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Is Water Pricing Policy Adequate to Reduce Water Demand for Drought Mitigation in Korea?

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Abstract: Korea experienced an unexpected drought in the southern Seoul metropolitan area from 2015 to 2017. After that, the Korean government has been drafting various policies to mitigate the effects of drought. However, these are primarily long-term drought policies, such as reservoir expansion. A comprehensive water demand reduction policy, which considers both short-term and long-term droughts, is also required. To confirm the effectiveness of the water pricing policy in Korea, we estimated the water demand reduction volume during droughts by assuming the drought and water pricing policy. We used two models for simulation: the severe drought area prediction (SDAP) model and the SD (system dynamics) model. The results showed the water demand reduction by price would not be significantly effective in Korea. We indicated that the effectiveness of policies could differ in each situation so that appropriate policies are needed for each country. This discussion could provide policy implications for other countries being at risk of droughts as well as the Korean government. Furthermore, we discussed non-price water policies that could be implemented in combination with the pricing policy in cases where the water pricing policy does not effectively reduce water demand.

Keywords: water pricing; water demand reduction; machine learning; system dynamics; simulation; drought mitigation

1. Introduction

Historically, Korea has been relatively rich in water supplies and has not had significant threats to water supply in drought. However, the southern Seoul metropolitan area suffered from unprecedented spring droughts during 2015–2017 [1,2]. The Korean government recognized the necessity for developing drought mitigation policies after this drought and begun proposing new policies since 2018. The proposed policies are mainly targeted to long-term droughts preparation using facilities such as dams and reservoirs to increase water supply [3].

Brears (2017) suggested that prior to planning to increase this water supply, improved water supply could be achieved by reducing existing water demand [4]. These reductions could be accomplished through the conservation of water by reducing usage derived from a water pricing system, setting public water saving targets, and encouraging people to save water by changing their lifestyle [4].

When looking at California's drought management policies that were implemented during a drought they experienced in 2012–2016 [5], the state seems to have improved its existing water usage, per Brears's (2017) [4] suggestions. The California government mentioned that the water pricing policy implemented in the last drought was an effective tool to reduce water demand and that it played an important role in conserving water over the long and short-term as a result [6]. California's successful policy for reduction by pricing of water demand provides a lesson [7] to Korea that existing water usage should be changed. Water is not an endless resource; therefore water demand reduction policies need to be implemented in addition to long-term policies that address increasing water supply [8,9].

However, In Korea, implementation of pricing policy for water demand reduction is challenging. The effectiveness of water pricing policy in Korea has not been well known, and the water price elasticity of demand in Korea has been quite different depending on the researchers, data, and models used [10]. Not only was there a negative response from politicians regarding the attempt to research water pricing policies [11] but Korean citizens are sensitive to raising water prices [10], even though the water rates are comparatively cheaper [12]. The Korean government might have focused on long-term drought mitigation, such as the water supply expansion, because of the difficulties of implementing a pricing policy to reduce the water demand. Thus, Korea's current drought mitigation policy is still insufficient to considering both long and short-term drought by improving existing water usage.

In this regard, our study simulated the policy effect by assuming that the water price policy was implemented during the spring drought in Korea. In particular, we have estimated the amount of available emergency agricultural water derived from the reduction in residential water usage during the drought period. To be specific, during the drought of Korea in 2015–2017, there was significant damage to agriculture, while the use of residential water was inconvenienced a little. Most cities worldwide do not face the risk of running out of the drinking water, but agriculture is not safe from the effects of drought [8]. Agricultural droughts require immediate mitigation because the crop death or stunted growth by the lack of water cannot be recover. Thus, the prompt water supply for agricultural drought mitigation is important in a drought period.

This study investigated whether the policy of water usage regulation by price would be effective in these severe drought areas in Korea. We predicted the severe agricultural drought area in the region spatially and simulated the effects of water pricing policy using the severe drought area prediction (SDAP) model [13] and the system dynamics (SD) model. The SDAP model was developed by our previous research [13] based on machine learning (ML). ML can produce good prediction performance based on big data; hence, it is already widely used as a means of prediction in many fields. In addition, SD was developed by Jay W. Forrester, a professor at Massachusetts Institute of Technology (MIT), [14] and is widely used in various fields, such as the military, politics, society, economy, and environment [15]. The SD model, which is composed of several causal connections, looks similar to the structural equation in that there are several independent and dependent variables. However, unlike the structural equation, it includes the concept of time and loop, which allows human behavior to be analyzed dynamically. Therefore, SD is a useful tool to analyze the effects of the policy changes in advance [16].

