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A hybrid approach to enhance streamflow simulation in data-constrained Himalayan basins: Combining the Glacio-Hydrological Degree-Day Model and Recurrent Neural Networks

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Abstract. The Glacio-hydrological Degree-day Model (GDM) is a distributed model but prone to uncertainties due to its conceptual nature, parameter estimation, and limited data in the Himalayan basins. To enhance accuracy without sacrificing interpretability, we propose a hybrid model, GDM-RNNs, combining GDM with Recurrent Neural Networks (RNNs). Three RNN types (Simple RNN, GRU, LSTM) are integrated with the GDM. Rather than directly predicting streamflow, RNNs forecast GDM's residual errors. We assessed performance across different data availability scenarios, with promising results. In limited data conditions (one year), GDM-RNNs (GDM-SimpleRNN, GDM-LSTM, GDM-GRU) outperformed standalone GDM and machine learning models. For GDM-SimpleRNN, NSE, R^2, and PBIAS were 0.85, 0.82, and -6.21, for GDM-LSTM 0.86, 0.79, and -6.37, and for GDM-GRU 0.85, 0.8, and -5.64, compared to GDM's 0.80, 0.63, and -4.78, respectively. Machine learning models yielded similar results, with SimpleRNN at 0.81, 0.7, and -16.6, LSTM at 0.79, 0.65, and -21.42, and GRU at 0.82, 0.75, and -12.29, respectively. Our study highlights the potential of machine learning in enhancing streamflow predictions in data-scarce Himalayan basins while preserving physical stream flow mechanisms.

1 Introduction

2 Material and methods

2.1 Study area

The study area, Marsyangdi River basin in the Nepal Himalayas (Fig. 1), spans 4,059 km^2, ranging from 355 to 7,819 meters above sea level. About 13.3% of the area is glacier-covered, mainly between 4,000 to 6,500 meters. The basin experiences the Indian Summer Monsoon (June-September) and occasional westerly disturbances post-monsoon (October-January). Geographically, it features diverse terrain, primarily on the southern slopes of the Central Himalayas, influenced by the Annapurna Massif in the northwest.

2.2 Glacio-Hydrological Degree-day Model (GDM)

The Glacio-hydrological Degree-day Model (GDM, Version 1.0) is a gridded hydrological model that evaluates the impact of various hydrological elements on river discharge (Kayastha and Kayastha, 2019). Operating daily, it incorporates snow melt, glacier ice melt, rainfall, and baseflow runoff components. GDM utilizes a degree-day method for glacier ice and snow melt, simplifying complex processes while minimizing data needs. Covering a 3 × 3 km grid area, GDM assigns GlobeLand30 land categories to each grid and employs daily temperature and precipitation data from reference stations. It determines rain or snow in grids based on a threshold temperature. Daily ice and snow melt in each grid consider debris-free and debris-covered ice, alongside glacierized and glacier-free regions.

The model computes surface runoff for each grid from precipitation, snowmelt, and icemelt. The cumulative surface runoff and base flow from all grids contribute to the total discharge, directed to the outlet using a combined flow equation involving recession coefficients.

2.3 Recurrent Neural Networks RNNs

Recurrent Neural Networks (RNNs) are capable of capturing non-linear connections in sequential data. They process input sequences element by element, utilizing a hidden state to retain information about past inputs, allowing predictions based on historical context. RNNs are suitable for regression problems, predicting continuous outputs from input sequences. Training involves employing regression loss functions like mean squared error or mean absolute error (Heaton et al., 2018).

