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Characterizing the hydraulic conductivity of soil based on the moving average of precipitation and groundwater level using a regional database

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ABSTRACT

Hydraulic conductivity is an important geological and geotechnical characteristic, necessary for flow-related problems and underground construction. In many countries, databases for hydrology parameters and groundwater level (GWL) are well established, often not fully utilized for directly estimating hydraulic conductivity characteristics. In this study, a method for estimating hydraulic conductivity based on a regionally established database of hydrological, geological, and geotechnical parameters is proposed. For this purpose, 68 databases of hydrological, geological and geotechnical parameters in different regions in Korea were collected and adopted to develop a data-based estimation method of soil hydraulic conductivity. The time response of GWL to precipitation was considered as a key influence factor on the hydraulic conductivity of soil, as it directly affected the infiltration process of rainfalls into soil deposits. Moving average (MA) of precipitation was introduced, which gave the best correlation to GWL, to account for the effect of accumulated precedent precipitation. Case examples were selected and used to check the validity of the proposed method.

Key words: database analysis, groundwater level, hydraulic conductivity, moving average, precipitation

HIGHLIGHTS

- Hydraulic conductivity of soil was estimated by hydrological and geological data.
- The time response of GWL to precipitation was a key factor that can estimate the hydraulic conductivity of soil.
- The concept of moving averge was adopted.

1. INTRODUCTION

Hydraulic conductivity is an important geological and geotechnical characteristic that is required for various flow-related problems, the design of underground structures and the selection of dewatering and waterproof methods for excavation (Boadu 2000; Lobbezoo & Vanapalli 2002; Ranaivomanana *et al.* 2017; Singh *et al.* 2019; Rehman *et al.* 2022). The hydraulic conductivity of soil is influenced by various factors such as soil type, grain size distribution, in situ void ratio, and inner particle configuration (Elhakim 2016; Fujikura 2019). Despite the importance of soil hydraulic conductivity in geological and geotechnical characterization, the evaluation of soil hydraulic conductivity remains a challenging task due to the heterogeneity of soil, difficulties in soil sampling and subsequent experimental procedure, and the large extent of flow area within soil deposit (López-Acosta *et al.* 2019).

The hydraulic conductivity of soil can be determined experimentally or empirically using a property-based correlation. Experimental methods include laboratory tests using soil samples and in situ tests, all costly and subjected to uncertainties associated with experimental procedure and variability of local soil conditions (Jabro 1992; Sahin 2016; López-Acosta *et al.* 2019; Singh *et al.* 2019; Sadeghi & Alipanahi 2020). Empirical correlation methods have also been often used in practice (Kozeny 1927; Carman 1956; Kenney *et al.* 1984; Boadu 2000; Chapuis 2004; Rosas *et al.* 2014; Wang *et al.* 2017). The empirical approach is cost-effective and has produced reasonable estimates in many practical cases, while limitedly valid and applicable for considered target soil type and grain size (Boadu 2000; Odong 2008).

Groundwater level (GWL) fluctuates owing to natural or anthropogenic reasons with characteristics that vary depending on hydrological, geological, and topographical conditions in a given area. The response rate of GWL fluctuation can also change depending on the duration and magnitude of precipitation and soil hydraulic conductivity (Hoque *et al.* 2007; Kim & Lee 2018). According to Kim & Lee (2018), in areas with a largely exposed ground surface, GWL is well correlated to precipitation due to the direct infiltration of rainfall into the ground. For such cases, a time lag occurs until GWL starts showing a response and actual fluctuation from the rainfall infiltration, which is all affected by soil hydraulic conductivity within the area.

In many countries, databases for hydrological and geological parameters are well established, often provided in a compiled format open to the public. However, such databases have not been sufficiently and effectively utilized in practice for the characterization of the hydraulic conductivity of soil, and few methods are currently available for the direct estimation of soil hydraulic conductivity using the databases. The hydraulic conductivity of soil is usually introduced as a regional-based property, rather than an individual elementary property, in the flow-related design and analysis. Therefore, it would be beneficial and could further enhance soil characterization if a method based on a regionally established database for estimating the hydraulic conductivity of soil is available.

In this study, a method for estimating the hydraulic conductivity of soil is proposed, focusing on the utilization of a regionally established database. For this purpose, databases at 68 different regions with hydraulic conductivity, precipitation, GWL, and other geographical parameters were established and adopted for the investigation. Based on the moving average (MA) and GWL response to precipitation at each region from the database, a correlation model of the soil hydraulic conductivity to the optimal MA period was proposed. 14 additional case examples were collected and adopted to check the validity of the proposed method.

2. HYDRAULIC CONDUCTIVITY AND INFLUENCE PARAMETERS

2.1. Determination of hydraulic conductivity for soil

The hydraulic conductivity of soil can be directly measured using laboratory tests such as constant or falling head tests, provided that a proper soil sample is available. However, results from laboratory tests indicate only the local hydraulic conductivity characteristics of sampled soil elements, which may not be valid for representing regionally applicable hydraulic conductivity characteristics (Lopez-Acosta *et al.* 2019). The procedure of soil sampling inevitably required for an experimental testing procedure is also always a challenging task. The hydraulic conductivity obtained from the laboratory tests is scale-dependent often exhibiting a larger range of variability than any other soil parameters (Boadu 2000; Elhakim 2016; Wang *et al.* 2020). In situ pumping tests with a monitoring well may be more suitable to obtain regionally applicable soil hydraulic conductivity characteristics as confirmed by El-Daly & Farag (2006) and Sahin (2016). However, it is obvious that the testing procedure is costly and time-consuming.

