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Enhancing Flow Direction in Geothermal Fields Using Sentinel-1 Data for Sustainability Water Management

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Abstract. This study develops a flow direction prediction model using Sentinel-1 satellite imagery during rainy and dry seasons through the Random Forest machine learning algorithm. The pre-processing stage includes radiometric calibration, terrain flattening, speckle filtering, and Doppler terrain correction. The processed DEM data is used to extract key topographic parameters: elevation, slope, and curvature, which are then utilized in the model. The model is built with 500 trees (n.trees), using a mtry of 2 for the rainy season and 3 for the dry season, and out-of-bag (OOB) error estimates of 8.76% and 9.32%, respectively. Model evaluation, conducted through a confusion matrix, reveals high performance, with average Overall Accuracy, Kappa Accuracy, User Accuracy, Sensitivity, and Specificity all at 0.98 or above. The analysis shows that during the rainy season, flow direction predominantly shifts northeast (16.48%), while in the dry season, it shifts northwest (16.85%). Slope significantly influences flow direction, with feature importance scores of 60.76% in the rainy season and 63.53% in the dry season. Slope is crucial as it dictates the speed and direction of water flow under gravity. This model could significantly contribute to geothermal field management by accurately predicting surface water flow, enhancing monitoring, and promoting sustainable water resource management.

1. Introduction

A deep understanding of surface water flow direction in geothermal fields with complex topography and seasonal climate variations is crucial for various environmental and engineering applications [1, 2]. Accurate prediction of water flow direction not only supports efficient water resource management but also ensures the sustainability of geothermal field operations. However, modeling flow direction presents significant challenges, particularly in capturing the dynamic conditions that occur during seasonal changes, such as rainy and dry seasons [3]. Traditional methods are often less effective in accommodating these variations due to their reliance on static models that do not adequately consider temporal changes in

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topography and water flow. These limitations are particularly critical in geothermal fields, where accurate monitoring and prediction of surface water flow are essential for managing groundwater reservoir recharge and supporting sustainable energy extraction. The study by E. E. Tantama et al., 2021, emphasizes that a precise understanding of flow direction can significantly enhance geothermal production efficiency and reduce environmental impacts [4]. Effective water flow management not only maximizes energy recovery but also contributes to more sustainable geothermal systems. This strategic approach is essential for developing geothermal energy solutions that are both reliable and environmentally responsible, ensuring the preservation of vital water resources for future needs [5, 6].

The primary objective of this study is to develop an accurate surface water flow direction prediction model using DEM data processed with the Lee Sigma filter, utilizing the Random Forest (RF) algorithm [7]. This approach aims to optimize the reliability of the model by carefully selecting hyperparameters, including the number of trees (n.trees) and adjusting the mtry value to account for seasonal variations [8]. Specifically, the study explores the use of a lower mtry value during the rainy season and a slightly higher value during the dry season to achieve optimal performance. The secondary objectives include evaluating the model's effectiveness under different seasonal conditions and assessing its accuracy through metrics such as Overall Accuracy, Kappa Accuracy, Sensitivity, Specificity, and User Accuracy [9]. Additionally, the research seeks to identify the most influential topographic parameters, with a particular focus on the role of slope in determining flow direction [10].

In the study by Hu et al. (2024), it is mentioned that conventional methods such as hydrogeophysical tracking, tracer methods, and injection techniques have been used to monitor groundwater flow direction. However, this study introduces an innovative approach by utilizing Sentinel-1 satellite imagery combined with the Random Forest machine learning algorithm, which is capable of predicting surface water flow direction with high accuracy in geothermal areas. The novelty of this research lies in the model's ability to dynamically capture seasonal variations, especially in identifying significant changes in water flow conditions during rainy and dry seasons, which is difficult to achieve with conventional methods [11]. Meanwhile, the study by Hao et al. (2023) discusses the seasonal dynamics of water circulation and exchange flows in shallow lagoon-inlet-coastal ocean systems. In this context, flow direction analysis was conducted based on DEM data obtained from Sentinel-1 imagery and applied to geothermal system monitoring. This approach not only enhances the reliability of water flow predictions but also provides a more advanced tool for sustainable water management in geothermal areas, highlighting the novelty in the application of satellite technology and spatial analysis algorithms for sustainable water management in geothermal systems [12].