Based on the results from these models, we discussed whether the water pricing policy is appropriate to reduce water demand for drought mitigation in Korea, and the reason for the occurrence of differences between the countries. In addition, we stated the water demand reduction policy using the non-pricing that could be complemented when pricing policies were not effective.

2. Study Area and Data

2.1. Study Area

We conducted a case study in the southern Seoul metropolitan area in Korea, called Gyeonggi Province. This study area is located between 36°50′ N and 37°35′ N latitudes and 126°30′ E and 127°35′ E longitudes (Figure 1), has been severely affected by unprecedented droughts during the spring from 2015 to 2017.

The south Gyeonggi Province in Korea has an average annual precipitation of approximately 1300 mm. During the spring drought of the south Gyeonggi Province from 2015 to 2017, however, the province only had 50% of the usual annual precipitation [2]. Accordingly, we simulated a policy of the water pricing effect in this southern Seoul metropolitan area on the assumption that there was a drought in 2018 and that water rates were raised.

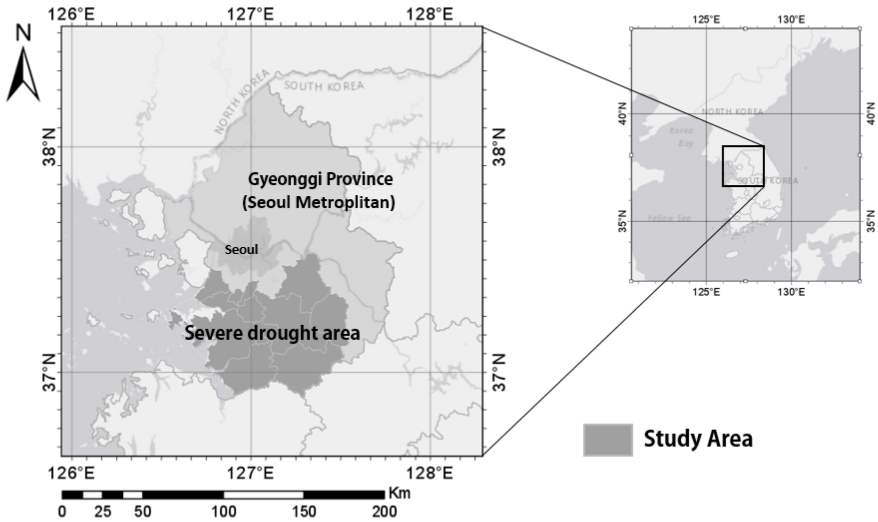

Figure 1. Location of the study area.

2.2. *Data*

The data used in the SDAP model were the Landsat 8 images and the Shuttle Radar Topography Mission (SRTM) digital elevation model (DEM) with 30 m resolution downloaded from the USGS EarthExplorer [17]. The programming language for analysis was Python 3.6.1 version for 64-bit windows platform and the software for spatial data processing was ArcGIS pro.

The data used in SD model, the daily usage of water per person, water price, population, and the information of the water source was referenced from My Water website [18] and Korean Statistical Information Service (KOSIS) [1]. Policy simulation was conducted using Vensim PLE version for Windows.

3. Methods

This study has the framework of two linked models, as shown in Figure 2, which is a structure that simulates policy by SD model based on the result of SDAP model [13]. The SDAP model (Figure 3) predicts the spatial distribution pattern of soil moisture after non-rainfall period using drought function trained by random forest (RF) algorithm [13]. The SD model (Figure 4) estimates the amount of water available to the provincial government by simulating the price increase policy for the drought-tolerant areas predicted in the previous process. We estimate the effectiveness of the policy through the estimated amount of water resources.

Similar to this, simulations method using linked two models (spatial information model and simulation model) already exist [19], and this is continuously influenced by the internal parameters between the two models connected to each other. In contrast, two models of our study are driven independently like modules so that the parameters of the simulation model are adjusted sequentially based on the predicted results from the spatial information model. Therefore, these models are easy to understand and apply. In addition, it can be improved by model and be used separately for each model depending on the purpose of use.