The empirical approach based on a correlation model to soil property is also often employed in practice (Hazen 1911; Kozeny 1927; Carman 1937, 1956; Kenney *et al.* 1984; Vukovic & Soro 1992; Kresic 1997; Boadu 2000; Chapuis 2004; Rosas *et al.* 2014; Wang *et al.* 2017). Table 1 summarizes various empirical correlation models commonly adopted to estimate hydraulic conductivity. Among these, the correlations proposed by Hazen (1911), Kozeny (1927) and Carman (1937, 1956) are popular in practice, due to the simplicity and the reasonableness of predicted results (Odong 2008; Elhakim 2016). The Kozeny-Carman equation was originally proposed by Kozeny (1927) and later modified by Carman (1937, 1956) to become the Kozeny-Carman equation (Chapuis & Aubertin 2003; El-Daly & Farag 2006). It is noted that each correlation model targets certain soil conditions, but does not cover all possible variable conditions in porous media (Odong 2008).

2.2. Fluctuation of GWL and influence factors

GWL fluctuates for a variety of reasons, including changes in annual precipitation, river stage, groundwater pumping, and other local activities, all possibly affecting the geotechnical stability of underground structures and foundations (Guttman 1999; Healy & Cook 2002; Almedeij & Al-Ruwaih 2006). Dominant influencing factors on GWL become different depending on the geotechnical, geological and geographical conditions in a given region, such as the hydraulic conductivity of soil, proximity to rivers, and ground surface conditions. In urban areas located near rivers, changes in river stage affect most significantly the fluctuation of GWL (Hoque *et al.* 2007; Kim & Lee 2019). In rural areas where ground surfaces are largely exposed, precipitation becomes the major influence factor on GWL, and the MA reflecting accumulated preceding rainfall is known to better describe the fluctuation of GWL (Kim & Lee 2022).

Table 1 | Correlation models for k based on grain size configuration

	Correlation equation	Remarks
Hazen (1911)	$k = C_H(D_{10})^2$	C_H = Hazen coefficient; D_{10} = effective grain size (0.1 mm < d_{10} < 3 mm)
Kozeny-Carman (Kozeny 1927; Carman 1937, 1956)	$k = \frac{g \cdot \rho_w}{\upsilon}\left[\frac{n^3}{(1-n)^2}\right]\frac{D_{10}^2}{180}$	n = porosity; g = acceleration of gravity; υ = kinematic viscosity; D_{10} = effective grain size; ρ_w = fluid density
Breyer (1964)	$k = \frac{g}{\upsilon} \times 6 \times 10^{-4} \times \log\frac{500}{U} d_{10}^2$	1 < uniformity coefficient < 20, 0.06 mm < effective grain size < 0.6 mm
Kenney *et al.* (1984)	$k = 0.005(D_5)^2$	D_5 = grain diameter for 5% passing
Vukovic & Soro (1992)	$k = \frac{g}{\upsilon} Cf(n)D_e^2$	g = acceleration of gravity; υ = viscosity; C = dimensionless coefficient; $f(n)$ = porosity function; D_e = effective grain diameter; n = porosity
Alyamani & Sen (1993)	$k = 1,300[I_o + 0.025(D_{50} - D_{10})]^2$	I_o = intercept in mm of the line by D_{50} and D_{10} with the grain size axis.
Carrier (2003)	$k = 1.99 \times 10^4\left(\frac{100\%}{\sum [f_i/(D_{avg})}\right)\left(\frac{1}{\mathrm{SF}}\right)^2 \frac{e^3}{1+e}$	f_i = particle fraction between two sieves; SF = shape factor; D_{avg} = average particle size; e = void ratio
Chapuis (2004)	$k = 2.4622\left[D_{10}^2 \frac{e^3}{1+e}\right]^{0.7825}$	D_{10} = effective grain size (0.03 mm < D_{10} < 3 mm); e = void ratio

The methods for estimating GWL can be categorized into knowledge-based and data-based approaches (Coppola *et al.* 2005; Sahoo & Jha 2013; Guzmán *et al.* 2016). The knowledge-based approach employs analytical and numerical models, explaining mathematically the flow of groundwater through soil (Serrano & Workman 1998; Batelaan *et al.* 2003; Trichakis *et al.* 2011; Sahoo & Jha 2013; Kim & Lee 2018, 2019). The data-based approach involves statistical correlation and calculation algorithm between selected influencing factors and GWL (Daliakopoulos *et al.* 2005; Fallah-Mehdipour *et al.* 2013; Sahoo & Jha 2013; Suryanarayana *et al.* 2014; Wen *et al.* 2015). It is noted that results predicted using the data-based approach are largely affected by datasets adopted in the calculation procedure for statistical calibration and training.

2.3. Moving average

A time lag occurs in the GWL response to precipitation, due to the infiltration time of rainfall into soil, which varies depending on the permeable characteristics of soil and ground surface conditions. It is indicated that accumulated precedent precipitation would be more dominant in changes in GWL, rather than simple daily precipitation. In that sense, MA is an effective parameter that can reflect the effect of precedent precipitation on GWL, for areas where the rainfall infiltration governs changes in GWL.

MA represents an accumulated precipitation for a specific past period, often adopted to explain changes in GWL (Guttman 1999; Almedeij & Al-Ruwaih 2006; Murray 2012). The value of MA is obtained as an average of total precipitation over a particular span of days given as the following relationship:

$$\mathrm{MA}_t = \frac{P_0 + P_{-1} + P_{-2} + \cdots + P_{-(t-1)}}{t} \quad (1)$$

where MA_t = moving average of precipitation over t days and P = daily measured precipitation. It should be noted that the values of MA_t become different depending on the considered number of past days. Usually, MA_t is designated as the one obtained for n past considered days that give the best correlation to the variable. It is therefore also referred to as the optimum moving average (MA_{opt}).

MA_t has been frequently adopted to describe the effect of preceding precipitation as an operating index for underground dams (Guttman 1999) and to analyze the correlation between precipitation and GWL (Yang & Kim 2011; Kim & Lee 2022). As MA reflects the actual infiltration time of rainfall into the ground to reach GWL, it is largely affected by the hydraulic conductivity of the soil. This implies that differences in MA_t in different regions are closely related to differences in soil type and hydraulic conductivity.