2. Research Methods

This study utilizes Sentinel-1 satellite imagery to predict surface water flow direction in geothermal areas during the rainy and dry seasons (**Fig. 1**). The first step involves data preprocessing, where the images captured during both seasons undergo several essential processes, including radiometric calibration, radiometric terrain flattening, speckle filtering using the Lee Sigma and Refined Lee methods, and Range Doppler Terrain Correction [13]. This process generates a Digital Elevation Model (DEM), which is then validated using statistical metrics such as RMSE, MRE, and MAE to ensure data quality and accuracy [14].

Once the DEM data is prepared, key parameters such as elevation, slope, and curvature are calculated for each pixel of the imagery. This data is combined with flow direction data from DEMNAS to create a training dataset, which is then split into 70% for training the model and 30% for testing. The study assumes that the seasonal variations in Sentinel-1 imagery are significant enough to influence the prediction of water flow direction and that radiometric terrain correction can reduce distortion caused by terrain topography, thereby enhancing model reliability[15].

The Random Forest (RF) machine learning model is employed to predict water flow direction, with hyperparameters such as the number of trees (n.trees), the number of variables tried at each split (mtry), and the out-of-bag (OOB) error rate being tuned for optimal performance [15]. The model is evaluated using metrics like Overall Accuracy, Kappa Accuracy, User Accuracy, Sensitivity, and Specificity, ensuring the model's robustness under various conditions [16].

The assumptions made in this study, such as the presumption of homogeneous DEM data, may impact the final predictive accuracy of the model. Therefore, the study also evaluates the importance of each feature (elevation, slope, curvature) in the final model, providing further insights into the factors influencing water flow direction and supporting more sustainable water resource management in geothermal areas [17].

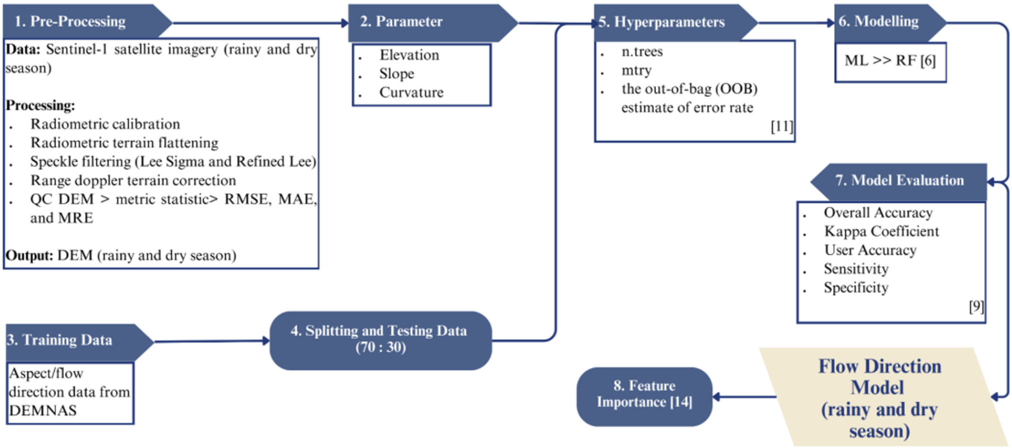


Fig. 1. Research Workflow

3. Results and Discussion

3.1 Results of Pre-Processing

In this study, the pre-processing stage was conducted systematically to produce accurate DEM data from Sentinel-1 satellite imagery, covering both rainy and dry seasons. This process began with radiometric calibration to ensure that the imagery used had high spectral accuracy. Following this, radiometric terrain flattening was applied to eliminate the effects of topography on the radar imagery, which was then followed by speckle filtering using the Lee Sigma and Refined Lee filters. These methods were chosen for their ability to reduce speckle noise without sacrificing important details in the imagery. The final step of pre-processing was the Range Doppler Terrain Correction, performed to correct geometric distortions in the imagery caused by satellite platform movements [13, 14].

