*water*

MDPI

*Article*

# Study on a Water-Level-Forecast Method Based on a Time Series Analysis of Urban River Basins—A Case Study of Shibuya River Basin in Tokyo

**Naoki Koyama [1,*], Mizuki Sakai [2] and Tadashi Yamada [1]**

[1] Research and Development Initiative, Chuo University, 1-13-27, Kasuga, Bunkyo-ku, Tokyo 112-8551, Japan
[2] Civil, Human and Environmental Engineering Course, Graduate School of Science and Engineering, Chuo University, 1-13-27, Kasuga, Bunkyo-ku, Tokyo 112-8551, Japan
* Correspondence: knaoki002@g.chuo-u.ac.jp; Tel.: +81-3-3817-1621

**Abstract:** In urban basins, localized torrential rain increases the water level of rivers in an extremely short time, thereby leading to flooding within an hour. Therefore, to achieve early evacuation, the water level should be accurately forecasted. The outflow process in urban areas employs the sewer system to discharge the water back to rivers. However, the data for the sewer system are not freely available, and it requires much work and time to design a physical model based on such data. Thus, a vector autoregressive model to develop a water level forecast system that uses observed rainfall and water level is being used. Additionally, this model was used to ensure information conducive to evacuation approximately 20 min in advance and to assess its forecast accuracy, despite the very limited data—water levels at one point and average rainfall at another—without the need to build a physical model such as that which is used in sewer pipe calculations. Compared to the observed water level, the calculated water level increased faster; and thus, the forecast leaned toward safety in evacuation. Furthermore, the data from past five torrential rainfall events to achieve a stable forecast; this method can be applied to basins with limited observation data. Therefore, these results indicate that this method can be applied as a water level forecast method for basins with an extremely fast flood arrival time.

**Keywords:** urban floods; forecast method; water level; vector auto regressive model; time series analysis



**Citation:** Koyama, N.; Sakai, M.; Yamada, T. Study on a Water-Level-Forecast Method Based on a Time Series Analysis of Urban River Basins—A Case Study of Shibuya River Basin in Tokyo. *Water* **2023**, *15*, 161. https://doi.org/10.3390/w15010161

Academic Editors: Akira Kawamura and Kei Nakagawa

Received: 27 November 2022
Revised: 22 December 2022
Accepted: 30 December 2022
Published: 31 December 2022



## 1. Introduction

Floods are the most frequently occurring natural disaster, causing damage every year worldwide. Specifically, the damage from "urban floods," which target cities, is substantial [1,2], and rapid urbanization is changing the scale and frequency of urban floods [3–7]. Rainwater that used to infiltrate the ground or was stored on the ground surface is now discharged into rivers as surface water due to urbanization, thereby increasing the flood damage in urban areas. Rainwater in urban areas is usually discharged through the sewer system, but when its discharge capacity is exceeded, rainwater that cannot be discharged to the sewer system remains on the ground surface, or it flows out of manholes, leading to inland floods. Furthermore, the increasingly extreme nature of weather phenomena due to climate change is a global issue, putting cities at risk [6–9]. In Japan, localized bursts of short torrential rain called "guerrilla rainstorms" are becoming more frequent in urban areas, and not only rainfall of 50 mm or more per hour, but also rainfall of 80 mm or more per hour has been observed an increasing number of times [8].

To manage these urban floods and protect urban functions, flood measures that consider an increase in external forces must be shifted due to climate change. Flood measures are generally divided as "structure measures" and "non-structure measures". According to Itsukushima et al. [10], structure measures against urban floods can be classified into three types: "rivers", "the sewer system", and "basins". Measures for "rivers" include embankment, channel excavation, and setting back of levees [11]. However, in Japanese cities, dense structures such as buildings and homes have been built along urban rivers, thereby complicating the construction of embankments and channel excavation. Furthermore, it is difficult to secure the land for constructing levees, while the project costs are massive, which also makes the measure difficult to implement. Measures for "the sewer system" include larger diameters for sewer pipes, underground storage facilities for sewage water, and so on, but enlarging the pipes in massive sewer systems is expensive and time consuming. Measures for "basins" could include the installation of a rainwater storage facility in each home to control discharge, the installation of a dry well or water storage facility for each city block, and so on. Kenji Kawaike et al. [12] assessed the flood control effect of these discharge control facilities, showing that they reduce flood damage. In addition, there are many studies that showed that green infrastructure measures, such as permeable pavements, rooftop greening, and green gardens are useful in flood mitigation [13–15]. However, in the case of mitigation measures where the unit is a building, such as discharge control facilities and the green infrastructure measures mentioned above, the flood control effect of each measure is limited; and thus, to achieve success in minimizing urban floods, measures at a scale of the entire basin are necessary. Thus, to achieve structure measures to reduce flood damage in urban areas, a massive amount of money and time is necessary. Therefore, measures at the level of each home that are easier to incorporate cannot truly solve the problems.

However, non-structure measures could include the provision of information during floods for rapid evacuation, and the provision of flood risk information to guide planned town building. As a manner of providing flood risk information, some institutions and countries provide a "hazard map" for each city [16–19]. However, while this "hazard map" is useful in informing individuals about the flood risk of the areas in which they live, it does not provide real-time information to determine evacuation. To that end, water level forecast information for urban rivers is necessary [20]. In Japan, the river water level is used to determine the issuance of evacuation information during floods. If the water level for rivers can be accurately forecast with a several-hour lead or for cities with a lead of less than an hour, evacuation can be appropriately guided. With accurate and fast forecasting of water levels, lead time can be ensured for evacuation, minimizing the damage from floods.

Water level forecast methods can be broadly divided into physical models and statistical models [21]. In this study, we focused on a statistical model, a vector autoregressive model of time series analysis, and hypothesized that applying this model to water level forecasts would lead to more accurate and fast forecasts.

Among statistical models, time series analysis and machine learning are the common flood forecast methods. Generally, flood forecast methods based on machine learning can consider nonlinearity of phenomena and have enjoyed rapid development in recent years [22–24]. However, statistical models, represented by autoregressive model of time series analysis, attempt to establish the relationship between multiple phenomena without internally describing physical process related to the past; and thus, it is called system theoretical transfer function models. Since the vector autoregressive model, a time series analysis method, employed in this study is a linear model, some might point out that it is unable to consider nonlinearity. However, urban river basins in this study are mostly paved by concrete, where the outflow process is relatively simple compared to mountain basins. Therefore, the effect of nonlinearity is likely minimal. Furthermore, multivariate autoregressive models have been used in various fields in the past and are being studied with the aim of applying them to water level forecasts in the field of hydrology [25–29]. For example, Niedzielski et al. forecasted the water level of Oder River in southern Poland using a multivariate autoregressive model [28,29]. However, many past studies on water level forecast focused on the time axis of hours, days, and months. There is no study that focused on urban rivers with an extremely short flood arrival time of less than an hour, and the validity of each forecast method remains unclear, the objective is to assess the accuracy of water level forecasts using this method.

Meanwhile, the outflow process of urban basins discharges rain to rivers through the sewer system; and thus, physical models that consider this outflow process and calculation methods that follow the flow of water through the sewer system have been extensively studied [30]. Specifically, commercial software is often used to forecast floods including the sewer system in urban areas, such as MIKE URBAN [31], Infoworks CS [32], and SWMM [33]. Many studies used these software programs to study flood forecast [34–36]. However, the sewer system pipe data and water level data are not easy to observe since these structures are underground, where the data on the network of pipes are not freely accessible, often being difficult to obtain [37,38]. In addition, the amount of data for pipes and manholes is massive even for a small urban basin of several 10 s of km$^2$. It takes massive work and time to design a water level forecast system based on physical models that include pipe calculations. In contrast, in the case of multivariate autoregressive model employed for this study, data required for the forecast are limited to observation data of rainfall and water levels. Thus, it is highly suited as a water level forecast system for urban rivers.

Therefore, in this study, a water level forecast method is developed which conductive to accommodates floods caused by localized torrential rains in order to reduce casualty loss of urban floods, which have become more frequent in recent years, with an aim of supporting more rapid issuance of evacuation information.

## 2. Study Area and Data

The target basin was Shibuya River Basin, which flows through Shibuya Ward, Tokyo Metropolis (Figure 1). Shibuya River is an urban river that flows along the site of the Tokyo Olympics. The basin area is approximately 12.5 km$^2$ with a length of approximately 2.6 km. Figure 1a shows Shibuya River Basin, where the red line shows the sewer system network, and the blue line shows Shibuya River. Other than the green areas that indicate Meiji Jingu Grand Shrine and Shinjuku Gyoen, a park, Shibuya River Basin is covered by structures. Rainwater passes through the sewer system and flows into Shibuya River. Figure 1b shows the sewer system pipeline network prepared from the sewer system ledger data managed by Bureau of Sewerage Tokyo Metropolitan Government [39]. The total length of the sewer system pipes is 243 km, with 8800 manholes. These numbers show how difficult it is to forecast the water level for the 2.6 km along the river upon plotting the entire pipeline network and manholes.

Next, the focal point is on torrential rainfall events caused by localized torrential rain. Figure 2 shows the localized torrential rain in Shibuya River Basin that occurred on May 18, 2017. Figure 2a shows Shibuya River under normal conditions. These photographs show that the river carries little water under normal conditions, and the buildings fill the area along the river right up to the embankment. Figure 2b shows the river during a flood. At the bottom of Figure 2 are the hyetograph and hydrograph at that time. These diagrams show that the time between the rainfall peak and the water level peak was ~30 min, showing the extremely fast flood arrival time. Therefore, urban basins with a small area have a short flood arrival time, resulting in an extremely short lead time for residents to evacuate.

