Deep Learning Models Filter Out Local Errors in Hydrological Data

Abhinav Gupta[1*] and Sean A. Mckenna[2]

[1]Division of Hydrologic Sciences, Desert Research Institute, Las Vegas, NV

[2]Division of Hydrologic Sciences, Desert Research Institute, Reno, NV

Corresponding author: Abhinav Gupta (abhigupta.1611@gmail.com)

*755 E Flamingo Rd., Las Vegas, NV, 89119

This preprint is not peer reviewed yet. The paper has been submitted to Geophysical Research Letters for peer-review.

Highlights

1. Adding global model outputs as input to a locally trained model can improve streamflow simulation accuracy.
2. Recession flow simulation may be improved by combining global and local information.
3. Global models avoid over-fitting to local epistemic errors and improve performance relative to local models.

Abstract

This study examines streamflow simulations using deep learning (DL) to: (1) Understand why global DL models trained on multiple watersheds outperform local DL models trained on single watersheds, and (2) Improve recession flow simulation accuracy. It introduces a novel modeling strategy called global-local (GL) modeling, where outputs from the global model are added as input to a locally trained model. The hypothesis is that the GL strategy can leverage both global and watershed-specific information in the form of local errors. GL models demonstrate enhanced accuracy in recession flow prediction for multiple watersheds compared to global and local models. However, considering the entire hydrograph, GL models perform worse than global models. GL model’s performance relative to the global model depends on whether hydrological data errors are predominantly stationary or nonstationary. Local nonstationary errors significantly contribute to the global model's superior performance over locally trained process-based and DL models.

Plain language summary

This study presents a new way to generate computer simulations of streamflow by using deep learning methods. The main idea is to use a learning model to extract information from many different watersheds and to also learn unique details of each watershed. These unique details include errors in data (rainfall and streamflow) that are watershed specific. This new approach improves the accuracy of streamflow predictions during recession when there is no rainfall, but it does not work as well when we look at the entire history of streamflow in which case a model built with information from all watersheds is superior. We also found that the errors in measuring the rainfall and streamflow data have a big impact on performance of the different models. Models trained with data from many watersheds are not as affected by these errors as much as models trained with data from just one watershed. This study shows the importance of accounting for errors in the data when building computer simulations of streamflow.

1. Introduction

Several rainfall-runoff models have been used for streamflow simulation including conceptual and process-based (PB) hydrological models (Singh, 1995), statistical time series models (i.e., data-based mechanistic modeling; Beven, 2011), machine learning (ML; Govindaraju, 2000) including deep learning models (DL; Shen & Lawson, 2021). For any approach, model parameters must be calibrated to match the available data which is typically streamflow time series at the watershed outlet. Each watershed is unique with respect to details of the rainfall-runoff processes and in terms of errors in hydrological data (Beven, 2000; Beven 2020). Therefore, it is prudent to calibrate rainfall-runoff models on data available within a single watershed where predictions are required. Examples of watershed-specific errors include systematic errors in rainfall magnitude dependent upon rain gauge density (Bárdossy & Anwar, 2022) and rain gauge locations (Moličová et al., 1997), and errors in rainfall timing (Gupta et al., 2023).

Recent work (e.g., Nearing et al., 2021; Li et al., 2022) has shown that a DL model trained on data across multiple watersheds (referred to as a global model in this study) typically outperforms DL models trained on single watersheds (referred to as local models). Further, the global DL models outperform the PB models in most watersheds (Kratzert et al., 2021). One reason that global DL models outperform the locally calibrated PB and DL models is the extra hydrological information available to the global DL models through data across different watersheds. Another reason for the improved performance may be that local, watershed-specific, nonstationary errors in hydrological data can degrade the performance of local DL and PB models (Beven, 2023) because a local DL model will fit these systematic errors while the global DL model will filter out these errors.

In the presence of local-systematic errors, one would expect that the residuals between observed and global model-predicted streamflow would have some non-random structure. In this study, we investigate whether there is any *learnable* structure in these residuals. To this end, we propose a simple and novel strategy that combines global and local modeling approaches to predict streamflow. The benefit of this strategy is that streamflow simulations can be more accurate than the ones simulated by a global model if there is any watershed-specific learnable (in some sense stationary) structure in the residuals.