Based on the visualization results of the DEM from both speckle filtering methods, Lee Sigma and Refined Lee, it is evident that the DEM generated using the Lee Sigma method during both the rainy and dry seasons exhibits clearer topographic details (**Fig. 2**). Scientific analysis supported by metric statistics (**Table 1**) shows that the Lee Sigma method has lower RMSE and MAE values compared to the Refined Lee method, particularly during the rainy season, with an RMSE of 5.62 and an MAE of 4.9. Although the MRE values between the two methods are very similar and consistent, the lower RMSE and MAE values of the Lee

Sigma method indicate that this DEM is more accurate and has less prediction error. Therefore, the DEM produced using the Lee Sigma method, especially during the rainy season, can be considered a more optimal input data for the machine learning process in predicting water flow direction in geothermal fields. The selection of this DEM as the basis for machine learning parameters is expected to enhance the accuracy and reliability of the developed prediction model [13, 14].

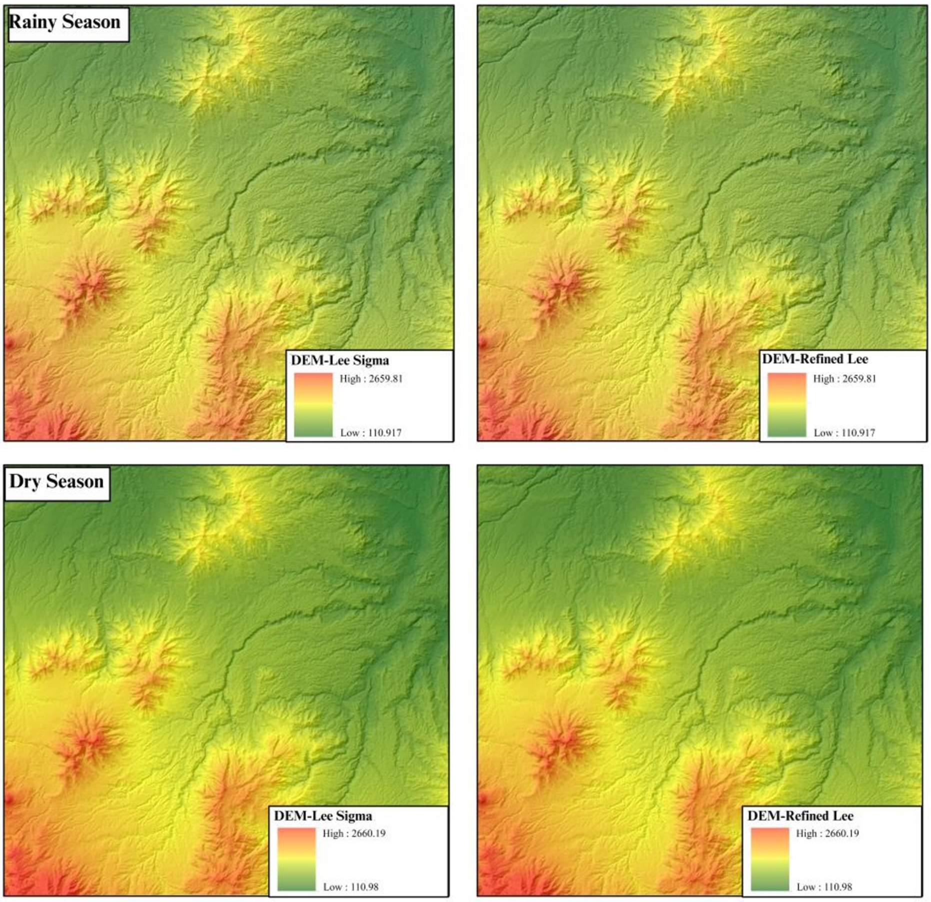


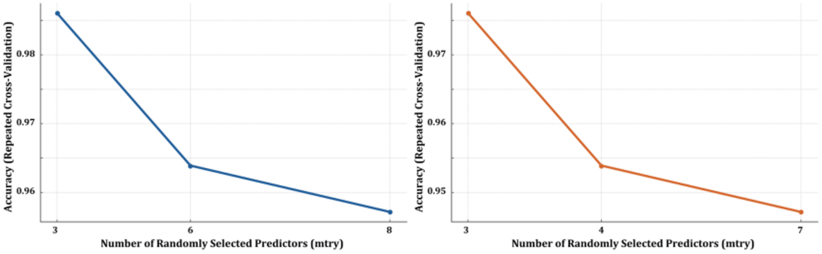
Fig. 2. Results of Final DEM from Range Doppler Correction on Sigma Lee and Refined Lee Filters

Table 1. Results of Metric Statistics

Season	**Speckle Filtering Method**	**Metric Statistics**		