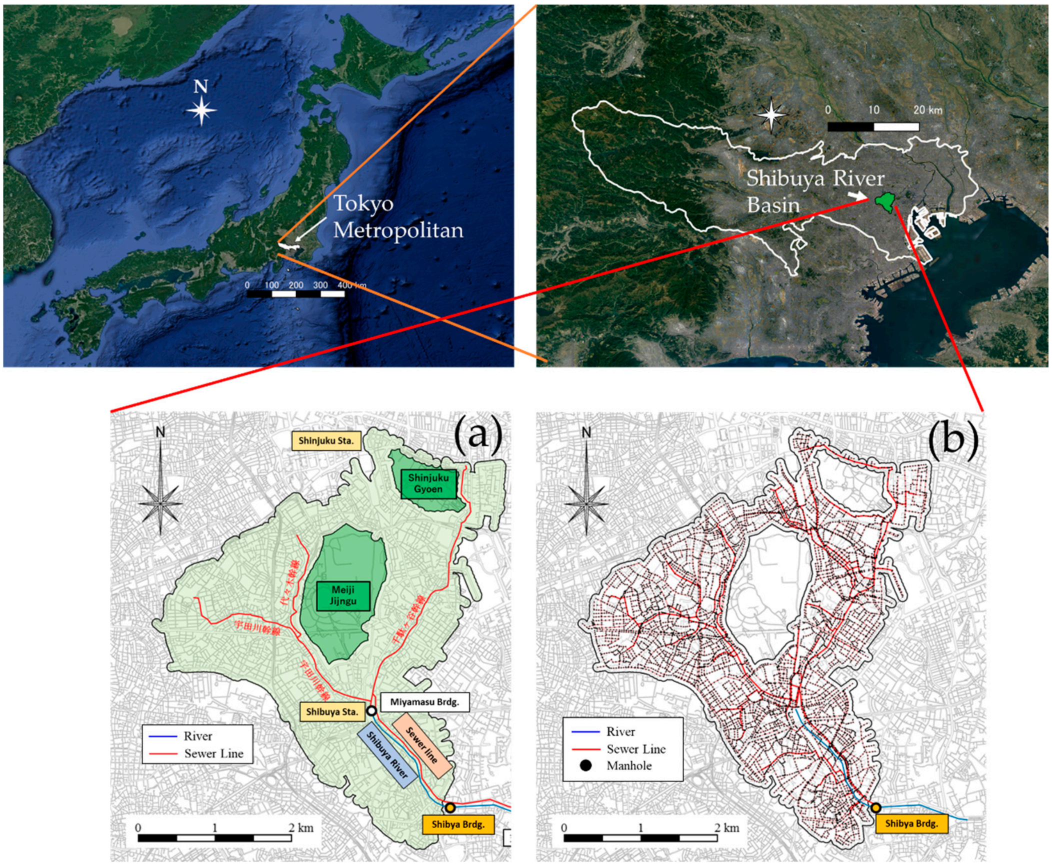


**Figure 1.** Location of the Study Area (**a**): Shibuya River Basin and (**b**): Pipeline Network.

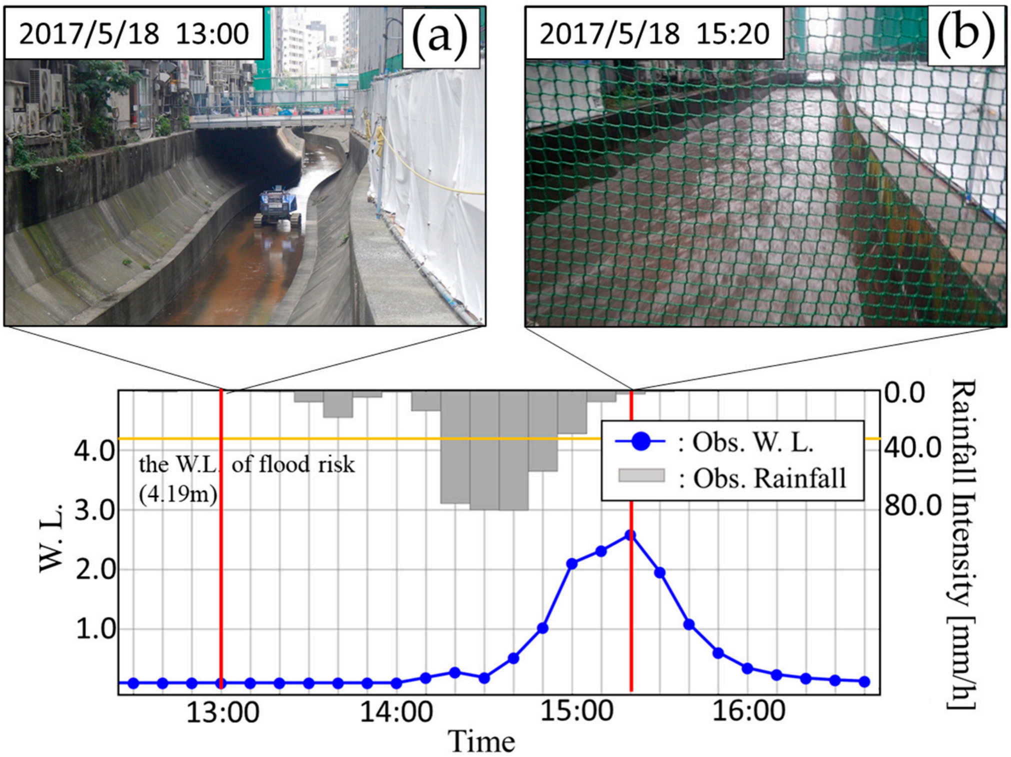


**Figure 2.** An example of localized torrential rain in Shibuya River Basin (18 May 2017). (**a**) State of the river during low conditions. (**b**) State of the river during of flooding.

There were nine torrential rainfall events were pinpointed. Figure 3 shows the rainfall and water level during each torrential event as a graph. Meanwhile, Figure 4 shows the difference in the rainfall peak and water level peak for each torrential rainfall event. Then, Table 1 shows the data figures used in Figure 3, with the maximum rainfall and maximum water level for each event. In most torrential rainfall events, the difference between the rainfall peak and water level peak was extremely short: 10–20 min. Next, the explanation about the observation data of rainfall and water level will be broken down. In Shibuya River Basin, there is one water level observation station [40] managed by Tokyo Metropolis (Figure 1b, orange circle), where observations are made every 10 min. As for the rainfall data, the rainfall observed data by the Xband-MP radar which installed by the Ministry of Land, Infrastructure, Transport and Tourism [41] were applied. Observations were taken every minute, and the 10 min average was taken to match the time resolution of the water level meter.

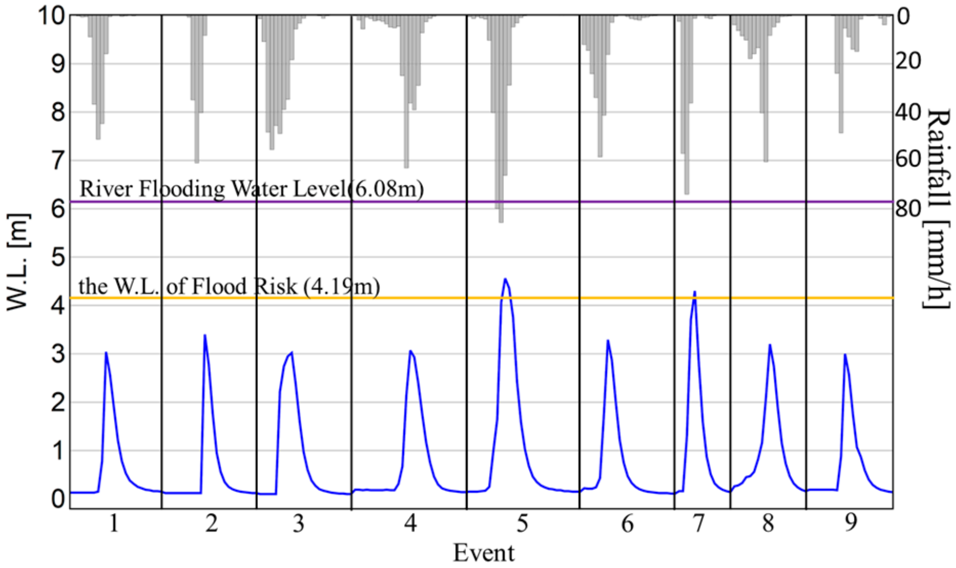


**Figure 3.** Localized torrential rainfall events since 2015 (9 Events).

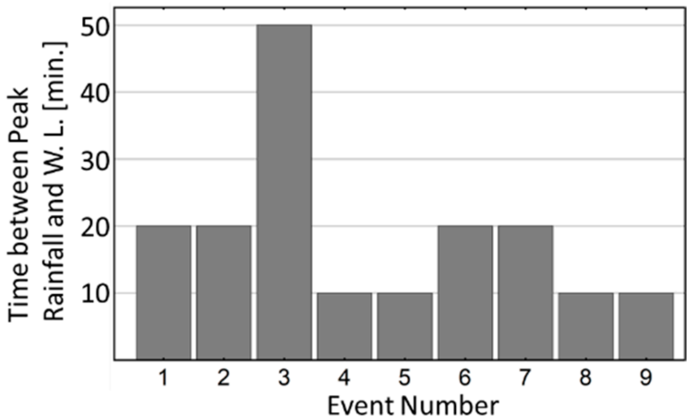


**Figure 4.** Difference in the time of the rainfall peak and water level peak for each torrential rainfall event.

**Table 1.** Observed numerical data on rainfall and water levels at each event, with colored maximum rainfall intensity and water level for each event.

