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Development of Pedo-Transfer Functions for the Saturated Hydraulic Conductivity of Forest Soil in South Korea Considering Forest Stand and Site Characteristics

Honggeun Lim [1], Hyunje Yang [1], Kun Woo Chun [2] and Hyung Tae Choi [1,*]

[1] Forest Conservation Department, National Institute of Forest Science, Seoul 02455, Korea; hgh3514@korea.kr (H.L.); yanghj2002@korea.kr (H.Y.)
[2] Department of Forest Resources, Kangwon National University, Chuncheon 24341, Korea; kwchun@kangwon.ac.kr
* Correspondence: choiht@korea.kr; Tel.: +82-2-961-2643

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Abstract: The saturated hydraulic conductivity (K_s) is one of the most important soil properties for many hydrological simulation models. Especially in South Korea, analyzing the K_s of the forest soil is essential for understanding the water cycle throughout the country, because forests cover almost two-thirds of the whole country. However, few studies have focused on the forest soil in the temperate climate zone on a nationwide scale. In this study, 1456 forest soil samples were collected throughout South Korea and pedo-transfer functions employed to predict the K_s were developed. The non-linearities of the soil and topographic features were considered with the pretreatment of variables, and the variance inflation factor was used for treating the multicollinearity problem. The forest stand and site characteristics were also categorized by an ANOVA and post hoc test due to their diversity. As a result, the K_s values were different for various forest stands and site characteristics, which was statistically significant. Additionally, the model performance was higher when both soil properties and topographic features were considered. The sensitivity analysis showed that the K_s was highly affected by the bulk density, sand fraction, slope, and upper catchment area. Therefore, the topographic features were as important in predicting the K_s as the soil properties of the forest soil.

Keywords: pedo-transfer function; saturated hydraulic conductivity; forest soil; forest stand; soil properties; topographic features; multiple linear regression model; sensitivity analysis

1. Introduction

The saturated hydraulic conductivity (K_s) is an important factor that represents the basic properties of soil. It can represent the rate of infiltration, so it is essential for understanding the water cycle through soil, such as water recharge, drainage, baseflow, and runoff generation [1]. To date, many hydraulic simulation models, such as TOPMODEL, HYDRUS, and DHSVM, have been developed to simulate the water flow in a catchment [2–4]. These models have several input variables for simulation, and the K_s is included in the model equations, which means that the K_s can directly influence the model outcomes [4]. Therefore, the K_s, which is relevant to the infiltration rate, is one of the most important input factors and highly affects the model output, such as runoff [5,6]. Moreover, in order to achieve the Sustainable Development Goals (SDGs) related to ensuring the availability and sustainable management of water, the estimation of soil properties that are closely related to the water yield simulation and forest water management is important [7,8].

Measuring the K_s of soil is, however, time-consuming. Therefore, to date, many pedo-transfer functions have been developed. A pedo-transfer function (PTF) is an equation that estimates the soil hydrological properties, such as K_s and soil water contents, based on soil property data that can be easily collected, such as those related to the soil texture, organic matter, and bulk density [9]. Since PTFs aim to estimate the soil properties over a wider range, the input factors employed for PTFs use variables that have already been investigated on a national scale or that can easily be investigated or calculated [10]. For predicting the K_s, the soil size distribution has been used as input data in many studies [11,12]. In addition, many attempts have been made to predict K_s more accurately by adding the porosity and soil texture [13] and organic matter [14,15]. In particular, in South Korea, forest covers about two-thirds of the land area of the whole country. Due to these geographical characteristics, forest soil characteristics must be considered for water resource management in South Korea [16]. There have been many efforts to develop soil property databases on not only a national scale but also different international scales [14,15]. However, there are few studies focused on the forest soil in the temperate climate zone on a nationwide scale. Puckett et al. [12] and Dane and Puckett [17] developed PTFs from ultisols found in unconsolidated sediments of the lower coastal plain. Jabro [11] developed PTFs by using various soil series collected from nine regions in five countries, which were in the Southern Cooperation Series Bulletins. Wosten et al. [15] used the soil database from HYPRES collected from 20 institutions from 12 European countries, and Julia et al. [14] used soil data collected from Spain. In this way, much research has been conducted with large database sets with various land use types. However, there is little research specifying the land use types or only focusing on the characteristics of the forest soil.

Forests comprise different kinds of trees and plants, which, in turn, affect the forest soil. Additionally, because of their complex topographic features, forest soils exhibit spatial variability. Differently from other soils such as cultivated land, grassland, and bare land, forest soils can be located in steep slope regions, sedimentary or eroded areas, or high-altitude areas. Therefore, forest soil is constantly affected by forest stand and site characteristics and it is essential to consider the forest stand and site characteristics for analyzing the soil properties in forests.

PTFs for predicting the K_s can be used in many ways. Chirico et al. [18] used PTFs for conducting a soil water budget simulation on a hillslope scale. Furthermore, Young et al. [19] estimated the soil properties such as the K_s with PTFs and predicted the water budget and evapotranspiration with a hydraulic simulation model. In this way, national-scale estimations of the K_s can be conducted. From available databases, a hydraulic simulation model can be used and an assessment of the forest water yield can be conducted.

To achieve this goal in South Korea, this study was conducted in order to present the characteristics of the K_s in forest soil based on 1456 forest soil samples. The forest type and site characteristics affecting K_s were analyzed. PTFs were employed to predict the K_s of the forest soil considering both the soil characteristics and topographic features. Through a sensitivity analysis, we determined which factors were highly involved in the K_s of the forest soil.

2. Materials and Methods

2.1. Geography of Study Sites

This study was conducted on forest soil throughout South Korea, and 1456 soil samples were collected from 731 sites with topsoil and subsoil for the investigation (three replications of each soil horizon, Figure 1). When the forest soil was sampled, the litter and humus layer was removed. After that, topsoil was collected at the horizon depth of 10 cm, and subsoil was collected at the horizon depth of 30 cm. South Korea is located at about 33 to 38 degrees latitude and 125 to 129 degrees longitude, and in the humid temperate climate zone. It is also affected by the continental air mass from the northern continent and the oceanic air mass because three sides of the whole country are surrounded by the sea. The mean annual precipitation is about 1343 mm, and most of the rainfall is concentrated in June to September. The average temperature in summer is about 23 to 25 degrees Celsius, so it is hot and humid, but the average temperature in winter is about −1 to 1 degrees Celsius, so it is cold and dry. Considering this, there are a large mean annual range of temperature and four distinct seasons.

