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Neural network modelling of rainfall interception in four different forest stands

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Abstract. The objective of this study is to reveal whether it is possible to predict rainfall, throughfall and stemflow in forest ecosystems with less effort, using several measurements of rainfall interception (hereafter 'interception') and an artificial neural network based linear regression model (ANN model). To this end, the Kerpe Research Forest in the province of Kocaeli, which houses stands of mixed deciduous-broadleaf forest (*Castanea sativa* Mill., *Fagus orientalis* Lipsky, *Quercus* spp.), black pine (*Pinus nigra* Arnold), maritime pine (*Pinus pinaster* Aiton) and Monterey pine (*Pinus radiata* D. Don), was selected study site. Four different forest stands were observed for a period of two years, during which rainfall, throughfall and stemflow measurements were conducted. These measurements were separately calculated for each individual stand, based on interception values and the use of stemflow data in strict accordance with the rainfall data, and the measured throughfall interception values were compared with values estimated by the ANN model. In this comparison, 70% of the total data was used for testing, and 30% was used for estimation and performance evaluation. No significant differences were found between values predicted with the help of the model and the measured values. In other words, interception values predicted by the ANN models were parallel with the measured values. In this study, the most success was achieved with the models of the Monterey pine stand (r^2 = 0.9968; Mean Squared Error *MSE* = 0.16) and the mixed deciduous forest stand (r^2 = 0.9964; *MSE* = 0.08), followed by models of the maritime pine stand (r^2 = 0.9405; *MSE* = 1.27) and the black pine stand (r^2 = 0.843, *MSE* = 17.36).
Keywords artificial neural network (ANN), throughfall, stemflow, interception, forest stands.

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Introduction

Maintaining continuous water production without disturbing the balance between protection and utilisation of natural resources may be possible. The main cause of the deterioration of natural resources is human impact, and forests are one of the natural resources that are most affected by this deterioration. Forests are generally allocated to one or more purposes, such as wood production, wildlife, recreation, food production and even production of clean, fresh water. Although forests are effective at protecting the soil by storing water and regulating its quality and flow regime, regulations aimed at flood prevention are also known to have positive hydrological and hydrochemical effects (Biron et al. 1999).

A drop of rain reaches the ground from the atmosphere via water cycle stages, indicating that the distribution of rainfall in the watershed that produces water determines the structure of silvicultural intervention techniques (Riekerk 1983, Callegari et al. 2003, Gökbulak et al. 2004, Brang et al. 2006). In this type of watershed, the key parameter is the phenomenon of interception, which prevents a drop of rain from reaching the soil and thus determines the amount of water produced. Interception refers to precipitation such as rain, snow or dew that does not reach the soil, but is kept on leaves, plant shoots and dead plant litter, and is rapidly returned to atmosphere by evaporation (Zhang et al. 1995).

In general, in addition to the amount of precipitation falling in open space, throughfall and stemflow values are required to determine the amount of interception. The amount of interception in forest ecosystems changes according to plant characteristics (crown closure, species, development stage, age, branch status, rough or slippery stem surfaces, etc.), plant community (forest, shrub or meadow), stand type, stand age and season (Çepel 1986, Özhan 2004). Table 1 shows the amount of interception as a percentage of rainfall calculated by different researchers for different tree species.

As seen in the table, conifers have higher interception values relative to broadleaf trees. In the winter, the amount of water that is intercepted by plants is substantially reduced due to the loss of leaves (Leyton & Carlisle 1959, Davie 1996, Drocher 1990, Özhan 2004). Indeed, the water efficacy of conifer stands and coppices would be better than that of deciduous stands under the same conditions (Bosch & Hewlett 1982, Özhan et al. 2008, North et al. 2009). This situation should not be ignored in regards to soil protection and reforestation activities in the watershed for effective water production. Hizal and Özer (1998) calculated the loss of water occurring through interception to be 8.752.672 m^3/hectare per year in the İstanbul Ömerli watershed.