3. ESTIMATION OF HYDRAULIC CONDUCTIVITY BASED ON MA

3.1. Database for GWL and hydrological characteristics

Precipitation causes changes in GWL and river stage, which can vary depending on regional geological and geographical conditions (Sahoo *et al.* 2017; Kim & Lee 2022). As described in Figure 1, the time lag takes between precipitation and GWL response due to the process of rainfall infiltration into the ground, which is largely dependent on the soil hydraulic conductivity characteristics within the soil zone. As described in Equation (1), the optimum moving average (MA_{opt}) for GWL is achieved at a certain optimum period (t_{opt}) that gives the best correlation to GWL. This indicates that a correlation between t_{opt} and hydraulic conductivity may also exist and can be established for a given region. If such a correlation can be properly identified, it would be possible to obtain more representative regional-based soil hydraulic conductivity characteristics, which can cover a wider area.

To investigate the correlation between t_{opt} and the hydraulic conductivity, a database was established, which contains various geological and hydrological information including the hydraulic conductivity, daily measured precipitation, changes in GWL, proximity to the river, and surface pavement ratio. A total of 68 different regions in Korea were selected and adopted in the database. The average time period for the collected data from the selected regions was 11.3 years. GWL and hydraulic conductivity (k) data were obtained from the National Groundwater Information Center (GIMS) and precipitation data were obtained from the Korea Meteorological Administration (KMA).

The locations of the selected regions for the database are shown in Figure 2. The conditions considered for the selected regions were that precipitation governed changes in GWL, and the ground surface was largely exposed with a surface paved ratio of less than 30%. It was also considered that the distance of the target region from near-by rivers was greater than 3 km, to ensure the governing influence of precipitation.

Figure 3 shows the statistical distributions of selected parameters from the database including the hydraulic conductivity (k), precipitation, data length, distance to river, and surface pavement ratio. The values of k ranged from 1.5×10^{-6} to 0.146 cm/s with an average of 0.0028 cm/s. As considered for the selection of target regions for the database, the values of distance to the river and surface pavement ratio were larger than 3 km and smaller than 30%, respectively, representing the conditions of precipitation dominant for GWL.

Figure 4 shows the time series data of precipitation and GWL in two example sites of the Yeoju and Hanam regions from the database. It was seen that the timing of highs and lows of annual precipitation were similarly consistent showing peaks during the rainy season in summer and lower range in winter. The variational characteristics of GWL fluctuation with time were also similar and consistent. Although there was no significant difference in the distribution pattern of precipitation by

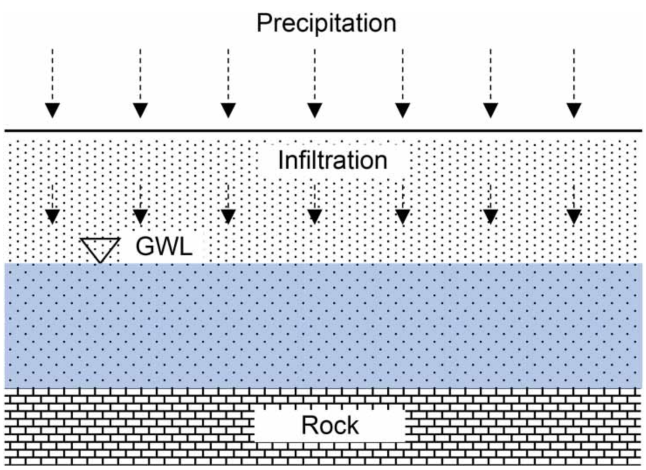

Figure 1 | GWL response to rainfall infiltration with precipitation.

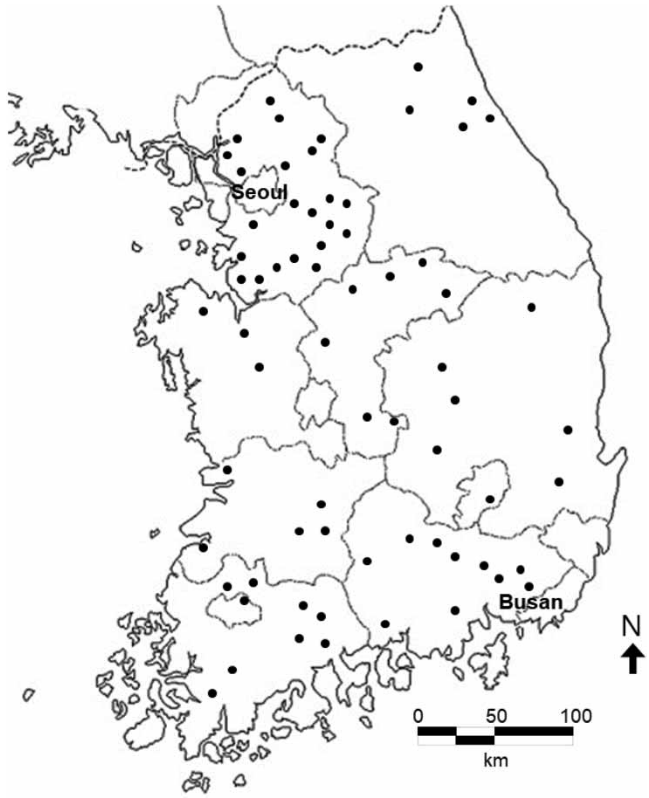

Figure 2 | Locations of test regions adopted for database.

region, the magnitudes and patterns observed from GWL were different depending on the location of the region and soil condition.

3.2. Effect of preceding precipitation on GWL

Using the precipitation and GWL data of the database, the values of MA_t and corresponding optimum period (t_{opt}) that gave the best correlation to GWL were obtained for all 68 regions. The determination of t_{opt} required an iterative calculation process, for which the time series of preceding precipitation days was raised until the best correlation to GWL was achieved. For this purpose, a specifically written program for the iterative calculation algorithm using time series data of precipitation and GWL to determine t_{opt} was prepared and adopted. Figure 5 shows the flow chart of the iterative calculation algorithm prepared in this study. Figure 6 shows examples at different regions for the determination of t_{opt}. The values of t_{opt} were determined based on the degree of the GWL correlation to past accumulated precipitation with different time periods. As shown in Figure 6, the values of t_{opt} were different depending on the considered region.