| Time [min.] | Rain 1 [mm/h] | W.L. 1 [m] | Rain 2 [mm/h] | W.L. 2 [m] | Rain 3 [mm/h] | W.L. 3 [m] | Rain 4 [mm/h] | W.L. 4 [m] | Rain 5 [mm/h] | W.L. 5 [m] | Rain 6 [mm/h] | W.L. 6 [m] | Rain 7 [mm/h] | W.L. 7 [m] | Rain 8 [mm/h] | W.L. 8 [m] | Rain 9 [mm/h] | W.L. 9 [m] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0.14 | 0 | 0.12 | 0 | 0.12 | 0 | 0.1 | 0 | 0.15 | 0 | 0.23 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 10 | 0 | 0.14 | 0 | 0.12 | 0 | 0.12 | 0 | 0.1 | 0 | 0.15 | 0 | 0.23 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 20 | 0 | 0.13 | 0 | 0.12 | 0 | 0.12 | 0 | 0.1 | 0 | 0.15 | 0 | 0.24 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 30 | 0 | 0.13 | 0 | 0.12 | 0 | 0.12 | 0 | 0.1 | 0 | 0.16 | 0 | 0.24 | 0 | 0.2 | 0 | 0.18 | 0 | 0.2 |
| 40 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0 | 0.16 | 0 | 0.24 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 50 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0 | 0.15 | 0 | 0.24 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 60 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0 | 0.15 | 0 | 0.24 | 0 | 0.2 | 0.47 | 0.18 | 0 | 0.19 |
| 70 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0.88 | 0.1 | 0 | 0.15 | 0 | 0.24 | 0 | 0.21 | 1.79 | 0.18 | 0 | 0.19 |
| 80 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 5.3 | 0.1 | 0 | 0.15 | 0 | 0.24 | 0 | 0.21 | 0.94 | 0.18 | 0 | 0.19 |
| 90 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0.76 | 0.1 | 0.61 | 0.15 | 0 | 0.25 | 0 | 0.21 | 0.07 | 0.18 | 0 | 0.19 |
| 100 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0.16 | 0.1 | 1.3 | 0.15 | 0 | 0.25 | 0 | 0.21 | 0.09 | 0.18 | 0 | 0.19 |
| 110 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0.5 | 0.15 | 0 | 0.25 | 0 | 0.21 | 0.16 | 0.18 | 0 | 0.19 |
| 120 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 1.04 | 0.16 | 0 | 0.25 | 0 | 0.21 | 1.44 | 0.19 | 0 | 0.19 |
| 130 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 1.54 | 0.17 | 0 | 0.25 | 0 | 0.21 | 6.93 | 0.18 | 0 | 0.19 |
| 140 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 10.32 | 0.25 | 0 | 0.25 | 0 | 0.21 | 2.25 | 0.18 | 0 | 0.19 |
| 150 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 40.22 | 0.98 | 0 | 0.25 | 0 | 0.21 | 3.23 | 0.29 | 0 | 0.19 |
| 160 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 79.8 | 1.65 | 0 | 0.25 | 0 | 0.21 | 5.07 | 0.28 | 0 | 0.19 |
| 170 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 85.69 | 4.07 | 0 | 0.25 | 0 | 0.21 | 1.22 | 0.27 | 0 | 0.19 |
| 180 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 66.18 | 4.56 | 0.03 | 0.25 | 0 | 0.2 | 0 | 0.25 | 0 | 0.19 |
| 190 | 0 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.1 | 28.87 | 4.36 | 0.14 | 0.25 | 0 | 0.21 | 0.01 | 0.21 | 0 | 0.19 |
| 200 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 4.82 | 3.76 | 0.65 | 0.25 | 0 | 0.21 | 0.29 | 0.19 | 0 | 0.2 |
| 210 | 0 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 3.1 | 2.43 | 0 | 0.25 | 0 | 0.21 | 0.07 | 0.18 | 0 | 0.19 |
| 220 | 0.26 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0.87 | 1.59 | 0 | 0.25 | 0 | 0.2 | 0.11 | 0.18 | 0 | 0.19 |
| 230 | 0.66 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.1 | 0.15 | 1.03 | 0 | 0.25 | 0 | 0.2 | 1.03 | 0.18 | 0 | 0.19 |
| 240 | 0.59 | 0.13 | 0 | 0.12 | 0 | 0.1 | 0 | 0.19 | 0 | 0.68 | 0 | 0.25 | 0 | 0.2 | 0.08 | 0.18 | 0 | 0.19 |
| 250 | 8.87 | 0.13 | 0 | 0.12 | 0 | 0.11 | 0 | 0.19 | 0 | 0.46 | 0 | 0.25 | 0 | 0.2 | 0.01 | 0.18 | 0 | 0.19 |
| 260 | 36.82 | 0.13 | 0.74 | 0.12 | 0 | 0.11 | 0 | 0.19 | 0 | 0.35 | 0 | 0.25 | 0 | 0.2 | 0.81 | 0.17 | 0 | 0.19 |
| 270 | 51.2 | 0.15 | 34.96 | 0.12 | 0 | 0.11 | 0 | 0.19 | 0 | 0.28 | 0 | 0.25 | 0 | 0.2 | 1.07 | 0.3 | 0 | 0.19 |
| 280 | 44.8 | 0.78 | 61 | 0.12 | 0 | 0.11 | 0 | 0.19 | 0 | 0.24 | 0 | 0.25 | 0 | 0.2 | 0.07 | 0.22 | 0 | 0.19 |
| 290 | 15.89 | 3.04 | 40.29 | 0.12 | 0 | 0.11 | 0 | 0.19 | 0 | 0.21 | 0 | 0.25 | 0 | 0.2 | 0 | 0.18 | 0 | 0.19 |
| 300 | 0.55 | 2.57 | 8.27 | 3.4 | 0 | 0.11 | 0 | 0.19 | 0 | 0.2 | 0 | 0.25 | 0 | 0.2 | 0.34 | 0.16 | 0 | 0.19 |
| 310 | 0 | 1.88 | 0.01 | 2.77 | 0 | 0.11 | 0 | 0.19 | 0 | 0.18 | 0 | 0.25 | 0 | 0.2 | 0.2 | 0.16 | 0 | 0.19 |
| 320 | 0 | 1.21 | 0 | 1.76 | 0 | 0.11 | 0 | 0.18 | 0 | 0.18 | 0 | 0.25 | 0 | 0.2 | 0.27 | 0.16 | 0 | 0.19 |