RNN components include an Input Layer, Recurrent Unit, Hidden State, Activation Function, Output Layer, Loss Function, and Optimization Algorithm. Hyperparameters in RNNs control network behaviour, impacting capacity, convergence speed, over fitting, sequence length, dropout, layers, activation function, optimization algorithm, learning rate decay, and early stopping (Heaton et al., 2018). Types of RNNs include Simple RNNs, LSTM, and GRU. Simple RNNs possess limited memory for short-term sequences (Bengio et al., 1994). LSTM introduces memory cells and gates controlling data flow, enabling long-term memory retention (Hochreiter and Schmidhuber, 1997). GRU combines input and forget gates into an update gate, requiring fewer parameters than LSTM, yet offering similar performance (Cho et al., 2014).

2.4 GDM-RNNs hybrid approach

The study introduces the GDM-RNNs hybrid approach, aiming to improve streamflow prediction by integrating GDM's physical constraints. This approach utilizes RNNs (Simple RNNs, GRU, LSTM) to forecast residual errors between observed and GDM-simulated inflows based on meteorological inputs. Given the complexity of quantifying these errors, the assumption is made that they exhibit identifiable patterns. The RNNs operate independently after GDM simulation to optimize error prediction without disturbing the physical constraints. Figure 2 outlines this hybrid process, involving the generation of simulated streamflow data via GDM, computation of residual errors, optimization, training of RNNs models using these errors and meteorological data, projection of future errors, and application of these predictions to enhance GDM simulations. This approach intends to improve traditional GDM simulations by accounting for predictive discrepancies originating from various uncertainties.

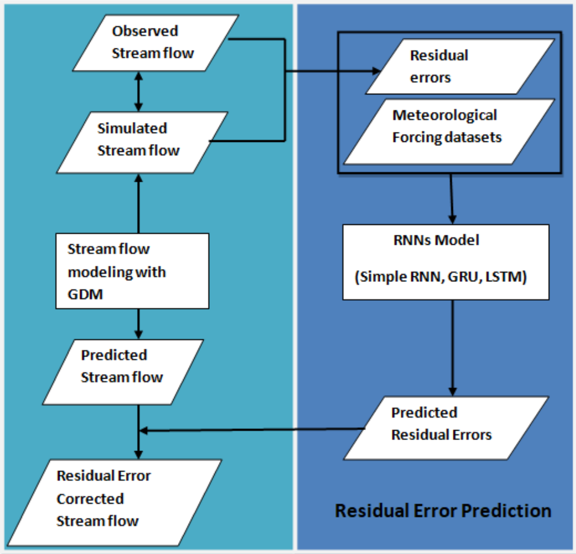

Figure 2. Schematic diagram of the GDM-RNN Hybrid process.

2.5 Input data

The daily air temperature, rainfall, and river flow data are obtained from the Department of Hydrology and Meteorology (DHM). Temperature and rainfall data from Khudi Bazar and Chame stations are used for the GDM, while Bimalnagar outlet station's discharge data validated the study. RNNs were trained using the climatic stations' temperature, rainfall data, and discharge data from Bimalnagar. The GDM relied on elevation information from ASTER Global Digital Elevation Model Version 2 and land cover data from GlobeLand30 dataset. Six land classes were identified and modified for uniform rainfall-runoff factors. Glacier identification was based on ICIMOD Glaciers Inventory of 2010's shape files.

2.6 Experimental designs

The study employed seven models: GDM, GDM-LSTM, LSTM, GDM-GRU, GRU, GDM-SimpleRNNs, and Simple RNNs. Each GDM model variant combined with Recurrent Neural Networks (RNNs) aimed to predict residual errors. RNNs were used for river discharge simulation and performance comparisons with GDM models and GDM-RNNs hybrids. Two data sets were used for calibration/training: a one-year dataset and a three-year dataset. GDM and RNNs were calibrated/trained using 2005 data and validated with 2008-2010 data. The GDM coupled with RNNs utilized 2005 data for calibration, predicting residual errors (2008-2010). Similarly, the experiment was repeated using data from 2005 to 2007 for calibration and training purposes. The models were then validated using 2008-2010 data. Discharge simulations by GDM (2008-2010) were corrected using predicted residual errors from RNNs, and the results were validated using observed discharge data (2008-2010).

