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BUILD A MATCHING SYSTEM BETWEEN CATCHMENT COMPLEXITY AND MODEL COMPLEXITY FOR BETTER FLOW MODELLING

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Hydrological models play an important role in water resource management and flood risk management. However, there is a lack of comparative analysis on the performance of those models to guide hydrologists to choose suitable models for the individual catchment conditions. This paper describes a two-level meta-analysis to develop a matching system between catchment complexity (based on catchment significant features CSFs) and model complexity (based on model types). The objective is to use the available CSFs information for choosing the most suitable model type for a given catchment. In this study, the CSFs include the elements of climate, soil type, land cover and catchment scale. Through the literature review, 119 assessments of flow model simulations based on 28 papers are chosen, with a total of 76 catchments. Specific choices of model and model types in small, medium and large catchments are explored. In particular, it is interesting to find that semi-distributed models are the most suitable model type for catchments with the area over 3000km^2.

INTRODUCTION

Hydrological models play a significant role in the simulation of river flow and decisions on water resource and flood risk management. Like most science and engineering fields, the development of hydrological models has been unprecedented, especially during the past decades. Complex hydrological models such as physically based distributed models have a great deal of advantages over lumped models in describing detailed hydrological processes. And it is generally recognized that physically based distributed models (with the use of spatially varied catchment characteristics) may offer outputs with higher resolution and accuracy than lumped models [1-4]. Although hydrological models are moving towards a direction with more complex structure and mathematical sophistication, the selection of a suitable model for a given catchment becomes even harder than it used to be.

Hence, the objective of this study is to review a large number of studies, with the initial step of learning from the differences and similarities between various catchments and between different hydrological models by using meta-analysis. After that suitable catchment features are selected to present catchment complexity and explore if any patterns would emerge between the categorized catchments and model types. Ideally an integrated matching system could be derived with a complete spectrum of catchment complexity and a complete spectrum of model complexity. However, due to restriction of time and insufficient coverage of model types and catchment diversities in existing publications, only a preliminary version of the matching system is attempted and presented in this paper.

METHODOLOGY

At Level 1, a meta-analysis is used to systematically assess the model performance under each chosen CSF in a broad way, to investigate the CSF's ability in representing catchment complexity. The benefit of using meta-analysis is that it covers a wide spectrum of possibilities (e.g. different models, various catchment characteristics) that go beyond what can be reasonably accomplished by a single case study. Generally speaking, there are five major steps toward a systematic literature survey in meta-analysis: framing the question, searching relevant publications, assessing study quality, summarizing the evidence and interpreting the findings [5].

For the five steps introduced in the meta-analysis, the initial task is to choose suitable papers in the literature and then gather useful information to be used in this study. For paper selection, publications in the international refereed journals (peer-reviewed journals) are scrutinized for results of river flow modelling. For information collection, since the idea of this study is to build a matching system between model complexity with various model types and catchment complexity with the identification based on CSFs, so comprehensive information on models, model types, locations, temporal scales (e.g. flow modelling in hourly or daily time interval) and CSFs are required. In this study climate region, soil type, land cover and catchment scale are chosen as CSFs. Moreover, it is observed that since there are great varieties of different hydrological models used in the chosen studies, so in order to generalize beyond individual studies, these models are grouped into four types as: black-box model, lumped model, semi-distributed model and fully-distributed model.

Furthermore, in order to improve the consistency of this study, several criteria are set for all the chosen papers to follow: a) this study only chooses the papers with Nash –Sutcliffe efficiency (NSE) [6] as model accuracy. This is because NSE is the most common and important performance measure used in hydrology. b) any papers with inappropriate model time interval are not included for assessment (the time interval should depend on the concentration time of a catchment, which is judged by the catchment scale), such as the studies carried out by [7, 8] who used daily time interval for small catchments (67km^2, 8-11km^2 respectively) which are not in line with other catchments. c) this study only focuses on flow modelling with the whole hydrograph, hence some of the papers on real time flood forecasting are excluded, such as the modelling results given by [8-12]. By applying the above criteria, only 28 out of 50 papers are kept and shown in the following parts of this study.

At Level 2, the most suitable CSF from Level 1 study is adopted as the sole indicator of catchment complexity, which is then used to pair with suitable model types. The selection of the most suitable CSF is by comparing the mean and variation of NSE performances under each CSF categorized group.

RESULTS

Comparative assessment of model types and CSFs (Level 1)

Model types

Figure 1 illustrates the NSE performances in terms of different model types. It can be seen that the performance of lumped models are the best among all, followed by semi-distributed models. Among all models, black-box models perform the worst.

