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A PSEUDO VALIDATION ALGORITHM FOR HYDROLOGICAL MODEL RELIABILITY ASSESSMENT

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A pseudo validation algorithm, which is capable of identifying the prediction uncertainty through recognizing and quantifying the different uncertainty sources in a hydrologic model, is manipulated as an instrument for hydrological model reliability assessment. For implementation, the pseudo validation algorithm is manipulated in order to compare TOPMODEL with different vertical flux calculation components, which have been applied to two Japanese basins. An index, which originates from the Nash-Sutcliffe efficiency, named Model Structure Indicating Index (MSII), is used to quantify the model reliability under different magnitudes of input uncertainty. The results show that within a small magnitude of input uncertainty, the reliability of a five parameter TOPMODEL is worse than a six parameter TOPMODEL. However, within larger magnitudes of the input uncertainty, the reliability of the five parameter TOPMODEL is better than that of the six parameter TOPMODEL, this shows that the pseudo validation algorithm can be used as a reference for hydrological modeling.

Key Words: *prediction uncertainty, model validation, TOPMODEL, hydrologic modeling*

1. INTRODUCTION

Commonly, validation is defined as the estimation of the confidence in the ability of any prediction model to perform with a certain qualitative outcome for its intended purpose. In hydrologic science, the term is often used to indicate a thorough model testing. It is a time-consuming process that requires a massive amount of data. Similar to the model calibration process, the quality/representativeness of the data used for model validation is extremely essential. However, in most cases, the accuracy of the input data is actually unknown. As a consequent of this, all hydrologic models are being calibrated, validated and manipulated under an unknown magnitude of input uncertainty. The reason why these models are still capable of regenerating a realistic and valid watershed response data series is due to the models' calibration processes. This fact has seldom been explicitly discussed.

The capability of a hydrologic model to regenerate a realistic and valid watershed response series under a certain level of data input uncertainty is highly related to the model structure. By acknowledging that input data (in this study, rainfall data) errors propagate and persist in hydrologic models, and corrupt the parameter estimation processes, a pseudo validation process can be performed by using limited observation data to assess the adaptability and reliability of a hydrologic model. Instead of acquiring massive amounts of observation data, the pseudo validation algorithm validates the model through observing the model behavior under different magnitudes of the input uncertainty[1)]. In this paper, the logic behind the algorithm is thoroughly discussed; then the validity of the algorithm is verified by demonstrating the comparisons of two TOPMODELs with different vertical flux structure. Moreover, it is shown that this method is used to access not only the validity of the model structure, but also the reliability of input data.

The basic idea of the algorithm is: if a model is capable to regenerate a realistic and valid watershed response series in the future under unknown magnitude of input uncertainty, it must capable to compensate the error contaminated data under certain level of input uncertainty by using the existed record data. To do this, first, the Monte Carlo simulation method is applied to add bias items into the model input data series (rainfall), and then the rainfall realizations, parameter space, and the model outcomes (outflow discharge) under different bias levels are acquired. Secondly, by examining the counter relationship between the model simulation outcomes, the calibration outcomes and the observed watershed response series (discharge), an uncertainty structure can be recognized. Finally, through this process, the parameter uncertainty, calibration uncertainty, and the model structure uncertainty, created by the input data uncertainty are recognized, separated, and quantified.

By applying this pseudo validation process, TOPMODELs with different vertical flux calculation components are compared by applying it to two Japanese watersheds.

The Nash-Sutcliffe effeciency[2] and an index which originated from the Nash-Sutcliffe efficiency named the Model Structure Indicating Index (MSII)[1], is used to quantify and assess the reliability of the candidate models, with a larger value of MSII indicating a hydrologic model with a poorer structure. The results show that within a small magnitude of input uncertainty, the reliability of a five parameter TOPMODEL is worse than a six parameter TOPMODEL. However, within a larger magnitude of input uncertainty, the reliability of a five parameter TOPMODEL is better than a six parameter TOPMODEL. This indicates that the pseudo validation algorithm can be used as an efficient instrument for water resources management in the areas of hydrological modeling and for rainfall runoff simulations of poorly recorded or ungauged basins.

2. DESCRIPTION OF THE ALGORITHM AND THE LOGIC BEHIND THE PROCESS

The straightest way to think about a pseudo validation algorithm is that: if a model is capable of predicting the future conditions of a particular type of catchment under a certain level of input error, it must be capable of predicting the current conditions as well, under a certain level of input error.