It is known that watersheds used for water production interact with each other. Gökbulak et al. (2004) stated that the river regimes of a watershed, and the amount and quality of water in the watershed, are determined by its climate, geology, topography, vegetation, usage and socio-economic structure, and it is possible to manage amount of runoff production with interventions affecting these factors. Serengil et al. (2007) determined that 11% thinning in the Belgrad Forest, İstanbul, had no effect on the amount of water produced by that watershed. Accuracy in determining the size of the watershed is directly proportional to the precision of sampling and the measurement of interception.

Simple rain collection containers can be used to determine the amount of open field precipitation and throughfall. However, when stemflow is also added, collection of water becomes both labour-intensive and costly. In some cases, the water collection mechanism may also deform the tree bark. On the other hand, harm to the stem by living organisms such as insects and birds reduce the sensitivity of flow measurements by the collecting mechanism. Due to the difficult working conditions for carrying out comprehensive inter-

Table 1 Interception amount as a function of tree age and crown closure (Özhan 1982, Çepel 1986)

	Tree Species	Interception (as a percentage of rainfall) (%)	References
Summary of interception values by tree species	Oak (coppice)	16.1	Balcı (1958)
	Beech	17.4	Çepel (1965)
	Oak	20.0	Çepel (1965)
	Oak	27.0	Xiao et al. (2000)
	Pine	31.1	Çepel (1965)
	Oak-Hornbeam (coppice)	15.3	Özyuvacı (1976)
	Pinus nigra	28.3	Özhan (1982)
	Oak	15.6	Özhan (1982)
	Hornbeam-Oak (coppice)	13.8	Özhan (1982)
	Pinus caribaea	12.8	Hall (2003)
	Douglas fir	22.8-25	Link et al. (2004)
	Norway spruce	48.0	Rutter et al. (1975)
	Eucalypt forest	10-15	Dunin et al. (2006)
Summary of interception values by age	*Pinus strobus* (10 years old)	15.0	Hewlett and Nutter (1969)
	Pinus strobus (35 years old)	19.0	Hewlett and Nutter (1969)
	Pinus strobus (60 years old)	26.0	Hewlett and Nutter (1969)
Summary of interception values for crown closure	Oak (1.00 crown closure of stand)	12.0	Sukachev and Dylis (1968)
	Oak (0.85 crown closure of stand)	8.0	Sukachev and Dylis (1968)
	Oak (0.75 crown closure of stand)	7.0	Sukachev and Dylis (1968)
	Oak (0.50 crown closure of stand)	4.0	Sukachev and Dylis (1968)

ception studies, in our country, the stemflow and throughfall measurements have remained inadequate apart from several studies (Çepel 1965, Özhan 1982, Zengin 1997).

When measuring interception in forest ecosystems, calculating the required components (throughfall and stemflow) gives the reference feature as similar mathematical or conceptual models for stands. For this reason, some studies have followed the path of estimating precipitation from simple models, including similar climate factors, tree species and habitat conditions of stands and throughfall. For instance, Roth and Chang (1981) developed and used the following formula to estimate longleaf pine (*Pinus palustris*) throughfall depending on only one parameter (the total rainfall):

$$T_h = 1.002 \cdot P - 0.0008 \cdot P^2 - 1.397$$

To estimate loblolly pine (*Pinus taeda*) throughfall:

$$T_h = 1.002 \cdot P - 0.0008 \cdot P^2 - 1.397$$

where: T_h - throughfall (mm) and P - total precipitation (mm).

Baloutsos et al. (2009) developed the following equation to measure interception and used the following formula to estimate stemflow depending on four parameters:

$$S_t = 0.104 \cdot P - 0.029 \cdot D - 0.019 \cdot WS - 0.034 \cdot MI$$

where: St - stemflow (mm), P - total rainfall (mm), D - rainfall duration (h), WS - (wind speed weighted average (km/h) and MI - maximum rainfall intensity (mm/hr).