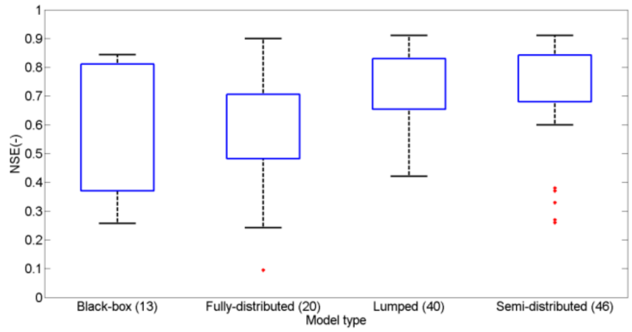

Figure 1. NSE of flow modelling stratified by model types (Level 1). The mean modelling results for each model type are 0.49, 0.58, 0.71 and 0.61 from the left to the right respectively. The number of catchments used for each model type is shown in bracket. The boxes indicate 25-75% percentiles. The red dots present outlier.

Climate type

Climate, as an important factor affecting evapotranspiration and precipitation, can be expected to influence performance of flow modelling. The results of NSE performances with respect to the four climate types are presented in Figure 2a), which shows that the average performance of flow modelling tends to be lower in mild temperate climate than in dry and tropical climates.

Soil type

Soil plays a significant role in the hydrological cycle, because various soil properties can affect the formation of runoff. The assessment of NSE performances with respect to the three soil types is presented in Figure 2b). It is clear that the performances of flow modelling carried out in silt based catchments are the best and also with the narrowest NSE range between 0.49 and 0.91.

Land cover

In addition to the impact of soil on flow modelling, land cover is also influential. As shown in Figure 2c), the forest group performs the worst among all land covers, and furthermore, it also has the largest NSE difference between the worst and the best cases (from as low as 0.10 to as high as 0.91). Comparatively, the performance of flow modelling in grasslands is more efficient.

Catchment scale

Catchment scale may be a useful indicator of catchment homogeneity. The results in Figure 2d) present a rather clear increase trend of the efficiency with catchment scale for all the studies. Compared with climate, soil and land cover, catchment scale shows stronger evidence as an indicator of catchment complexity. Therefore, catchment scale would be used to further explore the detailed catchment complexity in the next section.

Catchment scale match with model types (Level 2)

Considering the reason explained in the previous section, a further exploration is implemented to exam the ability of catchment scale in representing the catchment complexity, and then to build a matching system between catchment complexity and model complexity. For the existing

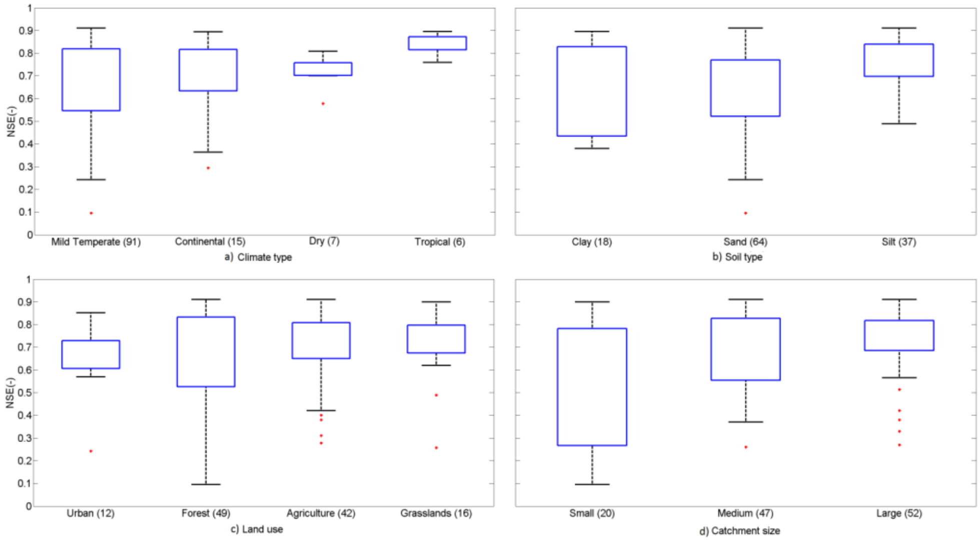

Figure 2. The NSE results of flow modelling, stratified by CSFs (Level 1). a) Climate regions: the mean simulation results for individual climate types are 0.59, 0.71, 0.72 and 0.84 from mild temperate climate to tropical climate; b) Soil type: the mean simulation results for clay, sand and silt are 0.59, 0.55 and 0.76 respectively; c) Land cover: the mean simulation results for urban, forest, agriculture and grasslands are 0.65, 0.55, 0.66 and 0.71 respectively; d) Catchment size: The mean simulation results for small (0-100km^2), medium (100-1000km^2), and large (>1000km^2) catchments are 0.39, 0.63 and 0.71 respectively. The number of catchments used for each CSF group is shown in brackets. The boxes indicate 25-75% percentiles. The red dots represent outliers.

