





Article

Evaluation of Rainfall Erosivity Factor Estimation Using Machine and Deep Learning Models

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Abstract: Rainfall erosivity factor (R-factor) is one of the Universal Soil Loss Equation (USLE) input parameters that account for impacts of rainfall intensity in estimating soil loss. Although many studies have calculated the R-factor using various empirical methods or the USLE method, these methods are time-consuming and require specialized knowledge for the user. The purpose of this study is to develop machine learning models to predict the R-factor faster and more accurately than the previous methods. For this, this study calculated R-factor using 1-min interval rainfall data for improved accuracy of the target value. First, the monthly R-factors were calculated using the USLE calculation method to identify the characteristics of monthly rainfall-runoff induced erosion. In turn, machine learning models were developed to predict the R-factor using the monthly R-factors calculated at 50 sites in Korea as target values. The machine learning algorithms used for this study were Decision Tree, K-Nearest Neighbors, Multilayer Perceptron, Random Forest, Gradient Boosting, eXtreme Gradient Boost, and Deep Neural Network. As a result of the validation with 20% randomly selected data, the Deep Neural Network (DNN), among seven models, showed the greatest prediction accuracy results. The DNN developed in this study was tested for six sites in Korea to demonstrate trained model performance with Nash–Sutcliffe Efficiency (NSE) and the coefficient of determination (R^2) of 0.87. This means that our findings show that DNN can be efficiently used to estimate monthly R-factor at the desired site with much less effort and time with total monthly precipitation, maximum daily precipitation, and maximum hourly precipitation data. It will be used not only to calculate soil erosion risk but also to establish soil conservation plans and identify areas at risk of soil disasters by calculating rainfall erosivity factors.

Keywords: rainfall erosivity factor; USLE R; machine learning; Deep Neural Network



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1. Introduction

Climate change and global warming have been concerns for hydrologists and environmentalists [1–3]. Hydrologic change is expected to be more aggressive as a result of rising global temperature, that consequently results in a change in the current rainfall patterns [4]. Moreover, the Intergovernmental Panel on Climate Change (IPCC) [5] report showed that increasing rainfall events and rainfall intensity are expected to occur in the coming years [6]. Due to the frequent occurrence of greater intensity rainfall events, rainfall erosivity will increase, thus topsoil will become more vulnerable to soil erosion [7]. Soil erosion by extreme intensive rainfall is a significant issue from agricultural and environmental perspectives [8]. A decrease in soil fertility, the inflow of sediment into the river ecosystem, reduction of crop yields, etc., will occur due to soil erosion [9,10]. Therefore, effective best management practices should be implemented for better sustainable management

of soil erosion. Furthermore, there is a need for a regional estimate of soil loss to proper decision-making related to appropriate control practice, since erosion occurs diversely over space and time [11].

During the last few decades, various empirical, physically based, and conceptual computer models [12] such as Soil and Water Assessment Tool (SWAT) [13], European Soil Erosion Model (EUROSEM) [14], Water Erosion Prediction Project (WEPP) [15], Sediment Assessment Tool for Effective Erosion Control (SATEEC) [16], Agricultural Non-Point Source Pollution Model (AGNPS) [17], Universal Soil Loss Equation (USLE) [18], Revised Universal Soil Loss Equation (RUSLE) [19] have been developed. Among the models, the USLE model is one of the most popular and widely used empirical erosion models to predict soil erosion because of its easy application and simple structures [20,21]. The USLE model [18] calculates the annual average amount of soil erosion by taking into account soil erosion factors, such as rainfall erosivity factors, soil erodibility factor, slope and length, crop and cover management factor, and conservation practice factor.

The Ministry of Environment of Korea has supported for use of USLE in planning and managing sustainable land management in Korea. To these ends, the USLE has been extensively used to predict soil erosion and evaluate various soil erosion best management practices (BMPs) in Korea. Various efforts have been made for the development of site-specific USLE parameters over the years [22]. Yu et al. [23] suggested monthly soil loss prediction at Daechong Dam basin in order to improve the limitation of annual soil loss prediction. They found that over 50% of the annual soil loss occurs during July and August. The rainfall erosivity factor (R-factor) is one of the factors to be parameterized in the evaluation of soil loss in the USLE. The R-factor values are affected by the distribution of rainfall amount and its intensity over time and space.

Rainfall erosivity has been widely investigated due to its impact on soil erosion studies worldwide. Rainfall data at intervals of less than 30 min are required to calculate USLE rainfall erosivity factors. The empirical equations related to R-factor based on rainfall data, such as daily, monthly, or yearly, available in various spatial and temporal extents, have been developed using numerous data [24,25].

Sholagberu et al. [26] proposed a regression equation based on annual precipitation because it is difficult to collect sub-hourly rainfall data to calculate maximum 30-min rainfall intensity. Risal et al. [27] proposed a regression equation that can calculate monthly rainfall erosivity factors from 10-min interval rainfall data. In addition, the Web Erosivity Module (WERM), web-based software that can calculate rainfall erosivity factor, was developed and made available at <http://www.envsys.co.kr/~werm>. In the study by Risal et al. [27] on the R-factor calculation for South Korea, 10-min interval rainfall data, which cannot give the exact estimate of maximum 30-min rainfall intensity, was used. The Korea Meteorological Administration (KMA) provides 1-min rainfall data for over 50 weather stations in Korea. Estimation of R-factor values for South Korea using a recent rainfall dataset is needed for present and future uses because climate change causes changes in precipitation pattern and intensity to some degrees. However, the process of calculation of R-factor from rainfall data is time-consuming, although the Web Erosivity Module (WERM) software can calculate rainfall erosivity factor [27]. Furthermore, the radar rainfall dataset can be used to calculate spatial USLE R raster values using Web Erosivity Model-Spatial (WERM-S) [28]. These days, Machine Learning/Deep Learning (ML/DL) has been suggested as an alternative to predict and simulate natural phenomena [29]. Thus, ML/DL has been used for the prediction of flow, water quality, and ecosystem services [30–34]. These studies have implied that ML/DL is an efficient and effective way to calculate R factor values using recent rainfall time-series data provided by the KMA.

The objective of this study is to develop machine learning models to predict the monthly R-factor values, which are comparable with those calculated by the USLE method. For this aim, we calculated R-factor using 1-min interval rainfall data to estimate the maximum 30-min rainfall intensity of the target values, which is monthly R factor values at 50 stations in S. Korea. In the previous study by Risal et al. [27], the R-factor values

for South Korea were calculated using 10-min interval rainfall data, which cannot give an exact estimate of maximum 30-min rainfall intensity. The procedure used in this study is shown in Figure 1.