Stemflow, throughfall, precipitation in an open space and the relationships among the interception is not linear. Thus, instead of the converted normal distribution of data that is typical for regression relationships, a non-linear relationship model that can fully simulate the data is needed.

In this study, an ANN-based interception model was developed depending only on throughfall and precipitation in open areas without needing any data related to stemflow amounts within stands.

Materials and methods

Study area

The research data used in this study were collected from the Kerpe Research Forest located in the northern part of the Kocaeli Peninsula, which is found in the Marmara region, 8 km to the north of the Black Sea coast, between 41°07'40" - 41°09'40" north latitudes and between 30°09'30" - 30°12'00" east longitudes (Figure 1).

This forest provided measurements of precipitation water in the stands of mixed deciduous, black pine, maritime pine and Monterey pine (Zengin 1997). Areas where these measurements were carried out were selected to be close to each other to ensure uniformity of climatic elements. It is important that the study include stands with different characteristics while remaining under similar influence of the rain and sun (Özhan 1982). In addition, variables such as slope, position (height, distance from the sea) and shape of the land were kept as uniform as possible because these variables can affect the distribution of rainfall. Although differences between stands affect the amount of interception, succession age or stand development, crown closure and differences in the management plans have the biggest influence in this regard. In this study, stands were not uniform in these features except for canopy density.

The estimation of interception is generally based on assumption that reaction of forest canopy was shaped by forest parameters such as density, age, mean height, mean diameter, biomass (Bosch & Hewlett 1982). Stand parameters can be indirectly indicated by the reaction of forest canopy (Danson & Plummer 1995). For this reason, different characteristics of stands were determined in Kerpe Research Forest and sampled in different stands according to age, height, canopy density and stand development (Table 2).