**Table 1.** *Cont.*

| Time [min.] | Rain 1 [mm/h] | W.L. 1 [m] | Rain 2 [mm/h] | W.L. 2 [m] | Rain 3 [mm/h] | W.L. 3 [m] | Rain 4 [mm/h] | W.L. 4 [m] | Rain 5 [mm/h] | W.L. 5 [m] | Rain 6 [mm/h] | W.L. 6 [m] | Rain 7 [mm/h] | W.L. 7 [m] | Rain 8 [mm/h] | W.L. 8 [m] | Rain 9 [mm/h] | W.L. 9 [m] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 330 | 0.44 | 0.78 | 0 | 0.95 | 0.04 | 0.11 | 0 | 0.18 | 0 | 0.16 | 0.04 | 0.25 | 0 | 0.2 | 0.17 | 0.16 | 0 | 0.19 |
| 340 | 0.22 | 0.53 | 0 | 0.56 | 1.42 | 0.11 | 0 | 0.19 | 0 | 0.16 | 0.19 | 0.25 | 1.03 | 0.2 | 0.62 | 0.16 | 0 | 0.19 |
| 350 | 0.02 | 0.38 | 0 | 0.35 | 0.41 | 0.11 | 0.12 | 0.19 | 0 | 0.15 | 0.09 | 0.25 | 0.02 | 0.19 | 2.25 | 0.18 | 0 | 0.19 |
| 360 | 0.17 | 0.31 | 0 | 0.25 | 9.97 | 0.11 | 1.96 | 0.19 | 0 | 0.15 | 0.15 | 0.25 | 0 | 0.18 | 0 | 0.18 | 0.12 | 0.19 |
| 370 | 0.03 | 0.25 | 0 | 0.2 | 8.7 | 0.1 | 5.63 | 0.18 | 0 | 0.15 | 0.32 | 0.25 | 0.21 | 0.17 | 0 | 0.17 | 23.95 | 0.18 |
| 380 | 0 | 0.22 | 0 | 0.17 | 1.98 | 0.1 | 0.78 | 0.19 | 0 | 0.14 | 0.57 | 0.25 | 24.12 | 0.16 | 0 | 0.16 | 48.66 | 0.88 |
| 390 | 0 | 0.19 | 0 | 0.15 | 0.55 | 0.1 | 1.29 | 0.18 | 0 | 0.14 | 0.5 | 0.24 | 9 | 0.16 | 0 | 0.16 | 5.26 | 3 |
| 400 | 0 | 0.18 | 0 | 0.14 | 0.04 | 0.1 | 2.22 | 0.18 | 0 | 0.14 | 12.07 | 0.22 | 3.18 | 0.16 | 0 | 0.16 | 8.91 | 2.57 |
| 410 | 0 | 0.16 | 0 | 0.13 | 0 | 0.1 | 2.02 | 0.18 | 0 | 0.14 | 14.48 | 0.21 | 1.28 | 0.16 | 0 | 0.16 | 14.06 | 1.75 |
| 420 | 0 | 0.16 | 0 | 0.12 | 0 | 0.1 | 2.5 | 0.18 | 0.01 | 0.13 | 24.17 | 0.21 | 0.51 | 0.16 | 0.02 | 0.16 | 14.92 | 1.07 |
| 430 | 0 | 0.15 | 0 | 0.12 | 0 | 0.1 | 3.5 | 0.19 | 0.03 | 0.13 | 34.01 | 0.24 | 0 | 0.16 | 0.06 | 0.16 | 1.57 | 0.87 |
| 440 | 0 | 0.14 | 0 | 0.11 | 0 | 0.1 | 4.86 | 0.18 | 0 | 0.12 | 58.56 | 0.43 | 0 | 0.16 | 0.3 | 0.16 | 0.04 | 0.59 |
| 450 | 0 | 0.14 | 0 | 0.11 | 0 | 0.1 | 5.21 | 0.18 | 0 | 0.12 | 41.32 | 1.76 | 0 | 0.16 | 0.18 | 0.16 | 0.18 | 0.4 |
| 460 | 0.06 | 0.14 | 0 | 0.11 | 0 | 0.1 | 4.56 | 0.31 | 0 | 0.12 | 16.17 | 3.29 | 0 | 0.15 | 0.04 | 0.16 | 0.11 | 0.29 |
| 470 | 0 | 0.13 | 0 | 0.11 | 0 | 0.1 | 24.93 | 0.67 | 0 | 0.12 | 2.92 | 2.87 | 0 | 0.16 | 0 | 0.16 | 0.04 | 0.23 |
| 480 | 0 | 0.13 | 0 | 0.11 | 0 | 0.1 | 63.09 | 2.14 | 0 | 0.11 | 0.35 | 2 | 0 | 0.16 | 0.12 | 0.16 | 1.26 | 0.19 |
| 490 | 0 | 0.13 | 0 | 0.11 | 0.01 | 0.1 | 36.2 | 3.07 | 0 | 0.11 | 0 | 1.21 | 0 | 0.16 | 0 | 0.16 | 3.92 | 0.17 |
| 500 | 0 | 0.13 | 0 | 0.1 | 1.42 | 0.1 | 39.04 | 2.93 | 5.98 | 0.1 | 0 | 0.75 | 0 | 0.16 | 0 | 0.16 | 0.5 | 0.15 |
| 510 | 0 | 0.13 | 0 | 0.1 | 10.87 | 0.1 | 28.98 | 2.4 | 10.68 | 0.1 | 0.55 | 0.47 | 0 | 0.16 | 0 | 0.16 | 0.1 | 0.14 |
| 520 | 0 | 0.13 | 0 | 0.1 | 48.34 | 0.1 | 7.19 | 1.76 | 3.04 | 0.1 | 1.31 | 0.33 | 0 | 0.16 | 0 | 0.16 | 0.58 | 0.13 |
| 530 | 0 | 0.13 | 0 | 0.1 | 55.49 | 0.1 | 2.61 | 1.17 | 2.65 | 0.1 | 1.7 | 0.25 | 0 | 0.16 | 0 | 0.16 | 0.1 | 0.12 |
| 540 | 0 | 0.13 | 0 | 0.1 | 45.55 | 0.1 | 1.24 | 0.75 | 0.32 | 0.09 | 1.93 | 0.2 | 0 | 0.16 | 0 | 0.16 | 0.04 | 0.12 |
| 550 | 0 | 0.13 | 0 | 0.1 | 48.86 | 2.22 | 0.43 | 0.46 | 0.5 | 0.09 | 0.89 | 0.17 | 0 | 0.16 | 0 | 0.16 | 0.42 | 0.11 |
| 560 | 0 | 0.13 | 0 | 0.1 | 38.94 | 2.74 | 0.01 | 0.3 | 0.19 | 0.09 | 0.65 | 0.15 | 0 | 0.16 | 0 | 0.16 | 0.29 | 0.11 |
| 570 | 0 | 0.13 | 0 | 0.1 | 34.7 | 2.95 | 0 | 0.22 | 0.01 | 0.09 | 0.23 | 0.14 | 0 | 0.16 | 1.63 | 0.16 | 1.13 | 0.11 |
| 580 | 0 | 0.13 | 0 | 0.1 | 18.4 | 3.02 | 0 | 0.19 | 0 | 0.09 | 0.14 | 0.13 | 0 | 0.16 | 3.47 | 0.16 | 1.46 | 0.1 |
| 590 | 0 | 0.13 | 0 | 0.1 | 5.68 | 2.37 | 0 | 0.17 | 0 | 0.09 | 0.04 | 0.12 | 0 | 0.16 | 5.06 | 0.16 | 0.91 | 0.1 |
| 600 | 0 | 0.13 | 0 | 0.1 | 3.21 | 1.6 | 0 | 0.16 | 0 | 0.09 | 0 | 0.12 | 2.5 | 0.16 | 2.61 | 0.17 | 0.22 | 0.1 |
| 610 | 0 | 0.12 | 0 | 0.1 | 1.13 | 0.97 | 0 | 0.15 | 0.26 | 0.1 | 0 | 0.12 | 57.05 | 0.16 | 14.52 | 0.17 | 0 | 0.1 |
| 620 | 0 | 0.12 | 0 | 0.1 | 0.05 | 0.6 | 0 | 0.14 | 0.64 | 0.1 | 0 | 0.11 | 73.98 | 1.31 | 7.66 | 0.2 | 0 | 0.1 |
| 630 | 0 | 0.12 | 0 | 0.1 | 0 | 0.38 | 0.01 | 0.14 | 3.77 | 0.1 | 0 | 0.11 | 36.22 | 3.71 | 3.91 | 0.26 | 0 | 0.1 |
| 640 | 0 | 0.12 | 0 | 0.1 | 0.03 | 0.27 | 0.13 | 0.14 | 5.34 | 0.16 | 0.11 | 0.11 | 1.25 | 4.3 | 6.31 | 0.28 | 0 | 0.1 |

**Table 1.** *Cont.*

| Time [min.] | Rain 1 [mm/h] | W.L. 1 [m] | Rain 2 [mm/h] | W.L. 2 [m] | Rain 3 [mm/h] | W.L. 3 [m] | Rain 4 [mm/h] | W.L. 4 [m] | Rain 5 [mm/h] | W.L. 5 [m] | Rain 6 [mm/h] | W.L. 6 [m] | Rain 7 [mm/h] | W.L. 7 [m] | Rain 8 [mm/h] | W.L. 8 [m] | Rain 9 [mm/h] | W.L. 9 [m] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 650 | 0 | 0.12 | 0 | 0.1 | 0.15 | 0.2 | 0.06 | 0.14 | 3.67 | 0.2 | 2.91 | 0.11 | 0.06 | 2.82 | 8.52 | 0.33 | 0 | 0.1 |
| 660 | 0 | 0.12 | 0 | 0.1 | 1.15 | 0.17 | 0 | 0.14 | 2.88 | 0.23 | 4.51 | 0.11 | 0.05 | 1.6 | 10.21 | 0.45 | 0 | 0.1 |
| 670 | 0 | 0.13 | 0 | 0.1 | 0.12 | 0.15 | 0 | 0.14 | 0.17 | 0.19 | 4.14 | 0.11 | 1 | 0.87 | 17.9 | 0.47 | 0 | 0.14 |
| 680 | 0 | 0.13 | 0 | 0.18 | 0 | 0.13 | 0 | 0.14 | 0 | 0.16 | 3.4 | 0.11 | 1.37 | 0.51 | 15.95 | 0.56 | 0 | 0.17 |
| 690 | 0 | 0.13 | 0 | 0.19 | 0 | 0.12 | 0 | 0.14 | 0 | 0.13 | 2.43 | 0.13 | 0.15 | 0.32 | 13.43 | 0.82 | 0 | 0.17 |
| 700 | 0 | 0.13 | 0 | 0.19 | 0 | 0.11 | 0 | 0.14 | 0 | 0.12 | 5.73 | 0.18 | 0 | 0.24 | 40.35 | 1.16 | 0 | 0.17 |
| 710 | 0 | 0.13 | 0 | 0.19 | 0 | 0.11 | 0 | 0.14 | 0 | 0.1 | 7.65 | 0.18 | 0 | 0.19 | 60.6 | 2.1 | 0 | 0.17 |
| 720 | 0 | 0.13 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 4.68 | 0.16 | 0 | 0.16 | 8.27 | 3.2 | 0 | 0.17 |
| 730 | 0 | 0.12 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 0.5 | 0.2 | 0 | 0.14 | 4.82 | 2.74 | 0 | 0.18 |
| 740 | 0 | 0.12 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 0 | 0.19 | 0 | 0.13 | 2.96 | 1.88 | 0 | 0.17 |
| 750 | 0 | 0.12 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.09 | 0 | 0.16 | 0 | 0.12 | 0.54 | 1.15 | 0 | 0.17 |
| 760 | 0 | 0.12 | 0 | 0.19 | 0 | 0.09 | 0 | 0.14 | 0 | 0.09 | 0 | 0.13 | 0 | 0.11 | 0.36 | 0.73 | 0 | 0.17 |
| 770 | 0 | 0.12 | 0 | 0.19 | 0 | 0.09 | 0 | 0.14 | 0 | 0.09 | 0 | 0.12 | 0 | 0.1 | 0.28 | 0.47 | 0 | 0.17 |
| 780 | 0 | 0.12 | 0 | 0.19 | 0 | 0.09 | 0 | 0.14 | 0 | 0.09 | 0 | 0.11 | 0 | 0.1 | 0.07 | 0.32 | 0 | 0.17 |
| 790 | 0 | 0.15 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 0 | 0.11 | 0 | 0.1 | 0 | 0.24 | 0 | 0.17 |
| 800 | 0 | 0.18 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.09 | 0 | 0.19 | 0 | 0.1 | 0 | 0.19 | 0 | 0.17 |
| 810 | 0 | 0.2 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 0 | 0.19 | 0 | 0.09 | 0 | 0.16 | 0 | 0.17 |
| 820 | 0 | 0.2 | 0 | 0.19 | 0 | 0.1 | 0 | 0.14 | 0 | 0.1 | 0 | 0.19 | 0 | 0.09 | 0 | 0.15 | 0 | 0.17 |
| 830 | 0 | 0.21 | 0 | 0.19 | 0 | 0.09 | 0 | 0.14 | 0 | 0.1 | 0 | 0.19 | 0.29 | 0.09 | 0 | 0.13 | 0 | 0.17 |

## 3. Analytical Method for Water Level Forecast with Time Series Analysis

### *3.1. About Vsector Autoregressive Model*

The time series analysis is a statistical model, which is used to relate phenomena with past data and forecast/control phenomena [42]. First, let us show the univariate autoregressive model equation used for the most basic time series analysis in Equation (1).

$$h_n = \sum_{i=1}^{N} a_i h_{n-i} + \varepsilon_n \tag{1}$$

where $h$ is an datum (water level), $n$ is an time, $a$ is a parameter, $N$ is a degree, and $\varepsilon$ is white noise.