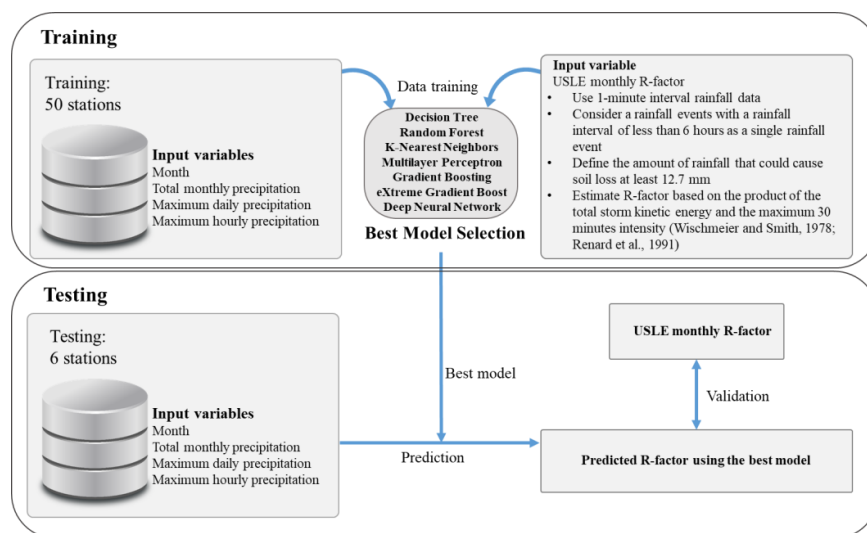


Figure 1. Study procedures.

2. Methods

2.1. Study Area

Figure 2 shows the location of weather stations where 1-min rainfall data have been observed over the years in South Korea. The fifty points marked in circles are observational stations that provide data used for training and validation to create machine learning models predicting rainfall erosivity factors, while six stations marked in green on the right map—Chuncheon, Gangneung, Suwon, Jeonju, Busan, and Namhae—represent the stations for the final evaluation of the results predicted by machine learning models selected through validation. Thiessen network presented using red lines of the map on the right shows a range of the weather environment around the weather stations.

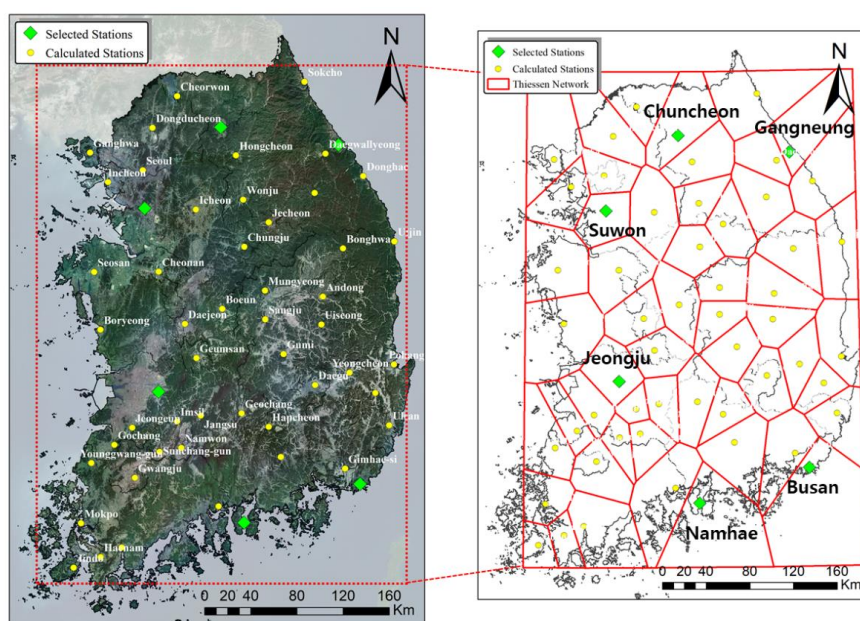


Figure 2. Weather stations in the study area.

2.2. Monthly Rainfall Erosivity Calculation

Monthly rainfall erosivity (R-factor) was calculated for each of the 50 weather stations in South Korea from 2013 to 2019. It was calculated based on the equation given in the USLE users' manual in order to calculate the R-factor value [18]. According to Wischmeier and Smith [18], a rainfall interval of fewer than six hours is considered a single rainfall event. In addition, the least amount of rainfall that could cause soil loss is at least 12.7 mm or more as specified in the USLE users' manual [35].

However, if the rainfall is 6.25 mm during 15 min, it is defined as a rainfall event that can cause soil loss. The calculations for each rainfall event are as follows.

$$\text{IF } I \leq 76 \text{ mm/hr} \rightarrow e = 0.119 + 0.0873 \log_{10} I \quad (1)$$

$$\text{IF } I > 76 \text{ mm/hr} \rightarrow e = 0.283 \quad (2)$$

$$E = \sum (e \times P) \quad (3)$$

$$R = E \times I_{30\max} \quad (4)$$

where I (mm h^{-1}) is the intensity of rainfall, e (MJ mm ha^{-1}) is unit rainfall energy, P (mm) is the rainfall volume during a given time period, E (MJ ha^{-1}) is the total storm kinetic energy, $I_{30\max}$ (mm h^{-1}) is the maximum 30-min intensity in the erosive event, and R ($\text{MJ mm ha}^{-1} \text{h}^{-1}$) is the rainfall erosivity factor. In this study, the monthly R-factor ($\text{MJ mm ha}^{-1} \text{h}^{-1} \text{month}^{-1}$) was estimated by calculating monthly E and multiplying it by $I_{30\max}$. In addition, the monthly rainfall erosivity factor was calculated using Equations (1)–(4) [18] using the 1-min precipitation data provided on the Meteorological Data Open Portal site of the KMA (Korea Meteorological Administration).

2.3. Machine Learning Models

Machine learning can be largely divided into supervised learning, unsupervised learning, and reinforcement learning [36,37]. In this study, supervised learning algorithms were used. A total of seven methods (Table 1) were used to build models to estimate R-factor. Table 1 shows the information on machine learning models utilized in this study.

Table 1. Description of machine learning models.

Machine Learning Models	Module	Function	Notation
Decision Tree	Sklearn.tree	DecisionTreeRegressor	DT
Random Forest	Sklearn.ensemble	RandomForestRegressor	RF
K-Nearest Neighbors	Sklearn.neighbors	KNeighborsRegressor	KN
Gradient Boosting	Sklearn.ensemble	GradientBoostingRegressor	GB
eXtreme Gradient Boost	xgboost.xgb	XGBRegressor	XGB
Multilayer Perceptron	Sklearn.neural_network	MLPRegressor	MLP
Deep Neural Network	Keras.models.Sequential	Dense, Dropout	DNN

Decision Tree, Random Forest, K-Nearest Neighbors, Gradient Boosting, and Multilayer Perceptron imported and used the related functions from the Scikit-learn module (Version: 0.21.3), while eXtreme gradient boost was taken from the XGboost library (License: Apache-2.0) and used the regression functions. Deep Neural Network is trained by taking Dense and Dropout functions from “Keras.models.Sequential” module of TensorFlow (Version: 2.0.0) and Keras (Version: 2.3.1) framework. In this study, the standardization method was used during the pre-process for raw data. Moreover, the “StandardScaler” function, a preprocessing library of Scikit-learn, was used.

2.3.1. Decision Tree

The Decision Tree (DT) model uses hierarchical structures to find structural patterns in data for constructing decision-making rules to estimate both dependent and independent variables [38]. It first learns by continuing the yes/no question to reach a decision [39]. In

this study, the DT model in the Scikit-learn supports only the pre-pruning. Entropy was based on classification and 2 for min_samples_split was given in Table 2.

Table 2. Critical hyperparameters in machine learning models.

