MAPPING STREAMFLOW CHARACTERISTICS IN THE MOST UPSTREAM BASINS THROUGHOUT JAPAN USING ARTIFICIAL NEURAL NETWORKS

Ryosuke ARAI1, Yasushi TOYODA2 and So KAZAMA3

1Member of JSCE, Research Scientist, Sustainable System Research Laboratory, Central Research Institute of Electric Power Industry (Abiko 1646, Abiko-shi, Chiba 270-1194, Japan) 
Doctoral Student, Graduate School of Engineering, Tohoku University (Aoba 6-6-06, Sendai 980-8579, Japan) 
E-mail: arai@criepi.denken.or.jp (Corresponding Author)

2Member of JSCE, Deputy Associate Vice President, Sustainable System Research Laboratory, Central Research Institute of Electric Power Industry (Abiko 1646, Abiko-shi, Chiba 270-1194, Japan) 
E-mail: toyo@criepi.denken.or.jp

3Member of JSCE, Professor, Graduate School of Engineering, Tohoku University (Aoba 6-6-06, Sendai 980-8579, Japan) 
E-mail: so.kazama.d3@tohoku.ac.jp

We developed and validated artificial neural networks (ANNs) to map the streamflow characteristics in the most upstream basins throughout Japan. The ANNs output mean annual runoff height (QMEAN) and percentiles of daily streamflow, including nine different groups, by inputting basin characteristics, including climate, land use, soils, geology, and topography. The generalization performances of the ANNs showed $R^2 = 0.70$ in the QMEAN and $R^2 = 0.20 – 0.74$ in the streamflow percentiles. We succeeded in mapping the streamflow characteristics in the most upstream basins throughout Japan, which reflected the rainfall and snowfall characteristics in the country. The streamflow characteristic maps revealed that developing run-of-river hydropower stations in heavy snowfall areas, such as the Tohoku and Hokuriku regions facing the Sea of Japan, is suitable.

Key Words: flow regime, run-of-river hydropower, data-driven approach, cross-validation

1. INTRODUCTION

Feed-in tariff schemes have been introduced for hydropower with an output of ≤30,000 kW since 2012 in Japan, which has attracted social attention for the development of small-scale run-of-river hydropower stations. Obtaining a flow duration curve is necessary for their development owing to the settings of the electric power output and maintenance streamflow. However, it requires gauging stations for streamflow data, which entail significant costs and time. Therefore, streamflow estimates in small and ungauged basins in Japan are important.

Beck et al.1) and Barbarossa et al.2) utilized the streamflow and basin characteristics of several thousand basins across the globe. Although Arai et al.3) developed ANNs targeting Japanese basins, they did not develop streamflow maps.

The objective of this study was to map the streamflow characteristics in most upstream basins throughout Japan. The basin size was set to approximately 10 km$^2$ to map streamflow characteristics. First, we selected target basins with negligible anthropogenic disturbances for the development of ANNs. Then, we trained ANNs that output streamflow characteristics based on the inputs of basin characteristics. Finally, maps for the streamflow characteristics in most upstream basins throughout Japan were produced using trained ANNs.
2. DEVELOPMENT AND VALIDATION
METHODS OF ANNs

In this study, we trained ANNs that can output streamflow characteristics by inputting basin characteristics, and then validated them. In this section, we describe the selection procedures for gauged basins, streamflow and basin characteristics, ANN design, training procedures, and validation methods.

(1) Selection procedures of gauged basins

We targeted gauged daily streamflow data published in the Database of Dams (http://mudam.nilim.go.jp/) and the Water Information System (http://www1.river.go.jp/). Considering the record period of streamflow and basin characteristics, we set the target period from 1981 to 2015. Because this study assumes the development of run-of-river hydropower stations in the most upstream basins, we eliminated artificial impacts on streamflow from the target basins. Specifically, we checked that there were no dams or hydropower stations in the target basins by referencing the Dam Yearbook4) and the map of the Geospatial Information Authority of Japan (https://maps.gsi.go.jp/). In addition, we set the selection criteria such that the minimum record period of streamflow was five years. Consequently, the number of target basins was 448. The catchment size and record period of the streamflow in the target basins are listed in Table 1.