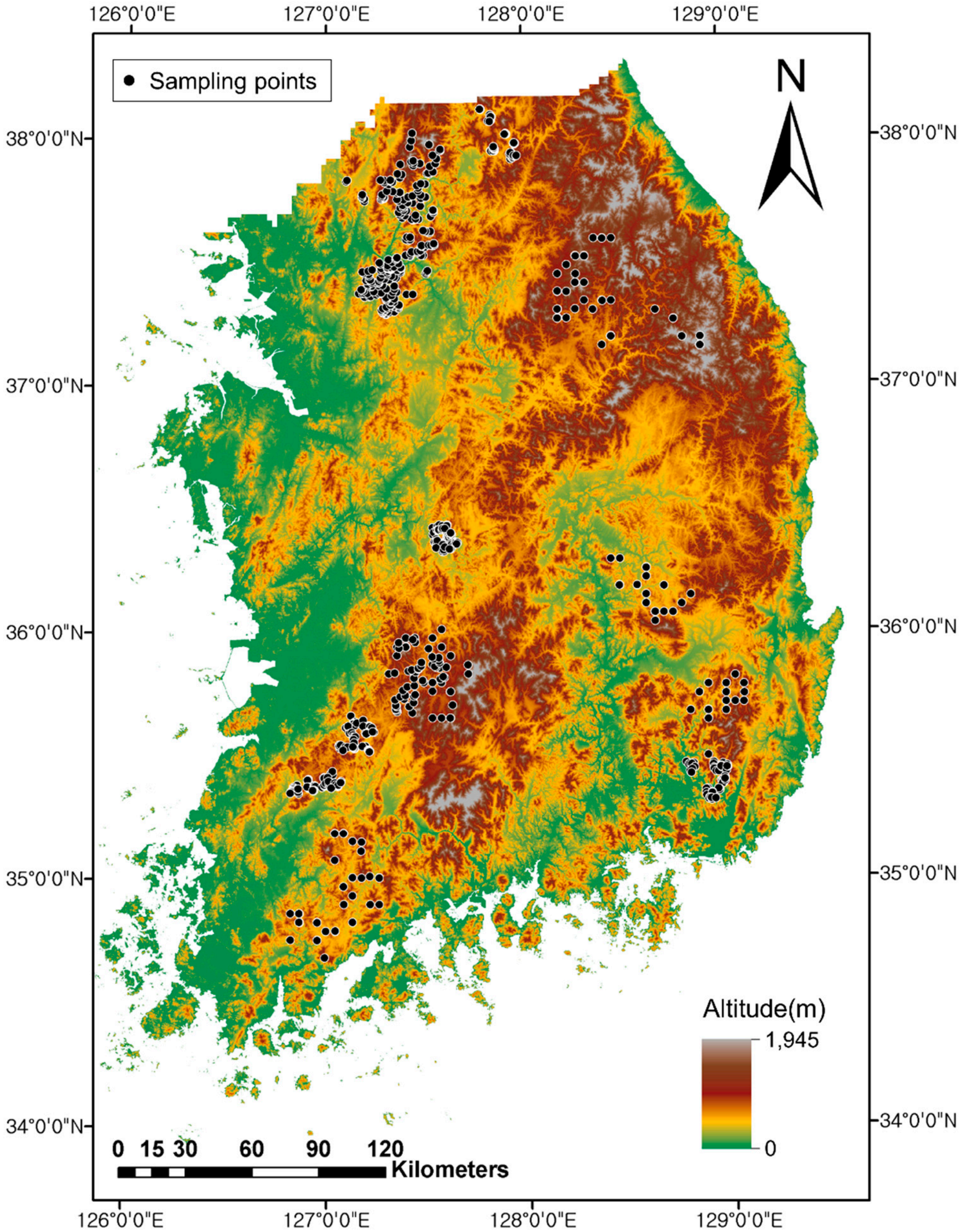

Figure 1. Distribution of collected forest soils in South Korea (1456 soil samples).

2.2. Soil Physical Properties and Topographic Features

Forest soil samples were collected through a 100 cc soil core sampler, and a total of 1456 soil samples were collected throughout the forest nationwide. Six properties were analyzed through laboratory experiments to investigate the physical properties of the soil. The analyzed soil properties were the saturated hydraulic conductivity; bulk density; sand, silt, and clay fraction; and organic matter (Table 1). The distribution of the 1456 soils across the USDA (United States Department of Agriculture) textural classes and the range of saturated hydraulic conductivity (K_s) by textural class are shown in Figure 2.

Table 1. Descriptive statistics for forest soil properties.

Soil Properties	Abb.	Unit	Min	Mean	Max	Std.	Skew.	Kurt.
Logarithmized Saturated Hydraulic Conductivity	Ln(K_s)	cm day^{-1}	0.37	6.57	8.98	1.21	−1.12	4.60
Bulk density	ρ_b	g cm^{-3}	0.45	1.03	1.59	0.19	0.12	2.78
Sand fraction	Sand	%	6.24	43.64	90.96	15.39	0.22	2.62
Silt fraction	Silt	%	1.46	33.01	81.36	12.66	0.07	2.39
Clay fraction	Clay	%	3.21	23.35	86.72	9.96	1.47	7.56
Organic matter	OM	%	2.08	9.16	29.71	3.53	1.09	4.94

Abbreviations: Abb, abbreviation; Std, standard deviation; Skew, skewness; Kurt, kurtosis.

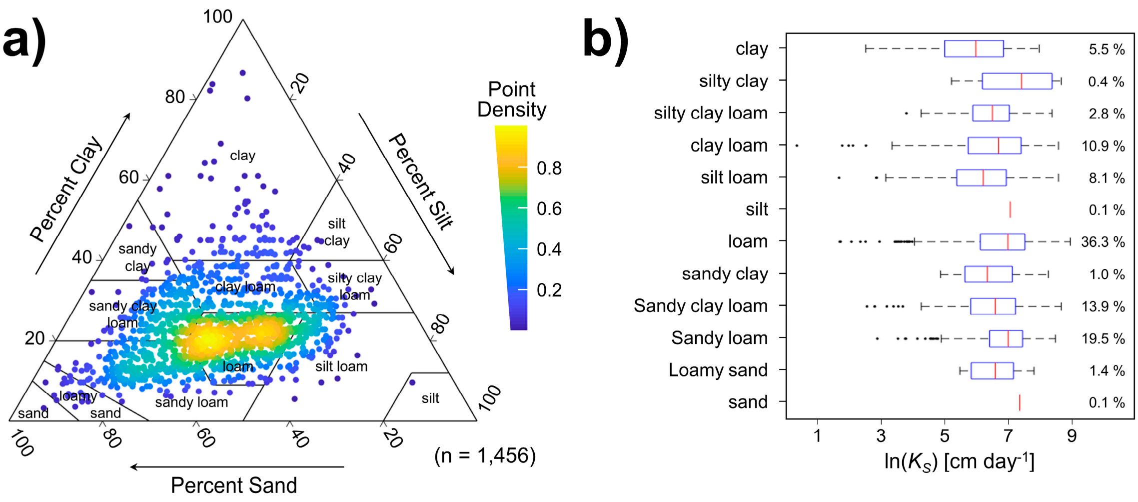

Figure 2. (**a**) Distribution of forest soils used in this study (n = 1456) across USDA textural classes and (**b**) ranges of the saturated hydraulic conductivity (K_s) and percent database by soil texture class.