Machine Learning Models	Hyperparameter
Decision Tree	criterion = "entropy", min_samples_split = 2
Random Forest	n_estimators = 52, min_samples_leaf = 1
K-Nearest Neighbors	n_neighbors = 3, weights = 'uniform', metric = 'minkowski'
Gradient Boosting	learning_rate = 0.01, min_samples_split = 4
eXtreme Gradient Boost	Booster = 'gbtree', max_depth = 10
Multilayer Perceptron	hidden_layer_sizes = (50,50,50), activation = "relu", solver = 'adam'
Deep Neural Network	kernel_initializer = 'normal', activation = "relu"

A model hyperparameter is a value that is set directly by the user when modeling. Table 2 shows the hyperparameter settings of the regressors used in this study.

2.3.2. Random Forest

Random Forest (RF) is a decision tree algorithm developed by Breiman [40] that applies the Bagging algorithm among the Classification and Registration Tree (CART) algorithm and the ensemble technique. RF creates multiple training data from a single dataset and performs multiple training. It generates several decision trees and improves predictability by integrating the decision trees [41]. Detailed tuning of the hyperparameter in RF is easier than an artificial neural network and support vector regression [42].

In this study, the hyperparameters in the RF are the following: 52 for n_estimators, and 1 for min_samples_leaf.

2.3.3. K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a non-parametric method which can be used for regression and classification [43]. In this study, KNN was used for regression. KNN is an algorithm that finds the nearest "K" neighborhood from the new data in training data and uses the most frequent class of these neighbors as a predicted value [44]. In this study, the number of the nearest neighbors in KNN's hyperparameter was set as 3. The weights were calculated using a simple mean, and the distance was calculated by the Minkowski method [45].

2.3.4. Gradient Boosting and eXtreme Gradient Boost

Gradient Boosting (GB) is an ensemble algorithm belonging to the boosting family that can perform classification and regression analysis [46,47]. In GB, the gradient reveals the weaknesses of the model that have been learned so far, whereas other machine learning models (e.g., DT and RF) focus on it to boost performance [48]. In other words, the advantage of gradient boosting is that the other loss functions can be used as much as possible. Therefore, the parameters that minimize the loss function that quantifies errors in the predictive model can be found for better R-factor prediction. In this study, the hyperparameters in the GB are the following: 0.01 for learning_rate, 4 for min_samples_split.

The eXtreme Gradient Boost (XGB) model is faster in training and classifying data than GB using parallel processing. It also has a regulatory function that prevents overfitting, which results in better predictive performance [49]. XGB is trained only by important features so that it calculates faster and performs better when compared to other algorithms [50,51]. The hyperparameters in the XGB are the following: gbtree for booster, and 10 for max_depth.

2.3.5. Multilayer Perceptron

Multilayer Perceptron (MLP) is a neural network that uses a back-propagation algorithm to learn weights [52]. MLP network consists of an input layer, a hidden layer, and an output layer (the R-factor). In this study, the hidden layer consisted of 50 nodes.

The hidden layers receive the signals from the nodes of the input layer and transform them into signals that are sent to all output nodes, transforming them into the last layer of outputs [53]. The output is used as input units in the subsequent layer. The connection between units in subsequent layers has a weight. MLP learns its weights by using the backpropagation algorithm [52].

2.3.6. Deep Neural Network

Deep Neural Network (DNN) is a predictive model that uses multiple layers of computational nodes for extracting features of existing data and depending on patterns learn to predict the outcome of some future input data [54]. The invention of the new optimizers enables us to train a large number of hyperparameters more quickly. In addition, the regularization and dropout allow us to avoid overfitting. The package used to build DNN in this study was TensorFlow developed by Google. In this study, the DNN model structure consisted of 7 dense layers and 1 dropout (Figure 3). Additional details about DNN can be found in Hinton et al. [55].

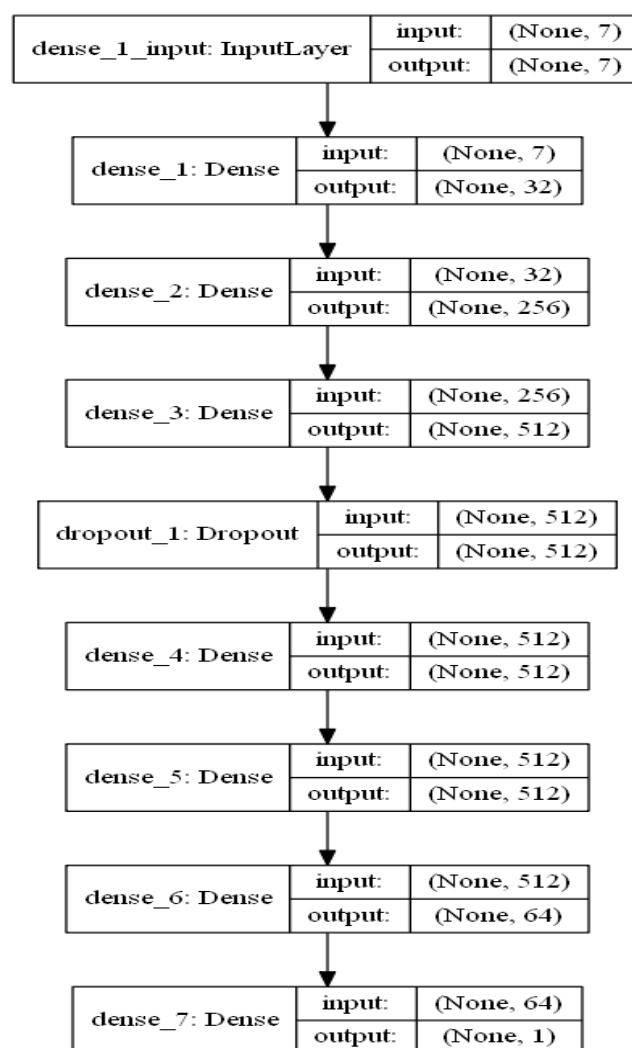


Figure 3. Illustration of the proposed Deep Neural Network (DNN) for rainfall erosivity (R-factor) prediction.

2.4. Input Data and Validation Method

Input data were compiled as shown in Table 3 to develop machine learning models to assess the R factor. The corresponding month from Jan. to Dec. was altered to numerical values, because rainfall patterns and their intensity may vary every month over space. Total monthly precipitation, maximum daily precipitation, and maximum hourly precipitation were calculated monthly and selected as the independent variables. The data can be easily downloaded in the form of monthly and hourly data among the Automated Synoptic Observation System (ASOS) data from the Korea Meteorological Administration (KMA)'s weather data opening portal site and organized as input data.

Table 3. The input data for machine learning models.

	Description	Count	Mean	std	Min	25%	50%	75%	Max
Input variable	month	month (1~12)	4087	6.49	3.45	1	3	6	12
	m_sum_r	the total amount of monthly precipitation	4087	96.45	97.01	0	30.90	66.20	1009.20
	d_max_r	maximum daily precipitation	4087	39.39	38.10	0	14.50	27.10	384.30
	h_max_r	maximum hourly precipitation	4087	11.84	12.69	0	4.00	7.50	197.50
Output variable	R-factor	R-factor	4087	419.10	1216.79	0	15.99	77.84	43,586.61

The monthly R-factors data in the manner presented in the USLE for the 50 selected sites from 2013 to 2019 were designated as target values, and as the features are given in Table 4, month (1–12), total monthly precipitation, maximum daily precipitation, and maximum hourly precipitation were designated as the features. Among the data, 80% of randomly selected data were trained, the model was created, and then the remaining 20% of data were used for the validation of the trained model.