Equation (1) expresses the water level at an arbitrary time $h_n$ as a product of the past water level time series $h_{n-i}$ and parameter $a_i$ in a linear sum with white noise $\varepsilon_i$. $N$ is a degree, which is the amount of past data considered. Since the parameter $a_i$ is the weight of the past observation values $h_{n-I}$, the size of $a_i$ expresses the impact of past observations made for $h_n$.

When considering real rivers, the flow rate of rivers gathers from distributaries upstream to downstream, and flow rate at each point interacts. Thus, the autoregressive model were expanded and expressed in Equation (2) the impact of each tributary included.

$$\begin{bmatrix} h_n^1 \\ h_n^2 \\ \vdots \\ h_n^p \end{bmatrix} = \sum_{i=1}^{N} \begin{bmatrix} a_{11}^i & a_{12}^i & \cdots & a_{1l}^i \\ a_{21}^i & a_{22}^i & & a_{2l}^i \\ \vdots & & \ddots & \vdots \\ a_{p1}^i & a_{p2}^i & \cdots & a_{pl}^i \end{bmatrix} \begin{bmatrix} h_{n-i}^1 \\ h_{n-i}^2 \\ \vdots \\ h_{n-i}^p \end{bmatrix} + \begin{bmatrix} \varepsilon_n^1 \\ \varepsilon_n^2 \\ \vdots \\ \varepsilon_n^p \end{bmatrix} \tag{2}$$

Equation (2) is a generalization of Equation (1), which is called multivariate autoregressive model or vector autoregressive model, where $N$ is the degree of the model, $P$ is the number of water levels used, $l$ is the order of the water level, $h_n^p$ is the water level at the point $p$ at time $n$, and $a_{pl}^i$ is the impact of the water level at the point $l$ on the water level at the point $p$ before the time $i$.

Furthermore, in the rainfall outflow process, rain falls on a basin, which infiltrates and outflows from the ground surface, flows into rivers and the sewer system, and becomes a water level at a certain point. Water level information at an arbitrary observation point is the final information in the rainfall outflow process, and the first start is the rainfall information. Thus, instead of only using the water level information, by adding the rainfall information, we can add the information prior to the water level information to the model, thereby considering the rapid rise in water levels in urban basins. Therefore, rainfall data were added into Equation (2) and hence Equation (3) is obtained.

$$\begin{bmatrix} h_n^1 \\ \vdots \\ h_n^p \\ r_n^1 \\ \vdots \\ r_n^s \end{bmatrix} = \sum_{i=1}^{N} \begin{bmatrix} a_{11}^i & \cdots & a_{1p}^i b_{11}^i & \cdots & b_{1s}^i \\ \vdots & \ddots & \vdots \quad \vdots & \ddots & \vdots \\ a_{p1}^i & \cdots & a_{pl}^i \, b_{11}^i & \cdots & b_{sm}^i \end{bmatrix} \begin{bmatrix} h_{n-i}^1 \\ \vdots \\ h_{n-i}^p \\ r_{n-i}^1 \\ \vdots \\ r_{n-i}^s \end{bmatrix} + \begin{bmatrix} \varepsilon_{qn}^1 \\ \vdots \\ \varepsilon_{qn}^p \\ \varepsilon_{rn}^1 \\ \vdots \\ \varepsilon_{rn}^s \end{bmatrix} \tag{3}$$

where $r$ is rainfall data and $s$ is the number of rainfall data, $m$ is the order of the rainfall, and $b_{sm}^i$ is the impact of the rainfall at the point $m$ on the rainfall at the point $s$ before the time $i$. With this Equation, we can see that water level and rainfall are used to obtain the water level at an arbitrary point. Next, let us explain the forecast method for water level. With Equation (3), the current water level and rainfall data are obtained from the past data; thus, by including the current data in this Equation, we can forecast one step ahead, which is expressed in Equation (4). Here, for simplification, we will only examine the water level in this Equation.

$$\hat{\mathbf{h}}^{p}_{n+1} = \sum_{i=1}^{N}\sum_{l=1}^{P} \mathbf{a}^{i}_{pl}\mathbf{h}^{l}_{n+1-i} + \varepsilon^{p}_{n} \quad (4)$$

where $\hat{\mathbf{h}}^{p}_{n+1}$ is the water level forecast. The forecast result is used recursively to forecast the next step, and when the forecast is performed after the time $x$, it can be expressed with Equation (5).

$$\hat{\mathbf{h}}^{p}_{n+x} = \sum_{j=1}^{x-1}\sum_{l=1}^{P} \mathbf{a}^{i}_{pl}\hat{\mathbf{h}}^{l}_{n+x-j} + \sum_{i=1}^{N-x}\sum_{l=1}^{P} \mathbf{a}^{i}_{pl}\mathbf{h}^{l}_{n+1-i} + \varepsilon^{p}_{n} \quad (5)$$

With the same line of thinking, a forecast can be made with Equation (5) that includes rainfall.

In this study, rainfall and water level were used to forecast the water level. In the case of the Shibuya River basin, the water level data used were limited to one point. For rainfall, since the area of the basin is small at 10 s of km$^2$, the fact that spatial distribution of rainfall is limited, hence the average rainfall for the basin. Since our goal was to provide information for evacuation during floods, forecasts up to 30 min ahead were calculated. The reason for predicting up to 30 min is that the flood arrival time in the target basin is several tens of minutes and the time from the start of the hydrograph to the peak can be predicted.

The characteristic of this model Is that forecasts can be made from the observation data up to the present point, which makes it applicable for areas without forecast rainfall data.

### 3.2. Methods to Design Water Level Forecast Model and Verify Its Accuracy

When designing the water level forecast model of Equation (5) used in this study, the number of water level data $P$ and the number of rainfall data S will be selected, while determining the degree $N$. As for the number of water level data, since there was only one water level observation station in the target basin, P = 1. For rainfall, assuming that the impact of the spatial distribution of rainfall was limited due to the small size of the basin (10 s of km$^2$). Thus, the model used the average rainfall for the basin with s = 1.

Next, for the degree $N$, Akaike Information Criterion (AIC) proposed by Akaike [43] is applied. $AIC$ is expressed with Equation (6).

$$AIC = -2\log(L) + 2K \quad (6)$$

where $L$ is the maximum log-likelihood and $K$ is the number of model parameters. Figure 5 shows the relationship between $AIC$ and the degree in this calculation. The smallest value in the $AIC$, N = 5, was selected.

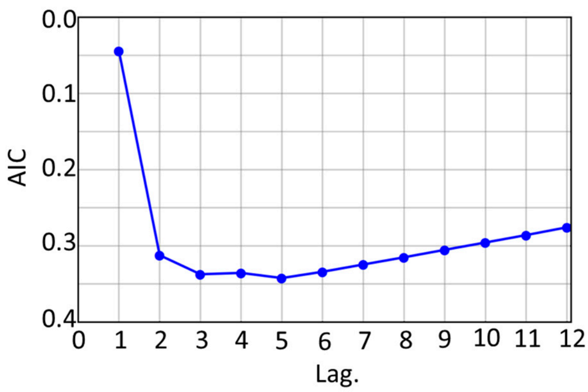


**Figure 5.** Relation of Lagged time and AIC.

The data were used to estimate parameters targeted nine localized torrential rainfalls since 2015 (Figure 3). Since the amount of data used to estimate the parameters for the water level forecast model was limited, we performed fold cross-validation that uses all limited data [44]. The steps of the fold cross-validation are as follows.

1. Target torrential rainfall event is divided into nine data sets as shown in Figure 3.
2. Data from one torrential rainfall event are used as the verification data.
3. Data from the remaining seven torrential rainfall events are used as the data set for parameter estimates.
4. With the set data, parameters are estimated and the accuracy is verified.
5. Steps 2, 3, and 4 are repeated to assess the accuracy of the forecast.

## 4. Results and Discussions

### *4.1. Verifying the Accuracy of the Forecast*

The perspective important to verify the accuracy of the water level forecast model is whether the accuracy of the rising flood is ensured. This is especially important for urban basins with a short flood arrival time as in the present study since the time used to evacuate is also short. In the case of urban rivers, basically, embankments are not soil but concrete. Thus, it is rare for the embankment to be breached, and most floods are caused by overtopping. Thus, the judgment criterion in such cases is whether the water would top the height of the embankment or not; thus, the accuracy of peak water level forecast is crucial.

We present the water level forecast results of the vector autoregressive model which uses rainfall and water level data. Figure 6 is the water level forecast result for all nine torrential rainfall events. First, let us look at the torrential rainfall event 5 with the highest peak water level. Figure shows that the during the water level rise, its increase is captured, but it is underestimated compared to the measured water level. This trend was observed in all 10 min, 20 min, and 30 min forecasts. Specifically, at the start of the event when only weak rainfall was observed, the water level forecast was extremely low. On the other hand, when strong rainfall of over 50 mm/h was observed, the difference with the observed water level became small.

