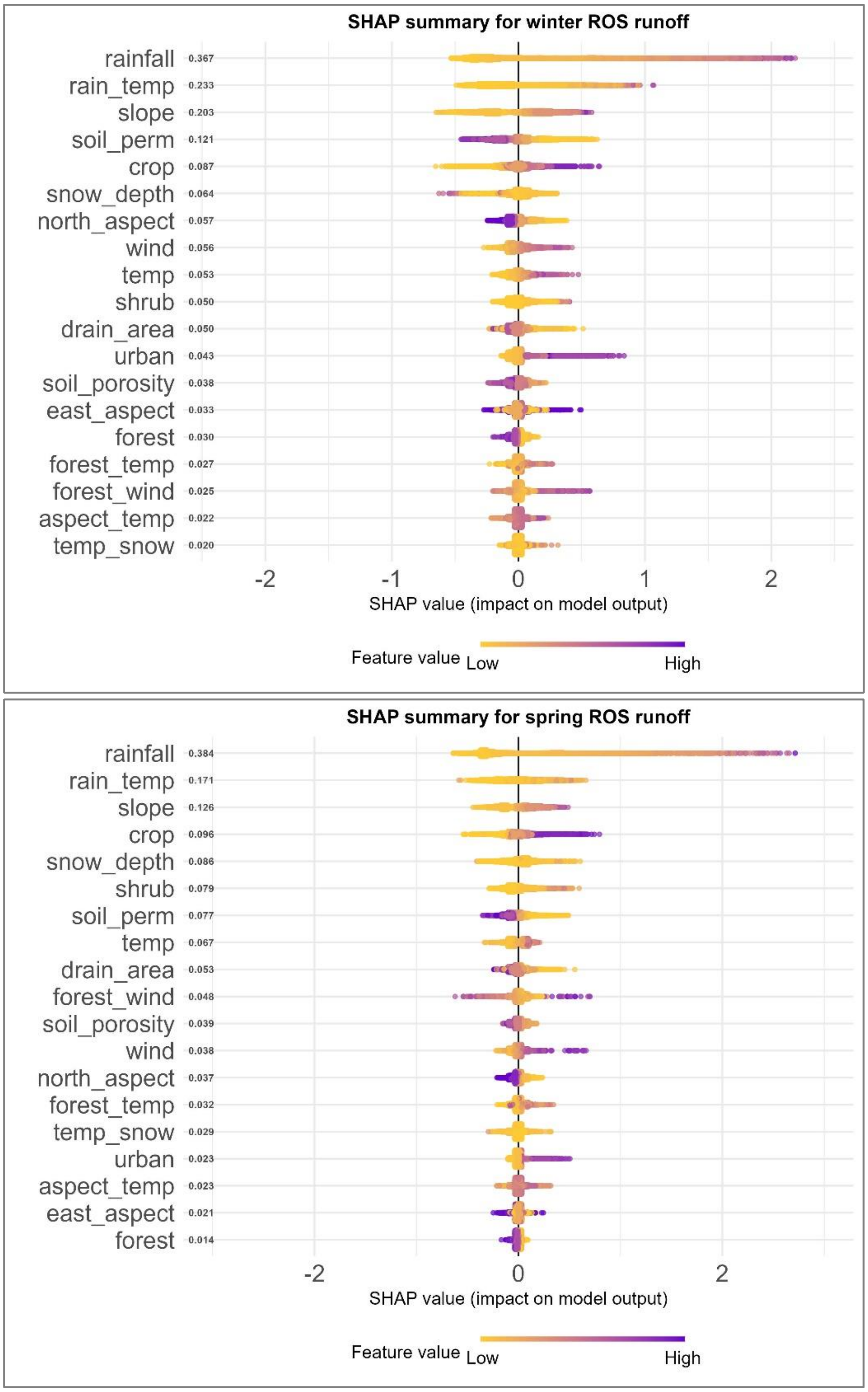

Figure 3. SHAP summary plots illustrating the seasonal differences in feature impacts on rain-on-snow (ROS) runoff for (a) winter and (b) spring across the US Great Lakes region and Ontario. Each point represents a SHAP value for a given feature, with color indicating feature magnitude (yellow = low, purple = high). Positive SHAP values indicate an increase in ROS runoff associated with that feature value, while negative values indicate a decrease.