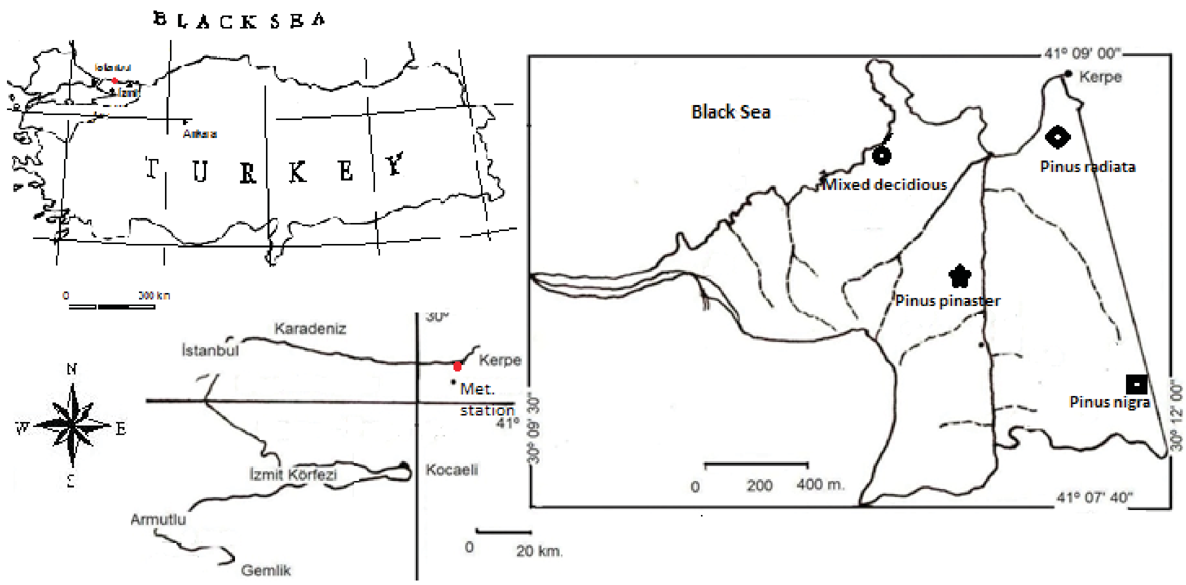

Figure 1 Location of stands in Kerpe Research Forest

Table 2 Some characteristics of stand parameters in Kerpe Research Forest

Type of Forest Stand	Size of area (ha)	Distance from sea (m)	Age of stand (years)	Canopy density	Height of mean tree (m)	Stand development
Mixed deciduous forest stand	100 (61% beech, 22% chestnut, 16% oak)	10	26	Fully stocked stand (1.0)	15 (Oak and Beech) 10 (chestnut)	Beech (47% thin pole stage, 53% thick pole stage), Chestnut (76% thin pole stage, 24% thick pole stage), Oak (66% thick pole stage, 34% thin pole size timber)
Pinus nigra forest stand	2.20	950	20	Fully stocked stand (1.0)	10	Thick pole stage
Pinus pinaster forest stand	19.50	425	20	Fully stocked stand (1.0)	15	74% thick pole stage 26% thin pole size timber
Pinus radiata forest stand	11.30	75	20	Fully stocked stand (1.0)	17	58% thick pole stage 42% thin pole size timber

The nearest weather station (N 41º04'- E 30º10') in the vicinity of the Kerpe research area is located in Kandıra. According to the Thornthwaite method, the region has a humid and mesothermal climate with some water shortage, which turns into a moderate climate near the ocean impulse (B2 B'2 sb'4). According to the results of a long observation period lasting for 15 years (1976-1990), the mean annual temperature is 14.5 °C. The coldest month is January (6.6 °C), and the hottest month is July (23.0 °C). According to the results of a 26-year observation period, the average annual precipitation is 1107.4 mm. Rainfall amounts in the winter (36.1%) and autumn (31.4 %) are greater than those observed in the spring (19.2%) and summer (13.3%).

Artificial Neural Network (ANN)

ANNs are product of artificial intelligence as black-box models. The ANN, which was developed after being inspired by the biological functioning of the human nervous system, is a black-box model (Figure 2). In recent years, it has been widely used in many fields such as environmental science, water resources, finance, electronics and medicine (Maier & Dandy 2000). ANNs consist of multiple layers. This ANN structures based on three main layers which are input layer, hidden layer and output layer (Figure 2). A layer may have several nodes. The layers connected with each other by weights.

As a basic neural network, this model consists of three main layers: input, hidden and output. As indicated by the figure, each input is multiplied by the weight coefficient (W_j) and transmitted to the hidden layer, implementing the function of f (Özkan et al. 2008).

$$Y_i = f(\sum w_{ji} x_i)$$

Totals obtained from the hidden layer (threshold, hyperbolic tangent, zero-based log-sigmoid, log-sigmoid and bipolar sigmoid) pass the f function and produce the output. In other words, the ANN uses the test data to pro-

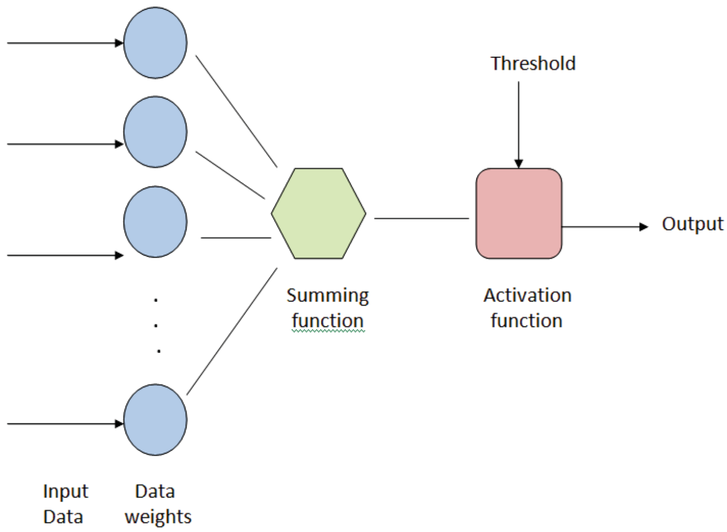

Figure 2 A simple ANN architecture (Şen 2004)

duce an output that determines the weight coefficients that address the relationship between the input variables and the estimated variables. The produced output is obtained by comparing the margin of error with the intended output. This method is called back-propagation, which is used to adjust the weights to reduce the margin of error of the algorithm. The network is trained by repeating this process several times (Sattari et al. 2007).