Next, let us look at the torrential rainfall event 2. With this torrential rainfall event, compared to the other torrential rainfall events, it takes $\geq$10 min to reach the peak water level. However, the flood arrival time for this torrential rainfall event 2 was the shortest at 10 min. In the case of such flood, the sign for the water level rise cannot be detected; and thus, it is considered the most dangerous urban flood. Figure 6 (event 2) shows that the rising trend of water level was forecast 20 min before the peak water level. The forecast was possible despite the fact that the observed water level had not risen at all. Therefore, using the proposed water level forecast model, forecasts are on the safe side from the viewpoint of evacuation.

In other flood events, forecast water levels were generally underestimated compared to the observed values; however, a rise in water level can be captured. Therefore, this method contributes to the decision to issue the evacuation information.

Next, Figure 7 shows the result of verifying the accuracy of peak water level forecast. This figure shows that generally, peak water level is underestimated in the forecast. However, other than the event 2, 10 min forecasts had an accuracy of 1 m or less compared to the observed values.

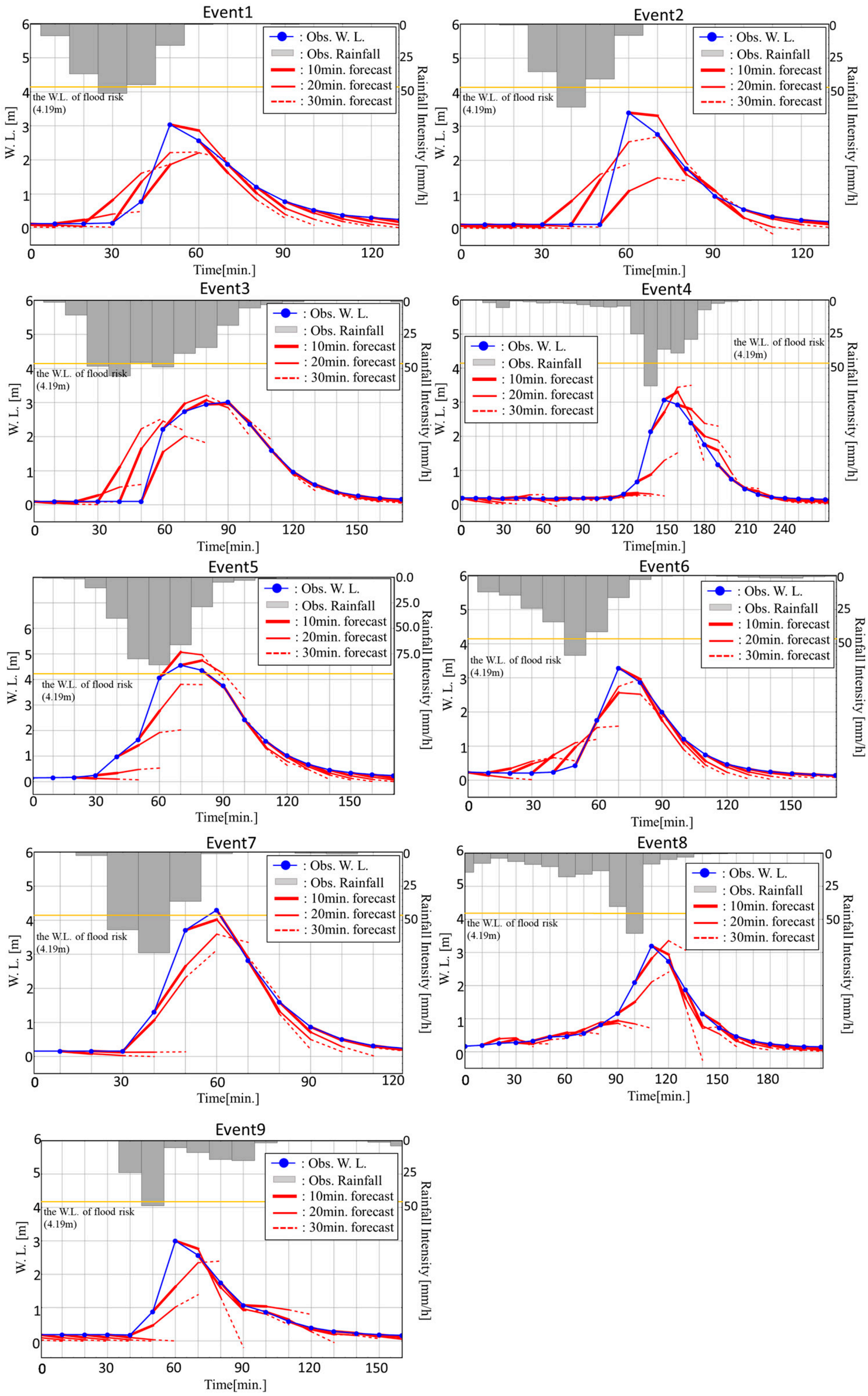


**Figure 6.** Forecasted water level results up to 30 min ahead for all events.

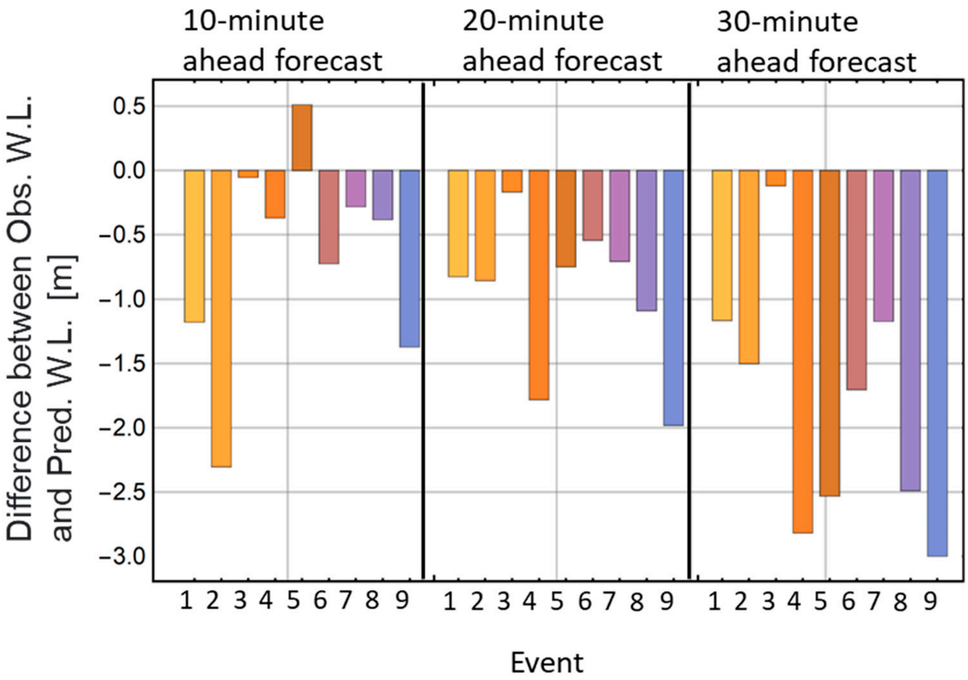


**Figure 7.** Difference in the observed water level and water level at the peak for each forecast time.

The overall accuracy of the 20 min forecast was lower, where the difference in the water level is approximatery1.5 m lower except for the torrential rainfall event 3.

The accuracy of the forecast for each torrential rainfall event, in the case of the above-mentioned event 2, was about 2 m lower in the 10 min forecast. This was likely since the heavy rain exceeding 50 mm/h already ended by the time for the 10 min forecast. In contrast, 20 min forecast had the peak difference with the observed value of less than 1 m. This was likely since heavy rainfall exceeding 50 mm/h was falling at the time of forecast. In the case of torrential rainfall event 3, the forecast was highly accurate for all 10 min, 20 min, and 30 min forecasts. Figure 6 shows that the time difference in the rainfall peak and the water level peak of torrential rainfall event 3 was longer than other torrential rainfall events. These results show that though the accuracy of the water level forecast is not favorable at the rise of the water level, the forecast was adequate once the water level rises close to the peak. This means that the peak water level can be forecast even when strong rainfall continues.

Figure 8 superimposes 10 min, 20 min, and 30 min forecasts with the observed water levels for all time periods from the rise to the fall of water level in the hydrograph for each torrential rainfall event. The red solid line is 45°, while the red dashed line is ±1 m of the red solid line. Figure 8a assesses observed and forecast values for 10 min ahead, which shows that most forecasts are within 1 m. In some cases, the forecast water levels rose during the normal condition (0.15 to 0.2 m) before the observed water levels rose. This shows that, as mentioned earlier, when heavy rain exceeding 50 mm/h was observed in each torrential rainfall event, the forecast was on the safe side. In the falling period of the hydrograph, the forecast was highly accurate. In addition, Figure 8 shows that 20 min and 30 min forecasts had lower water levels compared to the observed level as the forecast time increased.

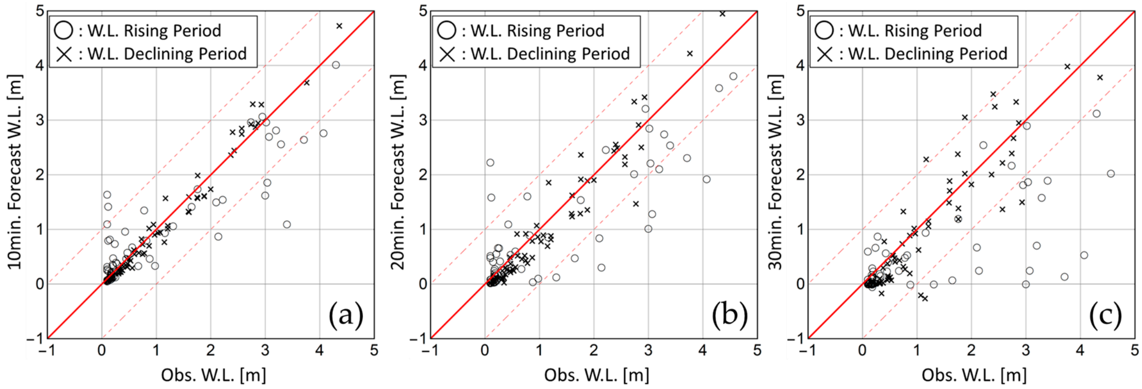


**Figure 8.** Comparison of the calculated and forecast values for the entire period in the hydrograph. (**a**): 10 min forecast, (**b**): 20 min forecast, and (**c**): 30 min forecast. Circles in figure are values during the rising period in the hydrograph, while cross are values during the falling period.