To check the uniqueness of t_{opt} for a given area and the effects of daily and accumulated precipitations on GWL, the values of GWL were correlated to daily measured precipitation and MA_t and compared for the case of the Dongducheon region contained in the database. The value of t_{opt} at this region was 161 days, which was determined following the procedure described previously. The compared results of the correlations were plotted in Figures 7(a) and 7(b) for precipitation and MA_{161}, respectively. It is clearly seen that MA_{161} was well correlated to GWL whereas the daily measured precipitation showed no meaningful correlation to GWL. These results shown in Figure 7 confirm that (1) the accumulated feature of precipitation is better correlated to GWL than daily precipitation; (2) a time delay takes place between precipitation and response to GWL; and (3) t_{opt} is unique for a given area.

The response of GWL to precipitation involves a time delay that occurs between the two components through rainfall infiltration into the ground, as shown in Figure 8(a). From the time series data of GWL and precipitation, the values of time delay (Δt) were obtained at each region and plotted in Figure 8(b) with t_{opt}. The values of Δt were determined by calculating

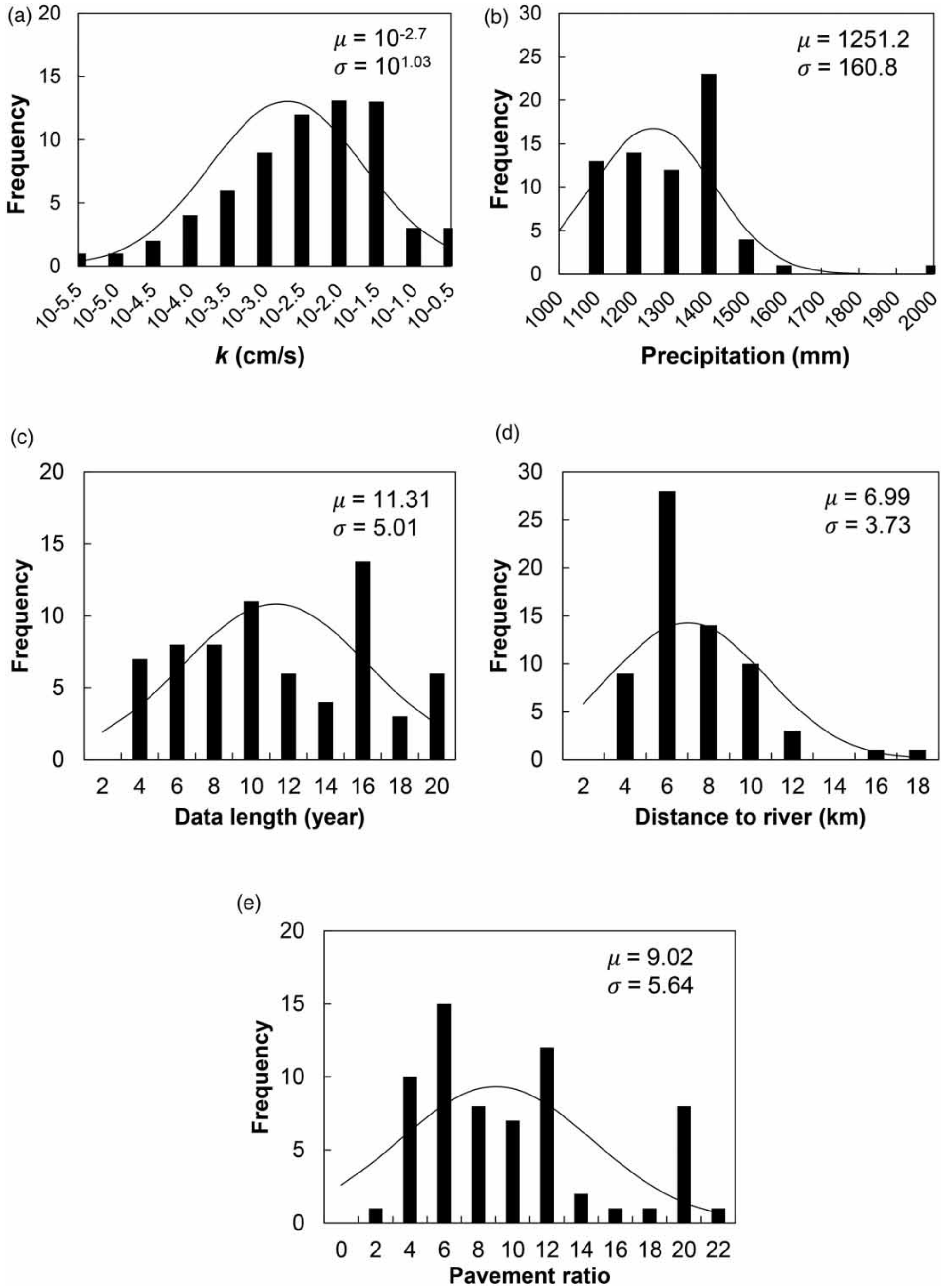

Figure 3 | Statistical distributions of considered parameters in database.

differences in days between peaks of precipitation and GWL and averaging through the considered time period. It is noted that Δt represents the physical travel time of rainfall from the soil surface to GWL. If GWL changed, Δt would change even for the same soil deposit. Δt is also affected by the moisture condition of soil above GWL as dry and unsaturated hydraulic conductivities are different. t_{opt} represents a statistical time period of accumulated precipitation until the best correlation to k is obtained. As the continuous time period of accumulated precipitation was considered at the best correlation condition, it is regarded that the effects of various influence components, including soil particle configuration, depth to GWL, vadose zone, and soil moisture condition, were reflected through the considered time period of t_{opt}. This implies that t_{opt} is unique for a given soil deposit.