studies, the catchment area varies from 0.36km^2 to 795500km^2; with such big differences, one model type is clearly incapable of covering all catchment scales. Hence in order to find the most suitable model types for various catchment scales, a correlation between catchment areas and model performances is firstly explored and presented in Figure 3, which is in respect to the four model types. As shown in Figure 3, there is an evident elevation of performances across all model types when the catchment expands. And furthermore, it is found that the general performance of fully-distributed models is unsatisfactory with their majority NSE efficiencies lower than 0.80. However, it is noted that when results of all model types are plotted in one figure, it is difficult to determine which model type is better for which catchment scale. The reason is because, semi-distributed models are popularly used in large catchments, however this does not yield to the conclusion that they are better in large catchments, as the number of studies for lumped models in large catchments is too small to compare. In addition, similar situation is found for lumped models in medium catchments. Therefore, in order to avoid the impacts of this preferred bias for catchment scale, datasets are further divided into small, medium and large catchments. Nevertheless, in Level 1 meta-analysis, only a rough definition of catchment size is adopted. In order to build a clearer pattern between different catchment sizes and corresponding suitable model types, the border lines between small and medium catchments, and between medium and large catchments need to be discovered. For this purpose, the trial and error method is applied to discover a suitable definition of catchment size groups. The border line between small and medium catchments is tuned firstly while the boundary

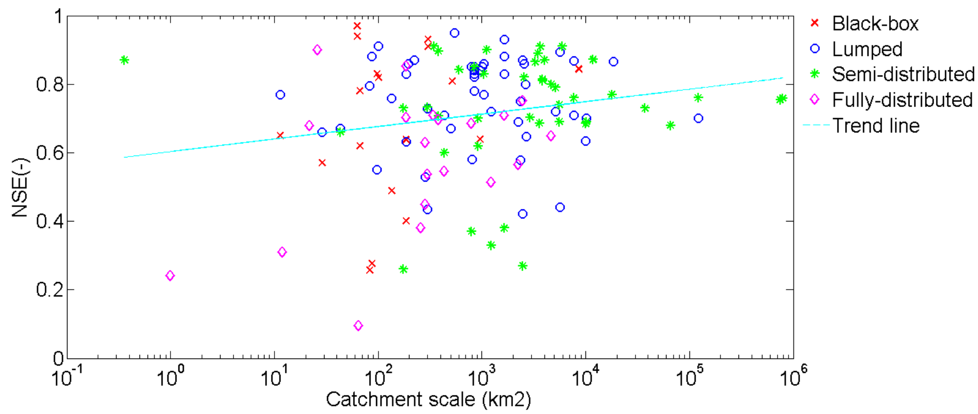

Figure 3. Performances across all model types with catchment scales in log. The trend line indicates the increase of model performance with the rise of catchment area.

between medium and large catchments is kept unchanged (use 50km^2 as changing steps). Until the pattern in small catchments is clear, the border line between medium and large catchments would then be tuned by applying the same method (with gradually increased changing steps from 50km^2 to 1000km^2). The final boundary is discovered as: small catchment between 0 and 200km^2; medium catchment between 200 and 3000km^2 and large catchment greater than 3000km^2. This result agrees with the definition in [13].

Figure 4 presents the performances of flow modelling in terms of different catchment size groups. Since the number of studies that use black-box models are too small, so these results have been excluded in this part. As the results presented in Figure 4, it is convincing to say that semi-distributed models give better modelling performance in large catchments. On the other hand, in small and medium catchments, there is no distinctive difference between model types, with only slightly better performance observed for lumped models in small catchments and semi-distributed models in medium catchments. In addition, it is obvious that there is still large disparity within each model type, e.g. for medium catchments, some of the lumped models surpass the semi-distributed models with efficiency as high as 0.85, i.e. Tank and Sacramento models used in [4, 14]. Therefore, it is necessary to perform a more specific classification within each model type. For this purpose, model names are used to stratify models in preferred and non-preferred (with 0.80 NSE as threshold) groups as shown in Table 1. It can be seen from Table 1 that SAC-SMA is not as suitable as Midlands Catchment Runoff Model (MCRM) in small catchments. And for medium and large catchments, the SWAT model is not efficient in both catchment sizes; comparatively, HBV model is better. The summary of Table 1 can be used as a simple matching system when other CSFs information are deficient, especially for catchments with areas over 3000km^2.