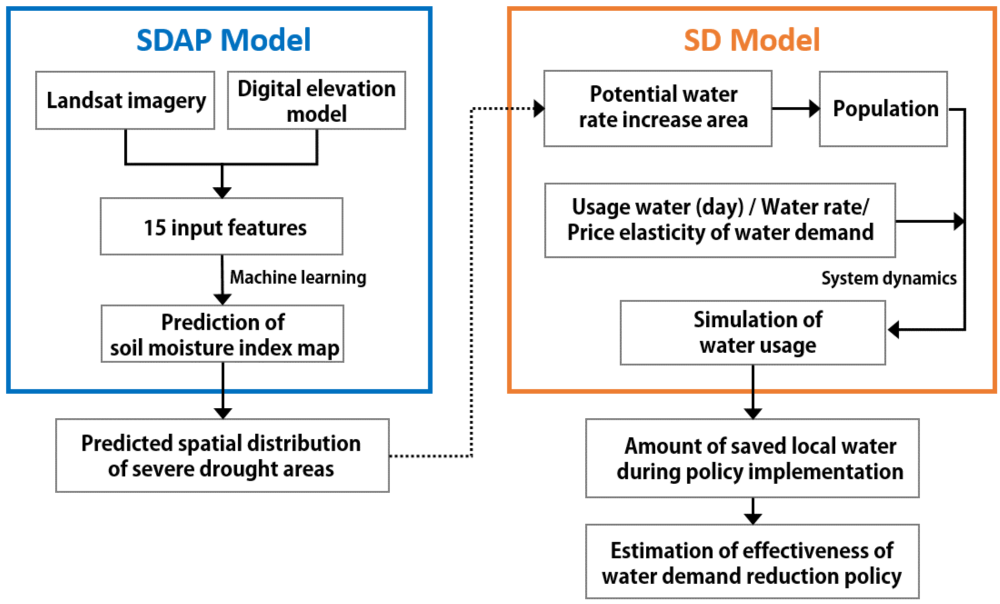

Figure 2. Framework of linked the severe drought area prediction (SDAP) model and the SD (system dynamics) model.

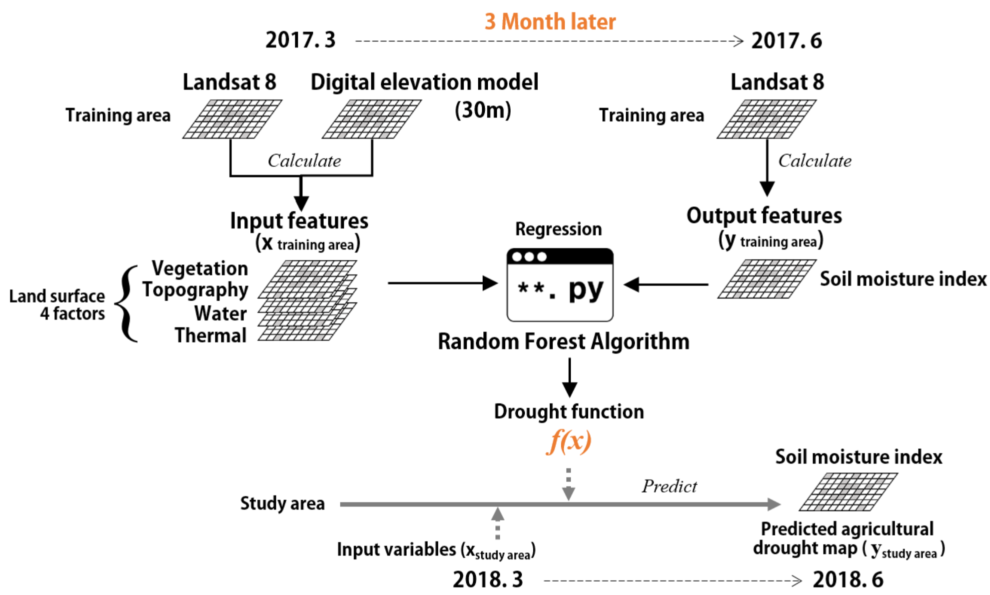

Figure 3. Structure of the SDAP Model.