### *4.2. The Number of Torrential Rainfall Events Necessary for Stable Water Level Forecast*

To verify the accuracy of water level forecasts by the present water level forecast method, it was calculated using all torrential rainfall events since 2015 that could be used in the target basin. However, in the basin of urban rivers, to which we want to introduce this method, the amount of data at the time of flood at the observation points is likely limited. Thus, we assessed the stability of forecast values when the number of torrential rainfall events used for parameter estimate was changed. For the assessment, the variations in the forecast values were examined by comparing them to the results of changing the number of torrential rainfall events used for parameter estimates between 1 and 7.

Table 2 shows the number of torrential rainfall events that can be prepared with the number of torrential events used to estimate parameters. The number of data sets that can be prepared varies based on the number of torrential rainfall events used to estimate parameters. The average of the dataset was taken for each forecast time of each torrential rainfall event and assessed the stability. *RMSE* was also used to validate the accuracy of the forecast. For the verification, the result of the hydrograph from the rise of the water level to the peak water level were applied, which is crucial during evacuation. *RMSE* is shown in Equation (7).

$$RMSE = \sqrt{\sum_{n=1}^{N_{peak}} \left(h_{ob}^{i} - h_{pre}^{i}\right)^{2} / N_{peak}} \tag{7}$$

where $h_{ob}^{i}$ is the observed values, $h_{pre}^{i}$ is the forecast values, and $N_{peak}$ is the amount of data.

**Table 2.** Number of events used for parameter estimation.

| Number of Flood Events Used | Number of Datasets |
|---|---|
| 1 | ${}_8C_1 = 8$ |
| 2 | ${}_8C_2 = 28$ |
| 3 | ${}_8C_3 = 56$ |
| 4 | ${}_8C_4 = 70$ |
| 5 | ${}_8C_5 = 56$ |
| 6 | ${}_8C_6 = 28$ |
| 7 | ${}_8C_1 = 8$ |

The torrential rainfall event that was the target of forecast in this verification was torrential rainfall event 5, where the water level rose the most (Figure 3). The result is shown in Figure 9. Frames 1 to 7 in Figure 9 show the number of torrential rainfall events used to estimate parameters (the number of torrential rainfall events used was changed between 1 and 7).

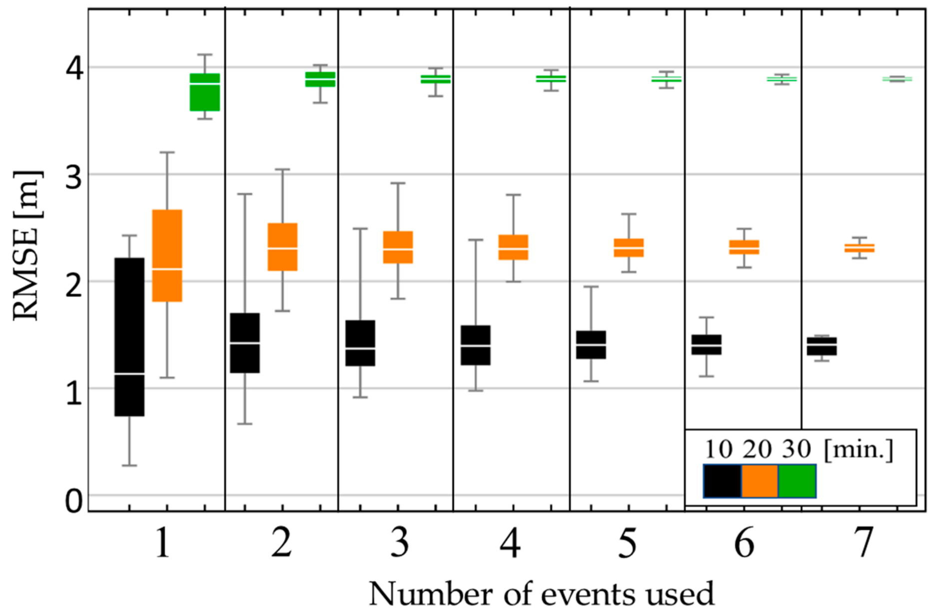


**Figure 9.** Differences in forecast accuracy for different numbers of flood events.

This result shows that the variations in the forecast values decreased when the number of torrential rainfall events used to estimate parameters was higher. Specifically, for the 10 min forecast (black bar), the range of variations in forecast values became notable based on the number of events. However, when we look at the average values, even for 10, 20, and 30 min forecasts, there was little difference in the average as long as at least two torrential rainfall events were used to estimate parameters. If there were about six torrential rainfall events, variations became small. Therefore, we assume that as long as there are data from about six large flood events, parameters become stable along with forecast values.

Data used for the water level forecast in this study included one of water level and one of rainfall. Since the water level data comprised the observation data from the station installed at the downstream side of the target, Shibuya River Basin, this is the final information in the rainfall outflow process, not allowing the use of upstream information (observation data). Therefore, the rainfall data at the start of the rainfall outflow process, and the information at the end of the process was limited to the water level information. Therefore, there was no information on the tributaries, which is the middle of the outflow process (in the case of this study, this would be the sewer system pipeline network). Thus, it was difficult to ensure the accuracy of the present forecast. If we could use the information from the upstream of the forecast point (water level observation station), we could design a forecast model with higher precision.

## 5. Conclusions

In this study, we designed a water level forecast method with the goal of providing early evacuation information in the basin of an urban river where the flood arrival time was extremely short at much less than one hour. Assessment of its accuracy is performed. For the water level forecast method, the vector autoregressive model was applied. For forecasting, the model only applied using real-time data of rainfall and water level.

The result showed that in the rising period of the hydrograph, forecast values were lower, but its difference was 1 m or less. Thus, it was sufficient information to encourage evacuation. In the case of localized torrential rainfall, it has been reported that evacuation times of a few minutes can be fatal [45]. The model's ability to forecast these tens of minutes is extremely important because the reality of localized torrential rainfall is that the time from the start of the rainfall to the peak water level is only a few tens of minutes, and these localized torrential rains frequently cause flooding damage in major cities in Japan. By incorporating the rainfall data into the forecast method, the rise in the water level was forecasted from the point when there was no rise in the real-time water level yet. Therefore, the present method can be used as a method to forecast water levels in basins without forecast rainfall data by only using observation data. The analysis did not take into account physical factors such as drainage systems by sewers, which means that the results obtained by using very limited data show that the method could be applied to many basins.

By changing the number of torrential rainfall events used to estimate the parameters of the water level forecast model, the numbers of torrential rainfall events were examined to calculate stable forecast values. The result showed that since five or more torrential rainfall events reduced the variations in the forecast values, as long as there are flood data from about five events, this model can be applied to urban river basins with limited observation data.

Finally, water level data from one point and rainfall data from one point to design this method was used. This was because there was only one water level observation station in the present target basin, but by using the upstream information, the accuracy of forecasts can be improved dramatically. However, there is hardly any location in Japan where the water level within the sewer system is being observed. To make more accurate forecasts to reduce the flood damage from short urban rivers, many rivers present similar challenges. The present method that allows forecasting of water levels even with a limited amount of data is useful in forecasting the water levels of urban rivers. Thus, to improve the accuracy of the present forecast method, it is necessary to increase the number of cases in other urban rivers for further verification.

**Author Contributions:** Conceptualization, N.K. and T.Y.; methodology, N.K.; software, N.K.; validation, N.K. and M.S.; formal analysis, N.K.; investigation, M.S.; resources, N.K.; data curation, M.S.; writing—original draft preparation, N.K.; writing—review and editing, N.K. and T.Y.; visualization, M.S.; supervision, T.Y.; project administration, T.Y.; funding acquisition, T.Y. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was supported by Unit for Research and Application Solution of Water-Related Disaster Science and Information of Research and Development Initiative (RDI), Chuo University.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** We would like to thank Tokyo Metropolitan Government and Tokyu Construction Co., Ltd. for assisting with data collection.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Jha, A.K.; Bloch, R.; Lamond, J. *Cities and Flooding: A Guide to Integrated Urban Flood Risk Management for the 21st Century*; The World Bank Press: Washington, DC, USA, 2012.
2. Galloway, G.; Brody, S.; Reilly, A.; Highfield, W.E. *The Growing Threat of Urban Flooding: A National Challenge*; University of Maryland: College Park, MD, USA; Texas A&M University: Galveston, TX, USA, 2018.
3. Hollis, G.E. The effects of urbanization on floods of different recurrence interval. *Water Resour. Res.* **1975**, *11*, 431–435. [CrossRef]
4. Morita, S.; Izumi, K. Quantitative analysis, the difference of flood runoff depth associated with urbanization. *Proc. Jpn. Conf. Hydraul.* **1985**, *29*, 19–24.
5. Muis, S.; Güneralp, B.; Jongman, B.; Aerts, J.C.; Ward, P.J. Flood risk and adaptation strategies under climate change and urban expansion: A probabilistic analysis using global data. *Sci. Total Environ.* **2015**, *538*, 445–457. [CrossRef] [PubMed]
6. Mahmoud, S.H.; Gan, T.Y. Urbanization and climate change implications in flood risk management: Developing an efficient decision support system for flood susceptibility mapping. *Sci. Total Environ.* **2018**, *636*, 152–167. [CrossRef] [PubMed]
7. Wang, S.; McGrath, R.; Hanfin, J.; Lynch, P.; Semmler, T.; Nolan, P. The impact of climate change on storm surges over Irish waters. *Ocean Model.* **2008**, *25*, 83–94. [CrossRef]
8. Suzuki, T. Japan's inundation risk map of storm surge under global warming and inundation damage function of coastal area. *Annu. J. Civ. Eng. Ocean.* **2012**, *68*, I-870–I-875. [CrossRef]