		RMSE	**MRE**	**MAE**
Rainy	**Lee Sigma**	**5.62**	**0.01**	**4.9**
	Refined Lee	5.82	0.01	5.07
Dry	**Lee Sigma**	**5.83**	**0.01**	**5.1**
	Refined Lee	5.86	0.01	5.1

3.2 Results of Hyperparameters

The comparison of hyperparameters based on seasons indicates that the selection of the number of randomly selected predictors (mtry) has a significant impact on the accuracy of the Random Forest (RF) model. During the rainy season (**Fig. 3**), the highest accuracy is achieved when mtry is set to 3, with a noticeable decrease in accuracy as mtry increases to 8. A similar pattern is observed during the dry season (**Table 2**), where the highest accuracy is also achieved with an mtry of 3, but it declines sharply as mtry increases to 7. These results suggest that, for both seasons, using a smaller mtry value tends to produce a model with better performance. The appropriate selection of mtry is crucial in building a reliable RF model, as it determines how many predictors are considered at each split in the decision tree formation process. Therefore, selecting an optimal mtry can significantly enhance the accuracy and reliability of the prediction model, especially when accounting for seasonal variations in geothermal fields [15].



(a) (b)

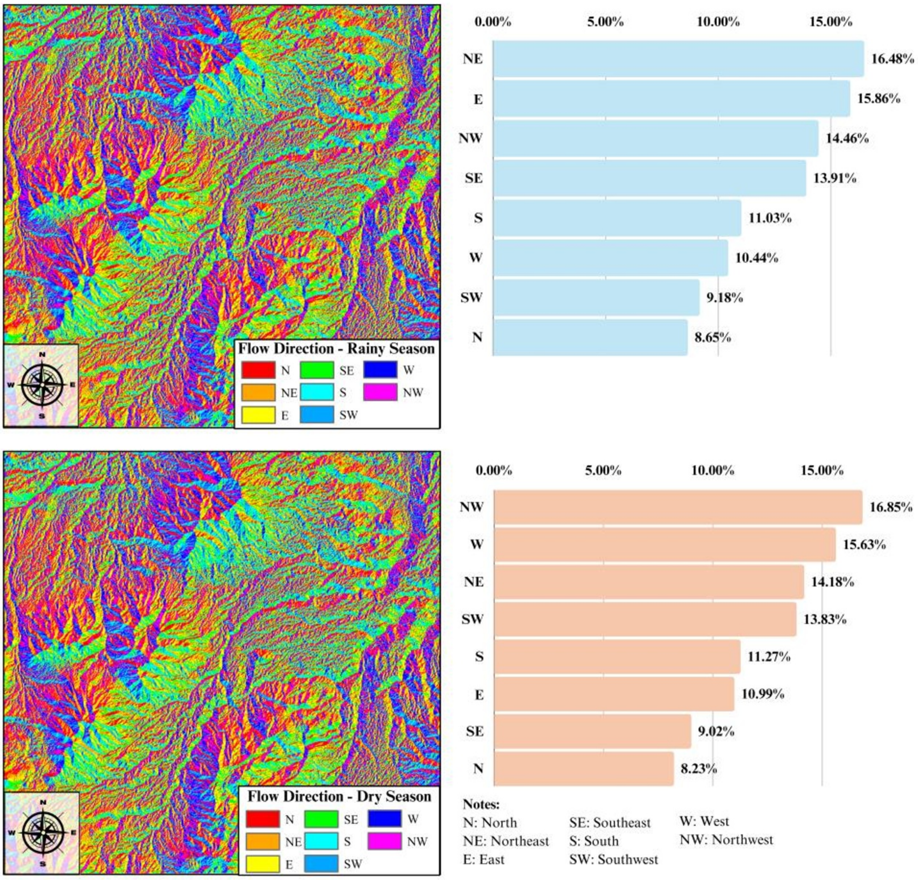
Fig. 3. Results of Cross Validation Hyperparameters (a) Rainy Season and (b) Dry Season