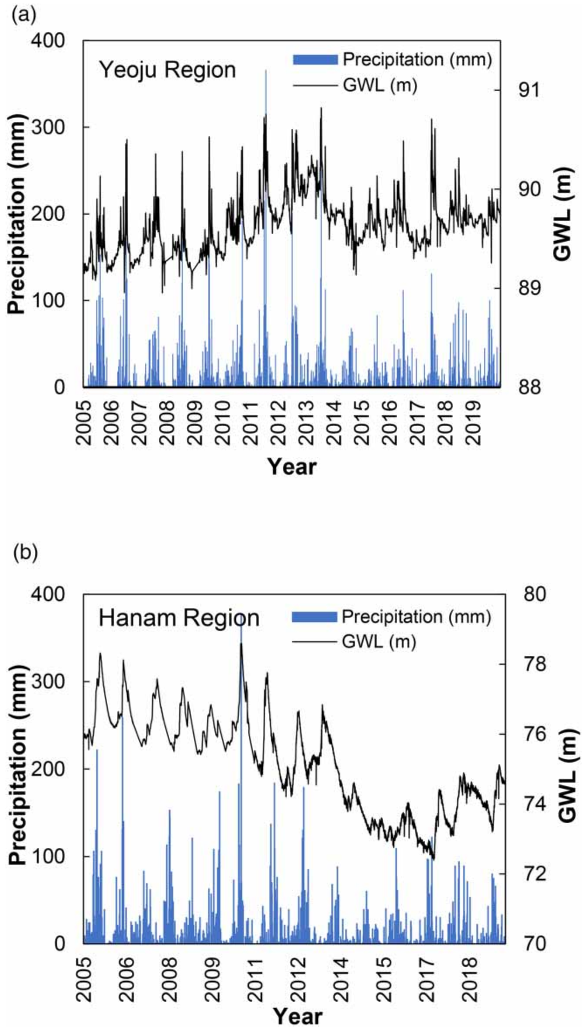

Figure 4 | Time history data of precipitation and GWL in (a) Yeoju and (b) Hanam regions.

As Δt and t_{opt} both represent the time delay characteristics of GWL response to precipitation, it is likely that these parameters are related to the hydraulic conductivity of the soil. Due to the differences between Δt and t_{opt} described previously, data scatters were observed from Figure 8(b), showing different magnitude scales for Δt and t_{opt}. Nonetheless, it is indicated that the smaller the hydraulic conductivity, the longer the values of Δt and t_{opt}, implying the slower response of GWL to precipitation. These two components will be further examined and considered for the correlation analysis of the hydraulic conductivity.

3.3. Evaluation of hydraulic conductivity to an optimum period for MA

The values of t_{opt} and hydraulic conductivity (k), obtained for each region of the database, were plotted together in Figure 9 in log and natural scales. The overall trend of the relationship between t_{opt} and k shown in Figure 9 indicates that the values of k decreased as the values of t_{opt} increased. Such a trend was reasonable because the soil condition with lower hydraulic conductivity would produce a longer time duration for rainfall infiltration into the ground and thus a longer response time of GWL.

From Figure 9 plotted for the values of t_{opt} and k, the correlation of k to t_{opt} was obtained from the regression analysis given as follows:

$$k = a(t_{opt})^{-b} \tag{2}$$

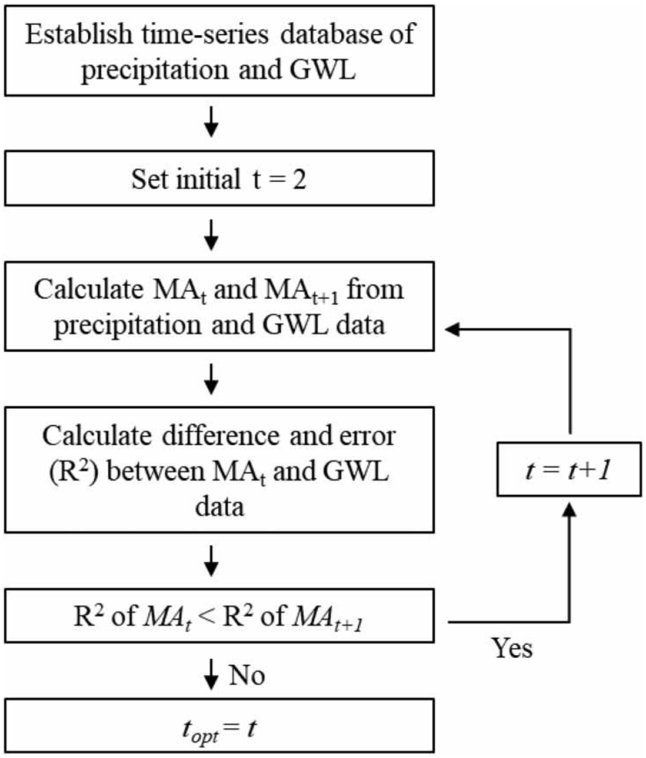

Figure 5 | Flow chart for iterative calculation.

where t_{opt} = optimum moving average period; a and b = correlation coefficients = 0.5761 and 1.563, respectively. Note that the correlation coefficients a and b of Equation (2) were obtained from the database adopted in this study. The accuracy and reliability of the proposed model can be further enhanced by continuously updating the database and calibrating the correlation coefficients of Equation (2). For other regions or countries, for example, it would be necessary to calibrate the values of a and b in Equation (2), to reflect the locality and regional characteristics of the correlation.

It is noted that the newly proposed correlation of Equation (2) was established based on the regional-based hydrological and geological characteristics, which were not specifically considered in the existing experimental and empirical approaches. The hydraulic conductivity of soil is spatially distributed in complex ways. The use of databases for piezometric level and precipitation would be effective to reflect the spatial variability of hydraulic conductivity. The proposed method is expected to further enhance the soil characterization process with a more efficient application of the regional database, leading to improved reliability of estimated results. It is also noted that the proposed k correlation model based on the GWL response time of t_{opt} can provide an effective tool for the input system of hydraulic conductivity, which would particularly benefit the widely adopted GIS-based regional analysis of flow and seepage problems. Cost effectiveness is another advantage as no experimental or testing procedure is involved.