Regardless of the system behaviour, in the black-box models used in the watersheds, the mechanism and character of the watershed are mathematically presented by a set of behavioural functions (Alp & Cığızoğlu 2004). Behavioural functions in the black-box models, which simulate the behaviours of the system functions, are structures that determine the optimal relationship of weight values using the optimum weight values of the relationship between the input and output data of the watershed. In other words, in an ANN architecture that requires determination of weight values, the aim is to maximise the level of accuracy of the produced outputs with one of the mathematical algorithms (Yurtoğlu 2005).

Due to the non-linear nature of the hydrological relationships, ANN parameters are calculated separately as the impact of any change in the system (ASCE 2000a,b). In the process of calibration, input parameters do not require as large a number of parameters as the distributed models. This is one of the advantages of the method. Furthermore, the data-integrated ANN model must fit the normal distribution, and such acceptance is not required to follow a particular trend in a scattering diagram (Şen 2004).

The several specific advantages of ANN techniques are: it uses valuable data about the relationship between input and output time series and it is simpler and quicker to use, since there is not require for large pretreatment of the data (Sudheer et al. 2002).

This study is the first time that, in this type of research, non-linear relationships between rainfall and vegetation have been determined using ANN algorithms. This research compared the measured values from pure and mixed stands with the values obtained using an ANN algorithm. Then, the performance of the model developed using an ANN was determined in relation to measured interception.

In the first stage of this research, interception in different stands was calculated as IC = Pg – Th – St. For this calculation, as shown in Figure 3, the amount of rain falling in each stand in open space (Pg) was determined with

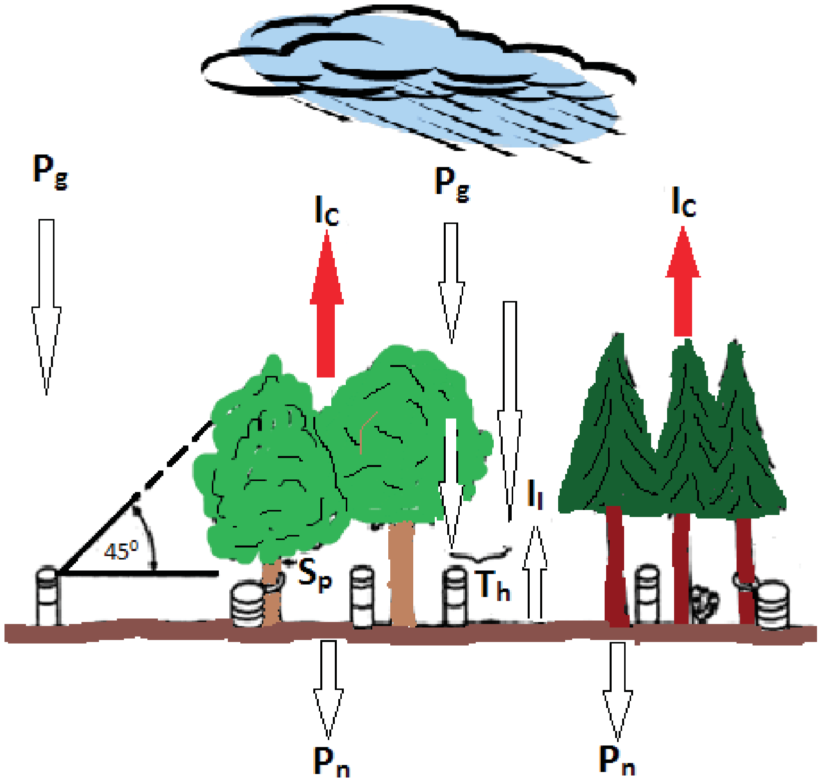

Figure 3 Elements of interception, where IC - interception of vegetation, II - interception of dead cover, Pg - rain falling on the open area, Pn - net rainfall, St - stemflow and Th - throughfall (Brooks et al. 1997)