To assess the performance of each machine learning model, Nash–Sutcliffe efficiency (*NSE*), Root Mean Squared Errors (*RMSE*), the Mean Absolute Error (*MAE*), and coefficient of determination (R^2) was used. Numerous studies indicated the appropriateness of these measures to assess the accuracy of hydrological models [56–58]. *NSE*, *RMSE*, *MAE*, and R^2 for evaluation of the model accuracy can be calculated from Equations (5)–(8).

$$NSE = 1 - \frac{\sum (O_t - M_t)^2}{\sum (O_t - \overline{O_t})^2} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum (O_t - M_t)^2}{n}} \quad (6)$$

$$MAE = \frac{1}{n} \sum |M_t - O_t| \quad (7)$$

$$R^2 = \frac{[\sum (O_t - \overline{O_t})(M_t - \overline{M_t})]^2}{\sum (O_t - \overline{O_t})^2 \sum (M_t - \overline{M_t})^2} \quad (8)$$

where O_t is the actual value of t , $\overline{O_t}$ is the mean of the actual value, M_t is the estimated value of t , $\overline{M_t}$ is the mean of the estimated value, and n is the total number of data.

Table 4. Monthly R-factor calculated by the Universal Soil Loss Equation (USLE).

Station Number	Station Name	R-Factor (MJ mm ha ⁻¹ h ⁻¹ month ⁻¹)												R-Factor (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)
		January	February	March	April	May	June	July	August	September	October	November	December	Annual
90	Sokcho	21	29	32	95	47	159	1039	2860	368	494	507	44	5694
95	Cheolwon	2	37	30	119	257	235	5867	2769	403	239	65	24	10,046
98	Dongducheon	2	69	31	91	287	455	3031	1364	424	228	47	24	6053
100	Daegwallyeong	4	19	20	79	577	194	1472	1669	453	237	40	8	4772
106	Donghae	17	29	34	207	27	157	592	1317	469	1461	128	8	4447
108	Seoul	0	31	37	95	284	266	2813	988	191	90	50	16	4861
112	Incheon	3	50	69	83	224	192	2193	897	406	480	88	27	4712
114	Wonju	2	22	31	83	284	699	2654	999	303	65	40	8	5189
127	Chungju	4	36	22	79	171	270	2075	1240	909	117	38	17	4978
129	Seosan	7	72	50	135	147	562	747	635	330	146	127	42	3000
130	Ulsan	86	16	47	292	24	227	590	470	360	2816	143	30	5100
133	Daejeon	8	47	50	182	72	602	1658	1293	494	181	96	24	4707
136	Andong	1	32	53	101	48	325	1142	808	368	176	33	14	3100
137	Sangju	6	18	67	105	45	361	1098	1143	420	273	51	19	3605
138	Pohang	7	46	106	139	40	233	417	1051	910	1478	51	23	4500
143	Daegu	1	8	57	80	67	313	548	1322	238	340	26	12	3013
152	Ulsan	15	36	122	141	154	287	751	1499	727	1709	77	74	5591
156	Gwangju	8	59	92	156	74	927	1249	2458	703	361	99	49	6236
165	Mokpo	15	112	117	227	177	630	1023	944	2094	493	85	127	6044
172	Gochang	12	24	137	151	77	399	1768	2235	614	273	77	21	5788
175	Jindo	18	43	231	559	511	598	738	1323	799	636	113	36	5606
201	Ganghwa	1	26	35	60	193	59	1922	1255	648	654	48	20	4921
203	Icheon	2	34	103	83	211	207	2284	1068	450	162	45	24	4673
212	Hongcheon	1	11	23	81	461	162	2220	934	223	51	29	8	4204
217	Jeongseon	1	20	18	75	117	126	2165	654	355	101	36	16	3686
221	Jecheon	3	26	21	90	158	265	1616	1162	405	80	43	12	3881
226	Boeun	8	19	42	106	62	482	2016	1102	583	163	77	15	4675
232	Cheonan	2	17	21	86	106	248	3408	1002	249	110	68	15	5333
235	Boryeong	5	73	47	142	127	322	878	849	1014	184	149	29	3820
238	Guemsan	5	17	52	154	48	483	1126	1059	447	148	37	17	3591
244	Imsil	3	9	83	106	67	369	2329	1416	632	224	44	16	5297
245	Jeongeup	11	18	106	160	265	318	1679	1930	521	207	46	27	5287
247	Namwon	8	19	78	159	52	704	2988	2304	479	586	88	49	7512
248	Jangsu	5	34	85	151	80	246	1997	1812	715	308	53	30	5516
251	Gochang	7	14	127	191	69	352	1448	2066	521	175	37	23	5029
252	Younggwang	7	15	130	178	114	292	994	2008	596	491	63	39	4928
253	Ginhae	7	43	220	200	339	385	1036	1600	1216	734	44	48	5872
254	Soonchang	4	14	93	194	89	456	1724	1304	629	363	58	16	4945
259	Gangjin	10	34	204	344	425	666	1156	9781	903	444	187	18	14,170
261	Haenam	10	15	223	206	177	595	965	1142	650	1250	83	91	5406
263	Uiryoong	4	24	121	184	156	334	629	1961	805	643	39	36	4936
266	Gwangyang	8	76	120	218	591	686	827	2488	2195	555	86	73	7924
271	Bonghwa	0	9	36	86	95	415	1154	706	327	98	28	13	2968
273	Mungyeong	7	18	54	139	102	331	1724	742	529	180	61	21	3908
278	Uiseong	1	6	69	101	74	220	632	647	326	106	31	7	2220
279	Gumi	3	12	68	103	95	380	1296	1442	554	364	32	14	4363
281	Yeongcheon	2	11	81	162	52	316	1259	1082	409	230	28	12	3643
283	Gyeongju	3	11	53	101	55	125	573	759	681	686	21	13	3081
284	Gochang	3	17	54	105	60	434	1184	1491	619	2246	33	55	6299
285	Hapcheon	2	22	57	173	105	700	1114	1646	810	676	47	24	5378

3. Results and Discussion

3.1. USLE R-Factor

For the selected 50 sites, monthly rainfall erosivity factors for each year from 2013 to 2019 were calculated, and the average monthly rainfall erosivity factors for seven years were obtained. Then, the seven-year average monthly rainfall erosivity, R-factor, was generated and shown in Table 1. Moreover, to give a comprehensive look at the degree of rainfall patterns by site, the average annual rainfall erosivity factor for each site is also presented in Table 4.

In this study, rainfall erosivity factor maps were generated to examine patterns of monthly R-factor calculated by USLE using rainfall data from 50 selected sites for evaluation. The R-factor distributions were mapped reflecting the geographical characteristics in South Korea (Figure 4). The high R-factor distribution in all regions during the summer months of July and August can be confirmed.