9. Ye, S.; Li, H.Y.; Leung, L.R.; Guo, J.; Ran, Q.; Demissie, Y.; Sivapalan, M. Understanding flood seasonality and its temporal shifts within the contiguous united states. *J. Hydrol. Meteorol.* **2017**, *18*, 1997–2009. [CrossRef]
10. Iwanaga, Y.; Ideta, k.; Sato, T.; Shimatani, Y. Study on outflow effect of on-site storage and soil improvement for small watershed. *J. Jpn. Soc. Civ. Eng. Ser B1 (Hydraul. Eng.)* **2016**, *72*, 49–58.
11. Tokyo Metropolitan Government: Tokyo Metropolitan Government Basic Policy on Torrential Rainfall Countermeasures (Revised). 2014. Available online: https://www.toshiseibi.metro.tokyo.lg.jp/kiban/gouu_houshin/ (accessed on 28 November 2022).
12. Kawaike, K.; Nakagawa, H. Mitigation Effect of ON-SITE Storage Facilities on Pluvial Inundation in Highly Urbanized Area. *J. Jpn. Soc. Civ. Eng. Ser. B1 (Hydraul. Eng.)* **2018**, *74*, I-1537–I-1542. [CrossRef]
13. Hou, J.M.; Liu, F.F.; Tong, Y.; Guo, K.H.; Ma, L.; Li, D. Numerical simulation for runoff regulation in rain garden using 2D hydrodynamic model. *Ecol. Eng.* **2020**, *153*, 105794. [CrossRef]
14. Gagliano, A.; Nocera, F.; Detommaso, M.; Evola, G. Thermal behavior of an extensive green roof: Numerical simulations and experimental investigations. *Int. J. Heat Mass Transf.* **2016**, *34*, 226–234. [CrossRef]
15. Liu, X.; Chui, T.F.M. Evaluation of green roof performance in mitigating the impact of extreme storms. *Water* **2019**, *11*, 815. [CrossRef]
16. CIMA Foundation. Input Paper Prepared for the Global Assessment Report on Disaster Risk Reduction 2015. 2015. Available online: https://www.preventionweb.net/english/hyogo/gar/2015/en/gar-pdf/GAR2015_EN.pdf?_gl=1*q6zrfx*_ga*MTI4MzUyNzU0OS4xNjY3NTY0NTQ3*_ga_D8G5WXP6YM*MTY2NzU2NDU0Ni4xLjEuMTY2NzU2NDYzMS4wLjAuMA (accessed on 28 November 2022).
17. JRC. River Flood Hazard Maps at European and Global Scale. Available online: https://data.jrc.ec.europa.eu/collection/id-0054 (accessed on 4 November 2022).
18. Winsemius, H.C.; Van Beek, L.P.H.; Jongman, B.; Ward, P.J.; Bouwman, A. A frame work for global river flood risk assessments. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 1871–1892. [CrossRef]
19. Ministry of Land, Infrastructure, Transport and Tourism. Hazard Map Portal Site. Available online: https://disaportal.gsi.go.jp/ (accessed on 4 November 2022).
20. Morooka, Y.; Yamada, T. Study on the characteristics of rainfall runoff in the Kinugawa river basin and the evacuation behavior of the residents at the time of Kanto and Tohoku flood disaster in September, 2015. *J. Disaster Res.* **2017**, *12*, 176–186. [CrossRef]
21. Beven, K.J. *Rainfall-Runoff Modeling*; Wiley: Hoboken, NJ, USA, 2001.
22. Fotovatikhah, F.; Herrera, M.; Shamshirband, S.; Chau, K.; Faizollahzadeh Ardabili, S.; Piran, M.J. Survey of computational intelligence as basis to big flood management: Challenges, research directions and future work. *Eng. Appl. Comp. Fluid Mech.* **2018**, *12*, 411–437. [CrossRef]
23. Yaseen, Z.M.; Sulaiman, S.O.; Deo, R.C.; Chau, K.W. An enhanced extreme learning machine model for river flow forecasting: State-of-the-art, practical applications in water resource engineering area and future research direction. *J. Hydrol.* **2019**, *569*, 387–408. [CrossRef]
24. Cho, M.; Kim, C.; Jung, K.; Jung, H. Water level prediction model applying a long short-term memory (lstm)–gated recurrent unit (gru) method for flood prediction. *Water* **2022**, *14*, 2221. [CrossRef]
25. Makoto, H.; Makoto, S.; Hironobu, M. Application of multivariate autoregressive model to groundwater behavior. *J. Hydraul. Eng.* **1995**, *1995*, 93–102.
26. Hartini, S.; Hadi, M.P.; Sudibyakto, S.; Poniman, A. Application of vector auto regression model for rainfall-river discharge analysis. *Forum Geogr.* **2015**, *29*, 1–10. [CrossRef]
27. Miedzielski, T. A data-based regional scale autoregressive rainfall-runoff model: A study from the odra river. *Stoch. Environ. Res. Risk Assess.* **2007**, *21*, 649–664. [CrossRef]
28. Niedzielski, T.; Miziński, B. Real-time hydrograph modelling in the upper nysa klodzka river basin (sw poland): A Two-Model hydrologic ensemble prediction approach. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 1555–1576. [CrossRef]
29. Ali, G. Cointegration VAR and VECM and ARIMAX econometric approaches for water quality variates. *J. Stat Econ. Methods* **2015**, *4*, 1–38.
30. Mignot, E.; Li, X.; Dewals, B. Experimental modelling of urban flooding: A review. *J. Hydrol.* **2019**, *568*, 334–342. [CrossRef]
31. Danish, D. Hydraulic Institutek: Mike Urban, Mike Urban. 2017. Available online: https://www.mikepoweredbydhi.com/products/mike-urban (accessed on 28 November 2022).
32. Mwh: InfoWorks CS, Innovyze. 2010. Available online: http://www.innovyze.com/products/infoworks (accessed on 28 November 2022).
33. Rossman, L. *Storm Water Management Model Users' Manual, Version 5.1*; Environmental Protection Agency: Washington, DC, USA, 2015.
34. Henonin, J.; Russo, B.; Mark, O.; Gourbesville, P. Real-time urban flood forecasting and modelling—A state of the art. *J. Hydroinf.* **2013**, *15*, 717–736. [CrossRef]
35. Wang, H.; Hu, Y.; Guo, Y.; Wu, Z.; Yan, D. Urban flood forecasting based on the coupling of numerical weather model and stormwater model: A case study of zhengzhou city. *J. Hydrol. Reg. Stud.* **2022**, *39*, 100985. [CrossRef]
36. Sidek, L.M.; Jaafar, A.S.; Majid, W.H.A.W.A.; Basri, H.; Marufuzzaman, M.; Fared, M.M.; Moon, W.C. High-resolution hydrological-hydraulic modeling of urban floods using infoworks ICM. *Sustainability* **2021**, *13*, 10259. [CrossRef]

37. Mair, M.; Zischg, J.; Rauch, W.; Sitzenfrei, R. Where to find water pipes and sewers?—On the correlation of infrastructure networks in the urban environment. *Water* **2017**, *9*, 146. [CrossRef]
38. Qi, W.; Ma, C.; Xu, H.; Chen, Z.; Zhao, K.; Han, H. A review on applications of urban flood models in flood mitigation strategies. *Nat. Hazards* **2021**, *108*, 31–62. [CrossRef]
39. Tokyo Metropolitan Government. Sewerage Registers System. Available online: http://www.gesuijoho.metro.tokyo.jp/semiswebsystem/TspAgreementWeb.aspx (accessed on 4 November 2022).
40. Tokyo Metropolitan Government. Comprehensive Information System for Flood and Disaster Prevention. Available online: https://www.kasen-suibo.metro.tokyo.lg.jp/im/uryosuii/tsim0102g.html (accessed on 4 November 2022).
41. National Institute for Land and Infrastructure Management Ministry of Land, Infrastructure, Transport and Tourism (NILIM), Japan. *Technical Documentation on the Practical Application of XRAIN (X-Band Polarimetric (Multi Parameter) Radar Information Network) Rainfall Observation*; Technical Note of NIKIM; NILIM: Tsukuba, Japan, 2016; Volume 909.
42. Hyndman, R.J.; Athanasopoulos, G. *Forecasting: Principles and Practice*; OTexts: Heathmont, VIC, Australia, 2014.
43. Akaike, H. A new look at the statistical model identification. *IEEE Trans. Autom. Control* **1974**, *6*, 716–723. [CrossRef]
44. Lachenbruch, P.A.; Mickey, M.R. Estimation of Error Rates in Discriminant Analysis. *Technometrics* **1968**, *10*, 1–11. [CrossRef]
45. Eiichi, N.; Hiroto, S.; Ryuta, N.; Hiroyuki, Y.; Kosei, Y. Early Detection of Baby-Rain-Cell Aloft in a Severe Storm and Risk Projection for Urban Flash Flood. *Adv. Meteorol.* **2017**, *2017*, 5962356. [CrossRef]