Previous studies have focused on the prediction of entire streamflow hydrographs using ML/DL (e.g., Ma et al., 2021; Li et al., 2022). This may result in suboptimal predictions of the recession flows (Knoben et al., 2020). Therefore, this study separately models recession flows. Accurate predictions of recession flows are important for water quality and ecological purposes. Recession flow dynamics are strongly governed by the geological properties of a watershed (Bear, 2013) and watershed geometry (Troch et al., 2003). High flow periods are also impacted by factors such as antecedent moisture conditions and rainfall patterns along with watershed-scale geomorphological structure (Lee & Delleur, 1972; Rodriguez-Iturbe & Rinaldo, 1997). Therefore, due to different controls on the dynamics of the two processes, a global DL model that is accurate for high-flow predictions may not be the best model for recession-flow predictions. Typically, Nash-Sutcliff Efficiency (NSE; Nash & Sutcliffe, 1970) or a similar metric is used as the objective function to be optimized during calibration that gives higher weight to the high flows. Therefore, separate modeling of recession flows is explored in this study.

The objective of this study is to test a new DL modeling strategy to combine global and local information for streamflow simulation, that can take advantage of both the ability of a global model to generalize across variability in multiple watersheds and the potential information available in the form of local errors in the hydrological data of a watershed. The proposed DL strategy is an attempt to extract meaningful information from the residuals between observed streamflows and the global model-predicted streamflows. Specifically, this study (1) provides insight into why the global DL models perform better than the locally trained DL and PB models, and (2) explores whether the streamflow simulation performance can be improved by the global-local strategy.

2. Deep learning (DL) models

A long short-term memory (LSTM) network is used as the basic DL model as it has been shown to yield state-of-the-art performance (Nearing et al., 2021). Details of the LSTM can be found in Kratzert et al. (2021) and Goodfellow et al. (2016). For this study, it suffices that LSTM is a variant of the gated recurrent neural network (Goodfellow et al., 2016), designed to address long-memory time series problems and is suitable for streamflow simulations. A single LSTM layer with 128 neurons was used in this study. Four types of models were trained in this study: (1) Trained using data from only the watershed where predictions are required (local model), (2) Trained using data from all the watersheds (global model), (3) A combination of global and local models where the output of a global model is appended with meteorological data and is passed through a local model (GL0 model), and (4) a combination of global and local models where the output of the global model is used as the sole input to the local model (GL1 model). The four modeling strategies are conceptually illustrated in Figure 1. In Figure 1, the symbol X_t denotes the meteorological data that varies with time t including precipitation, minimum and maximum temperatures, vapor pressure, and solar radiation. The symbol S denotes static attributes (see Addor et al., 2017) including soil and geological properties, topographical data, and the long-term climate of a watershed. The symbol k denotes the length of past meteorological data used as input to the LSTM.

Further, each of the four models was trained separately using data for both the entire hydrograph and data for recession flows only. Recession flows were defined as the flows during which rainfall was below 0.1 mm, beginning at least three days after the preceding peak streamflow. Thus, there were two global models used to predict streamflow, one for the entire streamflow hydrograph and one for recession flows. The numbers of local and GL models were twice the number of watersheds – two models for each watershed (one for recession and one for the entire hydrograph).

The value of k was set to 365 days for the ‘entire hydrograph models’ and 60 days for the ‘recession flow models’. The value of $k = 60$ day was deemed sufficient for recession flows as increasing it further did not improve the performance. NSE (in the form suggested by Kratzert et al., 2019) was used as a performance metric and the objective function to be maximized during model training. The separate models for recession flow periods were trained by giving a weight of 1 to all the recession flow time steps and a weight of 0 to other time steps. The training period for all the models was 1980-1989 water years, the validation period was 1990-1994 water years, and the testing period was 2001-2013 years. Simulated daily mean streamflow is the output of each model.

