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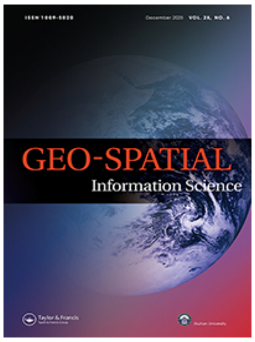

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Exploring machine learning approaches for precipitation downscaling

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ABSTRACT

Accurate precipitation has great significance in hydrological, climatological, and meteorological studies. Numerous efforts have been devoted to developing global satellite-derived precipitation products. However, their coarse spatial resolution typically prevented their applicability in regional flood predictions and agricultural management. To achieve reliable and finer-scale precipitation data, many techniques and frameworks have been employed to improve the resolution of the satellite-derived precipitation data. This study critically reviewed existing spatial downscaling approaches, specifically focusing on machine learning (ML)-based algorithms. Insights into the accuracy of these downscaling techniques were provided based on findings from published validation studies. Additionally, the environmental variables utilized in these approaches and the post-processing of residual correction and calibration after downscaling were categorized and analyzed, in which meticulous comparisons of their performance in various study areas were conducted. This study emphasized the importance of generating high-resolution precipitation, systematically evaluated the strengths and limitations of ML-based methods, aiming to identify existing research gaps and potential inconsistencies with previous studies, and ultimately highlighted future research trends and challenges.

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Downscaling; precipitation; machine learning; residual correction; calibration

1. Introduction

Precipitation, being a vital element in the global water cycle and energy balance, is a primary force in the hydrological and meteorological modeling (He et al. 2016; Kumar et al. 2021; Liu et al. 2018, 2022; Zhang et al. 2019). Accessing accurate precipitation data has great significance in water resource management and water-related emergency prevention (Liu 2021; Zeng et al. 2022). Under climate change, which may cause more frequent and severe weather events, including extreme precipitation, tropical cyclones, and storms, reliable precipitation data are even more essential for assessing their impacts and developing mitigation and adaptation strategies (Dikshit and Pradhan 2021; Ma et al. 2019; Shi 2020; Volosciuk et al. 2017). However, precipitation is also one of the most complicated climatic elements to simulate and predict, primarily owing to its pronounced spatiotemporal heterogeneity (Chen, Hu, and Li 2021).

In-situ measurements from the rain gauges and radar systems are considered the most accurate data. However, they are just point-based data with limited and unevenly distributed meteorological stations. They cannot reveal the geographical distribution of precipitation, particularly in some observation-sparse regions and ungauged areas (Sharifi, Saghafian, and Steinacker 2019; Shashikanth et al. 2014; Xu et al. 2015; Zhang et al. 2018). Alternatively, various satellite-derived datasets are available with more extensive spatial coverage (Taheri et al. 2020; Zhang et al. 2018). These include the Integrated Multi-satellitE Retrievals for GPM (IMERG) studied by Huffman et al. (2015), the Tropical Rainfall Measuring Mission (TRMM) studied by Huffman et al. (2010, 2007) and Vallejo-Bernal et al. (2021), and the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) developed by Ashouri et al. (2015) and Nguyen et al. (2018). Satellite-derived precipitation data generally provide global coverage, offering insights into precipitation patterns in remote or inaccessible regions where in-situ rain gauge networks may be constrained. Nevertheless, these datasets exhibit diverse spatial resolutions that might be suitable for global climate research and large-scale weather systems, but are coarse for local studies, such as urban flood monitoring and local hydrological assessments (Chen, Hu, and Li 2021; Duan and Bastiaanssen 2013a). To tackle this problem, spatial downscaling can be performed to improve their resolutions.

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Distinguished downscaling methods contain dynamical downscaling and statistical downscaling techniques, each with advantages and drawbacks (He et al. 2016). Dynamical downscaling involves using high-resolution numerical weather models to generate fine-scale precipitation data. It can be computationally intensive, requiring substantial computing resources. For example, Bárdossy and Pegram (2011) adopted the regional climate models (RCMs) for precipitation estimation instead of taking them directly from the Global Climate Models (GCM) simulation. They found that RCMs outputs with higher resolution were good at capturing rainfall patterns and distributions. Liu, Bray, and Han (2012) applied the Weather Research and Forecasting (WRF) model to downscale the rainfall data and investigate its performance under different downscaling ratios and different spatiotemporal distributions of precipitation intensity. Bao, Feng, and Wang (2015) also used WRF models for dynamical downscaling and prediction of future precipitation, and their results demonstrate that WRF models had great promise in the spatial downscaling of rainfall due to their better capturing of finer-scale meteorological processes. However, dynamical downscaling has a high computational intensity and resource demand (Shi 2020). It relies on many complex physical models and requires expertise in numerical weather prediction and modeling. In contrast, statistical downscaling has lower computational demand, and its performance has been widely explored in previous studies.

Statistical downscaling adopted the regression relationships between precipitation data and environmental factors and is not based on any physical assumptions (Kofidou, Stathopoulos, and Gemitzi 2023). Initially, some traditional regression methods were engaged to gain the correlation between precipitation and various independent predictors. For example, the exponential regression model could describe the annual relationship between precipitation and the Normalized Difference Vegetation Index (NDVI), which were used to estimate the finer-scale TRMM precipitation from the coarser-scale rainfall and NDVI patterns (Immerzeel, Rutten, and Droogers 2009). The association between NDVI and rainfall was captured by Foody (2003) over North Africa and was then used in the downscaling of precipitation. In addition to vegetation, there are regression relationships between topography and precipitation. Jia et al. (2011) presented a Multiple Linear Regression (MLR) model that explored the relationships between precipitation, topography, and NDVI across various scales (0.25°, 0.50°, 0.75°, and 1.00°). Chen, Yu, and Tang (2010) utilized the support vector machine (SVM) to spatially downscale precipitation from general circulation models (GCMs). He et al. (2016) introduced an RF-based approach for precipitation downscaling, employing two independent RFs, which improved extreme precipitation estimates. Jing et al. (2016a) and Liu et al. (2018) applied the classification and regression trees (CART) algorithm to downscale TRMM precipitation. Chen, Hu, and Li (2021) incorporated spatial autocorrelation into the RF algorithm, proposing the SRF for precipitation downscaling. XGBoost has been used to downscale terrestrial water storage from the Gravity Recovery and Climate Experiment (GRACE) satellite, demonstrating its significant potential in precipitation downscaling (Sahour et al. 2020; Zhang, Sun, and Chen 2021). Building on this integrated approach, two-step downscaling-calibration frameworks have been implemented, with their effectiveness demonstrated in multiple studies. For instance, Yan et al. (2021) proposed a downscaling-merging framework using RF and cokriging methods to merge downscaled satellite precipitation with gauge observations, resulting in highly accurate daily precipitation data. Ulloa et al. (2017) developed a two-step downscaling approach using monthly TRMM data in Ecuador's continental region, producing high-quality, fine-resolution monthly precipitation maps.