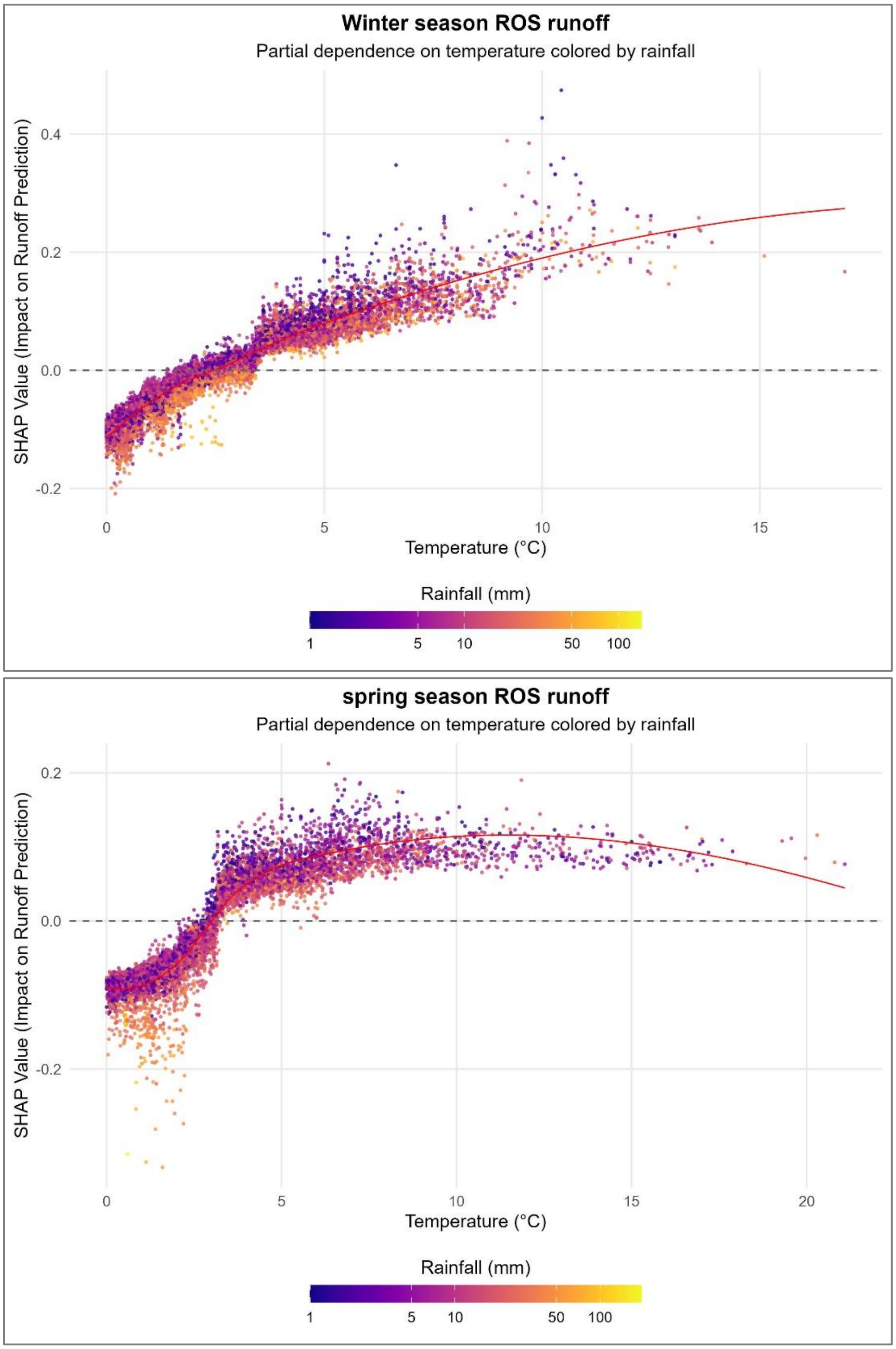

Figure 4. Partial dependence plots showing the relationship between temperature and rain-on-snow (ROS) runoff impact during winter and spring seasons. Points represent individual catchment-event combinations colored by rainfall amount (mm), with purple indicating low rainfall and yellow indicating high rainfall. The smooth curves (red lines) show the fitted relationships from generalized additive models.