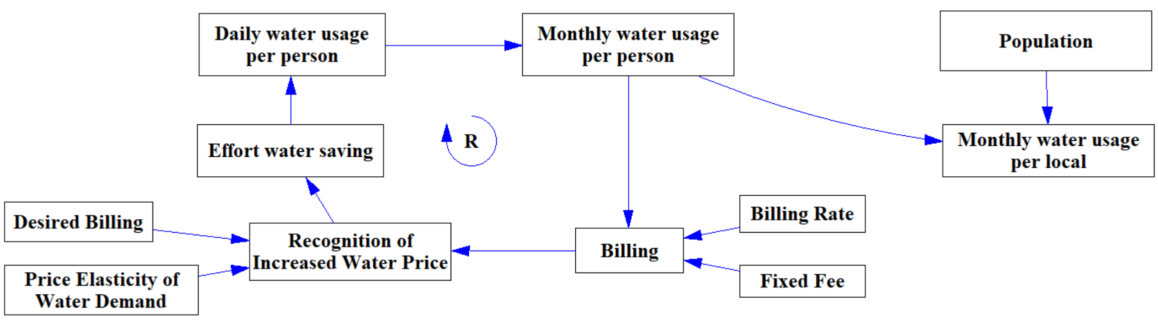

Figure 4. Structure of the SD model.

3.1. SDAP Model: Prediction Drought Spatial Distribution

Agricultural drought was trained and predicted by the following concept [13]. The soil moisture after non-rainfall periods remains different depending on the condition of the present land surface [20]. In this regard, we classified the land surface factors that affect the soil moisture into four categories: vegetation, topographic, water, and thermal factors during the non-rainfall period [13]. Thermal factors reduce soil moisture, whereas vegetation retards the loss of soil moisture by slowing down the increase in land surface heat [21]. Topography is another important determinant of soil moisture [22]. The land initial conditions such as existing water-containing state are also related to the soil moisture remaining after a drought period [20]. Thus, the present environmental conditions, such as these land surface factors, being regressed on the soil moisture after the non-rainfall period will make enable the short-term drought prediction of soil moisture.

Table 1 shows the 15 features (variables) that correspond to four land surface factor. These 15 features are regressed on the soil moisture index (SMI) of three months later of no precipitation and it is the input variables for the RF regression [13].

Table 1. Variables of the SDAP model for prediction severe drought area.

Land Surface Factors	Input Variables	Formula or Description	References
Vegetation	Enhanced vegetation index (EVI)	$2.5 \times ((NIR - Red)/(NIR + 6.0 \times Red - 7.5 \times Blue + 1)$	[23–25]
	Normalized difference vegetation index (NDVI)	$(NIR - Red)/(NIR - Red)$	[24–26]
	Soil-adjusted vegetation index (SAVI)	$((NIR - Red)/(NIR - Red + B)) \times (1 + 0.5)$	[24,25,27]
	Modified soil-adjusted vegetation Index (MSAVI)	$(2 \times NIR + 1 - sqrt((2 \times NIR + 1)^2 - 8 \times (NIR - Red)))/2$	[25,28]
Topography	Topographic wetness index (TWI)	$Ln\ (\alpha/tan\ \beta)$ [1]	[29]
	Slope	*Degree of slope*	[30,31]
	Aspect	*Degree of aspect*	[30,32]
Water	Normalized difference moisture index (NDMI)	$(NIR - SWIR_1)/(NIR + SWIR_1)$	[25,33]
	Modification of normalized difference water index (MNDWI)	$(Green - SWIR_1)/(Green + SWIR_1)$	[34]
	Moisture stress index (MSI)	*MidIR/NIR*	[35]
Thermal	Near infrared (NIR)	0.851–0.879 µm	[36]
	Short-wavelength infrared 1 ($SWIR_1$)	1.566–1.651 µm	[36]
	Short-wavelength infrared 2 ($SWIR_2$)	2.107–2.294 µm	[36]
	Thermal infrared sensor 1 ($TIRS_1$)	10.60–11.19 µm	[36]
	Thermal infrared sensor 2 ($TIRS_2$)	11.50–12.51 µm	[36]

[1] Where α is upslope area per unit contour length (m) which calculated as (flow accumulation + 1) × (cell size); β is the slope expressed in radians.