In the past decade, ML-based downscaling models have garnered significant attention. This study aims to provide insights and guide research gaps in ML-based precipitation downscaling. Specifically, the main contributions are summarized as follows:

(1) To provide a systematic review of the strengths and limitations of ML downscaling techniques and analyze their superiority.
(2) To analyze specific issues in downscaling, including the use of environmental factors, residual correction, and calibration procedures.
(3) To summarize the transferability of ML-based downscaling models and the application of transfer learning.
(4) To offer insights into future challenges and perspectives, including the generalization capacity and uncertainty quantification of the models.

The remainder of the paper is organized as follows: Section 2 introduces the ML-based downscaling framework and the classical ML- and DL-based downscaling methods. Section 3 presents a comparative study on the performance of ML downscaling models and discusses enhancements to conventional models. Section 4 addresses specific issues in precipitation downscaling, such as environmental factors and post-procedures. Section 5 summarizes the transferability of ML downscaling models and the application of transfer learning.

2. Background

2.1. ML-based downscaling framework

In the application of ML for precipitation downscaling, the process can be broadly summarized into three main stages: data preparation, the downscaling process itself, and post-processing (as shown in Figure 1) (Bechler, Vrac, and Bel 2015; Chen, Yu, and Tang 2010; Mahoney et al. 2013; Pan et al. 2019; Sinha et al. 2018; Zeng et al. 2021). While not universally applied in all studies, these three stages provided a structured way to conceptualize the typical workflow involved in an ML-based downscaling framework. First, the selection and preprocessing of environmental variables utilized as predictors in constructing downscaling models are crucial. These variables are often resampled to ensure consistency in resolution and alignment with the remote-sensing precipitation data. Second, establishing an ML-based model involves connecting the precipitation data and predictors at a coarser scale. The finer variables are then employed to drive and generate precipitation at a higher resolution (Abdollahipour, Ahmadi, and Aminnejad 2022; Kofidou, Stathopoulos, and Gemitzi 2023). Third, after the downscaled precipitation was obtained, it may include some inherent errors and uncertainty from the original satellite and need further improvement with the post-processing, such as the residual correction and calibration (Chen, Hu, and Li 2021; He et al. 2016).

In the first stage, data preparation included selecting environmental variables to construct the downscaling and pre-processing of these data. Many environmental factors showed strong correlations with precipitation, making them potential predictors to be included in downscaling models (Gebregiorgis and Hossain 2014; Ma et al. 2017; Zeng et al. 2021). For example, the topographic variables, including elevation, slope, and aspects, would affect the precipitation patterns and distribution (Chen, Hu, and Li 2021). The surface properties, such as land use, land cover, and land surface temperature (LST), can impact surface evapotranspiration and further the local rainfall patterns (Chai et al. 2021; Krishnan, Pradhan, and Indu 2022). Combining all these variables in a downscaling model might better represent the meteorological processes associated with precipitation. However, most studies typically selected only two or three factors to construct their downscaling models, as incorporating more factors would increase the complexity and uncertainty of the models, as well as lead to overfitting (Xu et al. 2015). The selection of environmental predictors may vary

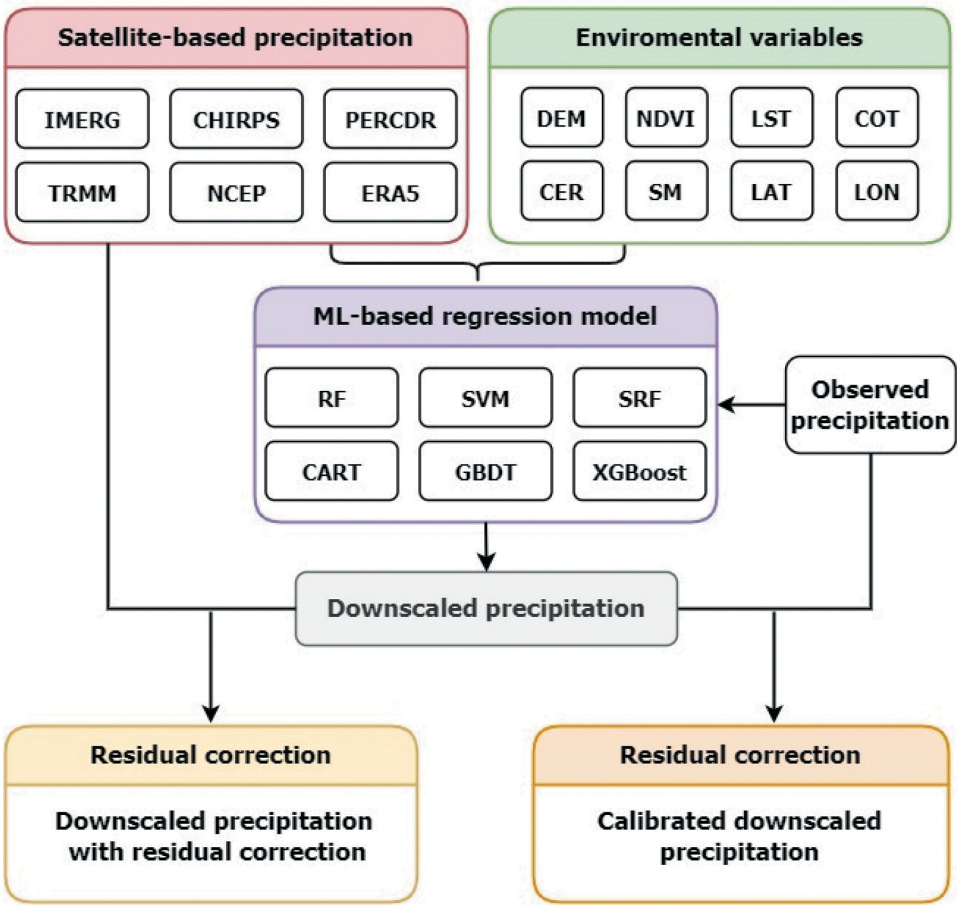

Figure 1. The flowchart of the ML-based downscaling framework: (a) data preparing, (b) downscaling, and (c) post-processing.

depending on the specific goals of the precipitation estimation and the regional characteristics, but the NDVI and DEM are the earliest and most commonly used factors in precipitation downscaling studies (Abdollahipour, Ahmadi, and Aminnejad 2022; Kofidou, Stathopoulos, and Gemitzi 2023).