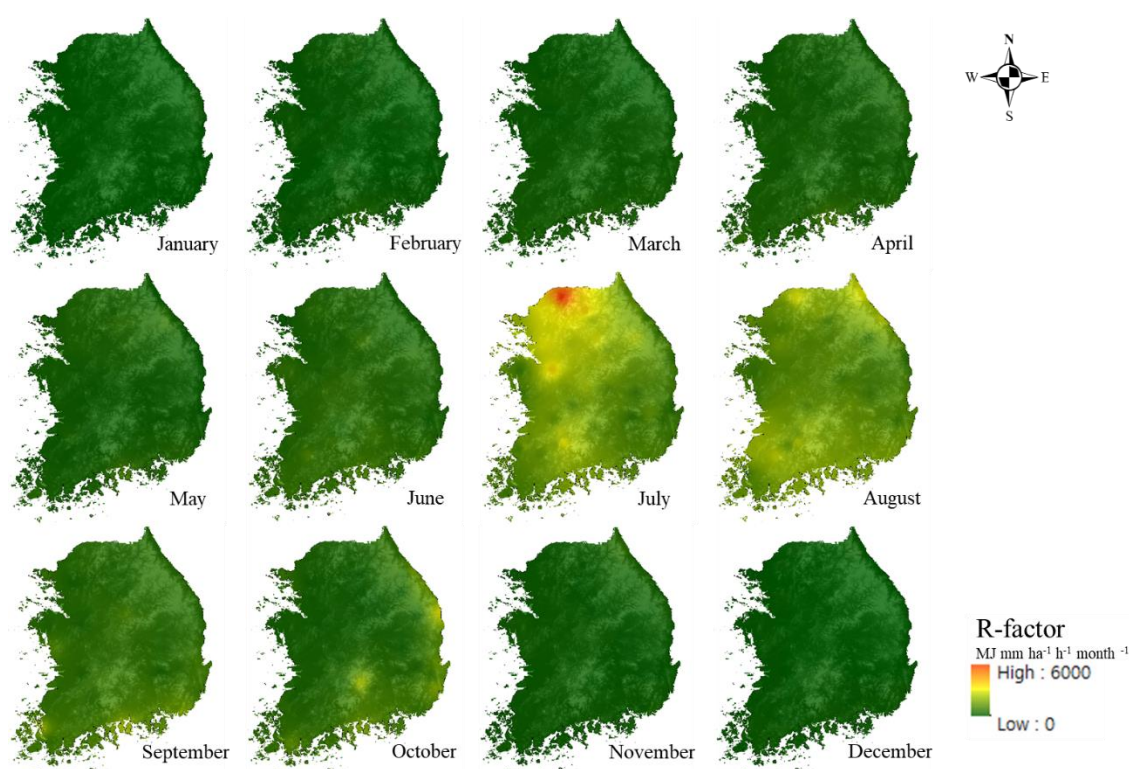


Figure 4. Spatial distribution of monthly R-factor calculated by USLE, using rainfall data from 50 weather stations for the period 2013–2019.

The monthly R-factors for two months from July to August contribute more than 50% of the total average annual R factor value of Korea. The rainfall occurs mainly in the wet season and the likelihood of erosion is very high compared to the dry season. In such a case, using the average annual R-factor value can give a misleading amount of soil erosion. For these reasons, the monthly R-factor would be helpful in analyzing the impact of the rainfall on soil erosion rather than the average annual R-factor.

3.2. Validation of Machine Learning Models

Table 5 shows the prediction accuracy results (*NSE*, *RMSE*, *MAE*, R^2) of seven machine learning models, by comparing the predicted R-factor. The results from the Deep Neural Network (DNN) showed the highest prediction accuracy with *NSE* 0.823, *RMSE* 398.623 MJ mm ha^{−1} h^{−1} month^{−1}, *MAE* 144.442 MJ mm ha^{−1} h^{−1} month^{−1}, and R^2 0.840.

Table 5. Prediction accuracy results of seven machine learning models.

Machine Learning Models	<i>NSE</i>	<i>RMSE</i> (MJ mm ha ^{−1} h ^{−1} month ^{−1})	<i>MAE</i> (MJ mm ha ^{−1} h ^{−1} month ^{−1})	R^2
Decision Tree	0.518	657.672	217.408	0.626
Multilayer Perceptron	0.732	490.055	158.847	0.783
K-Nearest Neighbors	0.817	405.327	149.923	0.794
Random Forest	0.800	423.345	148.147	0.799
Gradient Boosting	0.702	516.956	161.259	0.722
eXtreme Gradient Boost	0.791	433.230	159.275	0.788
Deep Neural Network	0.823	398.623	144.442	0.840

When comparing the results of DNN and the other machine learning models (Decision Tree, Random Forest, K-Nearest Neighbors, Multilayer Perceptron, Gradient Boosting, and eXtreme Gradient Boost), we can see that DNN provided more accurate prediction results over other machine learning algorithms. Moreover, the highest value of *NSE*, *RMSE*, *MAE*, and R^2 was found when the DNN was employed for the prediction R-factor values.

DNN had been proven for its good performance in a number of studies about the environment. In the study conducted by Liu et al. [59], the DNN showed better results, compared with results obtained by other machine learning algorithms, in predicting streamflow at Yangtze River. Nhu et al. [60] reported the DNN has the most impactful method in machine learning for the prediction of landslide susceptibility compared to other machine learning such as decision trees and logistic regression. In the study by Lee et al. [61], a DNN-based model showed good performance as a result of evaluating the heavy rain damage prediction compared to the recurrent neural network (RNN) in deep learning. Sit et al. [62] reported the DNN can be helpful in time-series forecasting for flood and support improving existing models. For these reasons, it has been shown that DNN performs better in various studies.

In this study, the second best-predicted model is the K-Nearest Neighbors (KNN). The result from the KNN model showed prediction accuracy with NSE 0.817, $RMSE$ 405.327 $MJ\ mm\ ha^{-1}\ h^{-1}\ month^{-1}$, MAE 149.923 $MJ\ mm\ ha^{-1}\ h^{-1}\ month^{-1}$, and R^2 0.794 which indicates that the KNN is the most effective, aside from DNN, in predicting R-factor. According to Kim et al. [63], KNN has good performance results in predicting the influent flow rate and four water qualities like chemical oxygen demand (COD), suspended solids (SS), total nitrogen (TN), and total phosphorus (TP) at a wastewater treatment plant.

On the other hand, Decision Tree has prediction accuracy, with NSE 0.518, $RMSE$ 657.672 $MJ\ mm\ ha^{-1}\ h^{-1}\ month^{-1}$, MAE 217.408, $MJ\ mm\ ha^{-1}\ month^{-1}$, and R^2 0.626. This means that Decision Tree is less predictable than other machine learning models (Random Forest, K-Nearest Neighbors, Multilayer Perceptron, Gradient Boosting, eXtreme Gradient Boost, and Deep Neural Network). Hong et al. [37] also reported Decision Tree has less accuracy for the prediction of dam inflow compared to other machine learning models (Decision tree, Multilayer perceptron, Random forest, Gradient boosting, Convolutional neural network, and Recurrent neural network-long short-term memory).

Figure 5 shows the scattering graphs of the R-factors predicted by the seven machine learning models and calculated by the USLE method. All machine learning results represent a rather distracting correlation with less agreement. However, in Figure 5h, the Deep Neural Network algorithms predicted USLE R values calculated using the method suggested by USLE users' manual with higher accuracy, NSE value of 0.823.