The algorithm[1] is used to test the stability of the predictive capability possessed by a hydrologic model under a certain magnitude of input uncertainty. The idea can be clarified by referring to the simplified modeling procedure depicted in **Fig.1,** which is modified according to Sargent[3].

In **Fig.1** the problem entity is the system to be modeled; the conceptual model is the mathematical representation of the problem entity developed for a particular study; the computerized model is the conceptual model implemented on a computer. The conceptual model is developed through an analysis and modeling phase; the computerized model is developed through a computer programming and implementation phase, and

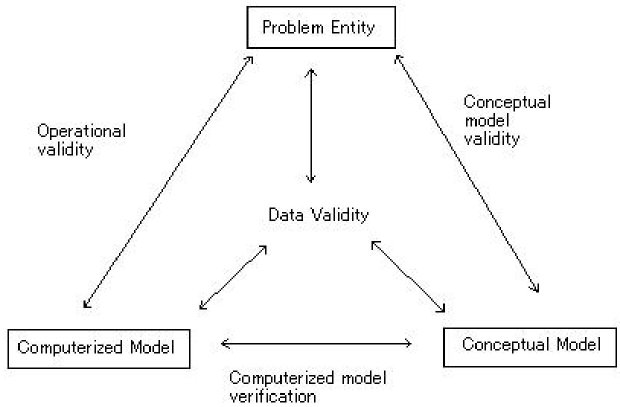

Fig.1 Algorithm for uncertainty recognition and quantification.

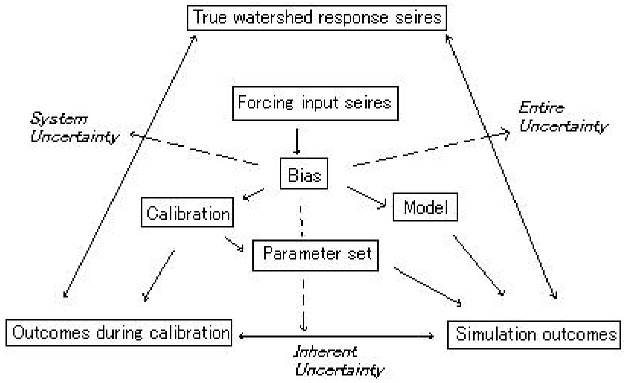

Fig.2 Diagram of uncertainty recognition and quantification.

inferences about the problem entity are obtained by conducting computer experiments on the computerized model in the experimentation phase. Conceptual model validity is the determination of whether or not the theories and assumptions underlying the conceptual model are correct and that the model representation of the problem entity is "reasonable" for the intended purpose of the model.

Computerized model verification ensures that the computer programming and implementation of the conceptual model is correct. This is often referred to as the model calibration process. Operational validity is the determination that the model's output behavior has sufficient accuracy for the model's intended purpose over the domain of the model's intended applicability. In most cases, this is the model validation process. Data validity ensures that the data necessary for model building, model evaluation and testing, and conducting the model experiments to solve the problem are adequate and correct[3]. However, the preciseness is an unknown.

Conventionally, these models require massive amounts of data for the validation process, which makes model validation an intricate mission to perform. Input data uncertainty makes data validity, which is located in the core position of the modeling scheme, difficult to perform. Since there is no way to assure the accuracy of the data used for model calibration and validation, the subsequent result is that the best calibrated parameter set may or may not equal to the "effective value", which will make a hydrologic model works properly. A feasible alternative to this is to recognize that within certain levels of input uncertainty, there is a possibility that a hydrologic model would still be capable to regenerate true watershed characteristics. In this sense, both the model calibration process and error propagation scheme induced by the model structure must be taken into consideration.