In the second procedure, downscaling involves establishing a regression between satellite precipitation data and environmental predictors at coarse resolution. The built model was validated using the gauged observation. The finer environmental variables were then adopted to drive and generate higher resolution precipitation data (Bárdossy and Pegram 2011; Chen, He, and Li 2024). During the construction of the downscaling model, different from other traditional statistical downscaling methods, when employing ML algorithms, a range of strategies need to be applied to improve its robustness and avoid overfitting. For example, the K-fold cross-validation and regularization were utilized to increase the diversity of training data (Ebtehaj, Foufoula-Georgiou, and Lerman 2012; Wiens et al. 2008). ML-based models, particularly deep learning (DL) models, are more capable of learning intricate patterns from data. However, the complexity makes them more susceptible to overfitting (Jabbar and Khan 2015). Focusing on preventing overfitting is a crucial distinction of ML-based downscaling models from other approaches, and these strategies were essential to ensure that ML models produce accurate, reliable, and generalizable results.

The final stage is post-processing, which aims to further improve the accuracy of the downscaled results. In general, two important post-processing steps are often applied: the residual correction (Themeßl, Gobiet, and Leuprecht 2011) and calibration (Cheema and Bastiaanssen 2012; Duan and Bastiaanssen 2013b). Residual correction was employed to mitigate the systematic errors or biases in the downscaled precipitation data. The residuals represented the differences between the downscaled high-resolution precipitation data and the original coarse satellite precipitation. They were computed and interpolated first; then, the downscaled precipitation values were adjusted by adding or subtracting the interpolated residuals. Residual correction ensured that the downscaled data were more consistent with the original satellite-based rainfall data, improving the overall accuracy of the downscaling results. Meanwhile, calibration is the process of modifying the downscaled results using data merging or fusion, and it integrates the ground-based measurements with the downscaled precipitation. These two techniques were used to correct the biases in the downscaling results and enhance their consistency with the original satellite data and observations (Abdollahipour, Ahmadi, and Aminnejad 2022).

2.2. Classic ML algorithms and DL for downscaling

Many ML-based approaches have been employed to improve the spatial resolution of precipitation derived from GCMs and satellite precipitation data. Techniques like RF, SVM, advanced algorithms such as SRF and XGBoost, and DL methods (CNN and LSTM) have demonstrated promising performance in capturing complex nonlinear relationships between climate variables and precipitation (Ali et al. 2023; Elnashar et al. 2020; Kofidou, Stathopoulos, and Gemitzi 2023; Najafi, Moradkhani, and Wherry 2011; Qian et al. 2021; Zhang et al. 2019). Among them, SVM and RF are the two most widely used ML algorithms (Abdollahipour, Ahmadi, and Aminnejad 2022; Bellier, Scheuerer, and Hamill 2020; Kofidou, Stathopoulos, and Gemitzi 2023). They showed good proficiency in capturing complex nonlinear relationships between precipitation and climate variables, and their effectiveness and applicability have been extensively validated and recognized in existing downscaling research.

SVM was notably used by Tripathi, Srinivas, and Nanjundiah (2006) to downscale monthly GCM precipitation data during the wet and dry seasons, which highlighted its adaptability to seasonal variations in precipitation patterns. SVM was also applied with the Probabilistic Global Search Lausanne algorithm to refine the spatial resolution of GCM rainfall outputs, demonstrating SVM's capability to enhance model precision through optimization techniques (Ghosh 2010). Many studies have explored how SVM models perform precipitation downscaling compared to other methods. For example, SVM was applied to downscale daily precipitation and showed better performance than the MLR and ER models (Anandhi et al. 2008). Yazdian, Salmani-Dehaghi, and Alijanian (2023) developed a promoted SVM model to improve the resolution of terrestrial water storage data of GRACE from 0.5° to 0.25°, and its superior performance over conventional regression models made it a more straightforward and more accurate option for spatial downscaling in hydrological applications. Moreover, the SVM, Relevance Vector Machine (RVM), Genetic Programming, and Artificial Neural Networks (ANN) model to downscale the precipitation data across the Australian State of Victoria and models based on SVM and RVM demonstrated superior performance across all regions.

SVM has demonstrated remarkable success in capturing complex relationships and improving the spatial resolution of precipitation. RF also offers advantages in handling large datasets and addressing complex spatial and temporal patterns. Below, the applications and advancements of RF in precipitation downscaling are explored in detail. RF is demonstrated to effectively downscale precipitation data from global climate models and achieve higher accuracy than traditional statistical downscaling methods (Gudmundsson et al. 2012). The performance of RF, MLR, and ER was compared in the downscaling of TRMM, and superior results from RF models were reported (Shi et al. 2015). He et al. (2016) extended the application of RF by introducing a double RF model that effectively captured the spatial and temporal patterns of precipitation, proving particularly useful for modeling extreme weather events. The integration of RF with cokriging methods has been instrumental in enhancing the resolution of Global Precipitation Measurement (GPM) data to 0.01°, preserving the accuracy of satellite observations while refining the spatial detail of precipitation distribution (Yan et al. 2021). In complex terrains with variable precipitation patterns, approaches combining RF with Gradient Boosting Decision Trees (GBDT) have shown superior performance, outperforming SVM in effectively resolving precipitation variability (Shen and Yong 2021).