(2) Streamflow characteristics

The mean annual runoff height (QMEAN) and percentiles of daily streamflow (Q1, Q5, Q10, Q20, Q50, Q80, Q90, Q95, and Q99) were set for the streamflow characteristics. The nine indices correspond to the exceedance probability of the daily streamflow calculated using the period-of-record flow duration curve. For example, Q1 had the highest value in the percentiles.

(3) Basin characteristics

We set 172 basin characteristics related to climate, land use, geology, soil, and topography (Table 2). The data sources and resolutions are listed in Table 2. Because these data sources were expressed by Geographic Information System (GIS), we integrated the basin characteristics using ArcGIS 10.6, and then extracted them from the coverage of each basin using digital elevation model (DEM) data5). The resolutions of the basin characteristics were adjusted using nearest neighbor interpolation so that we could treat the characteristics even at different resolutions (Table 2).

The precipitation and snow indices originated from daily data >1 (mm/d). We applied APHRO_JP6), which is an observed rainfall database throughout Japan, to the data source of the precipitation indices. The snow indices were applied to the Agro-Meteorological Grid Square Data7), which were calculated using a snow water equivalent model considering the heat and radiation balance. According to the Poisson process of precipitation events, the mean frequency of daily precipitation and daily snowfall was calculated as the reciprocals of the mean days until the next precipitation event. Additionally, we set an index of precipitation seasonality, which was used by Beck et al.8). This index was calculated by subtracting the monthly mean precipitation from the annual mean precipitation divided by 12, adding these values over all months, and finally dividing by annual mean precipitation. While the indices of precipitation and snow considered the time variability corresponding to the period of streamflow records, the other indices were set as constant values in the basin. Aridity index was calculated by dividing the mean annual precipitation by the annual potential evaporation. In this study, we applied the potential evaporation data developed by Zomer et al.9) to the aridity index. However, the mean annual precipitation based on APHRO_JP has temporal variability. Thus, we applied a 30-year average value originating from the National Land Numerical Information (http://nlftp.mlit.go.jp/ksj-e/index.html) to the mean annual precipitation in the calculation. The index of potential evapotranspiration seasonality was calculated equally with precipitation seasonality. Using multiple indices of geology and soil, previous studies have evaluated the relationships between streamflow and geology or soil6, 10, 11). Thus, we set indices for geology and soil based on these studies6, 10, 11).
| Description                                      | Subgroups | Unit | Data source                                      | Time variability | Resolution |
|--------------------------------------------------|-----------|------|-------------------------------------------------|------------------|------------|
| Mean annual precipitation                        |           | mm/y | APHRO_JP                                        | +                | 180 s      |
| Mean daily precipitation                         |           | mm/d | APHRO_JP                                        | +                | 180 s      |
| Mean frequency of daily precipitation            |           | 1/d  | APHRO_JP                                        | +                | 180 s      |
| Mean annual maximum daily precipitation          |           | mm/d | APHRO_JP                                        | +                | 180 s      |
| Precipitation seasonality                        |           |      | APHRO_JP                                        | +                | 180 s      |
| Standard deviation of mean annual precipitation  |           | mm/y | APHRO_JP                                        | +                | 180 s      |
| Mean annual snow water equivalent                |           | mm/y | Agro-Meteorological Grid Square Data            | +                | ~1 km      |
| Mean daily snow water equivalent                 |           | mm/d | Agro-Meteorological Grid Square Data            | +                | ~1 km      |
| Mean frequency of daily snowfall                 |           | 1/d  | Agro-Meteorological Grid Square Data            | +                | ~1 km      |
| Standard deviation of mean annual snow water     |           | mm/y | Agro-Meteorological Grid Square Data            | +                | ~1 km      |
| Mean annual potential evaporation                |           | mm/y | CGIAR-CSIF                                      | ~1 km            |            |
| Potential evaporation seasonality                |           |      | CGIAR-CSIF                                      | ~1 km            |            |
| Aridity index                                    |           |      | CGIAR-CSIF and National Land Numerical Information (G02) | ~1 km            |            |
| Mean temperature                                 |           | °C   | National Land Numerical Information (G02)       | ~1 km            |            |
| Maximum temperature                              |           | °C   | National Land Numerical Information (G02)       | ~1 km            |            |
| Minimum temperature                              |           | °C   | National Land Numerical Information (G02)       | ~1 km            |            |
| Amount of global solar radiation                 |           | MJ/m²| National Land Numerical Information (G02)       | ~1 km            |            |
| Sunshine duration                                |           | h    | National Land Numerical Information (G02)       | ~1 km            |            |