The RF algorithm that produces the drought function (hereafter $f(x)$) for predicting the SMI is one of the machine learning methods developed by Breiman [37]. The $f(x)$ was trained the actual drought that occurred in 2017 in this region, from March 23 to June 23 (approximately three months). We verified the $f(x)$ in our previous study. The training performance of $f(x)$ was $R^2 = 0.91$ and it can predict the SMI of the same period drought in the other year as $R^2 = 0.58$. Additionally, this $f(x)$ is characterized by the fact that the closer the drought is from the selected training area to be trained, the higher is the accuracy, and the $f(x)$ should be separately generated for each region and period. We predicted the soil moisture index of 26 June 2018 using the 15 features of 22 March 2018 and the $f(x)$.

The SMI from Sandholt et al. [38] was used as an output variable (target variable) for RF regression, which is suitable for representing soil moisture during the growing season of crops [35] since this index includes a vegetation index. Thus, the SMI is effective at predicting agricultural drought in the spring-summer period, which is the season examined in this study. For reference, this SMI has a real value between 0 and 1 and is most correlated with soil moisture at 20 cm soil depth [35].

We performed the following procedure to obtain a smooth SMI map, the final the severe drought area prediction map, after a non-rainfall period. Within the study area, 400,000 random points were generated and then the SMI value was inserted at the points. Subsequently, predicted agricultural drought maps were generated by the interpolation (natural neighbor) of all the points.

3.2. SD Model: Simulation of Increased Water Price Policy Implementation

Based on the predicted agricultural drought distribution map for the three months after the above analysis, we identified drought-critical areas. Then, we identified a water source that supplies water to the severe drought area and then found an administrative area used this water source jointly. The hypothetical policy simulated in this analysis applies to severe drought areas and collective-use residents temporarily in a three-month drought period. In a similar concept, in 2015, the California government announced that it must reduce water use by 25% in cities and towns of the severe drought area during the drought period [39,40].

To design a simulation model of a policy, it is preferable to create a causal map that can represent the causal relationship between the policy and changes in human behavior caused by the policy. Based on this causal map, the model is transformed into a model that can be simulated by entering a formula with variables and constants. These variables may be cumulative or contain constants. Figure 4 illustrates the process, which includes variables, where price increases result in the reduction of water usage. The definitions of SD model variables for the simulation are listed in Table 2.

Table 2. Variables of the SD model for policy simulation.

Variable	Type	Equation
Daily water usage per person	Level	water usage per day + (-) water saving effort initial value = 48.60 gallon [1]
Monthly water usage per person [2]	Auxiliary	water usage per day × 30 days × 0.003785
Billing	Auxiliary	fixed fee + (monthly water usage × billing rate)
Billing rate	Constant	Base = 0.92, Plan 1 = 1.10, Plan 2 = 1.28, Plan 3 = 1.46 (Unit: USD/m^3)
Fixed fee	Constant	1.50 USD
Recognition of increase water price	Auxiliary	whether (desired billing < current billing)
Desired billing [3]	Constant	6.63 USD/person per month
Price elasticity of water demand	Constant	−0.175
Water saving effort	Auxiliary	[4] the water demand changes rate (%) × water usage per day
Population [5]	Constant	7,969,432
Monthly water usage per local	Auxiliary	Monthly Water Usage per person × Population

[1] Average water usage per day in Korea [18]; [2] where 0.003785 is unit conversion (gallon to m^3). Water fee is charged per m^3; [3] existing monthly billing price; [4] water demand changes rate = water price changes rate (%) × the price elasticity of water demand; [5] severe drought area population + water source sharing area population.

The price elasticity of demand was primarily used to show the change in water usage caused by price fluctuations; it is calculated as follows:

$$\text{Price elasticity of demand} = \frac{dQ/Q}{dP/P} \tag{1}$$

where Q is the quantity of the demanded good and P is the price of the demanded good.

The price elasticity of demand for residential water is between −0.156 and −0.189 [10] in Korea, and we used the median value of −0.175 for this study. In addition to the average water rate for each municipality, the water rate used for the simulation was composed of the water billing based on a fixed fee and the usage rate.

We have assumed three policies based on increased water price. The base rate is 0.92 USD/m^3, which is the same as the current rate. Plan 1 was increased by 120% from the base rate to 1.10 USD/m^3; Plan 2 was increased by 140% to 1.28 USD/m^3; and Plan 3 was increased by 160% 1.46 USD/m^3. We then ascertained the amount of water saved for the three-month period by changing the individual water use of each plan. In particular, in Table 2, the desired billing implies the desire that the water billing will return to the previous level, thus the desired billing is calculated using the base rate.