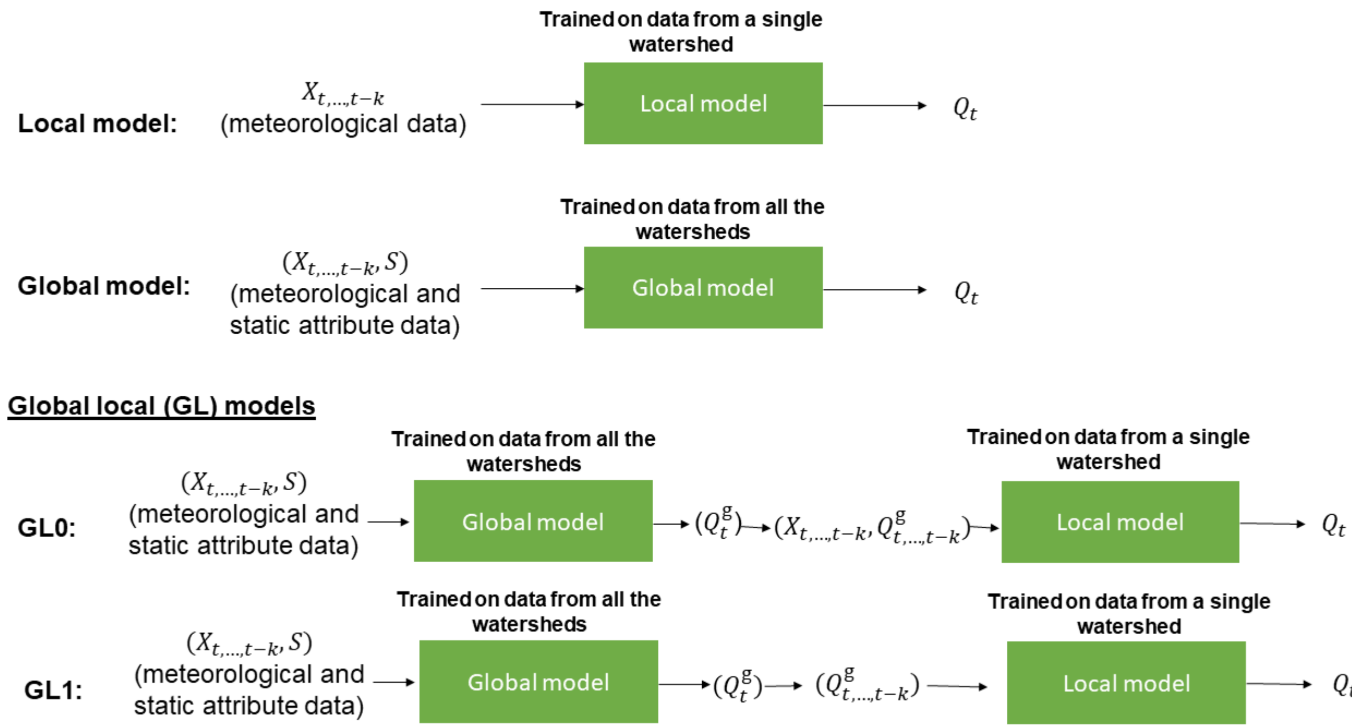

Figure 1. Illustrative description of the four models. The symbols $X_{t,\ldots t-k}$ and S denote the meteorological data at current and past k time-steps and static watershed attributes, respectively. Q_t denotes the final predicted streamflow in all the models and $Q_{t,\ldots,t-k}^g$ denotes the streamflow predicted by global models in the two global-local (GL) models at current time-step and past k time-steps.

3. Data

The Catchment Attributes and Meteorology for Large Sample Studies (CAMELS; Addor et al., 2017) dataset was used to develop different models. The CAMELS dataset contains daily timescale hydrometeorological and catchment attribute data from 671 watersheds across the USA (details of these attributes can be found in Addor et al., 2017). All the CAMELS watersheds are free of anthropogenic disturbances. In this study, 210 watersheds that were primarily driven by rainfall were used. These 210 watersheds (see Figure 4 below) cover most of the geographical regions of the USA and have different hydroclimatic conditions.

4. Comparison of model performance

Cumulative distribution functions (CDFs) of NSE values obtained by the four models (Figure 2a) show that global models outperformed the other three models in predicting the entire hydrograph. Local models performed the worst; the GL0 and GL1 models performed better than the local models. In most watersheds (Figure 2b), the global model outperformed, below the 1:1 line, the local models but there were a few watersheds for which the local models were better. GL0 and GL1 models performed similarly to the global model for a large number of watersheds (Figures 2c and 2d) but performed worse in several others. These results indicate that the global modeling strategy is the best (or at least as good as other strategies) for nearly all watersheds when the model is trained for the entire hydrograph and the evaluated using NSE.