Fig.2 depicts the schematic diagram of the pseudo validation algorithm manipulated in this study[4]. The bias items, which are located at the center of the structure, dominate the whole uncertainty propagation scheme. If the focus is only on the changing of the bias items and its impact on the model outcome, which is referred to as the entire uncertainty (EU) in this study, it can be seen as a sensitivity analysis of the input data error. By using the system uncertainty (SU), indicated by the predictive capability of the model under input uncertainty, the distance between system uncertainty and entire uncertainty indicates the effectiveness/goodness of the representativeness of the calibrated parameter sets, which can be referred to as a measure of model divergence[5]. Inherent uncertainty (IU) represents the variability of the parameter sets generated from specified input uncertainty levels. The distance between inherent uncertainty and entire uncertainty indicates the capability of model to adapt itself to the specified input uncertainty, which is dominated by the model structure. The quantified and categorized uncertainty: system uncertainty, entire uncertainty and inherent uncertainty are integrated into MSII, which enables it to evaluate the goodness of the model structure through observing its behavior under certain magnitudes of input uncertainty. (Detailed algorithm for the recognition, separation and the relationship between the categorized uncertainties is described in Chiang *et al*., 2005. [1])

Fig.3 depicts a schematic diagram of the uncertainty structures. In **Fig.3**, Q_o denotes observed discharge; Q_b denotes a model outcome with the best-fitted parameter set and Q_e: denotes a model outcome with a parameter set within the whole parameter space. ε_{SU}, ε_{EU} and ε_{IU} represent the difference of hydrographs amongst the observed data, estimated with a parameter set in the parameter space, and estimated with the best fitted parameter set. The system uncertainty, entire uncertainty and inherent uncertainty are evaluated by using ε_{SU}, ε_{EU} and ε_{IU} with Nash-Sutcliffe efficiency. The quantified and categorized uncertainties: system

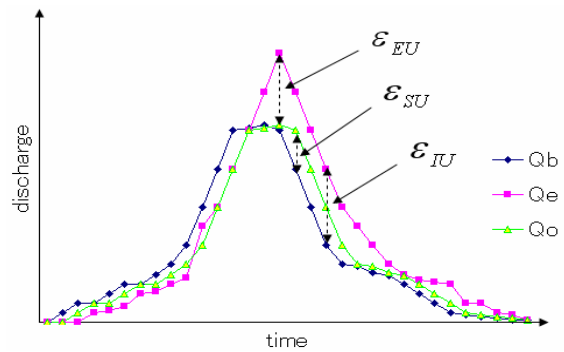

Fig.3 Schematic diagram of the uncertainty structures.

uncertainty, entire uncertainty and inherent uncertainty are integrated into MSII, which enables it to evaluate the goodness of the model structure through observing its behavior under certain magnitudes of the input uncertainty. Model Structure Indicating Index (MSII)[1] is defined as:

$$MSII = \frac{IU - EU}{SU} \qquad (1)$$

The difference between the entire and the inherent uncertainty is used as the numerator in the Eq.(1), while the system uncertainty is used as the denominator. The numerator is expected to be a smaller value if the model is considered to have a better chance of reproducing a realistic watershed response series. It is a measure of the possibility of a model to adapt itself to the input uncertainty. The larger the magnitude the less likely the model will be able to adapt itself to the error contaminated input data, which indicates the inability of the calibrated parameter space to drive the model to reproduce a realistic watershed response due to the insufficient structure of the hydrologic model.

The numerator shows a measure of the ability of a hydrologic model to adapt to the uncertainty contained input data. The numerator in itself is not enough to reveal the model structure, a component showing the model predictive capability is needed. The denominator of MSII indicates the effectiveness/goodness of the model calibration results and the predictive capability of the model, which therefore, enables it to reflect the calibration scheme explicitly. The index interprets the variance caused by the calibration process and model structure in a dimensionless form through the Nash-Sutcliffe efficiency. During the implementation of the model evaluation, the system uncertainties less than zero are excluded from the calculation of MSII due to its insignificance. Hence the smaller value of the MSII represents better model structure. The range of MSII is: $0 \le MSII < \infty$.

3. MODEL DESCRIPTION

In order to perform a pseudo validation process, TOPMODEL is used in this study. TOPMODEL is almost 30 years old and has been the subject of numerous applications to wide variety of catchments. The code used herein is a modification version based on the TOPMODEL 95.02 acquired from the official website of TOPMODEL (http://www.es.lancs.ac.uk/hfdg/topmodel.html). TOPMODEL is a set of programs for rainfall-runoff modeling in single or multiple subcatchment in a semi-distributed way and using girded elevation data for the catchment area. It is considered to be a physically based model as its parameters can be, theoretically measured in situ[6)7)]. Subcatchment discharge is routed to the catchment outlet by using a time-area diagram with a constant velocity throughout the catchment area, which is a parameter that needs to be calibrated. The infiltration excess mechanism and evapotransportation mechanism is not included in this study.