The elevation, slope, topographic wetness index (TWI; Equation (2)), upper catchment area (CA), plan curvature, and profile curvature were collected as the topographic features. The elevation and slope indicate the altitude and local slope at the site where the soil was collected, respectively. The topographic wetness index, also known as the compound topographic index (CTI), indicates the steady state wetness index by topographic features. The TWI is calculated by the local upper catchment area and local slope and is derived as follows:

$$\mathrm{TWI} = \frac{a}{tanb} \tag{1}$$

where a is the local upper catchment area draining through a certain point per unit contour length and $tanb$ is the local slope [20]. The plan curvature can represent the shape of the horizontal plane, and the profile curvature can represent the shape of the vertical plane. The TWI, plan curvature, and profile curvature were calculated with the GIS spatial analyst tool.

In addition, the characteristics of the forest stand and site from which the soil samples were collected were investigated. The forest stand was divided into three categories: coniferous forest, broadleaf forest, and mixed forest. Bedrock and landform were investigated as site characteristics. Bedrock was largely divided into five types, including igneous, sedimentary, and metamorphic rock, and landform was classified into five types, as defined in Table 2.

Table 2. Landform classification.

Classification	Definition
Flat	A flat area with a slope of less than 5 degrees
Gentle slope	A hill with a slope of less than 300 m
Lower concave segment	The lower part of the mountain with a concave shape
Cliff face	The middle part of the mountain with a slope
Upper convex segment	The upper part of the mountaintop

2.3. Multiple Linear Regression for PTFs

2.3.1. Pedo-Transfer Functions (PTFs) in Previous Research

We selected PTFs that have frequently been cited in the literature for comparing the K_s of forest soils in South Korea to the K_s from other international databases by estimating the saturated hydraulic conductivity using our database. Six PTF models were selected, and brief explanations and references are shown in Table 3. Subsequently, the forest soil characteristics of South Korea were compared with other soil conditions by comparing the measured and predicted saturated hydraulic conductivity, which were estimated by six PTFs with the measured soil physical characteristics as input data.

Table 3. Six pedo-transfer functions (PTFs; Equations (S1)–(S6)) of previous research used for estimating the saturated hydraulic conductivity and their required soil properties.

Reference	K_s Unit	Required Soil Properties for Estimation	Land Use Types
Puckett et al. [12]	mm h^{-1}	Clay	The lower coastal plain
Campbell and Shiozawa [21]	mm h^{-1}	Sand, Clay	na
Jarbro [11]	cm day^{-1}	Silt, Clay, ρ_b	na
Dane and Puckett [17]	mm h^{-1}	Clay	The lower coastal plain
Wosten et al. [15]	cm day^{-1}	Silt, Clay, Organic matter, ρ_b	na
Julia et al. [14]	mm h^{-1}	Sand, Clay, Organic matter	na

Note: ρ_b is the bulk density and na is not available. Soil databases from many previous studies were based on various land use types, so there was no clear information about land use types.

Six PTFs did not focus on the forest soil, and many previous studies were based on various land use types. There was also no clear information about the land use types because previous research was conducted primarily focusing on local regions in which soil surveys were carried out. The PTFs in previous research have been empirical equations. Therefore, the ranges of the soil properties from which each PTF was derived are represented in Table 4.

Table 4. Brief descriptive statistics for soil properties in previous research.

Soil Properties		Puckett et al.	Campbell and Shiozawa	Jarbro	Dane and Puckett	Woesten et al.	Julia et al.	This Study
Sand	min	34.6	9.0	17.0	34.6	0.8	14.0	6.2
(%)	max	88.5	89.0	96.0	88.5	58.0	94.2	91.0
Silt	min	7.4	na	0.2	7.4	0	na	1.5
(%)	max	35.8		52.0	35.8	23.3		81.4
Clay	min	1.4	5.0	1.0	1.4	0	2.3	3.2
(%)	max	42.1	47.0	44.0	42.1	18.7	54.1	86.7
Bulk density	min	1.52	na	1.26	1.52	0.95	na	0.45
(g cm^{-3})	max	1.86		1.97	1.86	1.58		1.59
$ln(K_s)$	min	na	na	−2.90	na	−0.76	na	0.37
(cm day^{-1})	max			8.34		3.91		8.98

Note: na is not available.

2.3.2. Preprocessing of Explanatory Variables

In this study, PTFs were developed with multiple linear regression analysis to estimate the logarithmized saturated hydraulic conductivity ($ln(K_s)$). Since the saturated hydraulic conductivity can have a non-linear relationship with soil characteristics and topographic features, logarithmized ($\ln(x)$), exponential (e^x), squared (x^2), and untreated (x) treatments were carried out, and linear correlations with $\ln(K_s)$ were compared. Subsequently, the most linearly correlated variable type was adopted as the explanatory variable for multiple linear regression. The Pearson correlation coefficient was used to confirm the linear correlation.

2.3.3. Detecting Multicollinearity Using the Variance Inflation Factor (VIF)

In multiple linear regression, when there is a correlation between variables, coefficients in the multiple regression equation can be unreasonable and unreliable values, which is called a multicollinearity problem. Because this happens when a linear correlation occurs between the explanatory variables, it is necessary to remove the highly correlated variable in order to produce a reasonable result [22]. The variance inflation factor (VIF) is one of the best methods for identifying the correlation between variables. Since the VIF is a numerical value after multiple linear regression analysis is performed between explanatory variables, the higher the linear correlation between the explanatory variables, the higher the value of the VIF. If the VIF is higher than 5, it is determined that there is multicollinearity and the variable is removed [23]. The variance inflation factor (VIF) for one explanatory variable (x_1) is derived as follows:

$$\mathrm{VIF}_{x_1} = \frac{1}{1 - R_{x_1}^2} \tag{2}$$

where R^2 is the coefficient of determination of the multiple regression equation, which is estimated with one variable x_1 as a response variable and other variables as explanatory variables.

2.4. Model Assessment

Seventy percent of the total data set was used for developing the PTFs, and the remaining 30%, the hold-out test data set, was used to verify the model. To assess the performance of the PTF model developed in each process, the root mean squared log-transformed error (RMSLE), mean log-transformed error (MLE), and coefficient of determination (R^2) were used, and these are defined as follows:

$$\mathrm{RMSLE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\ln\left(\widehat{K_s}\right)_i - \ln(K_s)_i\right]^2} \tag{3}$$

$$\mathrm{MLE} = \frac{1}{N}\sum_{i=1}^{N}\left|\ln\left(\widehat{K_s}\right)_i - \ln(K_s)_i\right| \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left[\ln\left(\widehat{K_s}\right)_i - \ln(K_s)_i\right]^2}{\sum_{i=1}^{N}\left[\ln\left(\overline{K_s}\right)_i - \ln(K_s)_i\right]^2}, \tag{5}$$

where n is the number of observation samples, K_s is the measured saturated hydraulic conductivity, $\widehat{K_s}$ is the predicted value from the PTFs, and $\overline{K_s}$ is the mean of the measured values. The RMSLE and MLE represent the differences between the measured and predicted values as absolute values, and the lower the performance of the model, the higher the values. The RMSLE is directly affected by the scale factor and reacts more sensitively to outliers than the MLE. R^2 is the dimensionless value that represents the correspondence between the measured data and the predicted data. This has a value between 0 and 1, and variables are more correlated as the R^2 nears 1.