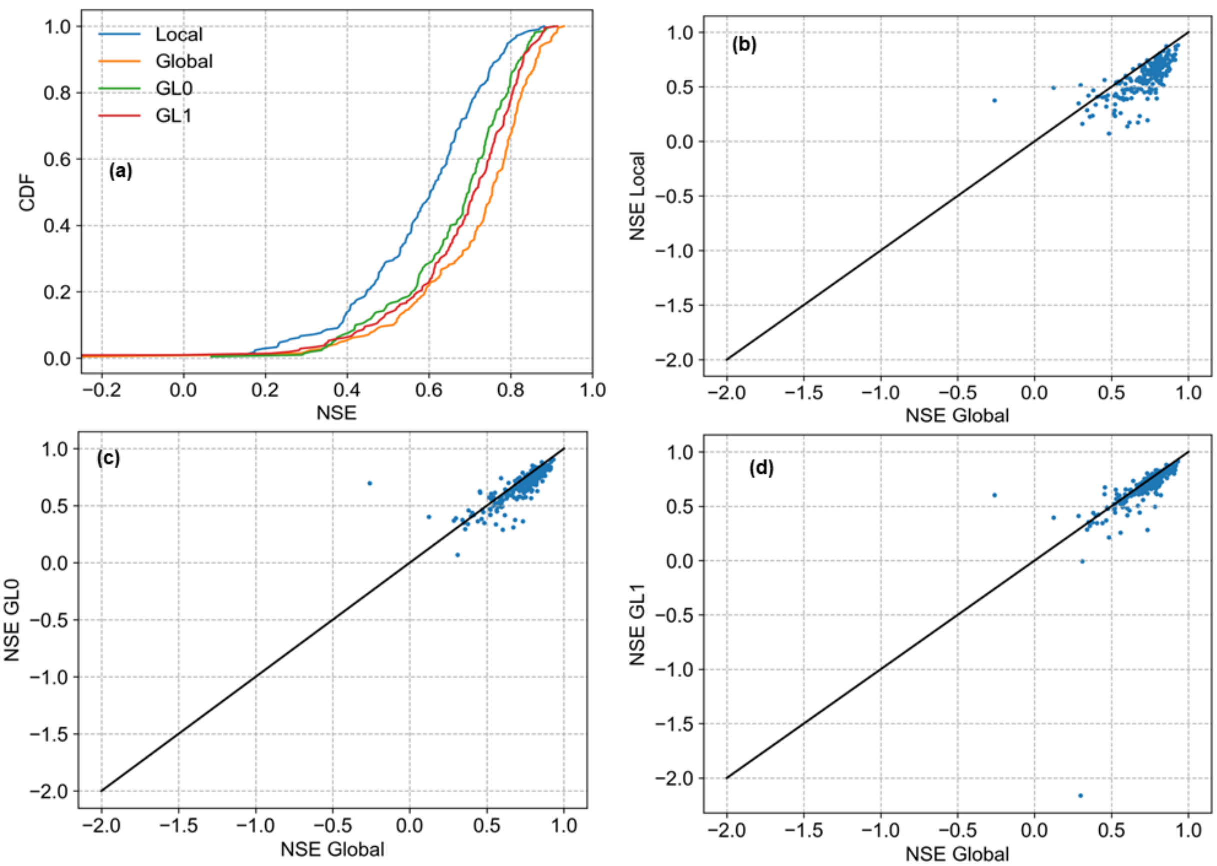

Figure 2. Entire hydrograph models. **(a)** Cumulative distribution function (CDF) of NSE values obtained by different models. The x-axis is clipped at -0.25. **(b), (c) and (d)** Comparisons of NSEs obtained by the global model to the NSEs obtained by other models.

When the models were trained to predict recession flows, no clear best strategy emerged (Figure 3a). Local models performed worse than the other three models for most watersheds but even then, there were many watersheds where local models performed better than the global model (Figure 3b). However, in all cases where the local models were better, the NSE values were below 0.35. Typically, the GL models outperformed the global model for the watersheds where NSE values obtained by the global model were low (< 0.5 approximately, Figures 3a, 3c, and 3d). Conversely, the global model outperformed GL models in watersheds where the global model NSE values were high (> 0.70 approximately). We conclude that the best model for recession flow depends upon the watershed being considered. Another noteworthy point is that GL0 and GL1 models yield significant improvement over the global model in some of the watersheds. Another conclusion is that local information, as captured in GL models, is useful for recession flow simulation but not for the full hydrograph. Thus, postprocessing of the global model predicted streamflow, as is done here, is a viable strategy for recession flow predictions, depending upon the watershed being considered.