Table 2. Results of Best Hyperparameters

Hyperparameters	**Season**	
	Rainy	**Dry**
n.trees	500	500
mtry	2	3
the out-of-bag (OOB)	8.76	9.32

3.3 Results of Flow Direction Model using Random Forest (RF)

The analysis of the flow direction prediction model developed using the Random Forest algorithm reveals significant differences in the dominant flow direction between the rainy and dry seasons (**Fig. 4**). Based on the visualization results, during the rainy season, the flow direction is predominantly shifted towards the Northeast with a percentage of 16.48%. Conversely, in the dry season, the dominant flow direction shifts to the Northwest with a percentage of 16.85%. The RF model effectively captures these dynamics, demonstrating high reliability in predicting flow direction according to the prevailing seasonal conditions. These findings are crucial for practical applications, particularly in water resource management and infrastructure planning in geothermal fields, where understanding changes in flow direction is essential for sustainability and operational efficiency [18].



Notes:
N: North
NE: Northeast
E: East
SE: Southeast
S: South
SW: Southwest
W: West
NW: Northwest

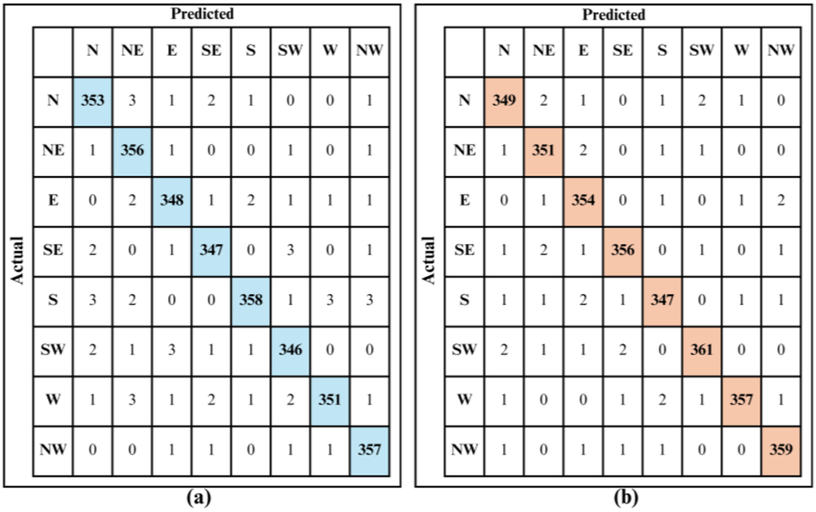
Fig. 4. Results of Flow Direction using Random Rorest (RF)

3.4 Results of Model Evaluation

The evaluation of the flow direction prediction model using a confusion matrix indicates that the Random Forest algorithm is capable of classifying flow directions with a high level of accuracy for both the rainy and dry seasons. In the confusion matrix (**Fig. 5**) for the rainy season **(a)**, the prominent diagonal suggests that the majority of the model's predictions align with the actual values, with only a few misclassifications across some directions. Similar results are observed during the dry season **(b)**, where most predictions fall along the diagonal, indicating accurate predictions. However, there is a slight shift in misclassifications, reflecting the changes in dominant flow directions between the two seasons. This evaluation confirms that the Random Forest model is highly reliable in predicting flow directions according to seasonal conditions, which is crucial for planning and managing water resources in geothermal fields [16].