The hydraulic conductivity of soil is closely related to the grain configuration of soil such as the constitution and distribution of particle and pore size as indicated in Table 1. This implies that t_{opt} may be a possible indicator of soil type provided that t_{opt} is well correlated to k. It also implies that the portion of granular materials in the soil is larger if the value of t_{opt} is small. It should also be noted that t_{opt} can be affected by morphological factors such as terrain slope, water table depth, and land cover.

Figure 10 shows the values of k with Δt in log and natural scales. As compared and discussed in Figure 8(b), Δt and t_{opt} both represent similar characteristics, related to the response time of GWL to precipitation. It is observed that the overall trend of k and Δt values shown in Figure 10 was similar, in only an approximate manner, to that of k and t_{opt} values shown in Figure 9. Note that Δt can change even for the same soil deposit depending on the depth location of GWL. The deeper the GWL is located, the longer the values of Δt would be produced. In fact, GWL often fluctuates periodically and varies with season.

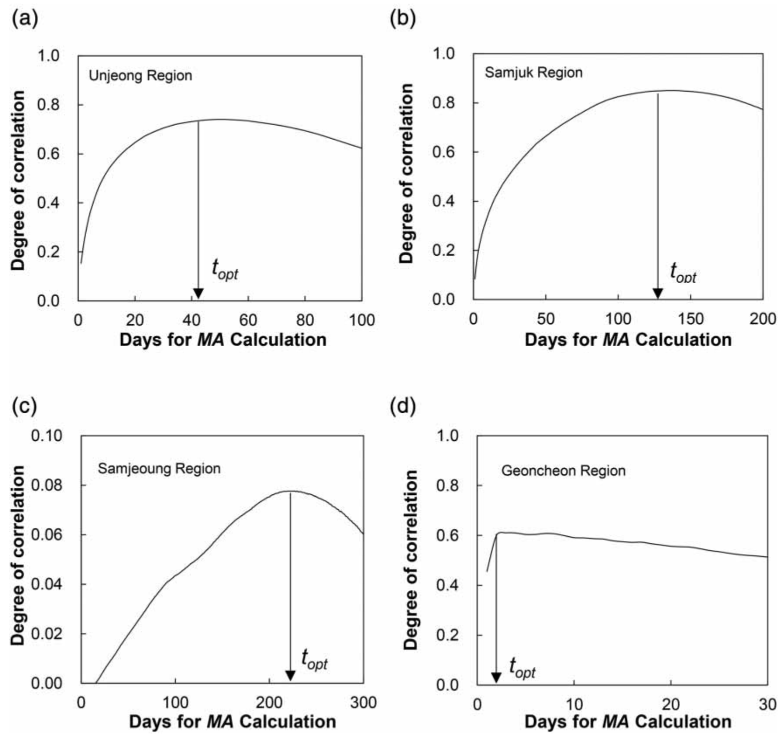

Figure 6 | Determination of optimum period for MA.

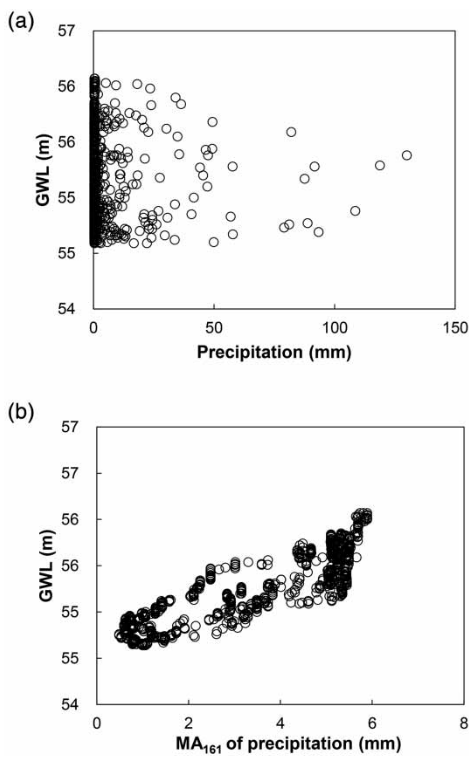

Figure 7 | Compared correlations of GWL to (a) precipitation and (b) MA_{161} of precipitation.

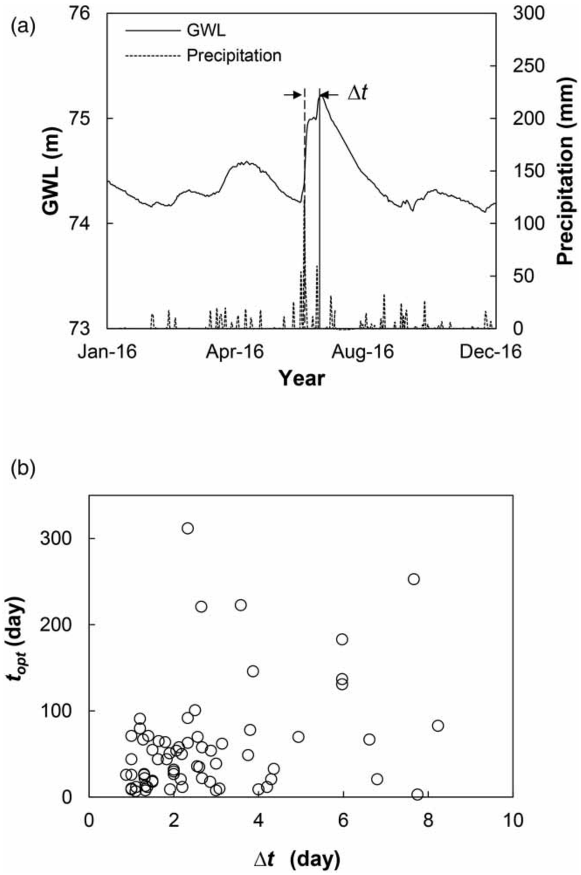

Figure 8 | Response of GWL to precipitation: (a) description of GWL response time (Δt) to precipitation and (b) compared values of t_{opt} and Δt.