Another advanced algorithm like XGBoost has been increasingly utilized for the downscaling of various hydrometeorological variables, such as wind speed (Li 2019), soil moisture (Karthikeyan and Mishra 2021), LST (Luo et al. 2021; Tu et al. 2022), air temperature (Sebbar et al. 2023), and daily reference evapotranspiration (Fan et al. 2021). For example, its application in wind speed estimation has significantly enhanced atmospheric monitoring and wind power site analysis by combining autoencoder-based deep residual networks, XGBoost, and RF. This two-stage method demonstrated substantial improvements in predictive accuracy compared to single-model approaches (Li 2019). In the estimation of multi-layer soil moisture profiles across ungauged locations in the United States, XGBoost effectively utilized climate and landscape data as predictors to achieve high-resolution soil moisture estimates at various depths (Karthikeyan and Mishra 2021). Additionally, in drought assessment for the Indus Basin Irrigation System, XGBoost outperformed other machine learning models in analyzing the temporal and spatial distribution of drought, as well as in identifying the GRACE groundwater drought index, demonstrating its capability to handle large datasets with complex relationships (Ali et al. 2022). In precipitation-related applications, XGBoost has also shown considerable promise. A bias correction method for short-term precipitation forecasts based on XGBoost achieved superior performance compared to traditional models like the equidistant cumulative distribution function matching model. By integrating multiple meteorological factors, the XGBoost model significantly improved the accuracy of precipitation forecasts, highlighting its potential in environmental modeling and climate studies (Dong et al. 2023).

Moreover, DL algorithms also showed great potential in generating high-resolution precipitation data. For instance, CNN-based models have shown superior performance in capturing the dominant spatial dynamics of precipitation compared to traditional methods like MLR, RF, and fully connected neural networks. By analyzing the connection between precipitation and environmental factors, CNN models effectively developed accurate downscaling frameworks (Pan et al. 2019). Combining LSTM and feedforward neural network techniques has further enhanced precipitation downscaling and prediction. This hybrid approach leverages LSTM's ability to handle sequential or time-series data and the feedforward neural network's strength in capturing spatial information. By integrating both, the model can effectively capture and reproduce the temporal and spatial dynamics of precipitation, leading to accurate reproduction of rainfall patterns (Tran Anh et al. 2019). Innovative DL methods, such as the super-resolution deep residual network (SRDRN), have been particularly successful in downscaling daily precipitation and temperature data. Features like residual blocks, batch normalization, and data augmentation have enabled SRDRN to extract spatial features effectively while preventing overfitting (Wang et al. 2021). Additionally, attention mechanism-based convolutional networks (AMCNs) with end-to-end architectures, residual modules, and specialized loss functions have delivered high-quality and reliable precipitation estimates (Jing et al. 2022). DL models excel in adapting to the complexities of spatial and temporal precipitation dynamics. Their ability to simultaneously capture these patterns makes them a promising approach for high-resolution precipitation estimation and modeling.

3. ML-based downscaling approaches

3.1. Comparative studies on the performance of ML downscaling models

ML techniques can enhance the spatial and temporal resolution of precipitation data derived from coarse GCMs or satellite observations. The increasing availability of high-resolution environmental data and the advancement of ML algorithms have significantly advanced this field. Researchers have employed various ML algorithms, including SVM, RF, ANN, and others, to improve precipitation data resolution. Despite the variety of ML algorithms used in precipitation downscaling, a crucial question remains: "Given the plethora of ML models, which algorithm performs the best?" To address this question, many comparative studies have been conducted, aiming to identify the most effective algorithm under different conditions. We reviewed and selected highly cited references to provide insights into the best-performing models in different studies (as shown in Table 1).

As shown in the table, Relevance Vector Machines (RVMs) stand out for their ability to select predictors tailored to each station and month, making the models adaptable to different climate regimes. This specificity and adaptability highlight the strength of RVM in handling diverse climatic conditions (Sachindra et al. 2018). Interestingly, simpler approaches like spline interpolation have occasionally outperformed more complex ML methods, particularly when using cloud optical and microphysical properties as predictors (Sharifi, Saghafian, and Steinacker 2019). This unexpected outcome suggests that simpler interpolation methods can sometimes be more effective than complex ML models, especially when specific predictor variables are available. Variable selection and adaptability are further exemplified by Multivariate Adaptive Regression Splines (MARS), which effectively avoid issues such as "boxy artifacts" by adaptively selecting relevant variables for each month (Tan et al. 2022). Similarly, regression kriging has demonstrated resilience in regions with sparse station distributions, emphasizing the critical role of spatial data quality and availability in ensuring model success (Ulloa et al. 2017).

Further studies found that Random Forests (RF) performed best in handling higher precipitation months with lower downscaling errors compared to other models like CART, KNN, and SVM (W. Jing et al. 2016b). Additionally, the Bias Correction and Spatial Disaggregation (BCSD) method has shown strengths in estimating statistical distributions and climate extremes, though its performance varied across different methods (Vandal, Kodra, and Ganguly 2019). This suggests that the effectiveness of an ML model can vary significantly depending on the specific application and environmental conditions.

Regional specificity also plays a pivotal role in model performance. For example, in India's Punjab region, Conditional Random Fields (CRFs) and k-Nearest Neighbors (KNNs) have been more successful than SVM in projecting precipitation probability density functions during the monsoon season (Raje and Mujumdar 2011). Similarly, Convolutional Neural Networks (CNNs) have excelled at reproducing geographic distributions of seasonal mean climates, though they exhibit trade-offs with temporal accuracy when compared to reanalysis data (Sun and Lan 2021). In regions with sparse monitoring infrastructure, models like SVM and Gradient Boosting Regression (GBR) have shown promise, particularly in extracting meaningful patterns from limited data (Ghorbanpour et al. 2021; Wu et al. 2022). For more computationally intensive applications, wavelet-based neural networks such as WT-NARX-NN have demonstrated superior accuracy in capturing regional precipitation patterns and extreme events, albeit with higher resource demands (Kumar et al. 2021).

Despite these findings, it is challenging to conclusively determine the best ML model for precipitation downscaling. The performance of ML algorithms is highly context-dependent, influenced by factors such as data types, regional climatic conditions, model calibration methods, and the inclusion of specific predictors. Therefore, while certain models may outperform others in specific contexts, a one-size-fits-all approach is not feasible. Future research should focus on developing tailored solutions that consider the unique characteristics of each application, emphasizing the need for context-specific model selection and calibration. This nuanced approach will help optimize the effectiveness of ML models in precipitation downscaling across diverse environmental and climatic conditions.