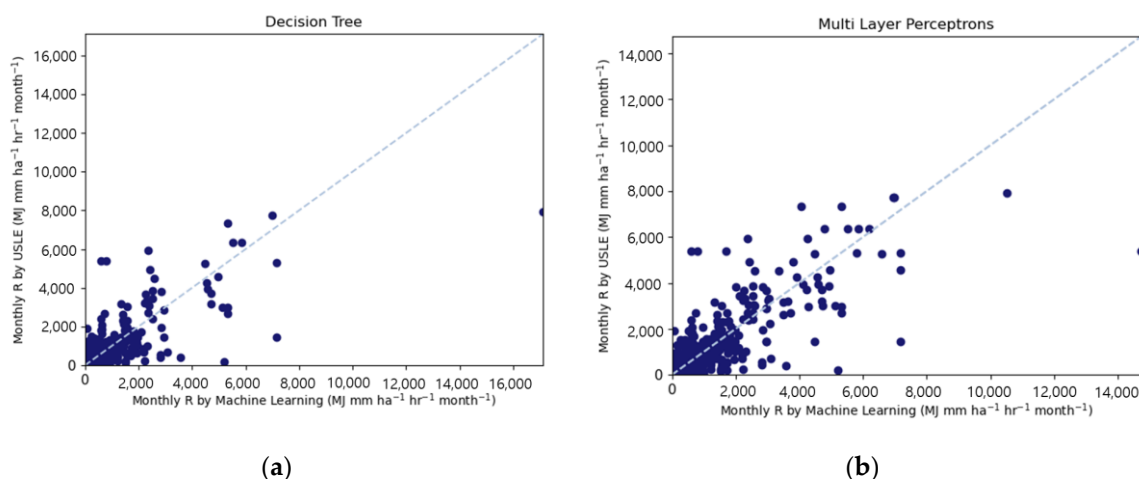


Figure 5. Cont.

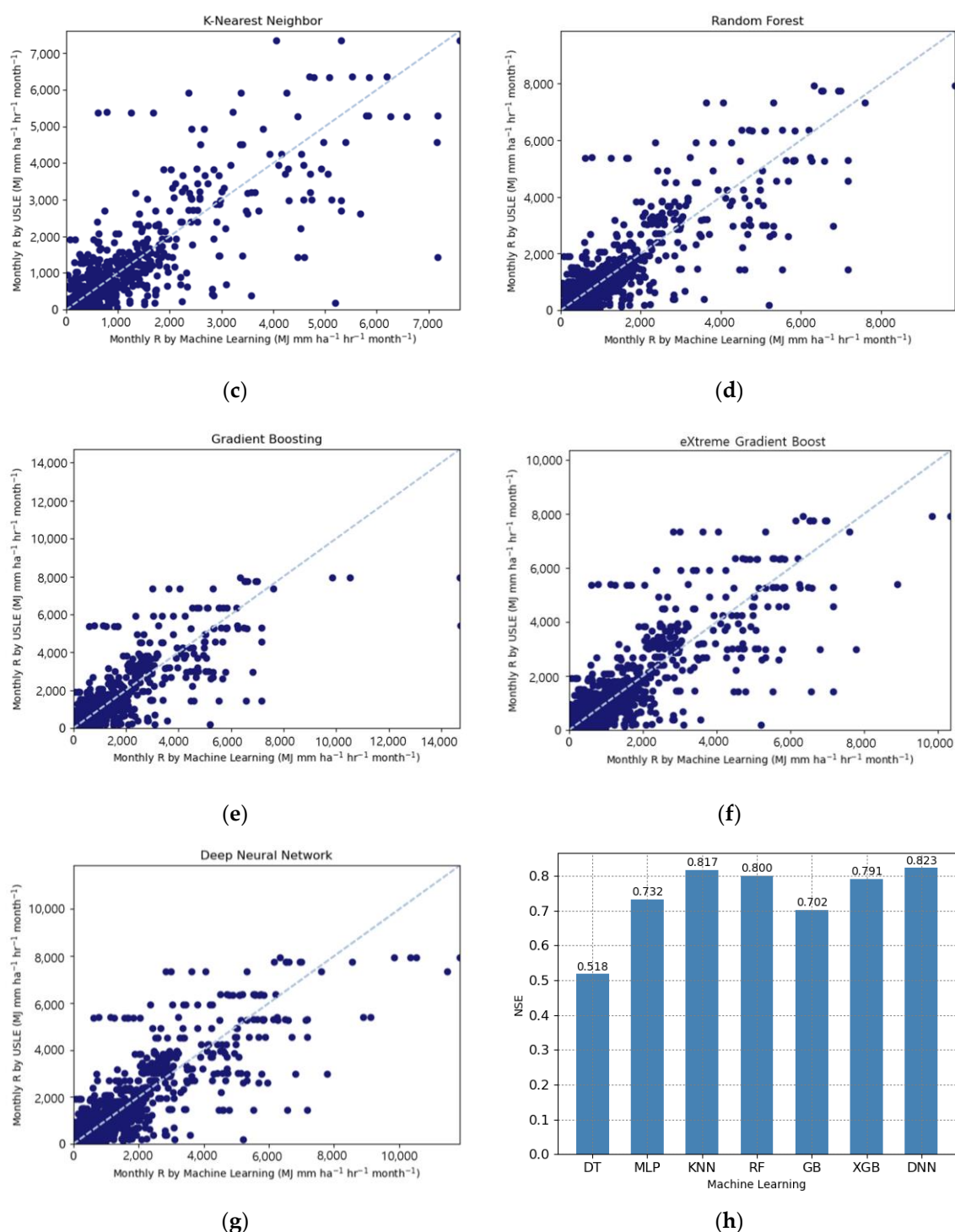


Figure 5. Comparison of (a) Decision Tree, (b) Multilayer Perceptron, (c) K-Nearest Neighbor, (d) Random Forest, (e) Gradient Boosting, (f) eXtreme Gradient Boost, and (g) Deep Neural Network calculated R-factor with validation data, and (h) comparison of machine learning accuracy.

Among the data, 80% of randomly selected data were trained, the model was created, and then the remaining 20% of data were used for the validation of the trained model. To prevent overfitting, the K-fold cross-validation was implemented for R^2 as shown in Table 6. As a result of the five attempts of K-fold cross-validation, the DNN showed the best results with an average R^2 of 0.783.

Table 6. K-fold cross validation results of seven machine learning models.