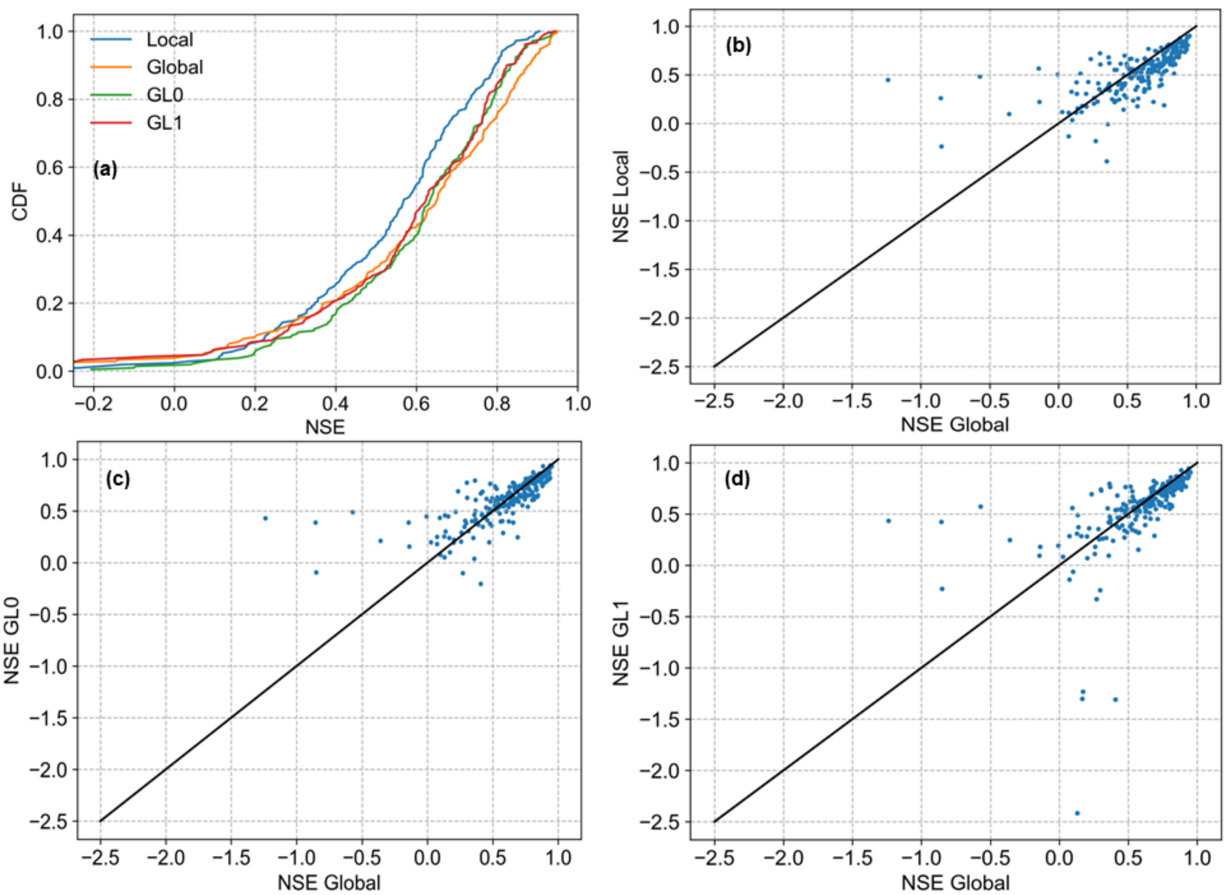

Figure 3. Recession flow models. **(a)** Cumulative distribution function (CDF) of NSE values obtained by different models. The x-axis is clipped at -0.25. **(b), (c) and (d)** Comparisons of NSEs obtained by the global model to the NSEs obtained by other models.

5. Role of errors in model performance

The hydrological data incur significant errors, primarily of epistemic nature, which can be specific to individual watersheds (referred to as local errors). The errors can be either systematic or non-systematic. A local DL model will fit the local systematic errors but a global DL model will not fit these local errors since doing so will degrade the performance of the global model in other watersheds. We hypothesize that the residuals between observed and global model-predicted streamflows in a watershed reflect the effect of the local systematic errors. These errors can be either stationary, nonstationary, or a combination of both. In the nonstationary category, the errors may or may not depend on the input. Even if some errors are dependent upon the model input, available data may not be enough to learn that dependency effectively making those errors input independent.