3.2. Enhancement made to conventional ML-based downscaling models

Significant advancements have been made in improving conventional ML-based downscaling models (as shown in Table 2), focusing on increasing the accuracy and applicability of these methods for high-resolution precipitation prediction. One key enhancement is the automation of feature extraction. While traditional models rely on manual feature selection, which is both time-consuming and error-prone, deep learning models can automatically identify complex spatial and temporal patterns. This capability significantly improves the accuracy of downscaled precipitation data by eliminating human bias in feature selection.

The development of advanced model architectures has further enhanced the performance of downscaling models. Architectures like U-NET, SR-GAN, and ConvLSTM are specifically designed to handle the intricate dependencies in climate data. These models excel at capturing complex relationships between climatic variables, resulting in more precise and reliable predictions. Additionally, the use of sophisticated loss functions, such as mean squared error (MSE) and perceptual loss, ensures that finer spatial details are retained in the downscaled outputs. This refinement is particularly critical in models like SR-GAN, where spatial accuracy is paramount.

Integrating data from multiple scales has also proven beneficial for improving downscaling performance. Leveraging coarse-scale GCM outputs alongside fine-scale observational datasets enables models to utilize a broader range of information, leading to better predictive accuracy (Vandal, Kodra, and Ganguly 2019). This multi-scale integration ensures that both large-

Table 1. Comparative studies on ML-based precipitation downscaling techniques and performance.

Reference	LR precipitation data	Environmental factors	Temporal resolution	Time period	Study domain	Downscaling models	Best performing algorithm
(Sachindra et al. 2018)	NCEP/NCAR	Air temperature, geopotential heights, relative and specific humidity, zonal and meridional wind speeds, sea level pressure, precipitable water content.	Monthly	1950–2014	Victoria, Australia	GP, ANN, SVM, RVM	RVM
(Sharifi, Saghafian, and Steinacker 2019)	IMERG	Cloud variables: cloud effective radius, cloud optical thickness, and cloud water path	Daily	Five Heavy Precipitation Events	Northeast Austria	MLR, ANN, spline	Spline
(Tan et al. 2022)	TRMM	Longitude, latitude, DEM, daytime and nighttime LST	Monthly	2006–2013	Yangtze River Economic Belt, China	RF, GWR, multivariate adaptive regression spline (MARS)	MARS
(Ulloa et al. 2017)	TRMM	Cloud top temperature, cloud fraction, NDVI, soil moisture	Monthly	2001–2011	Continental Ecuador, including Coast, Andes, and Amazon regions	Bilinear, ER, Regression kriging	Regression kriging with in situ data
(Jing et al. 2016a)	TRMM	Daytime and nighttime LST, NDVI, DEM, longitude, latitude	Monthly	Year of 2003, 2006, and 2009	North China	CART, KNN, SVM, RF	RF
(Vandal, Kodra, and Ganguly 2019)	GCMs and MERRA-2	Temperature, vertical wind, horizontal wind, specific humidity at 500 hpa, 700 hpa, and 850 hpa pressure levels; surface level temperature, sea level pressure, specific humidity	Daily	1980–2019	North-eastern United States	OLS, ELNET, SVM, MSSL, AE, CART, KNN, BCSD, Hybrid MSSL + BCSD	BCSD
(Raje and Mujumdar 2011)	CGCM3 for scenarios A1B, A2, and B1	Mean sea level pressure, surface-specific humidity, specific humidity at 850 hPa, surface temperature at 2 m, surface U-wind (zonal), surface V-wind (meridional)	Daily	Monsoon season, June to September, Historical data from 1951–2004; future projections for 2046–2065	Punjab region, India	CRF, KNN SVM	CRF and k-NN performed slightly better than SVM
(Sun and Lan 2021)	ECMWF Interim reanalysis (ERI)	Zonal and meridional winds, geopotential height, temperature, and humidity	Daily	1979–2017	China	CNN, CNN-PR, CNNdense, GLM, BCSD, BCCI	CNN for downscaling, BCSD for bias reduction
(Ghorbanpour et al. 2021)	TRMM	NDVI, DEM, LST	Annual and monthly	2009–2013	Lake Urmia Basin, Iran	SVM, RF, GWR, MLR, ER	SVM
(Wu et al. 2022)	Observed precipitation data	Longitude, latitude, elevation	Annual	1989–2018	Bangladesh	SVM, RE, GBR, MLR	GBR
(Kumar et al. 2021)	NCEP-NCAR	Geopotential heights, wind direction, vorticity, humidity, air temperature, mean sea level pressure, and meridional velocity	Daily	1948–2017	Krishna River Basin, India	MLR, ANN, SDSM, GP, WT-FF-NN, WT-NARX-NN,	WT-NARX-NN
(Xu et al. 2020)	CMIP5	–	Daily	1961–2018	Upper Han River Basin, China	SVR, MLP, RF, BMA, MLR, MME	BMA combined with SVR
(Kumar et al. 2023)	Gridded observation data	–	Daily	2005–2009	India	ConvLSTM, U-NET, SR-GAN	SR-GAN
(Chen et al. 2020)	IMERG	NDVI, LST, elevation, latitude, and longitude	Monthly and annual	2001–2015	Gansu Province, China	UR, MR, ANN, SVM, RF	RF
(Nasseri, Tavakol-Davani, and Zahraie 2013)	Gauged observations	Atmospheric variables including geo-potential heights, wind direction, vorticity, humidity, air temperature, mean sea level pressure, and meridional velocity	Daily	2000	Five climatological basins in Iran: Hamoon-Jazmoorian, Sefidrood, Mordab-Anzali, Shapoor-dalky, and Mond	MARS, MT, KNN, GA-SVM	Combination of MT and MARS

Table 2. Improvements in ML methods for precipitation downscaling.