In TOPMODEL, there are several parameters that need to be calibrated before model validation and implementation. Basically they are: *m*, the decay factor which is the controlling rate of decline transmissivity with increasing storage deficit; T_0, the hydraulic transmissivity; t_d : the time delay constant for vertical flux calculation; *RV*: the overland flow velocity. Q_0, the initial base flow and *Sr0*, the initial root zone storage deficit, which are specified at the start of simulation.

Inside TOPMODEL, the vertical drainage q_v from unsaturated zone storage at any point of topographic index class *i* is calculated either by Eq.(2):

$$q_{v_i} = \frac{Suz}{S_i t_d} \tag{2}$$

where *Suz* is the storage in the unsaturated zone, t_d is a time delay constant and S_i is a local storage deficit; or by Eq.(3)[8)]:

$$q_{v_i} = \alpha K_0 e^{-S_i / m} \tag{3}$$

where α is the effective vertical hydraulic gradient, K_0 is the saturated conductivity at the surface, and *m* is a model parameter controlling the rate of decline of transmissivity with increasing storage deficit. If the value of α is set to unity, thus assuming that the vertical flux is equal to the saturated hydraulic conductivity just at the water table, it is eliminated as a parameter[8)]. Eq.(2) is the equation of a linear store with a time constant $S_i t_d$ that increases with increasing depth to the water table[7)]. In the model, the K_0 is acquired by T_0, that means the number of the parameter are five (*m*, T_0, Q_0, *RV* and *Sr0*)or six (*m*, T_0, t_d, Q_0, *RV* and *Sr0*). The two TOPMODEL which use the different vertical flux computing components are applied for the performance of model quantitative comparison.

4. DATA DESCRIPTION

Two Japanese watersheds are used for the pseudo validation of the two TOPMODEL: Yasu River basin (387 km^2) and Kamishiba basin (211 km^2). The DEM data and the rainfall data used in the study are described as below:

(1) DEM data

For TOPMODEL, two data sets are needed before the simulation, the histogram of topographic index and the time-distance diagram, which are both acquired through DEMs in this study. 50m resolution raster DEM data is used for data extraction. The DEM algorithm manipulated in this study for preliminary processing (depression removing, flow direction determination and flow accumulation value calculation) is based on the algorithm proposed by Jenson and Domingue[9)]. Topographic index derivation was obtained by using DEM algorithm proposed by Quinn[10)].

(2) Rainfall and discharge data

Rainfall data of the Yasu River basin was collected from four rainfall gauging stations inside the watershed; they are Yasu, Minakuchi, Kouka and Oogawara. The average precipitation was obtained by using Thiessen polygon method. The discharge data for the Yasu River basin is collected from the ground gauging station and a rating curve is applied for transferring the water level to the discharge.

For the Kamishiba basin, a radar rainfall data with time interval of 10 minutes is transferred to the average rainfall with time interval of 1 hour along the corresponding catchment range. Discharge data is acquired from the inflow data of the Kamishiba dam.

For each watershed, one flood event is selected for Monte Carlo simulation. Random generated bias items are added to the original input series for every time step in order to formulate the rainfall realizations with specified distribution and standard deviations. A normal distribution with a mean

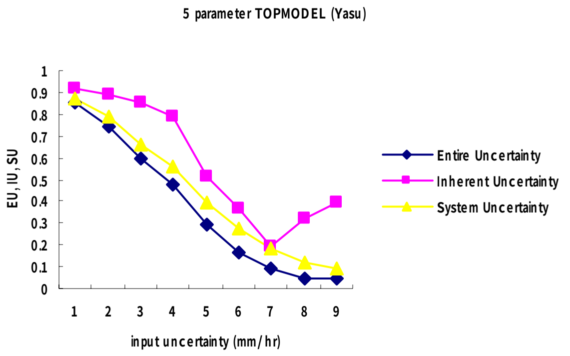

Fig.4 EU, IU and SU of the five parameter TOPMODEL which applying to the Yasu River basin.