The streamflow forecasts of various models were assessed utilizing three widely utilized measures for hydrological model evaluation: PBIAS, NSE, and R^2 (Moriasi et al., 2015).

3 Results and discussions

In the Glacio-Hydrological Degree-Day Model (GDM) calibration, adjustments are made in positive degree-day factors, snow and rain coefficients, and recession coefficient. Parameters are calibrated for one-year and three-year periods using observed streamflow data from the Marsyangdi basin. The model closely replicated observed data for both periods, with slightly better performance in the three-year calibration (Fig. 3). Although the model generally matched observed outflow, it tended to overestimate during low-flow periods due to challenges in accurately depicting precipitation distribution, especially in higher altitudes (Immerzeel et al., 2015; Bocchiola et al., 2011; Barry, 2012). Evaluation metrics (NSE, R^2, PBIAS) indicated a satisfactory fit but showed some bias, with the model overestimating in calibration and underestimating in validation (Table 1).

Table 1. NSE, R^2, and PBIAS metrics during GDM model calibration and validation periods.

Evaluation metric	One-year period Calibration		Three-Year period Calibration	
	Calibration	Validation	Calibration	Validation
NSE	0.80	0.80	0.82	0.81
R^2	0.68	0.63	0.74	0.7
PBIAS	7.2	-4.78	10.38	-1.27

In this study, RNNs models, Simple RNNs, LSTM, and GRU are trained using one-year and three-year datasets, employing diverse training parameters including network architecture, activation functions, optimization algorithms, loss functions, and training schedules. Models pre-processed input data through normalization and utilized Adam optimization with a mean absolute error loss function. The number of hidden layers and neurons varied among models; all had 4 input units and 1 output unit, with GRU and LSTM using 128 neurons in a hidden layer, while Simple RNN employed 32. The learning rate is constant at 0.01 but had varied schedules. In this study, the parameters of the RNNs models are selected using the grid search technique.

Analysis show superior performance of RNNs with three-year data over one-year data. LSTM and GRU exhibited better simulation of river discharge patterns than Simple RNNs, especially with extensive training data, indicating greater capacity to learn past streamflow behaviours. However, smaller datasets yielded only satisfactory results, suggesting the suitability of process-based models like GDM. Evaluation metrics demonstrated GRU's superior performance across NSE, R^2, and PBIAS for both one-year and three-year validation periods, while LSTM excelled slightly in R squared for the three-year period. SimpleRNN consistently performed the poorest (Table 2).

Positive PBIAS during training suggests model overestimation, potentially due to over fitting, while negative PBIAS during validation implies underestimation, indicating a lack of capturing relevant data aspects. Despite better performance on training data, the emphasis lies on a model's ability to generalize to new data, emphasizing the significance of validation results. Overall, GRU showcased superior performance in key metrics across different training periods, with LSTM showing competitive results in specific aspects.

Table 2. NSE, R^2, PBIAS for different RNNS used in RNNs only approach.

Evaluation metric		One year of Data usage for training		Three-year of data usage for training	
		Training period	Validation period	Training period	Validation period
Simple RNN	NSE	0.83	0.81	0.86	0.85
	R^2	0.86	0.7	0.87	0.78
	PBIAS	10.72	-16.6	12	-8.08
LSTM	NSE	0.88	0.79	0.85	0.85
	R^2	0.88	0.65	0.88	0.82
	PBIAS	2.82	-21.42	16.99	-7.84
GRU	NSE	0.87	0.82	0.93	0.87
	R^2	0.88	0.75	0.93	0.8
	PBIAS	9.89	-12.29	9.76	-11.85

Hybrid modelling combined GDM and three RNNs variants (SimpleRNNs, LSTM, GRU) to predict GDM residual errors. The hybrid approach split into simulating streamflow using GDM parameters and training RNNs to predict errors (Table 3). All RNNs featured a single hidden layer with 64 to 254 neurons, tanh activation in the hidden layer, and linear activation in the output layer, using Glorot uniform kernel initialization. Input data normalization is applied. Key hyper parameters varied, including dropout rates (0.2 to 0.6), Adam optimization, batch size equivalent to the entire training set, a sequence length of 365 days, and a fixed learning rate of 0.01. Learning rate schedules varied or were absent, employing strategies like exponential or inverse time-based decay. Grid search technique is used to select the best performing parameters.