2.5. Sensitivity Analysis

Sensitivity analysis can determine the effect of each explanatory variable on the response variable by confirming the amount of change in the response variable as the explanatory variable changes [24]. The coefficient of multiple linear regression (MLR) can represent the sensitivity of the variable because the explanatory and response variables have a linear relationship. Therefore, it is not necessary to conduct sensitivity analysis if MLR is adopted as a model. However, in this study, several MLRs were presented, not just one MLR, to estimate the saturated hydraulic conductivity. Additionally, each explanatory variable had nonlinearity throughout the preprocessing.

Each explanatory variable was varied by total 10 multipliers: 0.1, 0.25, 0.5, 0.8, 0.9, 1.1, 1.2, 2, 4, and 10. Each variable was multiplied while the others were kept constant. Moreover, the multiplied variable was used as the input variable in PTFs, and the output, which was the modified saturated hydraulic conductivity, was normalized (modified $ln(K_s)$/non-treated $ln(K_s)$) to determine the amount of change. A sensitivity run was only implemented once for the PTF model, because there was no variance between the output of each sensitivity run.

Statistical analyses, such as the Pearson correlation analysis, analysis of variation (ANOVA), multiple linear regression, and *p*-value determination, were conducted using the SPSS software. We confirmed that the result was statistically significant and rejected the null hypothesis when the *p*-value was less than 0.05.

3. Results

3.1. Saturated Hydraulic Conductivity in Forest Soil

Six PTFs were analyzed to confirm the difference between the K_s of the forest soil collected in this study and the K_s predicted by the PTFs in previous research. The K_s was calculated using 1456 soil physical characteristics as input factors for the PTFs in previous research. Six PTFs did not focus on the forest soil, and many previous studies were based on various land use types. There was also no clear information about land use types. Figure 3 also shows the predicted K_s from the PTFs in previous research and measured K_s in this study. Figure 3 shows the range of the logarithmized K_s on the left side and its probability density function on the right side.

The averaged logarithmized K_s of the forest soil was 6.6, and the average logarithmized K_s from the six PTFs using the same input data set varied from −2.1 to 3.6. The K_S of the forest soil that was observed in this study was about 10 to 10^3 times larger than the K_s predicted with the PTFs of previous research. Additionally, most of the predictions exhibited negative $ln(K_s)$, which means that the K_s was between 0 and e cm day^{-1} and thus very low. In this study, however, no negative values were observed. The ANOVA test also showed that the K_S of the forest soil was higher than the K_s predicted by previous research for forest soils, which was statistically significant. Considering the range of the soil properties in Table 4, the range of the soil size distribution is different. In particular, the bulk density of the forest soil is lower than the bulk density of the soils used in previous research. These discrepancies indicate differences of K_s, and the PTFs were difficult to use to rationally explain the K_S of the forest soil in South Korea.

3.2. Explanatory Variable Selection

The most appropriate treatment of the explanatory variables was selected to estimate K_s through soil characteristics and topographic features. For selecting the appropriate treatment, logarithmized ($ln(x)$), exponential (e^x), squared (x^2), and untreated treatments (x) were carried out for each variable, and the linear correlation with $ln(K_s)$ of each treatment was compared. Table 5 shows the best results of the correlation analysis of the explanatory variables. Among the soil properties, sand and organic matter had a higher linear correlation when logarithmized, and silt and clay had a higher correlation when squared (Table 5). In terms of the topographic features, the TWI was highly correlated with logarithmized treatment and CA was highly correlated when squared after being logarithmized.

The *p*-value of all the variables was statistically significantly correlated with the logarithmized K_s ($p < 0.05$), and the bulk density and organic matter showed a strong linear relationship.

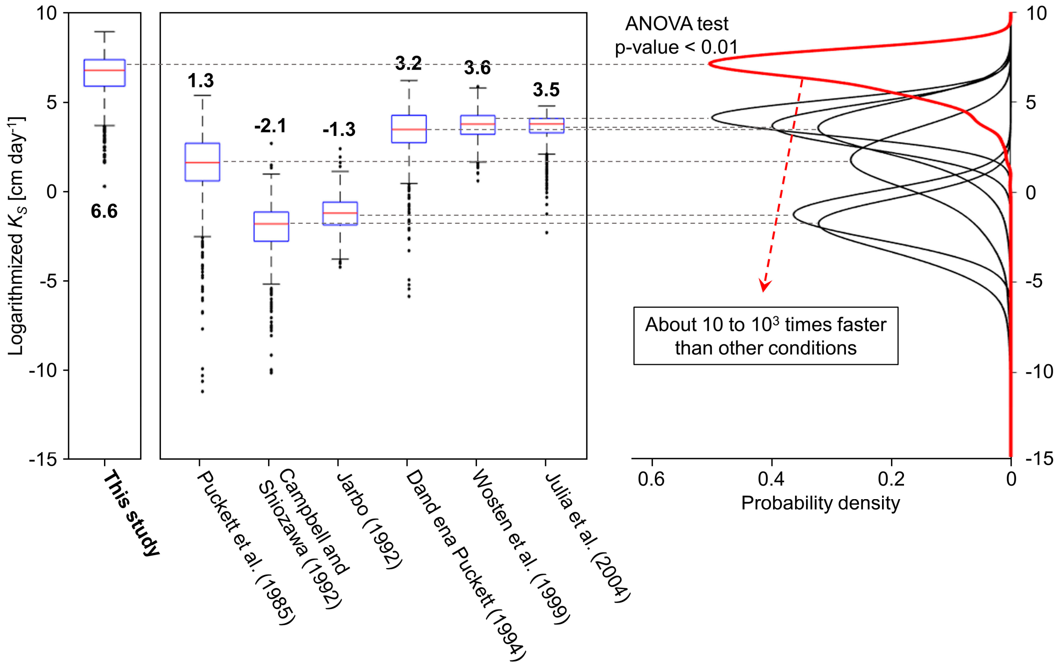

Figure 3. Mean values and ranges of the observed logarithmized K_s (saturated hydraulic conductivity) of forest soil in South Korea (this study), predicted logarithmized K_s based on PTFs presented in the literature, and kernel probability density functions of these logarithmized K_s. Six PTFs did not focus on the forest soil, and there are different ranges of the soil properties that previous research used.

Table 5. Relationship between $ln(K_s)$ and the best treatment of explanatory variables.