The accuracy testing, which involved Overall Accuracy and Kappa Accuracy (**Fig. 6**), shows that the Random Forest (RF) model performs consistently well in both the rainy and dry seasons. According to the test results, the Overall Accuracy for both seasons reached 0.98, indicating that the model is capable of classifying flow directions with a very high level of precision. Additionally, the Kappa Accuracy, which measures the agreement between the model’s predictions and the actual data after correcting for the possibility of random agreement, also shows high values, 0.97 in the rainy season and 0.98 in the dry season [19].

The accuracy testing, which involved Sensitivity, Specificity, and User Accuracy (**Fig. 7**), demonstrates that the Random Forest (RF) model performs consistently and robustly in predicting flow direction in both the rainy and dry seasons. According to the test results, Sensitivity and Specificity values for nearly all flow directions reached 0.99, indicating that this model is highly reliable in detecting the correct flow directions (Sensitivity) as well as in identifying incorrect directions (Specificity). The role of Sensitivity in the RF model is crucial as it ensures the model effectively captures all true occurrences, which is particularly relevant in the context of precise water resource monitoring. Specificity, on the other hand, plays a role in ensuring that the model does not produce false positives, thus maintaining accuracy and efficiency in decision-making. The high User Accuracy values, with most above 0.98, indicate that the model's predictions align closely with the actual observed data, providing confidence that the model's results are reliable for field implementation [20].



Predicted

Actual

	N	NE	E	SE	S	SW	W	NW
N	353	3	1	2	1	0	0	1
NE	1	356	1	0	0	1	0	1
E	0	2	348	1	2	1	1	1
SE	2	0	1	347	0	3	0	1
S	3	2	0	0	358	1	3	3
SW	2	1	3	1	1	346	0	0
W	1	3	1	2	1	2	351	1
NW	0	0	1	1	0	1	1	357

(a)

Predicted

Actual

	N	NE	E	SE	S	SW	W	NW
N	349	2	1	0	1	2	1	0
NE	1	351	2	0	1	1	0	0
E	0	1	354	0	1	0	1	2
SE	1	2	1	356	0	1	0	1
S	1	1	2	1	347	0	1	1
SW	2	1	1	2	0	361	0	0
W	1	0	0	1	2	1	357	1
NW	1	0	1	1	1	0	0	359

(b)

Fig. 5. Results of Confusion Matrix (a) Rainy Season and (b) Dry Season

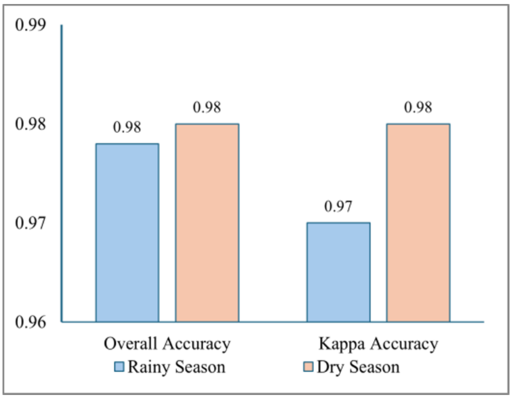
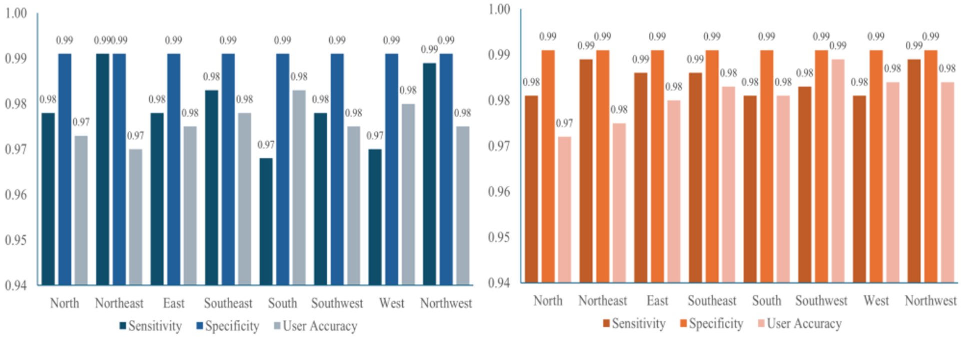