We used the system dynamics model to simulate the amount of water used and the amount of water acquired for six months in advance for each rate plan. Ultimately, we want to identify water conservation and, specifically, water conservation in the three months following the drought.

4. Results

4.1. Predicted Agricultural Drought Severity Areas

As a result of applying the SDAP model, we found four potential severe drought area and have confirmed that five farmland areas within the study area had a lower SMI than other areas, excluding the impervious areas (dark gray section in Figure 5). Following this, four water sources that are used in the four predicted agricultural drought severity areas (five administrative districts) were identified. The water sources are shared by nine administrative districts, including the four severe drought areas [18].

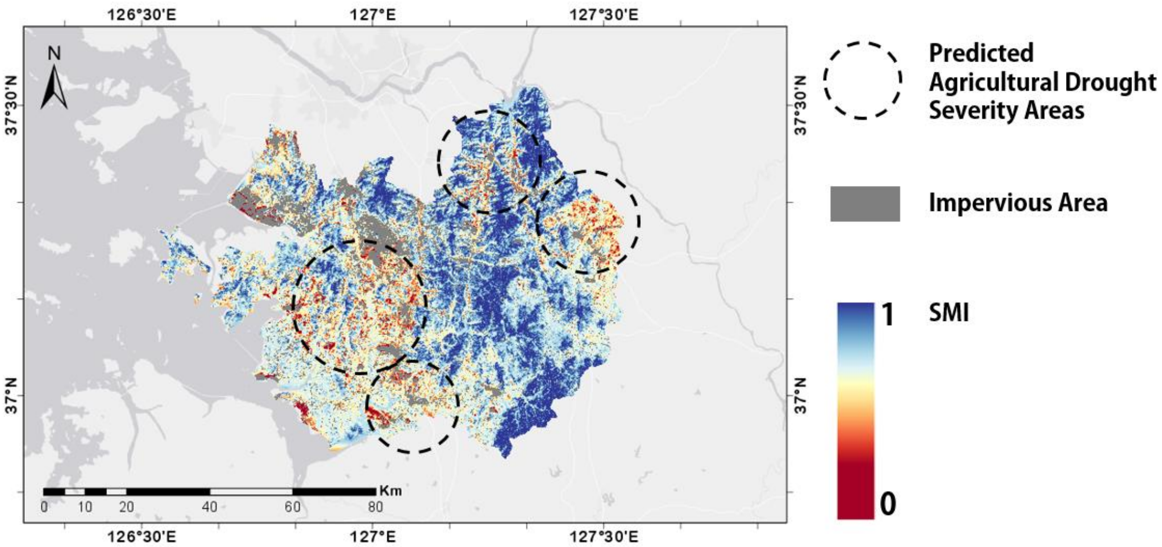

Figure 5. Predicted agricultural drought map (excluding for the impervious areas) after non-rainfall during the three-month period from 22 March 2018 to 26 June 2018.

4.2. Simulation of Water Pricing Policy Effect

When water price increase policies were implemented in the nine administrative districts during drought periods, the resulting individual water usage and the amount of water available for local governments are as shown in Figure 6. The effects in daily water usage began to appear three months after the implementation of the policy and thus little effect was observed during the period when water to be used for drought mitigation needed to be secured.