Some examples of these errors include the underestimation of rainfall magnitude by rain gauges caused by the wind effect, which represents a stationary error. The consistent underestimation of high rainfall volumes due to low rain gauge density (Bárdossy & Anwar, 2022) represents a rainfall-dependent nonstationary error. The change in rain gauge density over time may introduce rainfall-independent nonstationary errors. The occurrence of rare flood events during the testing period that were absent during the training period represents another type of input-independent nonstationary error.

Both the stationary errors and rainfall-dependent nonstationary errors result in residuals that have learnable structure, that is, there is information contained in the residuals that can be used to further improve the model performance. On the other hand, rainfall-independent nonstationary errors result in residuals that do not contain any learnable structure. Thus, depending upon which types of errors dominate the hydrological data fed to the DL models, the GL models would improve or worsen the streamflow simulation accuracy.

Figure 2 shows that the GL models performed worse than the global model in most of the watersheds when the entire hydrograph is considered. This means that the residual between the observed and the global model-predicted streamflow contains a nonstationary structure that cannot be learned by the local model. Therefore, we conclude that the systematic errors are predominantly nonstationary when the entire hydrograph is considered. This further implies that systematic nonstationary errors are one of the reasons that local DL models perform worse than the global model. This result highlights that any model calibrated to a single watershed will fit the local non-stationary errors and perform worse than a global model and we expect this result will also apply to PB models. This interpretation has consequences when PB models are compared to the global DL models because a global DL model may perform better not just because that they are able to extract more hydrological information from global data but also because PB models are often overfit to the local data.

Figure 3 shows that the GL models improved the performance compared to global models in many watersheds when only the recession flows were considered. This implies that a learnable structure exists in the residuals between observed and global model-predicted streamflow of these watersheds for recession flows. To further understand the utility of the GL modeling strategy for recession flows, each watershed was categorized into one of four categories based on performance relative to the global model as listed in Table 1. Figure 4 shows the locations of the categories of watersheds according to Table 1. There were several watersheds, especially in the eastern USA, that belonged to category 1 where the GL models significantly improved the performance for recession flows. Also, many watersheds belonged to category 2 where GL models degraded the performance. Therefore, we conclude that in several watersheds (category 1) the GL modeling strategy is better compared to either global or local modeling strategies as it allows the model to learn from both the hydrological information contained in the donor watersheds and the local systematic errors. A few watersheds belonged to category 3 where GL models did not result in any significant change in performance compared to the global model. These watersheds are spread across the USA. Only four watersheds belonged to category 4 where the GL strategy had mixed results in improving performance relative to the global model. Category 4 watersheds are also located in different geographical regions of the USA.

The GL modeling proved to be an effective strategy for recession flows (depending upon the watershed) but not for the entire hydrograph. This result may be due to the averaging of nonstationary rainfall errors when recession flows are considered since the nonstationarity of rainfall errors will more strongly impact the rising limb of the hydrograph than the recession flows. This may also be due to recession flows being more strongly controlled by local features of a watershed including the structure of groundwater systems, bank storage capacity, and vegetation characteristics.

Table 1. Categorization of watersheds based on dominant error types when modeling recession flows

Category	Effect on GL model performance compared to the performance of the global model	Dominant systematic error types
1	At least one GL model improves the performance while the other model does not change the performance	Stationary and input-dependent nonstationary errors
2	At least one GL model worsens the performance while the other model does not change the performance	Unlearnable nonstationary errors
3	No change in performance by any model	Neither learnable nor unlearnable errors dominate
4	GL1 improves the performance while GL0 worsens the performance	Stationary and unlearnable errors
	GL0 improves the performance while GL1 worsens the performance	Learnable nonstationary errors