Improvement area	Description
Feature Extraction	Deep learning models automate feature extraction, capturing complex spatial and temporal patterns.
Model Architecture	Advanced architectures like U-NET, SR-GAN, and ConvLSTM handle intricate dependencies in climate data.
Loss Functions	Use of sophisticated loss functions (e.g. MSE and perceptual loss in SR-GAN) to maintain finer spatial details.
Multi-Scale Integration	Leveraging both coarse-scale GCM outputs and fine-scale observational datasets for better predictive performance.
Non-Linear Relationships	Deep learning models with non-linear activation functions capture complex interactions between predictors and precipitation.
Generalization Capabilities	Techniques like data augmentation, dropout, and batch normalization prevent overfitting and enhance robustness.
Optimization Techniques	Advanced optimization methods (e.g. Adam) dynamically adjust learning rates for faster convergence and better performance.
Spatial Autocorrelation	Spatial Random Forest models account for spatial dependencies and improve prediction accuracy by leveraging spatial correlations.
Wet-Dry Classification	Combines Support Vector Classification (SVC) to identify wet and dry days with Support Vector Regression (SVR) to downscale rainfall on wet days.

scale patterns and local details are incorporated, making the predictions more robust and comprehensive.

Deep learning models equipped with non-linear activation functions offer another layer of advancement. These functions enhance the models' ability to capture the complex, non-linear interactions between predictors and precipitation, providing a more accurate representation of intricate climate relationships (Sachindra et al. 2018; Xu et al. 2020). Furthermore, techniques to improve generalization capabilities, such as data augmentation, dropout, and batch normalization, have been instrumental in preventing overfitting. These methods ensure that models can perform reliably on unseen data, enhancing their robustness in real-world applications (Kumar et al. 2021).

Efficient optimization techniques, such as the Adam optimizer, have also contributed to the advancements in downscaling models. By dynamically adjusting learning rates during training, these methods enable faster convergence and improved model performance, streamlining the training process. Together, these innovations in model architecture, data integration, loss functions, and optimization methods represent significant progress in the development of ML-based downscaling techniques, paving the way for more accurate and adaptable climate predictions.

Spatial Random Forest (Spatial-RF) models represent a significant advancement in climate downscaling by explicitly accounting for spatial dependencies, leveraging spatial correlations inherent in climatic data to improve prediction accuracy. Traditional RF models, while robust, often fail to capture the spatial continuity and relationships between neighboring locations, leading to inaccuracies in regions with sparse observational data or complex topography. Enhancing RF models with spatial autocorrelation – a principle stating that points closer in space are more likely to exhibit similar climatic characteristics – addresses this limitation. By incorporating spatial dependencies, Spatial-RF models effectively capture natural variability and precipitation patterns, which are critical for accurate climate predictions, particularly in data-sparse regions (Chen et al. 2020). Spatial Support Vector Machine (Spatial-SVM) models similarly enhance downscaling accuracy by integrating spatial autocorrelation. This ensures that the model recognizes and utilizes the relationship between neighboring data points. For instance, rainfall in one location is often correlated with rainfall in adjacent areas due to shared weather systems and geographic features. By including spatial dependencies, Spatial-SVM models can better reflect the true spatial distribution of climatic variables, resulting in more reliable predictions even in regions with limited observational data (Pham et al. 2019).

4. Transferability of ML downscaling models and transfer learning

The adoption and integration of ML into the downscaling of precipitation have a promising potential, effectively improving the resolution of remote sensing precipitation data. Another pivotal aspect of employing ML models in precipitation downscaling is their transferability. Transferability refers to the model's ability to generalize and apply the learned relationships from one geographical location (source domain) to another (target domain), potentially with different climatic characteristics (Jing et al. 2022; Wang et al. 2021; Wang et al. 2022). The transferability of ML-based downscaling models initially emerged as a solution to domains lacking abundant training data. It also allows for the development of scalable and adaptable downscaling models that can be efficiently applied to various regions without retraining from scratch, thus significantly saving computational resources and time. Therefore, it is crucial to address the heterogeneity of climatic zones and the variability in precipitation patterns across different regions.

The strategic methodologies used to actualize the transferability of ML models included transfer learning (Kimura et al. 2019; Li et al. 2021; Vrbančič and Podgorelec 2020; Zhao et al. 2021), domain adaptation (Islam et al. 2023; Sambath et al. 2022; Sauter and

Venema 2011), and multi-task learning (Bannai et al. 2023; Qiu et al. 2017; Vandal, Kodra, and Ganguly 2019; Xue et al. 2021). Among them, transfer learning has received prominence and broad application due to its flexibility and effectiveness in utilizing pre-trained models on large datasets to achieve significant improvements in performance on target tasks with relatively more minor datasets (Liu et al. 2022). Transfer learning involves a dual-phase process: pre-training and fine-tuning. During the pre-training phase, a model is trained on a large, often generic dataset (termed the source domain) to learn a wide array of features. Subsequently, during the fine-tuning phase, the model is adapted to a smaller, task-specific dataset (termed the target domain), enabling the application of previously acquired knowledge to the new task. This approach has demonstrated significant success, especially when large-scale labeled datasets are limited or costly to compile. Thus, transfer learning has been applied across diverse sectors, such as image classification (Pires de Lima and Marfurt 2019) and natural language processing (Zhang et al. 2019).

Meanwhile, transfer learning's effectiveness extends to water resources and climate science (Ma et al. 2016). The effectiveness of transfer learning also extends to water resources and climate science (Ma et al. 2016). A transfer learning-based framework has been proposed to merge the observations and the original TRMM data (Liu et al. 2022). Transfer learning has been explored to enhance flood susceptibility assessments in urban catchments, where flood inventory data are often scarce and insufficient for training traditional ML models (Zhao et al. 2021). A transfer LSTM model has been constructed to address the risk of overfitting and reduced accuracy for DL models induced by the limited daily soil moisture sample size in the Soil Moisture Active Passive L4 product (Li et al. 2021). Transfer learning has also been used to enhance a neural network-based flood model, which reduced the computational time and costs associated with extensive training and mitigating the impact of severe riverine floods in East Asia (Kimura et al. 2019).