Fig. 6. Results of Overall Accuracy and Kappa Accuracy



(a) **(b)**

Fig. 7. Results of Sensitivity, Specificity, and User Accuracy (a) Rainy Season and (b) Dry Season

3.5 Results of Feature Importance

The analysis of feature importance reveals that the parameters of elevation, slope, and curvature each play distinct roles in constructing a reliable model for predicting flow direction. Qualitatively, elevation provides a foundational understanding of terrain height, helping to establish the general flow from higher to lower areas. However, its direct impact is quantitatively less significant, as reflected by its lower feature importance scores of 10.53% during the rainy season and 10.06% during the dry season. In contrast, slope emerges as the most critical factor both qualitatively and quantitatively. Slope directly influences how water moves across the landscape, with steep areas leading to faster flow and flat areas potentially leading to pooling. This importance is quantitatively supported by high feature importance scores of 60.76% in the rainy season and 63.53% in the dry season. Curvature also plays a significant role by shaping the terrain's surface, influencing how water converges in concave areas or diverges in convex areas. While its influence is quantitatively less than that of slope-28.71% in the rainy season and 26.41% in the dry season-curvature remains crucial for refining the model's predictions. Together, these qualitative insights and quantitative data ensure that the model accurately accounts for the height, shape, and gradient of the terrain, leading to robust predictions of flow direction under different seasonal conditions [17].