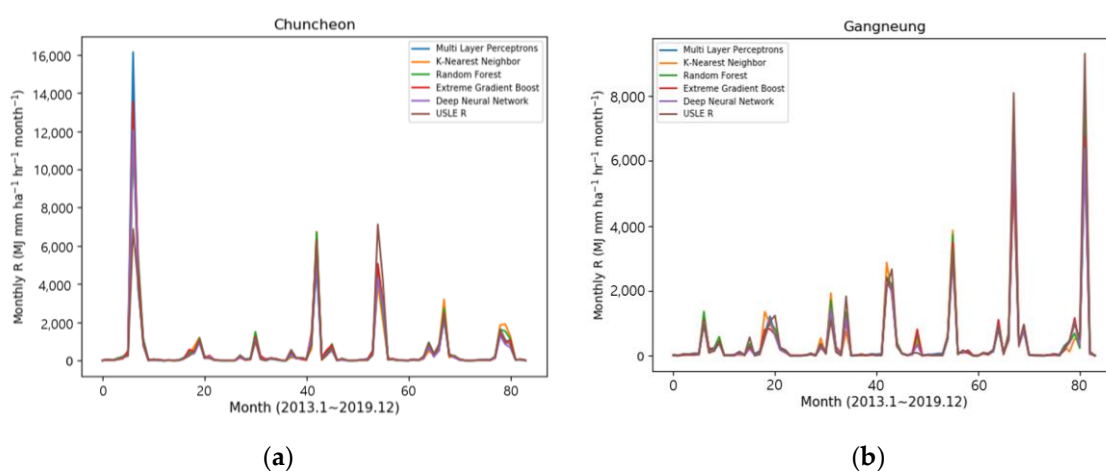
Fold	Coefficient of Determination (R^2)						
	Decision Tree	Multi-Layer Perceptron	K-Nearest Neighbors	Random Forest	Gradient Boosting	eXtreme Gradient Boost	Deep Neural Network
1	0.631	0.781	0.818	0.817	0.730	0.801	0.821
2	0.598	0.806	0.705	0.686	0.648	0.737	0.733
3	0.544	0.759	0.705	0.682	0.635	0.717	0.759
4	0.592	0.714	0.780	0.774	0.653	0.644	0.762
5	0.626	0.783	0.794	0.799	0.722	0.788	0.840
Average	0.598	0.769	0.760	0.752	0.678	0.737	0.783

Figure 6 shows the results of the prediction of the five machine learning models (i.e., Multilayer Perceptron, K-Nearest Neighbor, Random Forest, eXtreme Gradient Boost, and Deep Neural Network) at six sites for the testing of the selected models, as well as the time series comparison graph for 2013–2019 of the monthly R-factor values calculated on the USLE basis. At most sites, it showed that the time series trend fits well with a pattern similar to the USLE calculation value. In particular, looking at the distribution in Figure 6b Gangneung, the value of 9303 MJ mm ha⁻¹ h⁻¹ month⁻¹ in October 2019, which represented the peak value of the rainfall erosivity factor, was generally well predicted by all machine learning models. Among the models, the result of the Random Forest model estimated a similar value with 8133 MJ mm ha⁻¹ h⁻¹ month⁻¹.

On the other hand, among six sites, the time series distribution values of the model prediction result in Busan showed a slightly different pattern from the USLE calculation R-factor. In particular, the result was overestimated as the values of 8241 MJ mm ha⁻¹ h⁻¹ month⁻¹ in August 2014, and Multilayer Perceptron was almost twice overestimated at 16,725 MJ mm ha⁻¹ h⁻¹ month⁻¹.

However, the Random Forest (8188 MJ mm ha⁻¹ h⁻¹ month⁻¹) and eXtreme Gradient boost (8395 MJ mm ha⁻¹ h⁻¹ month⁻¹) algorithms were predicting very similar values. Therefore, the machine learning results could be seen as good at predicting the peak value.

A comparison of the machine learning model accuracies of *NSE* and R^2 of the test (validation) results at the six sites is shown in Figure 7. All five models had a coefficient of determination of 0.69 or higher, and the simulated values of the USLE method calculation and machine learning models showed high accuracy prediction. However, compared to Deep Neural Network, the *NSE* results of the four models (Multilayer Perceptron, K-Nearest Neighbor, Random Forest, eXtreme Gradient Boost) were less than 0.58, and the Deep Neural Network model showed 0.87 in both *NSE* and R^2 . Therefore, the monthly average value of the R-factor, predicted by the DNN would be a good candidate algorithm for USLE R factor prediction (Table 5 and Figure 7).

**Figure 6.** Cont.

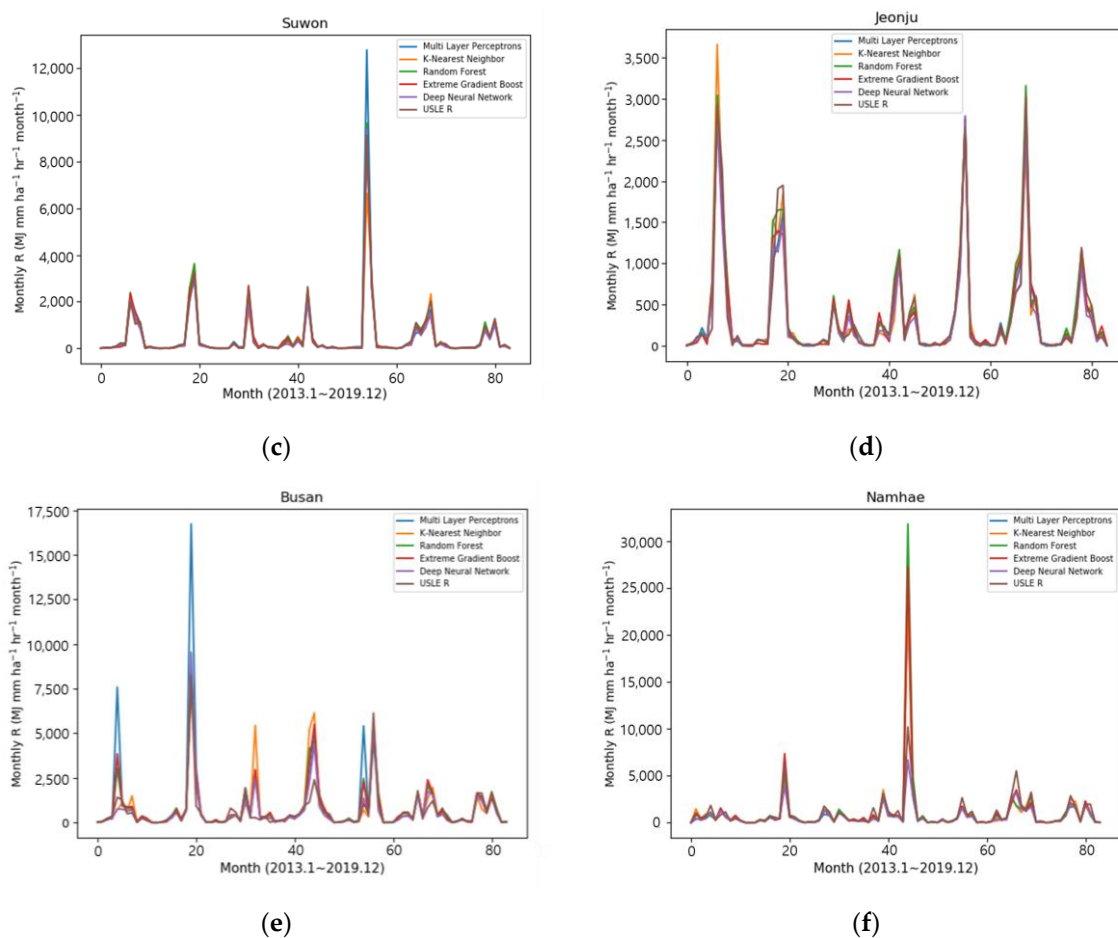


Figure 6. The comparisons of forecasting results of R-factor using machine learning in (a) Chuncheon, (b) Gangneung, (c) Suwon, (d) Jeonju, (e) Busan, and (f) Namhae.