Table 3. NSE, R^2, PBIAS for different GDM-RNNs models.

Evaluation metric		One year of Data usage for training		Three-year of data usage for training	
		Training period	Validation period	Training period	Validation period
GDM-Simple RNN	NSE	0.86	0.85	0.93	0.85
	R^2	0.88	0.82	0.93	0.78
	PBIAS	6.49	-6.21	6.16	-7.42
GDM-LSTM	NSE	0.88	0.86	0.9	0.88
	R^2	0.86	0.79	0.91	0.85
	PBIAS	6.96	-6.37	10.87	-2.22
GDM-GRU	NSE	0.87	0.85	0.85	0.85
	R^2	0.87	0.8	0.86	0.8
	PBIAS	10.4	-5.64	20.01	-0.04

The integration of GDM and RNNs models (GDM-RNNs) outperforms using RNNs solely for streamflow prediction. GDM-RNNs provides more stable predictions, using residual discrepancies as objectives while RNNs directly predicts streamflow. This disparity in objectives impacts the model forecasts, potentially causing greater systematic discrepancies in RNNs due to streamflow variability.

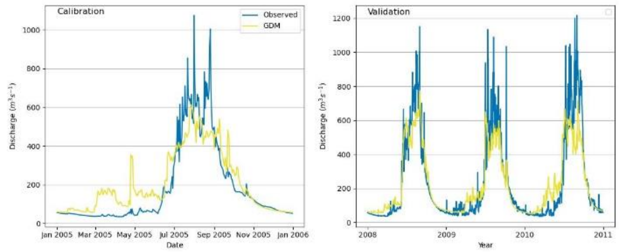

Figure 3. Observed vs. simulated discharges: GDM model in Marsyangdi basin (one-year calibration, three-year validation).

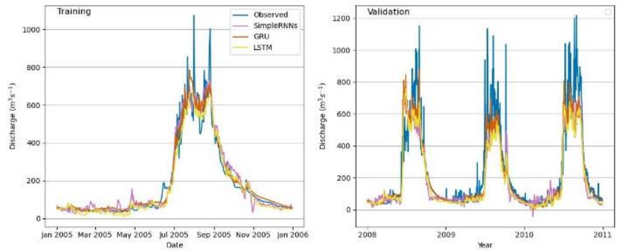

Figure 4. Observed vs. simulated discharges: different RNNs model in Marsyangdi basin (one-year calibration, three-year validation).

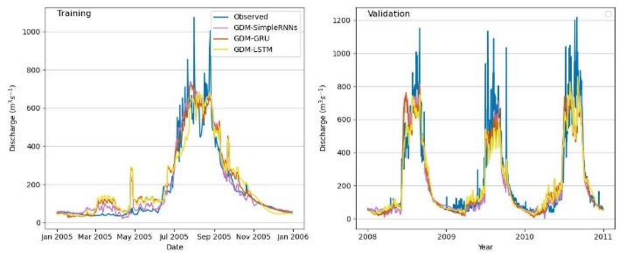

Figure 5. Observed vs. simulated discharges: different GDM-RNNs model in Marsyangdi basin (one-year calibration, three-year validation).