a standard rain gauge, throughfall (Th) in each stand was determined with a standard rain gauge and stemflow (St) was measured along the trunk with a spiral water collection mechanism (Brooks et al. 1997).

The measurements of 4 different forest stands (the mixed deciduous, black pine, maritime pine and Monterey pine stands) were conducted 2-6 times per month. The second stage of the research consisted of interception prediction through ANN. To this end, firstly, data were divided into two main groups: test data and estimation data. These major groups were also each divided into two groups, representing input and output data. The following table shows the groups of data used (Table 3).

Testing period is training mode for the neural networks and the second was estimating mode for the results of neural networks. A testing period uses a learning algorithm that compares the predicted output by model to the observed output and then adjusts the weight of the connections in a drawback manner. This study reports on the testing period of ANNs for interception modelling using precipitation, throughfall, stemflow and interception data. Precipitation, stemflow and interception data were also used in estimating period. Seventy per cent of the measured values were used for testing, and 30% of the values were used for estimation. In the ANN method, the calibration stage of the model was taken into consideration in the stemflow data groups, whereas there was no need for this step in the data set used to estimate these values.

Results

In total, 76 precipitation measurements (precipitation in the open area, the throughfall and the stemflow) were collected in the mixed de-

Table 3 The data used for the ANN model

Data	Testing period	Input data in the testing period	Precipitation in the open area Throughfall Stemflow
		Output data in the testing period	Interception
	Estimating period	Input data in the estimating period	Precipitation in the open area Stemflow
		Output data in the estimating period	Interception

Table 4 Summary statistical parameters of measured data belonging to different forest stands (Zengin, 1997)

			X_{ort}	X_{max}	X_{min}	C_{sx}	S_x
Testing period	Mixed deciduous stand	Precipitation	26.97	119.40	2.02	1.63	25.53
		Throughfall	17.76	88.75	1.56	1.94	16.49
		Stemflow	2.89	11.79	0.16	1.51	2.90
		Interception	6.32	35.59	0.06	2.08	7.51
	Pinus nigra stand	Precipitation	26.97	119.40	2.02	1.63	25.53
		Throughfall	16.06	73.54	1.40	1.70	15.49
		Stemflow	0.24	1.45	0.00	2.05	0.32
		Interception	10.67	44.41	0.56	1.71	10.19
	Pinus pinaster stand	Precipitation	26.97	119.40	2.02	1.63	25.53
		Throughfall	20.02	108.23	0.67	1.94	21.81
		Stemflow	0.13	1.07	0.00	2.46	0.22
		Interception	6.82	22.17	0.51	1.27	4.99
	Pinus radiata stand	Precipitation	26.97	119.40	2.02	1.63	25.53
		Throughfall	19.14	97.08	0.60	1.76	20.30
		Stemflow	0.70	3.92	0.00	1.71	0.96
		Interception	7.11	30.17	0.20	1.77	5.89
Estimating period	Mixed deciduous stand	Precipitation	28.26	87.41	4.03	1.19	22.52
		Throughfall	19.77	61.15	1.93	1.12	16.37
	Pinus nigra stand	Precipitation	28.26	87.41	4.03	1.19	22.52
		Throughfall	17.31	58.49	1.77	1.39	14.78
	Pinus pinaster stand	Precipitation	28.26	87.41	4.03	1.19	22.52
		Throughfall	20.58	78.23	1.04	1.63	19.63
	Pinus radiata stand	Precipitation	28.26	87.41	4.03	1.19	22.52
		Throughfall	18.51	72.19	0.52	1.59	17.91