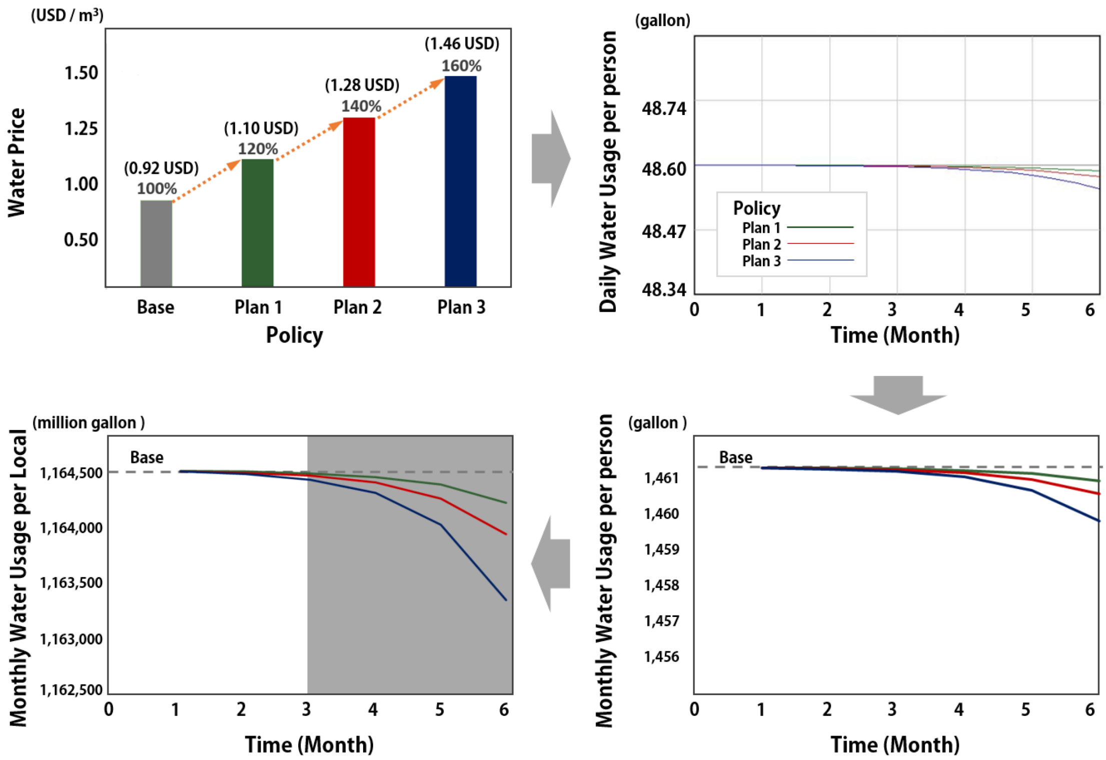

Figure 6. Changes in the amount of the water demand by increased water rate.

Table 3 shows how much water was secured each month after the plan had been implemented. It is expected that the amount of water to be secured during the three months of drought period will be considerably low and will not be an effective way to control water demand.

Table 3. Quantity of available water for drought mitigation.

Policy (Unit: Gallon)	One Month	Two Months	Three Months	Cumulative Amount
Plan 1	0	63,290	253,160	316,450
Plan 2	63,290	189,870	443,030	696,190
Plan 3	63,290	316,450	822,771	1,202,511

5. Discussion

5.1. Effectiveness of Water Demand Reduction Policy Price in Korea

Korea needs an effective policy to restrict water demand that can be implemented quickly during drought periods. However, our simulation results show that the water demand control policy based on water price increase during the 2015–2017 drought would not have been effective in Korea. This result also supports other studies that have shown that the price elasticity of water is inelastic in Korea and very high water rate is required to manage water demand [10]. Thus, if the policy to reduce water usage is based on only water price, it would not be effective in Korea.

We considered that the different outcomes were not only due to differences in the amount of water resources in each country, but also owing to culture differences in the water rate recognition and water use. For instance, most Koreans are reluctant to increase water rates [10] even though the water price is cheaper than in other countries [12]. Therefore, drought mitigation and water demand reduction policies must be developed considering the specific factors and situations within a region or country and not based solely on a policy's success elsewhere. While the water pricing is one of many ways to reduce water demand, it is not the only solution. For example, in California, a considerable amount of water is utilized for watering residential lawns. The California government, therefore, attempted to reduce the water use of individuals by restricting this activity, which resulted in a significant water use reduction [7]. In contrast, in Korea, there are not many houses with lawns. Thus, restricting this activity in Korea would not be effective. It would be more effective to reduce the demand of water, which is used indiscriminately in everyday life such as for showers, car washes, and dishwashing, because of the low water price.

A variety of results have been found after examining other studies about the effectiveness of pricing for reducing water demand. While some studies showed that water pricing is not effective at all [41], there are also opposing studies that showed it was effective [42]. In addition, there are several studies with the neutral position that the pricing policy is not completely ineffective, but only effective in a short period of time [43].

Our research aimed at confirming the effectiveness of water pricing policy in Korea to secure emergency agricultural water. During this process, we found a difference in the supply method of agricultural water between Korea and California. While Korea uses the direct water supply to the drought area, California supported the water indirectly. For example, in Korea, the residential water is used directly as emergency agricultural water during a severe drought. Korea is attempting to introduce the concept as the 'Smart Water Grid' to develop a system for managing and sharing water to support areas with water scarcity. Similarly, Singapore already operates an integrated water management system [44]. In contrast, California indirectly supported agricultural water by excluding agriculture from water regulations. The water demand reduction regulations of 25% only applied to residential, industrial and commercial water use [5,7,39]. Thus, depending on the circumstances of the region and country, both the water demand reduction method for drought mitigation and the water supply methods can vary. Therefore, in regions and countries facing a drought crisis, appropriate water demand reduction policies should be designed to fit the circumstance of each country using simulations considering both price and non-price policies.