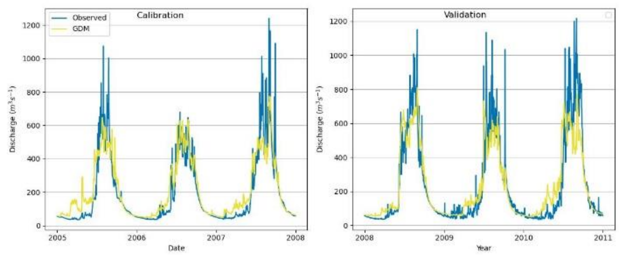

Figure 6. Observed vs. simulated discharges: GDM model in Marsyangdi basin (three-year calibration/validation).

GDM-RNNs (Figs. 4 to 8) simulation aligns better with physical discharge patterns, addressing issues like negative discharge seen in SimpleRNN (Fig. 4). It excels particularly with one-year observed discharge data, significantly improving simulations compared to RNNs with the same training data. GDM-RNNs enhances GDM's streamflow prediction by reducing uncertainties and effectively resolves high discharge issues in the pre-monsoon season. During the monsoon, GDM-RNNs (Fig. 8) closely matches observed discharge compared to GDM (Fig. 6) simulations.

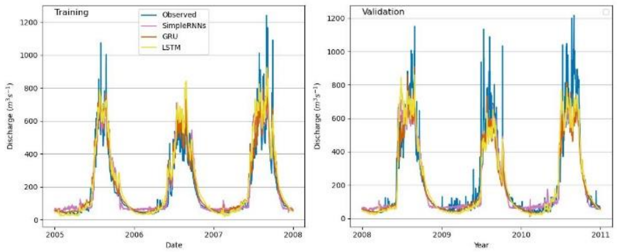

Figure 7. Observed vs. simulated discharges: different RNNs model in Marsyangdi basin (three-year calibration/validation).

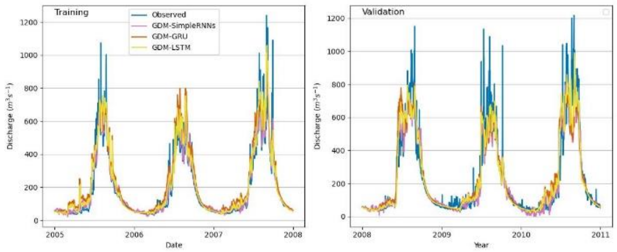

Figure 8. Observed vs. simulated discharges: different GDM-RNNs model in Marsyangdi basin (three-year calibration)

4 Conclusions

Our study highlights the effectiveness of utilizing LSTM, GRU, and SimpleRNN machine learning techniques to improve streamflow forecasting within the GDM model in the Marsyangdi River basin, Nepal. The amalgamation of GDM-RNNs significantly enhances predictive accuracy, notably in terms of NSE and coefficient of determination, while displaying comparable performance in PBIAS to GDM alone. The limitations of RNN, particularly in handling high variability datasets, contribute to disparities in PBIAS measures compared to GDM. Furthermore, while GDM shows consistent performance across varying calibration data amounts, RNNs benefit significantly from increased training data. Notably, the GDM-RNNs model displays superior adaptability with limited calibration and training data, showing notable improvements with increased data. GRU and LSTM outperform SimpleRNN due to their capacity to handle long-term dependencies, both in standalone RNN usage and in hybrid combinations.

Evaluation in a single basin with limited data showcases the robustness of GDM-RNNs and the potential of RNN implementation. Expanding validation with three years of data or across different basins would enhance its reliability. While comparing two datasets demonstrated promising results, examining additional data could further strengthen our approach.

5 Code availability

GDM V.2 and the code for Recuurent Neural Networks are available upon request.

6 Data availability

Hydro-meteorological data are available at the DHM, Government of Nepal.

7 Author contributions

DJ developed the main idea, run the models and wrote the manuscript. RBK, KLS and RK helped in data collection, GDM run and analysis.

8 Competing interests

The contact author has declared that neither they nor their co-authors have any competing interests.

9 Disclaimer

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10 Special issue statement

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