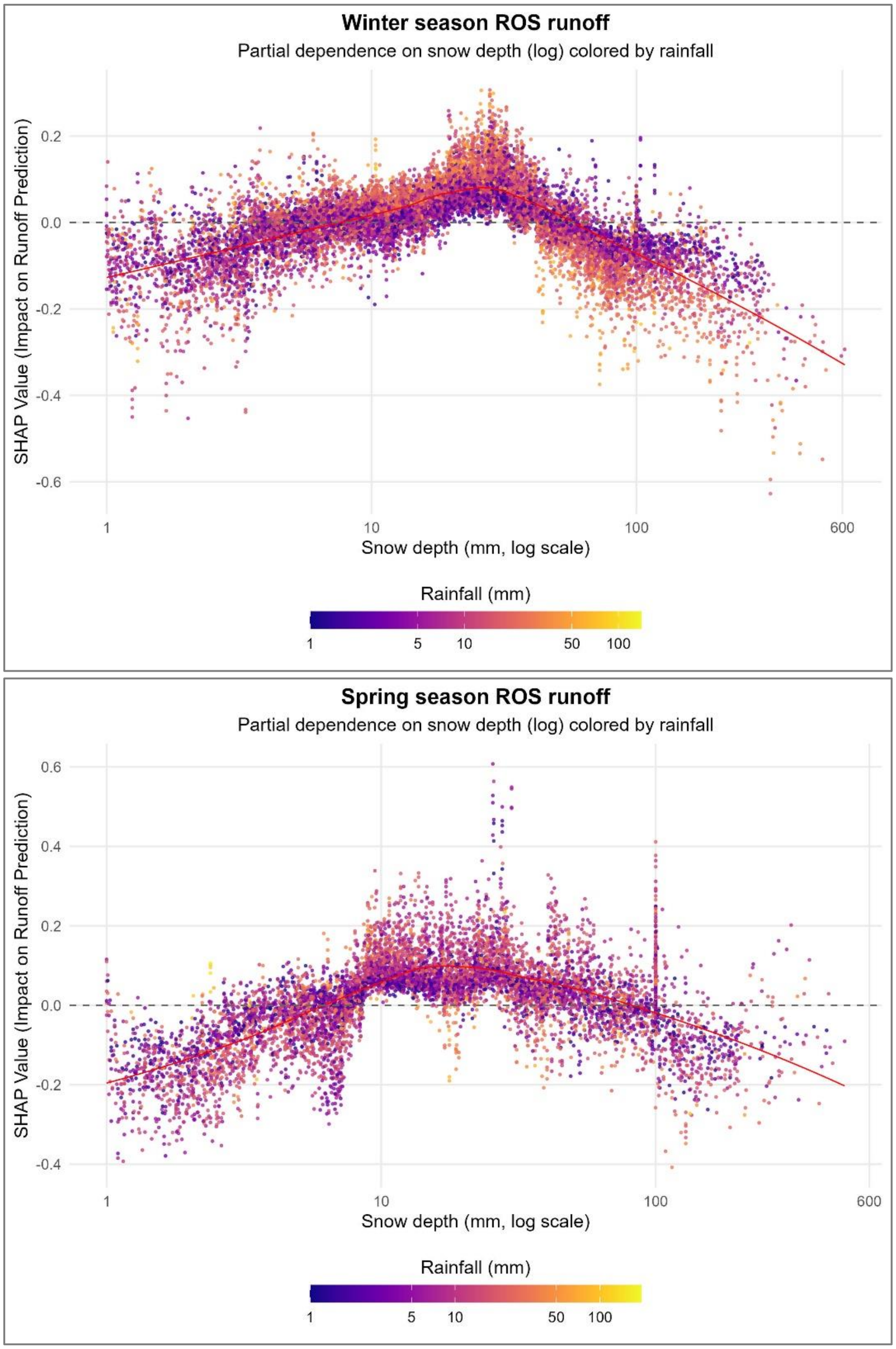

Figure 5. Partial dependence plots showing the relationship between snow depth and rain-on-snow (ROS) runoff impact during winter and spring seasons. Points represent individual catchment-event combinations colored by rainfall amount (mm), with purple indicating low rainfall and yellow indicating high rainfall. The smooth curves (red lines) show the fitted relationships from generalized additive models. Snow depth is displayed on a log scale (x-axis), while the y-axis shows the standardized impact on ROS runoff prediction.

Table 1. Performance metrics of the XGBoost model for predicting rain-on-snow (ROS) runoff in the US Great Lakes region (2000–2023), comparing winter and spring seasons. Metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean absolute percentage error (MAPE), coefficient of determination (R^2), Nash-Sutcliffe efficiency, and Spearman rank correlation for both training and testing datasets.

Performance Metric	**Winter**		**Spring**	
	Train	Test	Train	Test
RMSE	2.53	4.21	3.44	3.61
R^2	0.84	0.65	0.72	0.56
MAE	1.00	1.68	1.16	1.62
MAPE	323.96	516.82	317.25	535.19
Nash-Sutcliffe	0.81	0.59	0.64	0.49
Bias	0.52	0.77	0.65	0.70
Spearman Correlation	0.89	0.74	0.86	0.67