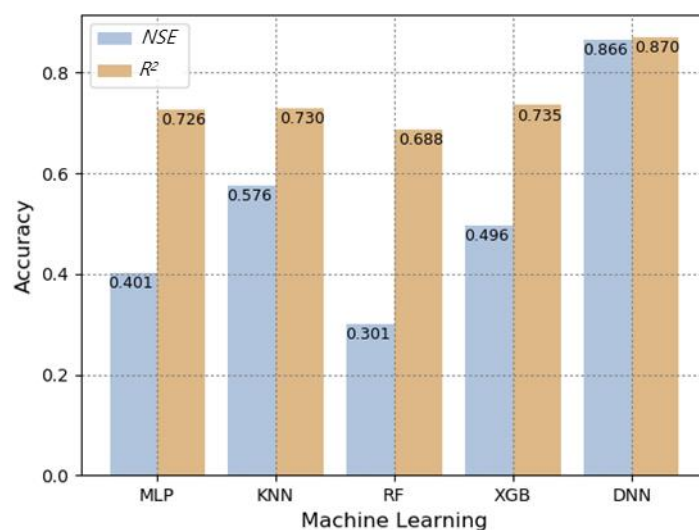


Figure 7. Comparison of prediction accuracy results by machine learning models in test sites.

Table 7 shows average monthly rainfall erosivity factor values at the six sites for testing, Chuncheon, Gangneung, Suwon, Jeonju, Busan, and Namhae, along with the USLE calculation and Deep Neural Network (DNN) prediction.

Table 7. Monthly R-factor calculated (C) by the previous method and predicted (M) by Deep Neural Network.

Station Number	Station Name	Method	R-Factor (MJ mm ha ⁻¹ h ⁻¹ month ⁻¹)												R-Factor (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)	NSE
			January	February	March	April	May	June	July	August	September	October	November	December	Annual	
101	Chuncheon	C	2	99	27	110	195	320	3466	1844	355	182	45	24	6670	0.814
		M	5	59	26	84	166	356	3543	1608	323	154	31	16	6372	
105	Gangneung	C	25	36	31	138	150	113	742	2476	390	1598	325	16	6040	0.874
		M	57	24	38	84	154	100	774	2189	287	1129	207	14	5055	
119	Suwon	C	3	29	80	115	278	165	2944	1463	388	107	84	27	5683	0.981
		M	5	36	56	88	210	156	2708	1352	312	85	52	19	5076	
146	Jeonju	C	7	17	104	105	108	526	1315	1511	311	240	67	21	4330	0.911
		M	7	16	80	103	95	581	1086	1261	310	153	50	19	3760	
159	Busan	C	32	79	199	408	472	781	1021	1729	1764	616	266	113	7479	0.883
		M	22	56	148	243	317	639	860	2205	2514	458	184	91	7736	
295	Namhae	C	19	407	366	946	892	1016	1608	1822	2169	1634	151	131	11,159	0.584
		M	14	161	198	748	607	867	1201	1164	1633	1010	85	110	7798	

Among average annual values, the results for Busan showed a good performance with the Deep Neural Network (DNN) resulting in the average annual value of the rainfall erosivity factor of $257 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ difference over the USLE calculation result. In the case of Chuncheon, DNN also showed a good performance with an average annual rainfall erosivity factor difference of $298 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ difference over the USLE calculation result. On the other hand, the USLE calculation results for Namhae showed an average annual value of the rainfall erosivity factor difference of $3361 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ greater than the DNN result.

This is because, in the case of Namhae, the rainfall tendency lasted for a long period in the dry season from February to June compared to the other testing sites like Chuncheon, Gangneung, Suwon, Jeonju, and Busan. Moreover, the monthly R-factor calculation of Namhae in dry seasons was two to four times more than other testing sites. In particular, the monthly R-factor for February in Namhae figure being about five times higher than the monthly R-factor in Busan. This means that if the single set of learning data has a huge deviation or variation from other sets, it may result in the uncertainty of the entire result data. Therefore, the monthly R-factor of Namhae in the dry season from is containing uncertainty. In the future study, when predicting the R-factor of the Namhae, DNN model analysis will be implemented in consideration of rainfall trends by supplement the historical rainfall data.

R-factor can be calculated by machine learning algorithms with high accuracy and time benefit. The spatio-temporal calculation of the rainfall erosivity factor using machine learning techniques can be utilized for the estimation of the soil erosion due to rainfall at the target value. The DNN will be incorporated into the WERM website in the near future after further validation.

4. Conclusions

The main objective of this study is to develop machine learning models to predict monthly R-factor values which are comparable with those calculated by the USLE method. For this, we calculated R-factor using 1-min interval rainfall data for improved accuracy of the target value. The machine learning and deep learning models used in this study were Decision Tree, K-Nearest Neighbors, Multilayer Perceptron, Random forest, Gradient boosting, eXtreme Gradient boost, and Deep Neural Network. All of the models except Decision Tress showed *NSE* and *R*² values of 0.7 or more, which means that most of the machine learning models showed high accuracy for predicting the R-factor. Among these, the Deep Neural Network (DNN) showed the best performance. As a result of the validation with 20% randomly selected data, DNN, among the seven models, showed the greatest prediction accuracy results with *NSE* 0.823, *RMSE* $398.623 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ month}^{-1}$, *MAE* $144.442 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ month}^{-1}$, and *R*² 0.840. Furthermore, the DNN developed in this study was tested for six sites (Chuncheon, Gangneung, Suwon, Jeonju, Busan, and Namhae) in S. Korea to demonstrate a trained model performance with *NSE* and *R*² of both 0.87. As a result of the comparative analysis of R-factor prediction through various models, the DNN was proven to be the best model for R-factor prediction in S. Korea with readily available rainfall data. The model accuracy and simplicity of machine learning and deep learning models insist that the models could replace traditional ways of calculating/estimating USLE R-factor values.

We found that the maximum 30 min intensity derived from 1-min interval rainfall data in this study is more accurate than that estimated from previous research. These methods can provide more accurate monthly, yearly, and event-based USLE R-factor for the entire period. Moreover, if the user has input data (month, the total amount of monthly precipitation, maximum daily precipitation, maximum hourly precipitation) as described in Table 3, the monthly R-factor can be easily calculated for the 50 specific stations in S. Korea by using the machine and deep learning models. Since the updated R-factor in this study reflected the recent rainfall data, which have high variability, it can improve the accuracy of the usage of the previous R-factor proposed by the Korean Ministry of

Environment [64] for future study. The results from this study can help the policymakers to update their guideline (Korean Ministry of Environment) [64] regarding the updated version of R-factors values for S. Korea.

It is expected that it will be used not only to calculate soil erosion risk but also to establish soil conservation plans and identify areas at risk of soil disasters by calculating rainfall erosivity factors at the desired temporal-spatial areas more easily and quickly.

However, this study evaluated the R-factor using machine learning models in S. Korean territory, under the monsoon region. Although deep learning models such as Deep Neural Network's applicability in S. Korea has been confirmed in this study, few studies have investigated and benchmarked the performances of a Deep Neural Network model-based USLE R-factor prediction trained. Therefore, future studies should be carried out for the diverse conditions of the other countries such as European countries, the United States, and African countries to broaden the applicability of machine learning technology in USLE R-factor (erosivity factor) analysis.

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