Conclusion

Hydrologic modelling has become a decisive research domain in hydrology, particularly facilitated by fast development of computing and mathematical algorithms. Hydrological models are increasing complex and computational. Therefore, to choose a suitable model for a given catchment is becoming a complex problem. Because there are some fundamental issues remain unsolved in the community such as what is the optimum way of measuring catchment

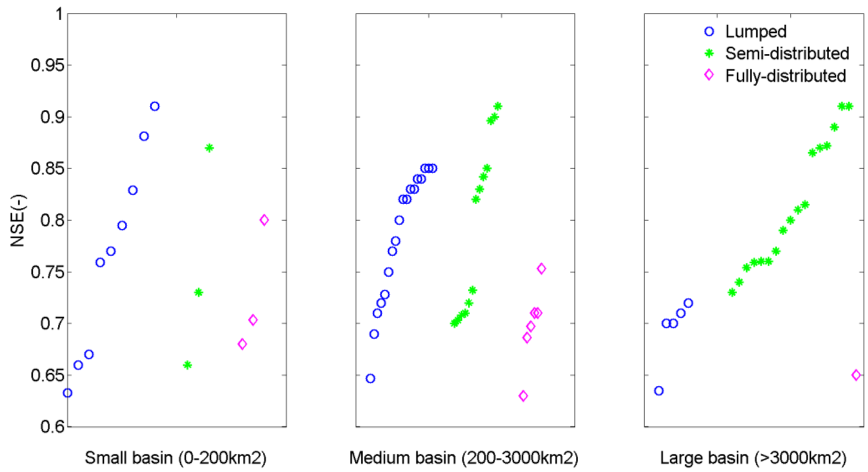

Figure 4. Relationship between model types and performances of flow modelling in respect to the most suitable border lines found for small, medium and large catchments. Within each catchment size group, the results are not shown in the order of catchment scales; instead they are sorted in the order of ascending NSE. The number of studies for black-box models is too small to compare, so these results are excluded. Also it is noted that only the NSE results that are above 0.60 are shown here for a better visual illustration (Level 2).

complexity and how to discriminate various hydrological models. Hence the motivation behind this study is to gather a large number of publications with different types of hydrological models and various catchment situations, to build a matching system between catchment complexity and model complexity. So that future hydrologists are able to assess various catchments and different hydrological models more accurately.

In this study, catchment size which has been classified into small, medium, and large size groups, which are then used as a sole indicator to present catchment complexity. As a result, a significant correlation between semi-distributed models and large catchments (>3000km^2) are uncovered. This attempt provides specific choice of models and model types across all catchment scales. However, this study has two limitations: firstly this is only a preliminary

Table 1. The preferred and non-preferred models used for small, medium and large catchments. The model names in the table are ordered from the most occurred to the least occurred, with the occurrence shown in brackets. When two models have the same number of occurrence, the one with lower NSE shows first in the non-preferred group, and the model with higher NSE is listed first in the preferred group (Level 2). *PDM in small catchments is used as a semi-distributed model; TOPMODEL in medium catchments is used as a lumped model; ARNO in large catchments is used as a semi-distributed model

Models	**Small catchment**		**Medium catchment**		**Large catchment**
	M2	M3	M2	M3	M3
Preferred (NSE>0.8)	MCRM$_{(4)}$ SAC-SMA$_{(1)}$	TOPMODEL$_{(1)}$	SAC-SMA$_{(4)}$ Xinanjiang$_{(2)}$	HBV$_{(2)}$ TOPMODEL$_{(2)}$	HBV$_{(4)}$ BTOPMC$_{(3)}$
Not preferred (NSE<0.8)	SAC-SMA$_{(2)}$ PDM$_{(1)}$	PDM*$_{(1)}$ HSPV$_{(1)}$	SAC-SMA$_{(4)}$ PDM$_{(2)}$	SWAT$_{(3)}$ HSPF$_{(1)}$	SWAT$_{(5)}$ BTOPMC$_{(2)}$

version of the matching system between catchment complexity and model complexity, so it does not cover the full spectrum of papers; secondly there are some conflicting information exist between different papers. Therefore in order to tackle the aforementioned limitations, a physically based fully distributed hydrological model with virtual catchments will be employed in our future study. Through which, a sophisticated matching system between model complexity and catchment complexity could be realized. And in addition, a flexible adaptive hydrological model with modern optimization techniques will also be beneficial for the system validation.

Since the hydrology community have already spent a great deal of effort utilizing various hydrological models and choosing a model that may not be suitable for a given catchment, so a clear matching system between catchment complexity and model complexity is the pivotal step towards the broader goals. We hope that this study will be a small step toward further engaging community in advancing the research of catchment complexity and model complexity for the sake of improved flow modelling and forecasting.

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