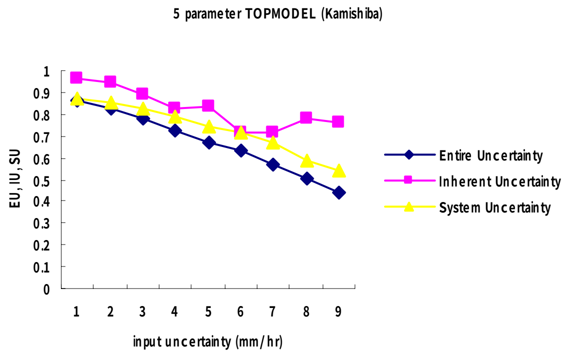

Fig.6 EU, IU and SU of the five parameter TOPMODEL which applying to the Kamishiba basin.

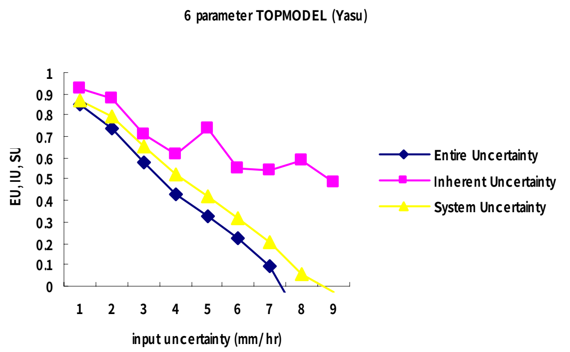

Fig.5 EU, IU and SU of the six parameter TOPMODEL which applying to the Yasu River basin.

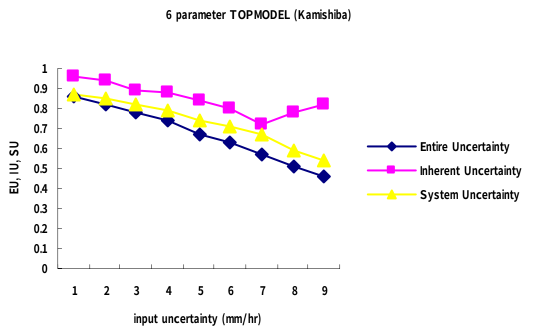

Fig.7 EU, IU and SU of the six parameter TOPMODEL which applying to the Kamishiba basin.

equals to zero and standard deviation from 1.0 to 9.0 (mm/hr) is used to generate the rainfall realizations under specific magnitude of input uncertainty. For each specific magnitude of input uncertainty, 100 rainfall realizations and 100 parameter sets are derived. 10,000 model outcomes are generated from the combination of the 100 rainfall realizations and the 100 parameter sets of input from the two TOPMODEL which were derived previously.

5. RESULTS

The variation of the categorized uncertainty (entire, inherent and system uncertainty) under different levels of input uncertainty is acquired through the pseudo validation process. **Fig.4** through **Fig.7** are the variation of the categorized uncertainty of the five and six parameter TOPMODEL applied in the Yasu River basin and the Kamishiba basin.

The results show that there is a similar tendency within larger magnitudes of the input uncertainty, for the five parameter TOPMODEL to outperform the six parameter TOPMODEL. Another interesting result is that apparently the performance of the TOPMODEL (no matter what the vertical calculation component is), when applied to the Kamishiba basin, is better than the TOPMODEL applied to the Yasu River basin. This indicates that the application of TOPMODEL on the Kamishiba basin is more appropriate than the application on the Yasu River basin. Another explanation is the quality/representativeness of the rainfall and discharge data, which were used for the pseudo validation process. Since the average rainfall data acquired for the Kamishiba basin is transferred from the calibrated radar data, the precision is higher than the average rainfall data acquired for the Yasu River basin, which is transferred from four ground gauging stations. This is a good proof that the quality of the data used for validation is essential, and the proposed method well reflects this condition. **Fig.8** is the MSII of the TOPMODEL with different vertical calculation components applied to the different catchments. As described in the previous section, a smaller magnitude of MSII indicates a better model structure/reliability against the level of input uncertainty.

The rapid ascending tendency of the six parameter TOPMODEL, when applied to the Yasu

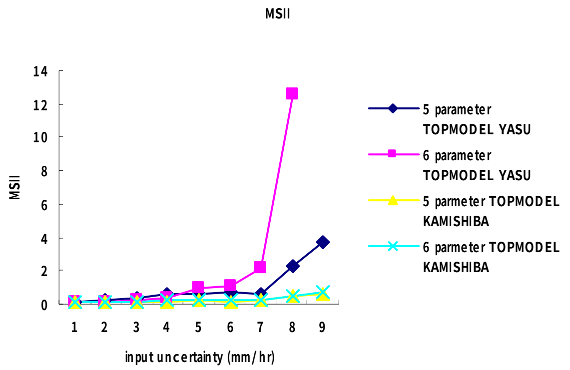

Fig.8 MSII of the TOPMODEL with different vertical calculation component which applying to different catchment.