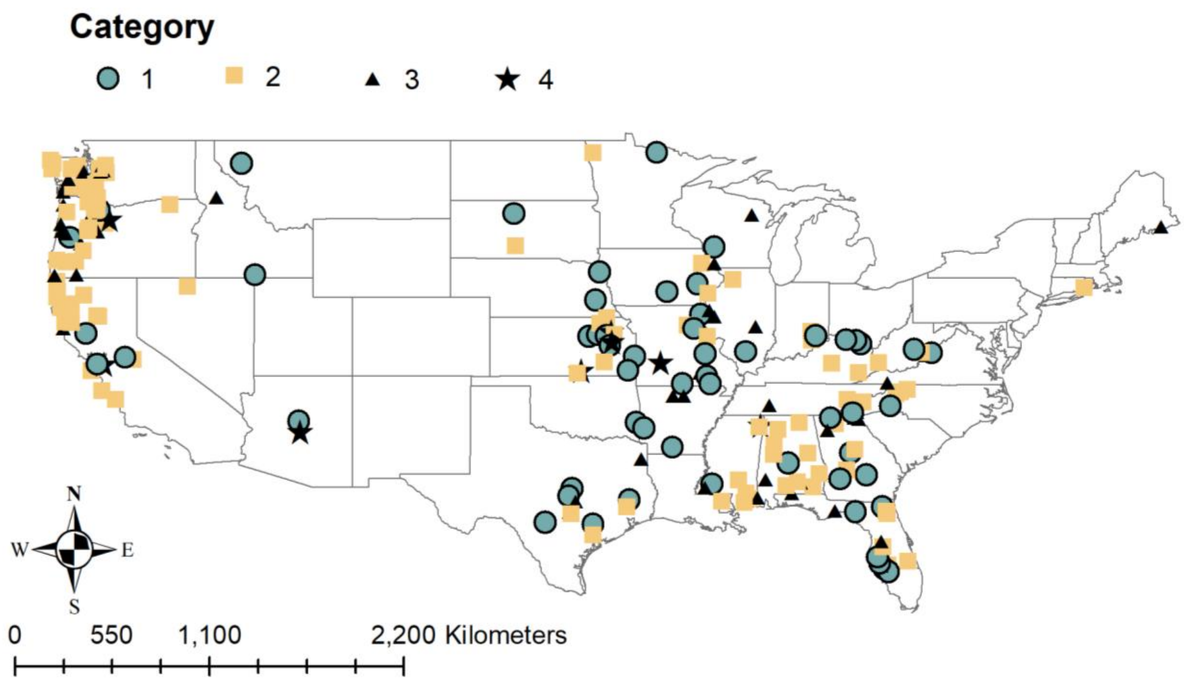

Figure 4. Categorization of watersheds in the CAMELS dataset based on the difference in the performance of global and GL models. See Table 1 for an explanation of the 4 categories.

6. Discussions and Conclusions

The advent of DL models allows for extraction of hydrological information from multiple watersheds to calibrate watershed-specific models. As shown in this study, different combinations of global and local information can be applied to obtain the most accurate model. Three modeling strategies were tested: local modeling, global modeling, and two combinations of global and local modeling (GL models). The best modeling strategy depended upon the watershed and the portion of the hydrograph being considered. The global modeling strategy was better than other strategies for most of the watersheds in predicting the entire hydrograph. When only the recession flows were considered, the global models were less dominant and GL models outperformed the global model for several watersheds. There were many watersheds where GL models and the global model performed similarly. These results echo the discussion by Beven (2023) that it is not possible to define a general best model for all purposes and all watersheds.

The idea behind using the GL models is to take advantage of the hydrologic information contained in the global dataset and the information contained in the form of the local systematic errors. The effect of the local errors will be reflected in the residuals between observed and global model-predicted streamflow. If the residuals corresponding to a watershed have a dominantly unlearnable nonstationary structure, the GL model will worsen the performance compared to the global model. It can be concluded that the systematic errors are predominantly unlearnable and nonstationary when the entire hydrograph is considered; this is why GL models do not improve performance in this case. The nonstationary effects are averaged out when only the recession flows are considered; therefore, the GL models improve the performance compared to the global model in several watersheds in this case.

This study provides an important insight into why the global models perform better than the local DL models and PB models calibrated to a single watershed. The local DL and PB models fit the systematic nonstationary errors while the global models filter out these errors. Local DL and PB models are essentially overfitting the local erroneous data whereas global models with a much larger training set can generalize over data from a broad set of watersheds. It is noted that the generalization occurs not just because the global DL models are able to extract hydrologically relevant information from the donor watersheds but also because they are able to filter the watershed-specific errors. The presence of epistemic errors in the hydrological data of a watershed has implications for the PB model validation strategy as discussed in Beven (2019) and Gupta et al. (2023), and also for comparison between PB models and global DL models.