Selected Explanatory Variables		PCC	*p*-Value	VIF before the Removal	Multi-Collinearity	VIF after the Removal
Soil properties	ρ_b (-)	−0.46	<0.01	2.25	X	2.25
	ln(sand) (%)	0.14	<0.01	16.67	O	1.67
	Silt^2 (%)	−0.08	<0.01	12.78	O; removed	-
	Clay^2 (%)	−0.14	<0.01	7.87	O	1.48
	ln(OM) (%)	0.26	<0.01	1.89	X	1.87
Topographic feature	Elevation (m)	−0.05	0.039	1.21	X	1.17
	Slope (%)	−0.23	<0.01	1.11	X	1.11
	ln(TWI) (-)	0.09	<0.01	1.46	X	1.46
	(ln(CA))^2 (m^2)	0.07	<0.01	1.07	X	1.07
	Plan curvature	−0.08	<0.01	3.77	X	3.77
	Profile curvature	−0.08	<0.01	3.84	X	3.83

Note: PCC is the Pearson correlation coefficient and VIF is the variance inflation factor. The silt variable was removed because of the multicollinearity problem. After the removal, there was no multicollinearity in the variables (VIF < 5).

The VIF is calculated with both soil and topographic features, and values greater than 5 were found in the sand, silt, and clay fractions. This is because the sand, silt, and clay fractions are factors that are organically related to each other, so one of these factors must be removed to solve this multicollinearity problem. Sand was logarithmized, but silt and clay were squared, so sand might have a weaker linear correlation with silt and clay. Therefore, silt was removed, since silt had higher VIF values than clay. After removing silt, the VIF values of all the variables were less than 5, which indicates that there is no multicollinearity problem.

3.3. Categories with Statistical Analysis

Forest soil is affected by various forest stand and site characteristics, in addition to the soil and topographic features given in Table 6. Therefore, we analyzed the differences in K_s by forest type, bedrock, landform, and soil layer (Table 6). The forest types were divided into three types: coniferous, broadleaved, and mixed forest. Moreover, bedrock was classified into igneous, sedimentary, and metamorphic rock. Landform was classified into five categories (Table 2), and the soil layers were classified as topsoil and subsoil.

Table 6. The K_s differences by forest type, bedrock, landform, and soil layer obtained by ANOVA.

Classification		N	K_s	$ln(K_s)$	Post Hoc Analysis	F-Value	p-Value
Forest type	Coniferous	714	632.70	6.45	a	14.14	<0.01
	Broadleaf	550	796.32	6.68	b		
	Mixed	192	812.41	6.70	b		
Bedrock	Igneous	331	658.52	6.49	a	13.46	<0.01
	Sedimentary	329	454.86	6.12	a		
	Metamorphic	796	888.91	6.79	b		
Landform	Flat	175	454.86	6.12	a	20.38	<0.01
	Gentle slope	209	550.04	6.31	a		
	LCS	633	992.27	6.90	b		
	Cliff face	237	658.52	6.49	a		
	UCS	202	487.85	6.19	a		
Soil layer	Topsoil	728	880.07	6.78	a	20.99	<0.01
	Subsoil	728	578.25	6.36	b		

Note: LCS is the lower concave segment, UCS is the upper convex segment, and n is the number of samples. Forest type, bedrock, landform, and soil layer exhibit significant differences in K_s ($p < 0.01$). Post hoc analysis was conducted with Tukey's method, and bold values have higher K_s than others. ANOVA was conducted with the SPSS statistic software package.

According to ANOVA analysis and Tukey's post hoc analysis, the soil located in broadleaf and mixed forest had a higher saturated hydraulic conductivity than the soil located in coniferous forest ($p < 0.01$). Furthermore, the soil with metamorphic rock as a bedrock had a higher saturated hydraulic conductivity than the soil with igneous and sedimentary rock ($p < 0.01$). By landform classification, the soil located in the lower concave segment was statistically significantly higher than that in others ($p < 0.01$), with no statistical differences in the other four landforms except the lower concave segment. Moreover, the topsoil had a higher K_s than subsoil ($p < 0.01$).

The overall data set was divided into several categories because there were statistically significant differences in K_s by forest type, bedrock, landform, and soil layer, as shown in Table 6. As a result of the post hoc analysis of the forest type, bedrock, landform, and soil layer, all of the four forest stands and site characteristics could be classified into two categories: relatively fast K_s and relatively slow K_s. The total data set, therefore, was classified into 16 categories, depending on the characteristics of the forest type, bedrock, landform, and soil layer (Table 7).

Table 7. Sixteen categories based on forest stand, geological, and topographical features.

Categories	Forest Type	Bedrock	Landform	Soil Layer	Number of Soil Samples
1	Coniferous	I & S	Other LF	Subsoil	130
2	Coniferous	I & S	Other LF	Topsoil	132
3	Coniferous	I & S	L.C.S.	Subsoil	51
4	Coniferous	I & S	L.C.S.	Topsoil	51
5	Coniferous	Metamorphic	Other LF	Subsoil	84
6	Coniferous	Metamorphic	Other LF	Topsoil	84

Table 7. *Cont.*

Categories	Forest Type	Bedrock	Landform	Soil Layer	Number of Soil Samples
7	Coniferous	Metamorphic	L.C.S.	Subsoil	91
8	Coniferous	Metamorphic	L.C.S.	Topsoil	91
9	B & M	I & S	Other LF	Subsoil	109
10	B & M	I & S	Other LF	Topsoil	110
11	B & M	I & S	L.C.S.	Subsoil	39
12	B & M	I & S	L.C.S.	Topsoil	38
13	B & M	Metamorphic	Other LF	Subsoil	87
14	B & M	Metamorphic	Other LF	Topsoil	87
15	B & M	Metamorphic	L.C.S.	Subsoil	137
16	B & M	Metamorphic	L.C.S.	Topsoil	135

Abbreviations: B & M, broadleaf or mixed forest; I & S, igneous or sedimentary bedrock; Other LF, four landforms except the lower concave segment; L.C.S., lower concave segment (Table 2).

3.4. Development of the Pedo-Transfer Function

The soil data were classified into 16 categories, and multiple linear regression analysis was conducted for each category. Since most PTF studies have only been conducted with soil characteristics to date, multiple linear regression analysis was conducted twice: with soil characteristics only and with soil characteristics and topographic features. Table 8 shows the results of multiple linear regression analysis with only soil characteristics as the input data. Additionally, Table 9 shows the results of multiple linear regression analysis with topographic features in addition to soil characteristics. Tables 8 and 9 show the regression coefficients of each variable according to multiple linear regression, and full equations are available in the Supplementary Materials (Table S1 and S2).

Figure 4 shows the measured and predicted K_s with the developed PTFs with 16 categories. The model was developed using 70% of the total data set and validated with the remaining hold-out test data set. In the calibration phase, the coefficient of determination with only soil properties was 0.37 but increased to 0.43 when topographic features were added as input data. Moreover, the coefficient of determination values, 0.37 and 0.43, are significantly different from 0. The model performance also increased in the validation phase. The RMSLE and MLE, which show the deviation of the measured and predicted values, also decreased from 0.931 and 0.724 to 0.920 and 0.709, respectively. The model performance was improved when topographic features were taken into account in both calibration and validation.