In that sense, t_{opt} would be a better option for establishing the correlation of k as it reflects the effects of both GWL depth and preceding precipitation. The main focus and contribution of this study are therefore on the use of t_{opt}.

4. CASE EXAMPLES AND COMPARISON

To check the validity of the proposed correlation model for the estimation of k, 14 additional case examples in Korea were collected and obtained from the same sources as those used for the database previously described. Considered necessary parameters were then obtained from the 14 cases and adopted for comparing measured and predicted values of k. The collected case examples are summarized in Table 2. For the selection of the newly introduced case examples in Table 2, the similar geographical conditions of low surface paved ratio as those for the previous database were considered to maintain the consistency of the prediction. For GWL and precipitation data at each case region, the values of t_{opt} were obtained following the same procedure described in Figure 5 and adopted in the prediction.

For all cases in Table 2, the values of k were predicted using the proposed correlation model of Equation (2) and compared with the measured values in Figure 11. For comparison, existing representative empirical correlations of Hazen (1911), Breyer (1964) and Chapuis (2004), all based on grain size configuration and popular in practice, were also adopted, and calculated results were included in Figure 11. From Figure 11, it was observed that the predicted values of k for the range smaller than 0.01 cm/s were in reasonably close agreement with measured values. For the range of k larger than 0.01 cm/s, the predicted values were smaller than the measured values. Overall, the coefficient of determination (R^2) for the proposed method was higher than for the existing methods adopted in the comparison. It should also be noted that the proposed method takes advantage of the fact that the correlation can be further enhanced by updating the model parameters through a continuous and additional collection of test cases in a given region. Based on the comparison of the measured and predicted values of k, it is indicated that the proposed method is sufficiently effective and applicable in practice.

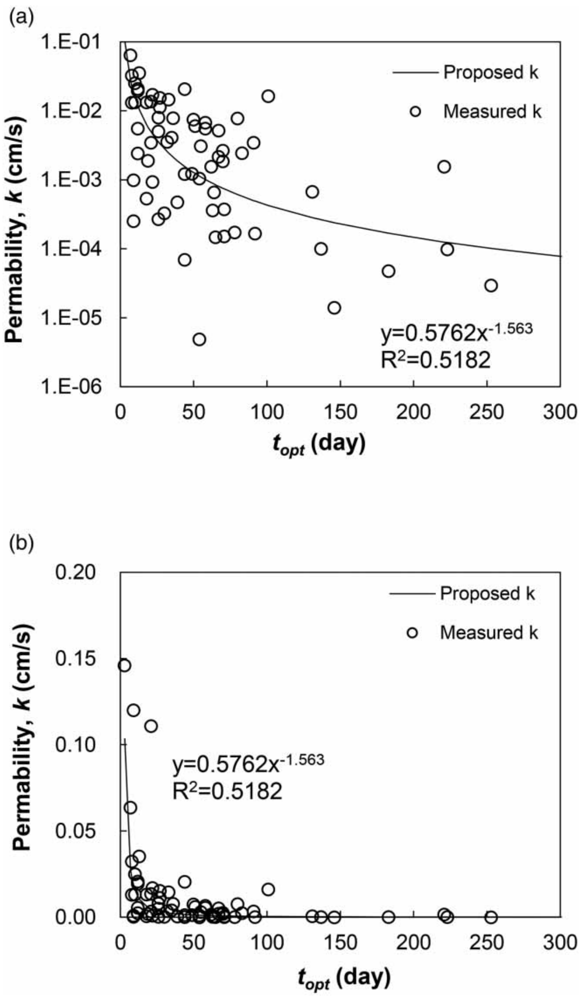

Figure 9 | Values of k with t_{opt} in (a) log scale and (b) natural scale.

5. SUMMARY AND CONCLUSIONS

The hydraulic conductivity (k) is an important geological and geotechnical characteristic that is required for soil characterization, design of underground structures and other flow-related problems. In this study, a method for estimating hydraulic conductivity was proposed, focusing on the utilization of a regionally established database of hydrological and geological parameters. The time response of GWL to precipitation was considered as a key influencing factor on the regional characteristics of the hydraulic conductivity, which was considered based on the optimum time period (t_{opt}) of moving average (MA_t).

To investigate the correlation between t_{opt} and k, a database of 68 different regions was established, which contains various geological and hydrological parameters. The values of MA_t and t_{opt} that gave the best correlation to GWL were obtained for all regions from the database. It was shown that MA_t was well correlated to GWL whereas the daily measured precipitation showed no meaningful correlation to GWL, indicating that the effect of preceding precipitation was important. It was found that the smaller the hydraulic conductivity at a given region, the longer the t_{opt} with the slower response of GWL.

Based on the findings and matches of the considered parameter from the database, a correlation model between t_{opt} and the hydraulic conductivity (k) was established. The overall trend of the proposed correlation was sufficiently consistent, showing that the values of k decreased as t_{opt} increased. Such a trend was reasonable because a soil condition with lower hydraulic conductivity would produce a longer time of rainfall infiltration into the ground and thus a longer response time of GWL. The newly proposed correlation model was beneficially effective and advantageous, in that an experimental and empirical procedure is not required whereas the applicability and utilization of the regional database is further enhanced. For the

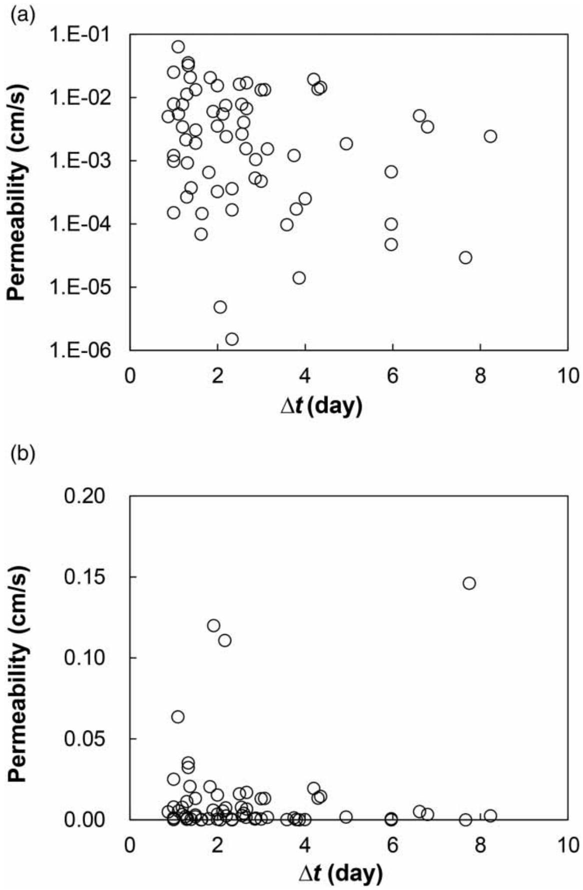

Figure 10 | Values of k with Δt in (a) log scale and (b) natural scale.