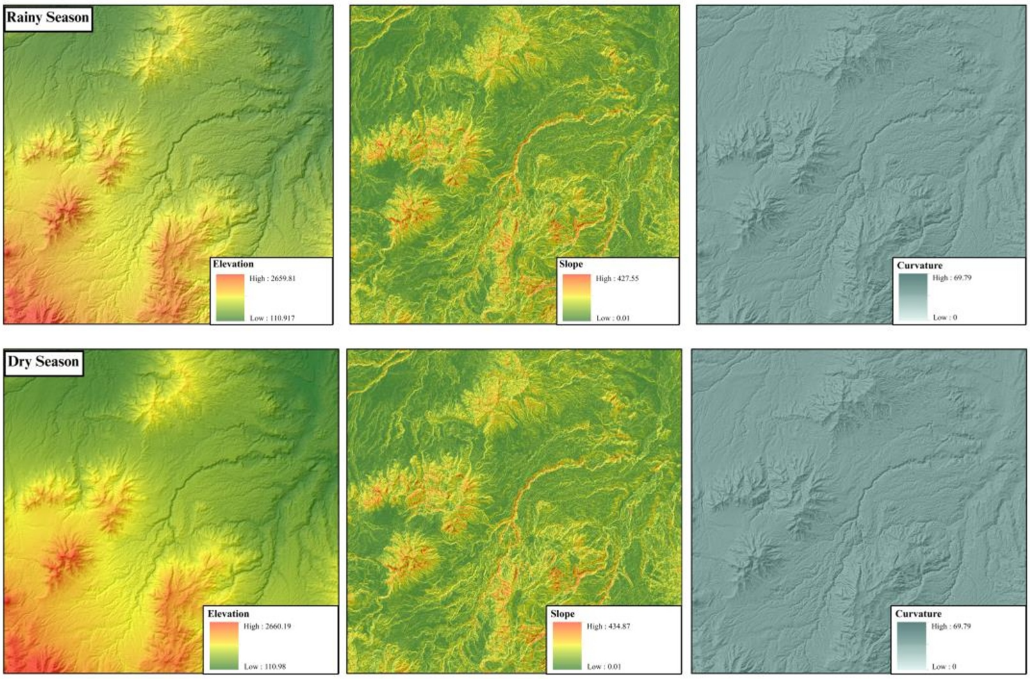


Fig. 8. Parameters Used to Build the Flow Direction Model

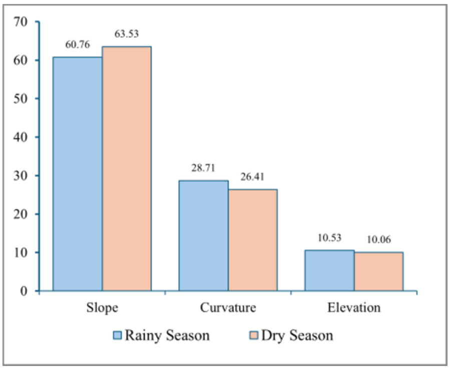


Fig. 9. Results of Feature Importance

3.6 Discussion

The pre-processing results tested using metric statistics show that the DEM processed with the Lee Sigma filter has lower RMSE, MAE, and MRE values compared to other filters, making it the chosen data input for building the Random Forest (RF) model to ensure higher accuracy and reliability [14, 21]. The best hyperparameters results indicate that using 500 trees (n.trees) with a lower mtry value (2) during the rainy season and a slightly higher value (3) during the dry season provides optimal performance, as reflected in the low out-of-bag (OOB) error rates of 8.76% in the rainy season and 9.32% in the dry season [15]. The RF model effectively captures the shifts in flow direction, predominantly towards the Northeast during the rainy season (16.48%) and shifting to the Northwest during the dry season (16.85%), demonstrating the model's reliability in predicting flow direction according to seasonal conditions [22]. The high Overall Accuracy and Kappa Accuracy further affirm the

RF model's robustness and reliability in predicting flow directions across various seasonal conditions [19]. Additionally, strong Sensitivity, Specificity, and User Accuracy confirm the model's precision in identifying flow directions with low error rates, making it suitable for practical applications in water resource management and geothermal infrastructure planning [20]. Slope, as the dominant parameter in both seasons, with feature importance values of 60.76% during the rainy season and 63.53% during the dry season, significantly influences flow direction as the gradient determines the speed and gravitational pull that affect water flow, causing the flow to follow the path with the steepest slope [17].

The changes in flow direction reflect the impact of seasonal variations on water flow patterns in the studied area, highlighting the need to consider additional parameters such as changes in rainfall intensity and evaporation patterns that contribute to shifts in flow direction in future research. Rainfall intensity and evaporation patterns are derived from satellite data. Rainfall intensity is obtained from the processing of CHIRPS satellite data, while evaporation patterns are derived from NDVI, the SEBAL model (Surface Energy Balance Algorithm for Land), SMAP (Soil Moisture Active Passive), and MODIS (Moderate Resolution Imaging Spectroradiometer) [23–26]. This research provides insights that can support the monitoring and sustainability of surface fluids in geothermal fields and ensure sustainable water management in geothermal areas.

4. Conclusions

The conclusions and recommendations derived from this study are as follows:

- **Model Development:** The optimal selection of hyperparameters, including the use of 500 trees (n.trees) and adjusting the mtry value according to seasonal variations (mtry = 2 during the rainy season and mtry = 3 during the dry season), has been shown to significantly enhance the reliability of water flow direction predictions.
- **Seasonal Variation Analysis:** The model successfully identified significant shifts in flow direction, with a predominance towards the Northeast (16.48%) during the rainy season and towards the Northwest (16.85%) during the dry season, demonstrating the model's sensitivity to seasonal changes.
- **Model Performance Evaluation:** The evaluation metrics indicate excellent model performance, with an Overall Accuracy of 0.98, Kappa Accuracy ranging from 0.97 to 0.98, Sensitivity and Specificity both at 0.99, and User Accuracy above 0.98, reflecting a very low error rate in predictions.
- **Feature Importance Identification:** Slope was identified as the most dominant parameter influencing flow direction, with feature importance values of 60.76% during the rainy season and 63.53% during the dry season, underscoring its critical role in the prediction model.
- **Recommendation:** Based on these findings, it is recommended that future research integrates additional parameters such as rainfall intensity and evaporation patterns—derived from satellite data like CHIRPS, NDVI, SEBAL, SMAP, and MODIS—to further refine flow direction models and enhance the monitoring and sustainability of surface fluids in geothermal fields, ensuring more effective and sustainable water management.

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