Table 8. Regression coefficients of categorical PTFs for the logarithmized saturated hydraulic conductivity with only soil properties.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
ρ_b	−4.899	−3.988	−4.274	−2.890	−3.163	−3.452	−4.875	−1.325	−3.852	−3.939	−6.909	−4.797	−4.589	−2.265	−1.693	−0.666
ln(Sand)	0.803	0.748	1.553	0.690	0.634	0.889	1.867	1.269	0.858	0.543	−0.003	−0.248	0.731	0.502	0.768	−0.300
Clay2 *	1.752	1.094	6.362	0.004	1.129	2.227	−1.251	−1.255	2.435	1.116	−5.136	−6.104	1.064	3.735	2.554	−2.392
ln(OM)	−0.158	0.314	1.201	−0.219	−0.516	−0.016	−0.470	0.073	−1.209	−0.852	−1.934	−0.766	−1.764	−0.659	−0.124	−0.019
Intercept	8.730	7.042	2.570	7.207	8.503	6.615	5.758	3.374	9.527	10.433	18.003	14.270	11.948	8.270	5.942	9.317

Note: Clay2 * is clay2 × 10^{-4}. The regression coefficients of clay2 were too small, so the constant was multiplied to make them readable. In total, 16 categories were classified according to Table 7, and these values are the regression coefficients from multiple linear regression.

Table 9. Regression coefficients of categorical PTFs for the logarithmized saturated hydraulic conductivity with topographic features in addition to soil properties.

Categories	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
ρ_b	−3.499	−2.753	−3.147	−3.531	−2.385	−3.157	−3.402	−0.991	−4.559	−3.945	−4.622	−3.496	−3.675	−2.469	−1.793	−0.774
ln(Sand)	1.018	1.168	0.955	0.793	0.524	0.637	1.159	1.029	0.930	0.724	−0.865	0.006	1.323	0.686	1.233	−0.118
$Clay^2$ *	1.266	2.294	−3.235	−2.111	−2.267	−0.532	−4.992	−1.668	2.473	3.831	−9.888	−3.558	3.744	7.769	4.963	−1.178
ln(OM)	0.978	1.035	0.215	0.669	0.002	−0.386	0.186	0.204	−1.055	−1.368	−1.402	−0.412	−0.675	−0.927	−0.205	0.012
Elevation *	−0.505	−1.193	0.348	−0.929	0.398	0.546	−1.006	−0.127	−0.466	−0.348	0.882	3.129	−1.409	−0.675	−1.291	−0.031
Slope	−0.031	−0.041	−0.051	−0.060	−0.030	−0.027	−0.014	−0.019	−0.034	−0.007	−0.104	−0.060	−0.002	0.005	−0.017	0.000
ln(TWI)	−0.078	−0.049	−0.263	−0.284	0.128	0.062	0.007	−0.079	0.133	0.047	0.205	−0.116	0.248	0.253	−0.006	0.039
CA^2 *	−0.208	0.530	1.136	1.097	0.354	1.449	0.754	1.232	0.021	0.615	−1.471	0.503	1.227	2.011	−0.418	0.207
Plan curvature	0.903	0.281	−0.001	−1.342	0.921	−0.838	0.312	−0.124	−1.077	−2.362	−0.021	0.690	0.360	−0.388	−0.089	−0.560
Profile curvature	−0.448	−0.312	−0.392	0.574	−0.433	0.660	0.049	0.249	0.725	1.432	−0.642	−1.495	0.145	0.672	−0.170	0.182
Intercept	5.260	3.769	7.480	7.714	7.386	8.366	6.123	4.108	10.514	10.847	19.924	11.621	5.714	7.264	5.145	8.404

Note: $Clay^2$ * is $clay^2 \times 10^{-4}$; elevation* is elevation × 10^{-3}; CA^2 * is $CA^2 \times 10^{-2}$. The regression coefficients of $clay^2$, elevation, and CA^2 were too small, so the constant was multiplied to make them readable. In total, 16 categories were classified according to Table 7, and these values are coefficients from multiple linear regression.

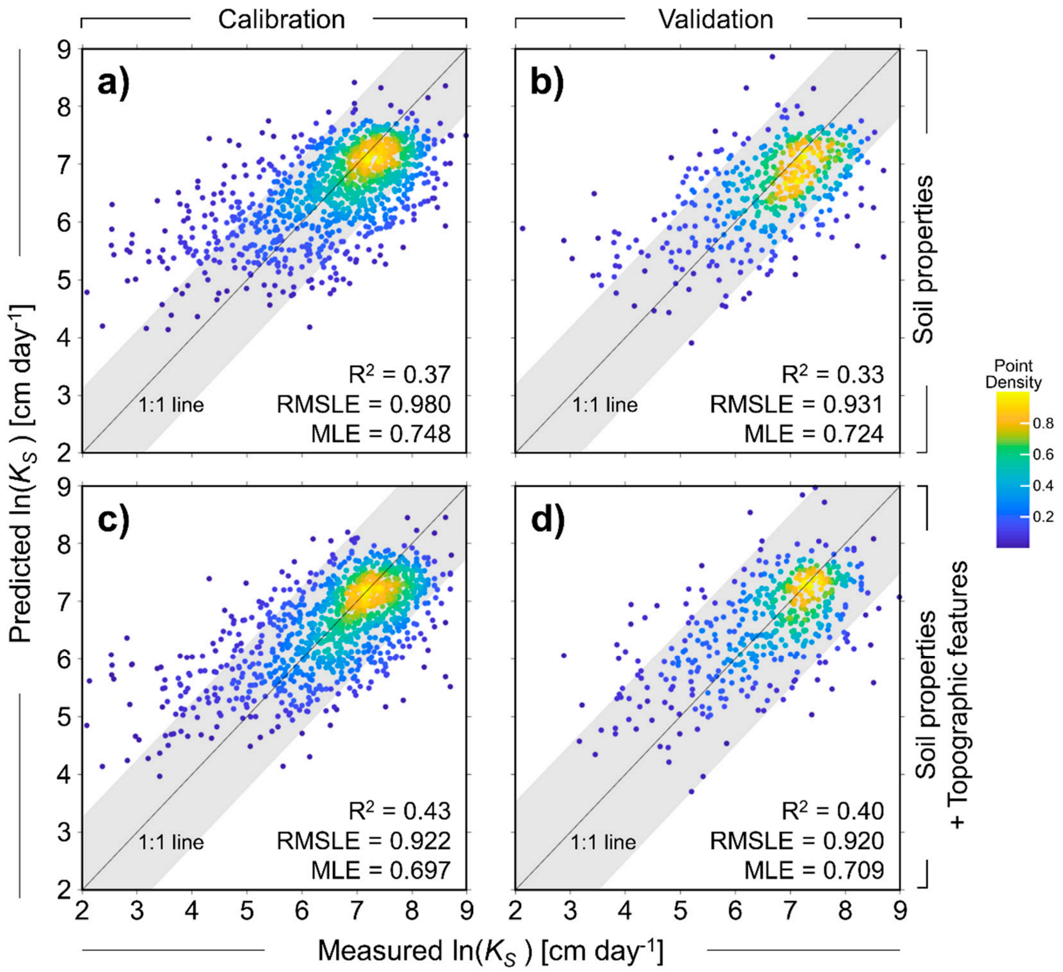

Figure 4. Relationship between the measured and predicted logarithmic K_s value. Multiple linear regressions were conducted with the calibration data set, which represented 70% of the total data set, and validated by the validation data set, which consisted of the rest of the data. (**a**,**b**) show analysis with only soil properties, and (**c**,**d**) show analysis with topographic features in addition to soil properties. The grayed-out parts are the ranges of the 95% prediction interval limits of the 1:1 lines.