Open Research

Data used in this study are freely available online and appropriate references have been provided in the main text.

Acknowledgments

AG was supported by the Sulo and Aileen Maki Postdoctoral Fellowship at DRI during this work. This support is gratefully acknowledged.

References

Bárdossy, A., & Anwar, F. (2022). Why our rainfall-runoff models keep underestimating the peak flows? Hydrology and Earth System Sciences Discussions, 1-30.

Bear, J. (2013). Dynamics of fluids in porous media. Courier Corporation.

Beven, K. (2019). Towards a methodology for testing models as hypotheses in the inexact sciences. Proceedings of the Royal Society A, 475(2224), 20180862.

Beven, K. (2020). Deep learning, hydrological processes and the uniqueness of place. Hydrological Processes, 34(16), 3608-3613.

Beven, K. (2023). Benchmarking Hydrological Models for an Uncertain Future. Hydrological Processes, e14882.

Beven, K. J. (2000). Uniqueness of place and process representations in hydrological modelling. Hydrology and Earth System Sciences, 4(2), 203-213.

Beven, K. J. (2011). Rainfall-runoff modelling: the primer. John Wiley & Sons.

Beven, K., & Smith, P. (2015). Concepts of information content and likelihood in parameter calibration for hydrological simulation models. Journal of Hydrologic Engineering, 20(1), A4014010.

Frame, J. M., Kratzert, F., Gupta, H. V., Ullrich, P., & Nearing, G. S. (2023). On strictly enforced mass conservation constraints for modelling the Rainfall-Runoff process. Hydrological Processes, 37(3), e14847.

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

Govindaraju, R. S. (2000). Artificial neural networks in hydrology. I: Preliminary concepts. Journal of Hydrologic Engineering, 5(2), 115-123.

Gupta, A., Govindaraju, R. S., Li, P. C., & Merwade, V. (2023). On Constructing Limits-of-Acceptability in Watershed Hydrology using Decision Trees. Advances in Water Resources, 104486.

Knoben, W. J., Freer, J. E., Peel, M. C., Fowler, K. J. A., & Woods, R. A. (2020). A brief analysis of conceptual model structure uncertainty using 36 models and 559 catchments. Water Resources Research, 56(9), e2019WR025975.

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. Hydrology and Earth System Sciences, 23(12), 5089-5110.

Lee, H. T., & Delleur, J. W. (1972). A program for Estimating runoff from Indiana watersheds, Part III: analysis of geomorphologic data and a Dynamic Contributing Area Model for Runoff Estimation.

Li, X., Khandelwal, A., Jia, X., Cutler, K., Ghosh, R., Renganathan, A., ... & Kumar, V. (2022). Regionalization in a global hydrologic deep learning model: from physical descriptors to random vectors. Water Resources Research, 58(8), e2021WR031794.

Ma, K., Feng, D., Lawson, K., Tsai, W. P., Liang, C., Huang, X., ... & Shen, C. (2021). Transferring hydrologic data across continents–leveraging data-rich regions to improve hydrologic prediction in data-sparse regions. Water Resources Research, *57*(5), e2020WR028600.

Moličová, H., Grimaldi, M., Bonell, M., & Hubert, P. (1997). Using TOPMODEL towards identifying and modelling the hydrological patterns within a headwater, humid, tropical catchment. Hydrological Processes, 11(9), 1169-1196.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. Journal of Hydrology, 10(3), 282-290.

Nearing, G. S., Kratzert, F., Sampson, A. K., Pelissier, C. S., Klotz, D., Frame, J. M., ... & Gupta, H. V. (2021). What role does hydrological science play in the age of machine learning? Water Resources Research, 57(3), e2020WR028091.

Rodriguez-Iturbe, I., & Rinaldo, A. (1997). Fractal river basins: chance and self-organization. Cambridge University Press.

Shen, C., & Lawson, K. (2021). Applications of deep learning in hydrology. Deep Learning for the Earth Sciences: A Comprehensive Approach to Remote Sensing, Climate Science, and Geosciences, 283-297.

Singh, V. P. (1995). Computer models of watershed hydrology. Water Resources Publications.

Troch, P. A., Paniconi, C., & Emiel van Loon, A. E. (2003). Hillslope-storage Boussinesq model for subsurface flow and variable source areas along complex hillslopes: 1. Formulation and characteristic response. Water Resources Research, 39(11).