Domain adaptation techniques are designed to minimize the discrepancy between the source and target domains, enabling a model trained in one domain to perform effectively in another (Sambath et al. 2022). It deploys this discrepancy to adjust the model such that it can generalize to new, unseen environments. Key approaches in domain adaptation include instance reweighting, feature alignment, and adversarial training, which help to align the distributional characteristics of data from different domains. Multi-task learning involves simultaneously training a model on multiple related tasks and promoting the learning of relevant generalized features across tasks (Bannai et al. 2023). By sharing representations between different tasks, multi-task learning can effectively maximize commonalities and differences across tasks to enhance learning efficiency and model robustness. Despite their benefits, both domain adaptation and multi-task learning are considered more niche compared to transfer learning. These complexities can lead to higher computational costs and more involved optimization processes.

The transferability of ML models also provided significant potential for regions without substantial datasets. These ungauged basins present significant challenges in hydrological and meteorological modeling due to the lack of observations on streamflow, precipitation, and other climatic variables. The primary issue in these basins is the difficulty in calibrating and validating hydrological models, which depend heavily on observed data to fit parameters and verify model accuracy (Kratzert et al. 2019; Rasheed et al. 2022; Worland, Farmer, and Kiang 2018). To mitigate it, conventional regionalization approaches, including physical similarity methods and spatial proximity methods, were applied (Li et al. 2010; Pool, Vis, and Seibert 2021; Yadav, Wagener, and Gupta 2007). These methods used the hydrological, geographical, and climatological similarities to transfer knowledge from gauged to ungauged basins. Regionalization approaches are grounded in well-understood physical and geographical principles and are generally more transparent and more accessible to interpret (Arsenault and Brissette 2014).

However, these approaches may oversimplify complex hydrological processes by relying heavily on empirical relationships that may not hold under changing climatic conditions (Guo et al. 2021; Razavi and Coulibaly 2013; Song et al. 2019). Their effectiveness highly depends on the availability of similar, gauged catchments, which may not always be available. Scaling these methods to larger or more diverse regions can be challenging because they often require re-assessment and adjustment of the regionalization. Alternatively, transfer learning enhanced the adaptation of ML models to varied environmental conditions and significantly reduced the time and resources required for model development (Choi, Lee, and Kim 2022; Kratzert et al. 2019). Furthermore, the ability of transfer learning to handle complex, non-linear hydrological processes under changing climatic conditions improved its reliability and applicability in diverse geographical settings. This highlighted its potential as a transformative tool in addressing the challenges of ungauged basins. The integration of transfer learning could potentially revolutionize predictions and management strategies in hydrology, making it crucial for future research and applications in water resource management under challenging environments.

5. Specific issues in precipitation downscaling

5.1. Environmental factors used in downscaling models

Integrating environmental predictors into downscaling modeling has proven essential for enhancing their accuracy. The association between precipitation and these variables has been robustly demonstrated across various studies, highlighting their importance in developing downscaling models (Chen, Yu, and Tang 2010; Najafi, Moradkhani, and Wherry 2011; Park 2013; Tamaki et al. 2018). As stated above, the correlation between precipitation, DEM, and NDVI has been commonly used and verified in previous studies. For example, the association between NDVI and rainfall was initially captured by Foody (2003) over North Africa and then used to downscale precipitation. The relationship between annual precipitation and NDVI was used to estimate the finer-scale TRMM precipitation based on the exponential regression model. In addition to vegetation, there are strong regression relationships between topography and precipitation. The relationships between precipitation, topography, and NDVI have been explored across multiple scales (0.25°, 0.50°, 0.75°, and 1.00°) using MLR (Jia et al. 2011). The GWR model has been used to establish regression relationships between NDVI, DEM, and TRMM precipitation, producing downscaled precipitation data at 1 km resolution (Y. Chen et al. 2018). A systematic exploration of spatial variation in precipitation from NDVI and DEM was also conducted using the GWR model (Xu et al. 2015). These studies demonstrated the efficacy of using NDVI and DEM as predictors in downscaling models.

Integrating LST into precipitation downscaling models has also shown promising advancements. For instance, the relationships between precipitation, topography, and NDVI have been explored across multiple scales (0.25°, 0.50°, 0.75°, and 1.00°) using MLR (Jia et al. 2011). The GWR model has been used to establish regression relationships between NDVI, DEM, and TRMM precipitation, producing downscaled precipitation data at 1 km resolution (Chen et al. 2018). A systematic exploration of spatial variation in precipitation from NDVI and DEM was also conducted using the GWR model (Xu et al. 2015). These studies illustrated the potential of including LST in precipitation downscaling models.

In addition, other factors, such as properties associated with clouds, humidity (Zhu et al. 2017), wind (Zhang, Sun, and Chen 2021), soil moisture (He et al. 2023), and even air temperature (He et al. 2016), were employed in the downscaling of precipitation. While the relationships between these factors and precipitation have been recognized, and their impact mechanisms have been explained to some extent, incorporating these factors into downscaling models is still relatively scarce in the current research. For example, cloud properties are crucial inputs for numerical weather prediction models and climate models. However, their application in precipitation downscaling was limited in short-term precipitation events with daily or sub-daily temporal resolutions (Ma et al. 2019; Sharifi, Saghafian, and Steinacker 2019). The application and effectiveness of these factors in downscaled models across different regions and time scales request a more comprehensive exploration in further work.

Therefore, selecting the most influential environmental predictors is crucial for enhancing model accuracy and applicability. Among the various potential predictors, NDVI, DEM, and LST are prominently used due to their significant influence on precipitation patterns and their proven effectiveness in numerous studies (Ghorbanpour et al. 2021; Jing et al. 2016a; Li et al. 2019). They are increasingly applied to downscaling models because of their strong meteorological relevance and their availability of high-quality satellite data. Accessibility allows more accessible employment of these predictors across various geographical regions and climatic conditions, advancing the generalizability and applicability of downscaling models.

5.2. Post-procedures: residual correction and calibration

Residual correction is conducted to minimize the disparity between the downscaled outcomes and the initial satellite precipitation data. The residuals represented rainfall that regression models with environmental factors cannot explain. They are calculated at a coarse resolution from the satellite-based data and are interpolated to a finer resolution by different techniques. For example, a simple spline tension interpolator was used to attain high-resolution residuals (Duan and Bastiaanssen 2013a; Immerzeel, Rutten, and Droogers 2009; Jia et al. 2011; Jing et al. 2016b; Lu et al. 2020; Zhan et al. 2018) and their results indicated that incorporating residual correction could enhance the precision of downscaled precipitation, highlighting its indispensable role within the downscaling framework. The bilinear resampling technique has been employed to produce the residual map at a finer resolution of 1 km, with significant improvements observed after residual correction (Sharifi, Saghafian, and Steinacker 2019). Several interpolation methods, including Inverse Distance Weighting (IDW), spline regularization, spline tension, ordinary kriging, and simple kriging, have been compared during residual correction, with simple kriging demonstrating the highest performance (Zhang et al. 2018).