3.5. Model Sensitivity

Ten variables were analyzed for sensitivity analysis, and four highly sensitive variables were selected (Figure 5). All multipliers were not applied to variables having the upper limit. For example, for the sand fraction, since the maximum value of the sand fraction is 100%, the sensitivity analysis was performed up to multiplier 4. Sensitivity analysis showed that the bulk density and sand fraction, which are soil properties, and the slope and catchment area, which are topographic features, had the great effect on K_s. K_s was increased when the sand fraction and catchment area increased, and K_s was decreased when the bulk density and slope increased. However, clay, organic matter, elevation, TWI, plan curvature, and profile curvature did not significantly affect the K_s.

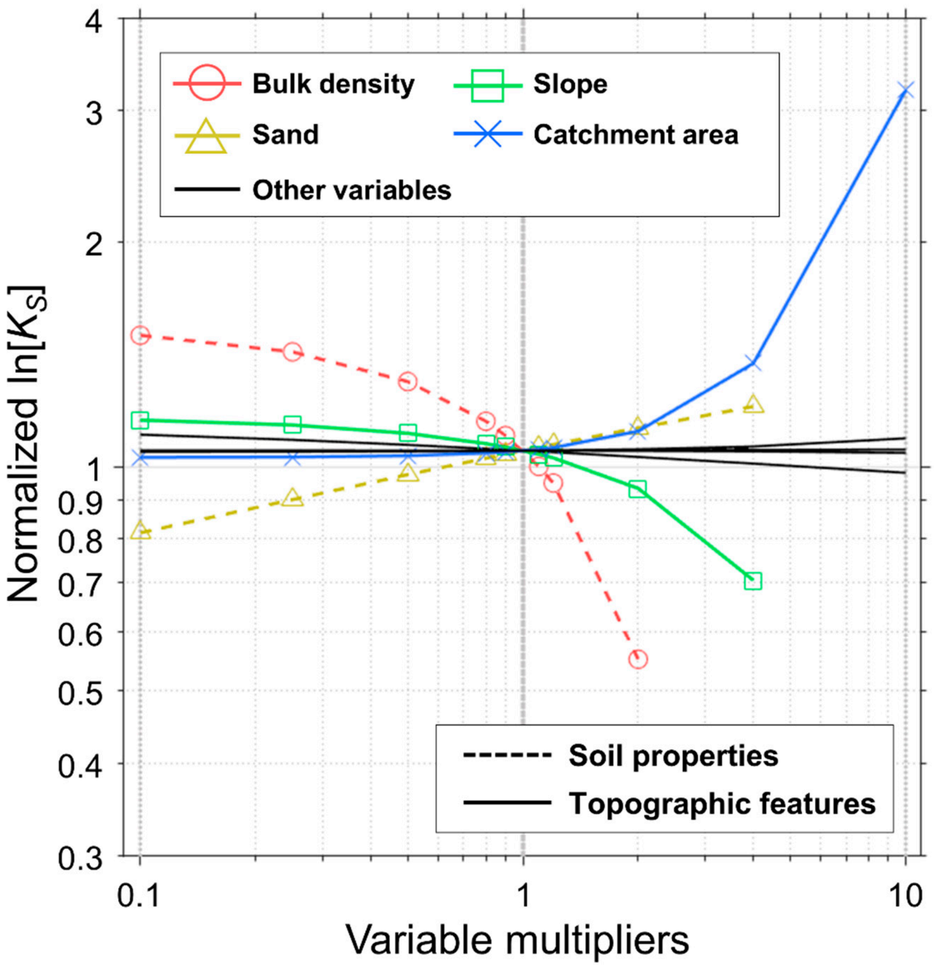

Figure 5. Sensitivity results for logarithmized K_s. Only the four most sensitive variables are colored, and the variables of soil properties are shown with dashed lines. Large vertical differences from the line y = 1 indicate a relatively high sensitivity for estimating the saturated hydraulic conductivity.

4. Discussion

4.1. Different Characteristics of K_S in Forest Soil

Figure 3 shows the use of the PTFs from previous research to estimate the K_s of the forest soil. The measured K_s was more than 10 times larger than the K_s predicted by previous research. Using the PTFs of previous research can therefore lead to the underestimation of the K_s of forest soil. Because they did not focus on the forest soil and the ranges of the soil properties used for developing the PTFs were different. Unlike the soil of cultivated land, grassland, or bare land, forest soil is not compacted and large and small pores are widely distributed. Therefore, forest soil has a relatively low bulk density. As presented in Table 4, the ranges of the soil size distribution in previous research and this study are similar. On the other hand, the bulk density of the forest soil in South Korea was smaller and beyond the range of previous research. This could be one of the reasons for the higher K_s of forest soil in South Korea.

In forests, various types of plants are growing and have a great influence on the soil hydrology [25,26]. Piaszczyk et al. [27] showed that dead trees in forests can have a great impact on the soil's physical properties. Furthermore, some studies have shown that organic matter produced from the roots of trees or understory plants in forests has a significant impact on the physical structure of forest soil [22,23,28]. Due to these characteristics, forest soil has a high permeability.

4.2. K_S Differences by Forest Stand, Geological, and Topographical Features

Forest soil can be affected by a number of topographical factors and the type of forest stand. As shown in Table 6, it was found that differences in the K_s by forest stand, bedrock, and landform were statistically significant. First, there was a difference in the K_s for different forest stands, where the K_s of broadleaf and mixed forests was higher than that of coniferous forest. The type of forest can have a great influence on the soil hydrology [25]. This can be explained by the root distribution difference between coniferous and broadleaf trees. Burch [24] demonstrated that coniferous trees have straight roots in a vertical direction, while broad-leafed trees spread wide in the lateral direction and produce a large number of rootlets. In other words, in the case of broadleaf and mixed forests, it is assumed that the pores of the soil are more advanced than those of coniferous forests due to the root system of trees, and thus, broadleaf and mixed forests have higher K_s. Secondly, almost all of the broadleaf trees in South Korea are deciduous trees, which can produce a thicker litter layer than coniferous trees. Litter layers can produce higher organic carbon contents, which are related to lower bulk densities [27,29], so the K_s increases.

Soil is made by weathering from the bedrock. Therefore, soil properties are highly affected by the bedrock. Plaster and Sherwood [30] showed that soil from metamorphic rock can include a high rate of the sand fraction. On the other hand, soil with fine particles is produced from sedimentary rock. Table 6 shows that the soil from sedimentary rock had the lowest K_S, and the soil from metamorphic rock had the highest K_s. The 1456 samples of forest soil also showed that the sand fracture contents were 40.6%, 35.6%, and 48.2% in igneous, sedimentary, and metamorphic rock, respectively, from which it was confirmed that soil from metamorphic rock has the highest permeability. This is consistent with the analysis of previous research [30].