**Land use**

| Description                                      | Subgroups | Unit | Data source                                      | Resolution |
|--------------------------------------------------|-----------|------|-------------------------------------------------|------------|
| Land use classification of National Land Numerical Information | 11 % | National Land Numerical Information (L03-b_r) | ~100 m     |

**Geology and soils**

| Description                                      | Subgroups | Unit | Data source                                      | Resolution |
|--------------------------------------------------|-----------|------|-------------------------------------------------|------------|
| Large classification of surface geology          | 79 %      |      | National Land Numerical Information (G05_003)   | ~1 km      |
| Geological time                                   | 7 %       |      | National Land Numerical Information (G05_003)   | ~1 km      |
| Geological classification of Mushiake et al.¹⁰  | 6 %       |      | National Land Numerical Information (G05_003)   | ~1 km      |
| Soil classification of National Land Numerical Information | 7 % |      | National Land Numerical Information (G05_004)   | ~1 km      |
| Soil classification of Yokoo et al.¹¹           | 3 %       |      | National Land Numerical Information (G05_004)   | ~1 km      |

**Topography**

| Description                                      | Subgroups | Unit | Data source                                      | Resolution |
|--------------------------------------------------|-----------|------|-------------------------------------------------|------------|
| Topographical classification of National Land Numerical Information | 40 % |      | National Land Numerical Information (G05_002)   | ~1 km      |
| Maximum elevation                                | m         |      | HydroSHEDS                                      | 15 s       |
| Minimum elevation                                | m         |      | HydroSHEDS                                      | 15 s       |
| Catchment size                                   | km²       |      | HydroSHEDS                                      | 15 s       |
(4) Design of ANNs

We developed ANNs with two middle layers (Fig. 1(a)). The locations of the neurons are expressed by \( i \) and \( j \), as shown in Fig. 1(a). The number of neurons corresponded to 10 in both layers. The ANNs structure was designed by trial and error to maximize its performance. The ANNs output the streamflow characteristics in the output layer by inputting basin characteristics into the input layer. We developed ANNs that output the QMEAN and streamflow percentiles. This means that the number of neurons in the output layer corresponded to one and nine in the ANNs for the QMEAN and streamflow percentiles, respectively. When outputting the streamflow percentiles, the estimated values must decrease from Q1 to Q99.

To ensure that the ANNs learned the order of the streamflow percentiles, we designed ANNs with nine neurons in the output layer for the streamflow percentiles. Generally, ANNs with enormous input variables tend to overfit, and redundant input variables show the highest average performance in all groups. In this study, we employed upper-ranked variables that showed the highest average performance in all streamflow percentiles.

In general, ANNs can obtain outputs through forward propagation from the input to the output layer. In this process, the following equation is applied:

\[
y_{i,j} = f(u_{i,j}) = f(b_{i,j} + \sum_{i,j} x_{i,j}w_{i,j})
\]

where \( y_{i,j} \) is the output of neuron \((i, j)\), \( f(u_{i,j}) \) is the activating function, \( l \) is the number of neurons in the upper layer, \( x_{i,j} \) is the input of neuron \((i, j)\), and \( w_{i,j} \) and \( b_{i,j} \) express the weight and bias, respectively. A schematic representation of Eq. (1) is shown in Fig. 1(b). In this study, we employed the rectified linear function \( f_{\text{ReLU}}(u_{i,j}) \) in the middle layer and identity function \( f_{\text{out}}(u_{i,j}) \) in the output layer as the activating function. These equations are expressed as follows:

\[
f_{\text{ReLU}}(u_{i,j}) = \max(u_{i,j}, 0) \tag{2}
\]

\[
f_{\text{out}}(u_{i,j}) = u_{i,j}. \tag{3}
\]