5.2. Non-Price Policy for Water Demand Reduction

In Korea, the non-price policies should be implemented with high-level water pricing to achieve effective water demand reduction [10]. There are some related studies on the effectiveness of non-price factors for controlling water demand to support this view. For example, one study showed that water use can be reduced by simply increasing the frequency of water bills without a price control policy [45]. Another study found that the non-price method for reducing water demand, such as water-saving campaigns in times of drought or water-saving equipment for showers and toilets, can also be effective [12].

The use of system dynamics techniques, including human dynamics by policy, can be repeatedly verified and tested against policies that have never been implemented, thus helping to develop policies tailored to each country's circumstances. In addition, the results of the analysis can be used as a resource for public consensus for the implementation of amicable policies. Furthermore, in Korea, SD can be used to simulate and repeatedly revise policies that include both price and non-price factors, creating an effective water management policy for drought response.

Figure 7 presents our proposed combination model including price and non-price factors that may be helpful for future research to develop a plan and understand the relation between reducing water demand and human actions. This SD model includes non-price factors that can be used to reduce water demand, such as increasing the billing frequency by using tax incomes generated from the increased water rate, implementing water-saving campaigns to raise awareness, and supplying water-saving household devices (such as water-saving faucets and toilet seats), which would thereby lead to effective water saving. However, these causal relationships along with the concepts and ideas depicted on the graph are beyond the scope of this research.

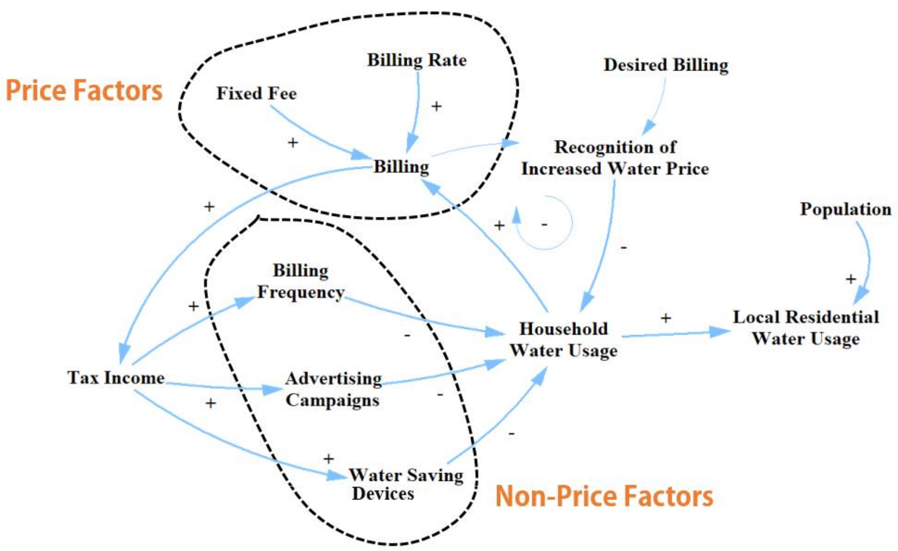

Figure 7. The SD model included price and non-price factors for saving residential water.

6. Conclusions

In this study, we used machine learning and remote sensing data in Korea to predict the soil moisture map that will occur three months after non-rainfall, as well as to identify areas with severe drought conditions based on the predicted agricultural drought maps. The system dynamics method was used to simulate the water price increase policy for the study area and confirm the amount of water available during the drought period. The simulation results showed that the amount of saved water was not significant, and, therefore, the water pricing policy for drought mitigation is not effective in Korea. However, the effectiveness of the pricing policy for water demand reduction cannot be generalized because the implement effects could be various depending on the situation in each country, such as culture and water reserves differences. Thus, the policy for drought should take an appropriate approach depending on the situation of each country. In future studies, further discussion of water conservation policies for drought mitigation is possible through simulation using models including price and non-price policies.

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