The K_s of forest soil also differed, depending on the landform. The lower concave segment is the part where the soil does not erode but is deposited, unlike other landforms. As the soil is deposited, the soil is not compacted, so there is a lot of space for water to move in the soil, which is the reason for the high K_s. The 1456 samples showed a lower bulk density in the lower concave segment than other landforms. Martin [31] also identified that the soil property changes were those associated with the downward movement of water and soil, and there was a deeper topsoil depth and higher organic matter content in the lower concave segment, which is the lower part of the mountain. These differences can lead to high K_s. Topsoil and subsoil also showed a difference in K_s. Subsoil is located below topsoil, so the soil compaction derived from the gravity leads to lower K_s. The subsoil soil layer also has lower organic matter contents than topsoil, which can lead to higher bulk densities and lower and lower K_s [27,29]. In this study, topsoil contained 2.5% more organic matter than subsoil.

Forest soil is affected by various topographical factors, such as the forest type, bedrocks, and the landform directly related to the erosion and sedimentation. Therefore, in order to understand the characteristics of the K_s, all of these factors must be considered and analyzed.

4.3. Relationship between K_S and Soil and Topographic Features

The relationship between K_s and soil and topographic features can be found in Tables 8 and 9. If the coefficient is positive, the variable is positively correlated with the K_s. Therefore, K_s increases as the sand fraction and upper catchment area increase, and K_s decreases as the bulk density, elevation, and slope increase. The sand fraction and bulk density are directly related to the porosity. Therefore, a higher sand fraction and lower bulk density result in a high porosity, which can lead to a higher K_s. The lower the elevation, the higher the K_s, and this can be explained by the erosion and deposition process in the mountain slope. In other words, a low elevation area is also the part where the forest soil is deposited, so the soil layer is getting deeper and a higher porosity can be formed [32]. However, it can be highly related to the relationship between the elevation and other topographic features. In the lower concave segment, the K_s is higher than that of other landform types (Table 6). This could be the major reason for the negative relationship between the K_s and the elevation, and further research is needed to clarify the effects of the elevation on the K_s. The slope and catchment area can also be explained by similar reasons. The erosion progresses as the slope increases; on the other hand, deposition progresses as the slope decreases. Additionally, as the upper catchment area increases, more water and soil are transported down the hill. In other words, the lower the elevation and the lower the slope, which is related to the bigger upper catchment area, the deeper the soil layer and the lower the bulk density, which leads to higher K_s.

The organic matter, TWI, plan curvature, and profile curvature, however, did not significantly affect the K_s. Nemes [33] explained that the organic matter in soil may increase the total porosity of the soil, thereby increasing the hydraulic conductivity, but in contrast, it can reduce the K_s by retaining the water. In other words, one measure of organic matter contents alone cannot fully explain the K_s since the effect of organic matter on the K_s of forest soil is complex. The TWI, plan curvature, and profile curvature were also used as important factors for estimating the moisture content of soil, which is one of the most important soil properties [34]. However, it was found that these factors did not have a significant role in explaining the K_s.

Figure 4 shows that the model's performance increased when the topographic features were added, which can be confirmed through the sensitivity analysis (Figure 5). Four highly sensitive variables are the bulk density, sand fraction, slope, and catchment area, which can explain the K_s well. The bulk density and sand fraction are soil properties, but the slope and catchment area, which are topographic features, also highly affected the K_s. In other words, it can be seen that K_s is not only directly affected by soil properties but also greatly affected by topographic features. Therefore, topographic features should be considered when forest soil characteristic analyses are carried out.

4.4. Limitations and Suggestions for Future Research

In this study, non-linearity was considered by conducting the preprocessing of 10 soil and topographic characteristic variables to estimate K_s. Furthermore, 16 categories were divided through statistical analysis and the linear relationship with K_s was analyzed for each category. We confirmed that the soil properties and topographic features highly affect the K_s of forest soil in this study. In South Korea, a soil investigation is being conducted on a national scale. With these database and topographic data, the K_s can be estimated on a national scale by using the PTFs. Because a lot of hydraulic simulation models use the K_s as an important input variable, these PTFs can be useful for running these models and for understanding the water cycle.

This model, however, still does not have a high performance. This is because the K_s of forest soil is affected by more site and environmental factors than the above variables used in this study. Moreover, it is difficult to explain all of these nonlinear relationships with simple multiple linear regression. Therefore, it may be possible to construct a model with a higher performance when the other factors highly related to the K_s are found and analyzed. Recently, machine learning has been used to develop a model that predicts the K_s, in which case the performance of the model is increased [1,34]. However, the machine learning model is difficult to access for other researchers, so it is not easily available for other researchers. For these reasons, the machine learning model was not covered in this paper. Further research can use artificial intelligence and deep learning technology to check the nonlinear relationship between the K_s and various topographical factors in forest soil, and then use several nonlinear models to develop PTFs with a high performance. In addition, it is expected that a more accurate prediction of K_s on a national scale can be conducted when artificial intelligence and the deep learning model is developed using these forest soil data.

5. Conclusions

In South Korea, forest covers about two-thirds of the land area of the whole country. Due to these geographical characteristics, understanding the soil properties in forests is important for sustainable water management. The K_s is one of the most important input variables for running a hydraulic simulation model. Therefore, developing PTFs for predicting the K_s is necessary. In this study, data from 1456 sampling points were collected throughout South Korea, which are located in the temperate climate zone, and PTFs to predict the K_s from soil and topographic features were developed. The K_s of the broadleaf and mixed forests was higher than that of the coniferous forests, which is because of the root characteristic differences and the litter layer by forest type. The K_s of the soil based on igneous and sedimentary rocks was higher than that of the soil based on metamorphic rocks. This is because of the formation of sandy soil during the weathering of metamorphic rocks. In addition, soil located in the lower concave segment had a lower bulk density and higher K_s because the soil located in the lower concave segment is deposited rather than eroded, unlike other landforms. Furthermore, the K_s of subsoil was lower than that of topsoil due to soil compaction by gravity and organic matter contents. Many previous researchers have only considered soil properties to predict the K_s. However, since forests display spatial variability, topographic features should be considered, in addition to soil properties. The PTF model performance increased when topographic features were added. As a result, the K_s of the forest soil was increased when the bulk density, clay, elevation, and slope were decreased and the sand fraction and upper catchment area were increased. The organic matter, TWI, plan curvature, and profile curvature did not highly affect the K_s of the forest soil. According to the sensitivity analysis, the bulk density, sand fraction, slope, and catchment area highly affected the K_s. Therefore, the topographic features were as important in predicting the K_s as the soil properties of the forest soil.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-4441/12/8/2217/s1, Equations S1–S6: Six PTFs were selected (Table 3) and their equation were showed. Table S1: Regression equations of categorical PTFs for the logarithmized saturated hydraulic conductivity with only soil properties. Table S2: Regression equations of categorical PTFs for the logarithmized saturated hydraulic conductivity with topographic features in addition to soil properties.

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