Table 2 | Case examples for validation

No.	Location	Data period (year)	t_{opt} (day)	R^{a}_{pave} (%)	k (cm/s)
1	Gosung	2003–2019	61	2.88	0.000902
2	Cheolwon	2006–2019	41	3.73	0.002033
3	Yangu	2015–2019	97	2.51	0.00240
4	Yongwol	2000–2019	69	2.03	0.000351
5	Pyungchang	2016–2019	26	2.28	0.018000
6	Hwacheon	2003–2019	26	1.54	0.002400
7	Changneong	2016–2019	14	6.97	0.043138
8	Hamyang	2013–2019	87	3.54	0.000216
9	Andong	2012–2019	102	3.56	0.000246
10	Waryong	2012–2019	27	3.56	0.001179
11	Gangjin	2012–2019	20	5.4	0.000576
12	Kimjae	2004–2019	19	10.56	0.002065
13	Dangjin	2017–2019	32	10.05	0.000803
14	Boryung	2017–2019	64	7.45	0.012117

[a]R_{pave} indicates the surface pavement ratio.

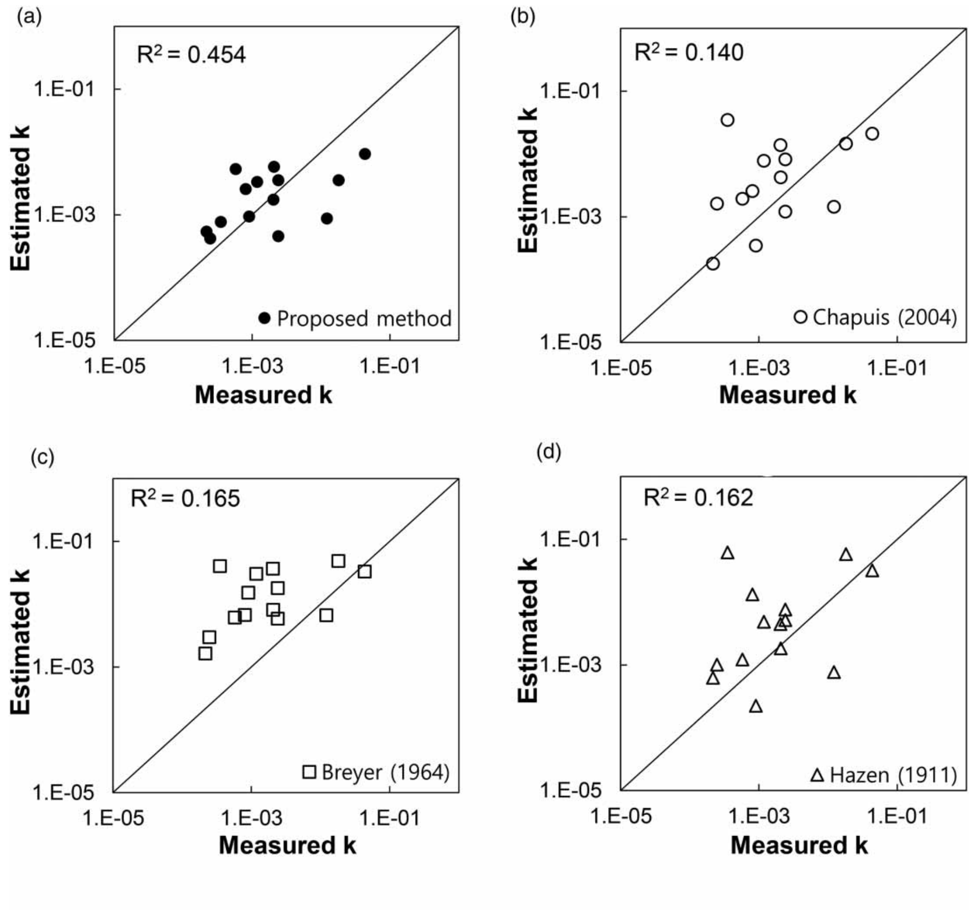

Figure 11 | Comparison of measured and predicted hydraulic conductivities (*k*) with (a) the proposed method and (b) method by Chapuis (2004); (c) method by Breyer (1964); and (d) method by Hazen (1911).

general applicability of the proposed method, the correlation coefficients of the proposed model can be further updated if additional datasets are available, or databases of other regions are targeted. Once the correlation model is established for a given region, the correlation is valid for estimating k using t_{opt} in areas within the region or neighboring regions unless geological and geotechnical conditions are not dramatically different.

To check the validity of the proposed correlation model, 14 additional case examples were collected and adopted in the comparison between measured and predicted values of k. The predicted values of k using the proposed method showed a consistent level of prediction, compared to those obtained using other existing methods, indicating that the proposed method is sufficiently effective and applicable in practice.

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DATA AVAILABILITY STATEMENT

Groundwater level and Hydraulic conductivity data: National Groundwater Information Center. (https://www.gims.go.kr/micro1.do). Precipitation data: Korea Meteorological Administration. (https://data.kma.go.kr/stcs/grnd/grndRnList.do?pgmNo=69/).

CONFLICT OF INTEREST

The authors declare there is no conflict.

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