(5) Training procedures of ANNs

The learning of ANNs was achieved by optimizing \( w_{i,j} \) and \( b_{i,j} \) such that the output error was minimized. We applied a stochastic gradient descent (SGD) to the optimization method\(^{(5)}\). In addition, we employed a mini-batch training approach\(^{(4)}\), in which the learning data were randomly segmented (mini-batch), data in a mini-batch were used for learning, and then \( w_{i,j} \) and \( b_{i,j} \) were updated at once. For a sample within a mini-batch, errors were obtained by forward propagation from the input to the output layer. In this study, we employed the mean square error for the cost function \( E_h \):

\[
E_h = \frac{1}{2} \sum_{k=1}^{K} (y_{k,4} - T_k)^2 \tag{4}
\]

where \( K \) is the number of output variables, and \( T_k \) is the true value for \( y_{k,4} \). In addition, the error in mini-batch \( E \) is expressed as

\[
E = \frac{1}{H} \sum_{h=1}^{H} E_h \tag{5}
\]

where \( H \) is the number of samples in the mini-batch. Next, \( w_{i,j} \) was updated by SGD as follows:

\[
w_{i,j}(t+1) = w_{i,j}(t) - \eta_{i,j} \frac{\partial E}{\partial w_{i,j}(t)} = w_{i,j}(t) - \eta_{i,j} \sum_{k=1}^{K} \frac{\partial E_h}{\partial w_{i,j}(t)} \tag{6}
\]

where \( t \) is the number of learning steps, and \( \eta_{i,j} \) is the learning coefficient. Gradient \( \frac{\partial E_h}{\partial w_{i,j}(t)} \) in Eq. (6) was obtained using a back-propagation algorithm\(^{(4)}\). The value \( b_{i,j} \) was also updated using the same approach used for \( w_{i,j} \).

(6) Validation methods of ANNs

In this study, we conducted five-fold cross-validations to evaluate the generalization performance. First, we separated all target basins (448) into five groups. Next, we set one group as the test data and the other four groups as the training data. After the learning process, we calculated the determination coefficient \( R^2 \) between the true and output values for the training data groups to evaluate the training accuracy. To evaluate generalization performance, we calculated the \( R^2 \) between the true and output values for the test data group. The \( R^2 \) values were calculated for the QMEAN and streamflow percentiles. This validation step was repeated five times to include all the target basins as the test data group. Finally, we averaged these \( R^2 \) values.
3. MAPPING METHOD OF STREAMFLOW CHARACTERISTICS IN THE MOST UPSTREAM BASINS

Although the learning data were limited in Section 2 owing to cross-validation, we trained the ANNs by utilizing all the data to map streamflow characteristics. To identify the mapped basins, we searched basins with areas of 10 km² throughout Japan using DEM data. As a result, 8,901 basins were identified, and their characteristics were extracted. The basin characteristic data, which considered time variability (indices of precipitation and snow; Table 2), were set to the 10-year period from 2001 to 2010. Next, the streamflow characteristics in the 8,901 basins were output by inputting the basin characteristics into the trained ANNs. We also noted that the 8,901 basins were not selected by considering artificial impacts on streamflow, such as dams and hydropower stations. In addition, all basins were located in lowland areas, which may not be suitable for the development of run-of-river hydropower stations.

4. RESULTS AND DISCUSSION

(1) Generalization performance of ANNs

In this study, we heuristically selected the basin characteristics employed in the ANNs based on ρ between the basin and streamflow characteristics. Specifically, the basin characteristics with high values of ρ were preferentially selected. As a result, when applying the top 10 basin characteristics to the ANNs, the generalization performance was good in both the QMEAN and streamflow percentiles. Thus, we employed the top 10 basin characteristics as the input variables (Table 3). Because the average performance in all streamflow percentiles showed the highest value when applying the top 10 basin characteristics in Q20, we employed these for the input variables. The highest value was comparable to that of the other streamflow percentiles ($R^2 = 0.44–0.47$).

The results of the five-hold cross-validations are shown in Fig. 2. The performance of the training data was better than that of the testing data (generalization performance) for all streamflow characteristics. The generalization performance of the QMEAN was good ($R^2 = 0.70$). Although the generalization performances of Q10 and Q20 were good ($R^2 \geq 0.70$), the performance decreased from Q10 to Q99 (Fig. 2). According to previous studies, low streamflow has been controlled by geology in Japan. However, these studies targeted non-snowfall basins. In contrast, our target basins were located throughout Japan. Thus, the low streamflow indices in this study can be affected by not only geology but also snowmelt. This combined effect can complicate the estimation of low streamflow indices. Beck et al. conducted cross-validations of ANNs using an enormous amount of data from 4,079 basins across the globe, which reported excellent performance. For example, the $R^2$ values for QMEAN and Q99 were 0.88 and 0.66, respectively. In addition, they released global streamflow maps. Thus, we validated the maps using our target basins in Japan (Fig. 2). As a result, our performance was better than that of Beck et al. for all streamflow characteristics (Fig. 2). In addition, the $R^2$ values of Beck et al. for QMEAN and Q99 were 0.47 and 0.16, respectively (Fig. 2), which indicates the difficulty of estimating streamflow characteristics in Japan. One of the reasons for this could be wind-induced snowfall undercatch by rain-gauge observations. Generally, snowflakes are difficult to catch by rain gauges because of wind, and the amount