River basin, implies that it has the lowest reliability against increasing inputs of uncertainty amongst the four tests. The five parameter TOPMODEL, when applied to the Kamishiba basin, reveals that it has the best reliability against the different levels of input uncertainty due to its MSII mildly ascending tendency. The reason that the five parameter TOPMODEL is more stable than the six parameter TOPMODEL is due to the physical bases of its parameter. Even the time delay constant t_d performs well during small magnitudes of the input uncertainty, with increasing input uncertainties, parameters lacking physical bases are incapable to compensate for these discrepancies. The results also implicitly indicate that if the quality/ representativeness of the data used for validation process is high preciseness, the model structure won't matter the simulation so much.

6. CONCLUSIONS AND DISCUSSIONS

In this study, a pseudo validation algorithm was manipulated and is used to assess TOPMODEL in the context of different vertical flux calculation components when applied to two Japanese catchments. The results show that TOPMODEL with five parameters perform better than the six parameters TOPMODEL, both in the Yasu River basin and in the Kamishiba basin under a larger magnitude of the input uncertainty, but for smaller magnitudes of the input uncertainty, the opposite is true. TOPMODEL with five parameters is more stable than the one with six parameters in both catchments. The adaptability of the TOPMODEL when applied to the Kamishiba basin catchment was superior to that of the catchments in the Yasu River basin. This indicates that the quality/ representativeness of the observed data of the the Kamishiba basin is better than that of the Yasu river basin.

The algorithm generates the parameter set space by introducing noise items into input data with a specified probability distribution. This reflects the truth that the parameter uncertainty came from the uncertainty of data at hand and the way the model structure responds to it. This indicates the pseudo validation algorithm is not only capable of assessing the reliability of the hydrologic model structure and the calibration process, but also implicitly indicates the quality and the representativeness of the data used for validation process.

According to the research results, the pseudo validation algorithm can be an efficient instrument for model refinement assessment. However, various rainfall styles should also be taken into consideration. This will be done in the following research.

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REFERENCES

1) Chiang, S., Tachikawa, Y. and Takara, K.: An approach to uncertainty identification in hydrological modeling: *Annual of Hydraulic Engineering, JSCE*, Vol.49, pp. 211-216, 2005.
2) Nash, J. E., and Sutcliffe, J. V.: River flow forecasting through conceptual models, Part 1, A discussion of principles: *Journal of Hydrology*, Vol.10, pp. 282-290, 1970.
3) Sargent, R. G.: Validation and verifocation of simulation models. The 1999 Winter Simulation Conference, 5 – 8 December 1999, Squaw Peak, Phoenix, AZ. In *Proceedings of the 1999 Winter Simulation Conference*, pp. 39-59, 1999.
4) Chiang, S.: *Hydrologic Model Comparison and Refinement through Uncertainty Recognition and Quantification*, Doctoral Thesis, Kyoto University, 2005.
5) Sage, A. D. and Melsa, J. L.: *Estimation Theory with Applications to Communication and Control*. McGraw-Hill, New York, 1971.
6) Beven, K., and Kirkby, M. J.: A Physically based variable contributing area model of catchments hydrology: *Hydrological Sciences Bulletin*, Vol.24, pp. 43-69, 1979.
7) Beven, K.: Topmodel: A Critique: *Hydrological Processes*, Vol.11(9), pp. 1069-1085, 1997.
8) Beven, K., Lamb, R., Quinn, P., Romanowicz, R. and Freer J.: TOPMODEL, *Computer models of watershed hydrology*, Water Resources Publications, pp. 627-668, 1995.
9) Jenson, S. K. and Domingue, J. O.: Extracting Topographic Structure from Digital Elevation Data for Geographic Information-System Analysis, *Photogrammetric Engineering and Remote Sensing*, Vol.54, pp. 1593-1600, 1988.
10) Quinn, P., Beven, K., Chevallier, P. and Planchon, O.: The Prediction of Hillslope Flow Paths for Distributed Hydrological Modeling Using Digital Terrain Models: *Hydrological Processes*, Vol.5, pp. 59-79, 1991.

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