These residual correction studies mainly utilize traditional interpolation methods, with limited incorporation of ML-based techniques. They consistently demonstrate residual correction's effectiveness in improving downscaled precipitation's accuracy. However, some studies, such as those using spline tension interpolator-based residual correction, reported a decrease in the accuracy of downscaled precipitation (Xu et al. 2015). Similarly, residual correction using Kriging models showed worse performance (Zhao 2021). These mixed findings indicate that while some studies confirm the benefit of residual correction in enhancing the precision of downscaling, others suggest it may compromise the effectiveness of the downscaling process. Consequently, there has yet to be a definitive consensus on the efficacy of residual correction, and many downscaling frameworks tend to exclude residual correction procedures.

Geographical differential analysis (GDA) and geographical ratio analysis (GRA) were identified as the predominant methods for calibration in various studies (Cheema and Bastiaanssen 2012). These two methods were adopted to calibrate the downscaled precipitation from TRMM by Duan and Bastiaanssen (2013a) for the first time. GDA adjusted downscaled data based on deviations from observed ground measurements. GRA modified the data using ratios, effectively maintaining relative differences across different spatial resolutions, which can be particularly advantageous in areas with complex geographical features. The effectiveness of these two methods may vary based on regional characteristics. For example, research conducted in mountainous regions affected by monsoon climates has demonstrated that while both GDA and GRA improve the resolution and accuracy of precipitation data, GRA might provide superior accuracy due to its ability to maintain proportional differences accurately across scales (Arshad et al. 2021; Duan and Bastiaanssen 2013b; Zhang et al. 2018). Moreover, the GDA exhibited superior effectiveness when applied to precipitation data at a finer scale. Numerous studies have illustrated the substantial enhancement of downscaling results through GDA calibration (Ali et al. 2022; Chen et al. 2018; Ghorbanpour et al. 2021).

Recently, ML-based techniques have been applied in calibration procedures (Chen, He, and Li 2024, 2020, 2018; Lu et al. 2020). Chen, Hu, and Li (2021) employed the SRF model in the downscaling and calibration stages. For the calibration process, the incorporation of spatial autocorrelation within the SRF model was particularly significant, as it achieved better-calibrated precipitation than the GDA model. Using the SRF in calibration not only obtained higher accuracy but also maintained the spatial integrity of the precipitation patterns. Jing et al. (2022) proposed a new downscaling-calibration method called AMCN – Geoi-DBN for fine-resolution precipitation estimation. An AMCN model was used for spatial downscaling, and a geo-intelligent deep belief network (Geoi-DBN) was applied to merge the ground and satellite data. These cascaded networks effectively improved the resolution and accuracy of rainfall monitoring and forecasting. ML-based calibration improved the accuracy of precipitation estimates from models compared to observed data, which was considered a form of data fusion. In general, GDA provided straightforward corrections that are easier to implement. ML-based calibration methods were a more flexible and robust framework capable of handling complex and multi-source data. There has been limited research on applying ML methods in the calibration process of downscaled precipitation. However, significant research that used ML methods for the fusion and merging of different precipitation data sources has shown great effectiveness. Therefore, ML algorithms hold great potential for applications in the calibration process.

6. Conclusions and outlook

This review systematically examined the application of ML techniques in downscaling precipitation data. The study was structured around three main stages: data preparation, the downscaling process, and post-processing. Key environmental predictors such as NDVI, DEM, and LST were identified and discussed for their roles in improving the accuracy of downscaled precipitation models. We also explored various ML algorithms, including SVM, RF, and advanced DL models like CNNs and LSTMs, highlighting their strengths and comparative performance in different scenarios.

The review provided insights into specific issues related to precipitation downscaling, such as the importance of residual correction and calibration procedures. We examined the transferability of ML models and the application of transfer learning, demonstrating their potential to adapt models to different geographical regions and climatic conditions. In conclusion, the three-stage framework (data preparation, downscaling, and post-processing) effectively structures the ML-based downscaling process, addressing key challenges and ensuring systematic improvements in precipitation data accuracy. Integrating key environmental predictors like NDVI, DEM, and LST significantly enhances the performance of downscaling models, although the inclusion of too many predictors can lead to model complexity and overfitting. ML algorithms, particularly DL models, show superior capability in capturing complex spatial and temporal patterns in precipitation data. Techniques like SVM, RF, and newer DL models have demonstrated varying degrees of success, depending on the specific context and application. Residual correction and calibration are crucial post-processing steps that significantly enhance the accuracy of downscaled precipitation data. Traditional methods have been effective, but there is potential for further improvement using ML-based techniques. Transfer learning and related methodologies have shown great promise in extending the applicability of ML models to different regions and climatic conditions. This adaptability is crucial for developing scalable and efficient downscaling models, especially in data-scarce regions.

Future research should focus on refining ML-based downscaling models by developing more sophisticated architectures and incorporating advanced techniques to prevent overfitting and enhance robustness. Exploring additional environmental factors and their integration into downscaling models can further improve accuracy and applicability. There is a need for continued innovation in post-processing methodologies, particularly in leveraging ML techniques for residual correction and calibration to enhance downscaled data accuracy. Further exploration of transfer learning, domain adaptation, and multi-task learning will be essential to improve model adaptability and efficiency across diverse regions and climatic conditions. Developing strategies to handle ungauged basins and data-scarce regions through advanced ML techniques will be critical for improving hydrological predictions and resource management under changing environmental conditions.

Therefore, the integration of ML techniques in precipitation downscaling holds significant promise. By addressing current challenges and leveraging advanced methodologies, researchers can enhance the accuracy, reliability, and generalizability of downscaled precipitation data, contributing to more effective climate and water resource management.

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Data availability statement

Data will be made available from the corresponding author, Qiming Zhou, upon reasonable request.

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