| Basin characteristics | QMEAN | Streamflow percentiles |
|-----------------------|-------|------------------------|
| Mean annual precipitation | + | + |
| Mean frequency of daily precipitation | + | + |
| Precipitation seasonality | + | + |
| Mean annual snow water equivalent | + | |
| Mean daily snow water equivalent | + | + |
| Mean frequency of daily snowfall | + | |
| Aridity index | + | + |
| Sunshine duration | + | + |
| Agricultural land except rice paddy | + | + |
| Forest area | + | |
| Rocky ground | + | |
| Podozolic soil (dry) | + | + |

Fig. 2 Validation results of ANNs.
of snowfall is underestimated\(^{15}\). Japan has one of the heaviest snowfall areas (the Tohoku and Hokuriku regions facing the Japan Sea) in the world. This situation indicates that it is difficult to estimate the streamflow characteristics in Japan. However, a recent study corrected the wind-induced snowfall undercatch\(^{16}\), whose database has been open to the public. This database may be used to improve the performance of ANNs.

(2) Streamflow characteristic maps in the most upstream basins

The QMEAN and Q1 maps are shown in Fig. 3. The accuracies of the maps correspond to the generalization performance (Fig. 2). The QMEAN was highest in heavy snowfall areas in the Tohoku and Hokuriku regions facing the Sea of Japan, and was also high in the typhoon-prone areas of Kyushu, Shikoku, and Kinki facing the Pacific Ocean. Q1 was highest in typhoon-prone areas, which reflected the flooding effects caused by heavy rains.

We can estimate that abundant low streamflow yields stable and high electric power energy in run-of-river hydropower schemes\(^ {17}\). Thus, we extracted the most upstream basins showing the top 1%, 5%, and 10% for all indices of QMEAN, Q80, Q90, Q95, and Q99, which can be assumed to be optimal sites for the development of run-of-river hydropower stations. In this study, these basins were named Class1, Class5, and Class10, respectively, as shown in Fig. 4. To identify the regionalities of the optimal sites, we investigated their number in first-class basins (Fig. 4). The first-class basins were directly managed by the central government, with a total of 109 basins. As a result, we confirmed two Class1 sites in the Mogami River basin and a Class1 site in the Shinano and Arakawa (Uetsu) river basins, respectively. In addition, the top three basins for the Class5 sites were the Shinano, Mogami, and Arakawa (Uetsu) river basins, and the top three basins for the Class10 sites corresponded to the Shinano, Mogami, and Agano river basins. Therefore, our results indicate that it is suitable to develop run-of-river hydropower stations in the heavy snowfall areas of the Tohoku and Hokuriku regions facing the Sea of Japan, which reflects that the amount of snowfall is important for the development of run-of-river hydropower stations.

5. CONCLUSIONS

Using 448 gauged basins in Japan, this study developed ANNs that output streamflow characteristics by inputting basin characteristics. The generalization performances of the ANNs showed \( R^2 = 0.70 \) in the QMEAN and \( R^2 = 0.20\text{–}0.74 \) in the streamflow percentiles. We validated the generalization performance of global streamflow characteristic maps\(^ {13}\) in Japan, which revealed that our performance was higher than that of global maps\(^ {13}\). Additionally, we developed streamflow characteristic maps that reflect
the rainfall and snowfall characteristics in Japan. Finally, our results indicate that it is suitable to develop run-of-river hydropower stations in the heavy snowfall areas of the Tohoku and Hokuriku regions facing the Sea of Japan. A potential measure to improve the performance of ANNs can be to apply a precipitation database that corrects the wind-induced snowfall undercatch.

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