ciduous-broadleaf stand, the black pine stand, the maritime pine stand and the Monterey pine stand, and the interception values were measured using these data (Zengin 1997). Table 4 indicates the average value (X_{ort}), the maximum value (X_{max}), the minimum value (X_{min}), the skewness (C_{sx}) and standard deviation (S_x) values given by the testing and estimating parameters of the measured data.

The low and positive coefficient of skewness indicates that the distribution is slightly distorted to the right. In this study, measured values were used for calibration and prediction. The activation function has different prediction methods, such as a hidden number of layers, the learning rate and the weight of the values of input data shaped by the different ANN architecture, and these methods are used to estimate interception (Table 5).

The weight values of the model, the training rate and the ANN structure providing the minimum square error were determined after different combinations tried. When measuring different stands, interception prediction and measurement are difficult, and the possibility of error is high. Two parameters (precipitation in open spaces and throughfall) were used, without the parameter of stemflow. Validation (Estimated) data and measured data were compared with r^2 in Figure 3. With the ANN algorithm, correlations are higher with the estimated values of interception (Figure 4).

As can be seen from Figure 3, the most successful interception prediction with the neural network algorithms were in the Monterey pine stand ($r^2 = 0.9968$) and the mixed deciduous-broadleaf forest stand ($r^2 = 0.9964$). The maritime pine stand ($r^2 = 0.9495$) and the black pine stand ($r^2 = 0.843$) followed the first two in terms of success of prediction. Thus, predicting an ANN interception model based on rainfall and throughfall values without a need for a stemflow parameter, which is one of the important components to measure for interception, was successful. Interception models (I) estimated for each of the stands are demonstrated below (Table 6).

Discussion

In our study, we evaluated different types of stands to predict interception using with ANN and compared the results with the coefficient of determination (r^2) and Mean Squared Error (*MSE*). All neural network models perform high coefficient of determination and lower mean squared errors. However ANN models were not show similar perform in terms of some stand parameters. The simple derivative can be found by differentiating perform of ANN models with respect to stand parameters of distance from the sea. The performances of model (r^2 and *MSE*) were over the direct propotion to the distance from the sea.

As stated above, interception by the forest ecosystem is one of the factors that affect the water budget of a watershed. To regulate water production, silvicultural tools are particularly valuable because of the process of reduction. This factor is of vital importance in planning water production of the watershed. Estimation of interception is required by forest researchers because of the fact that the estimation of interception plays an important role for permanent soil water. Therefore, estimating the amount of interception through simple models saves a

Table 5 Determined components of neural network with the best results for different stands

Components of neural network	Mixed deciduous stand	*Pinus nigra* stand	*Pinus pinaster* stand	*Pinus radiata* stand
Iteration number (Epoch)	10000	10000	10000	10000
Weight values of the input data	0.2	0.5	0.2	0.4
Training rate	0.3	0.3	0.3	0.3
ANN structure (input, hidden, output)	3-5-1	3-4-1	3-6-1	3-4-1

Table 6 Improved linear regression model of interception for different stands (I - interception, P - precipitation and T_h - throughfall)

Type of Forest Stand	R^2	*MSE*	ANN-based linear regression model (estimation period)
Mixed deciduous forest stand	0.9964	0.08	$I - 0.94 \cdot P - 1.05 \cdot T_h$
Pinus nigra forest stand	0.8430	17.36	$I - 0.22 \cdot P + 0.30 \cdot T_h$
Pinus pinaster forest stand	0.9405	1.27	$I - 0.92 \cdot P - 0.88 \cdot T_h$
Pinus radiata forest stand	0.9968	0.16	$I - 1.11 \cdot P - 1.19 \cdot T_h$

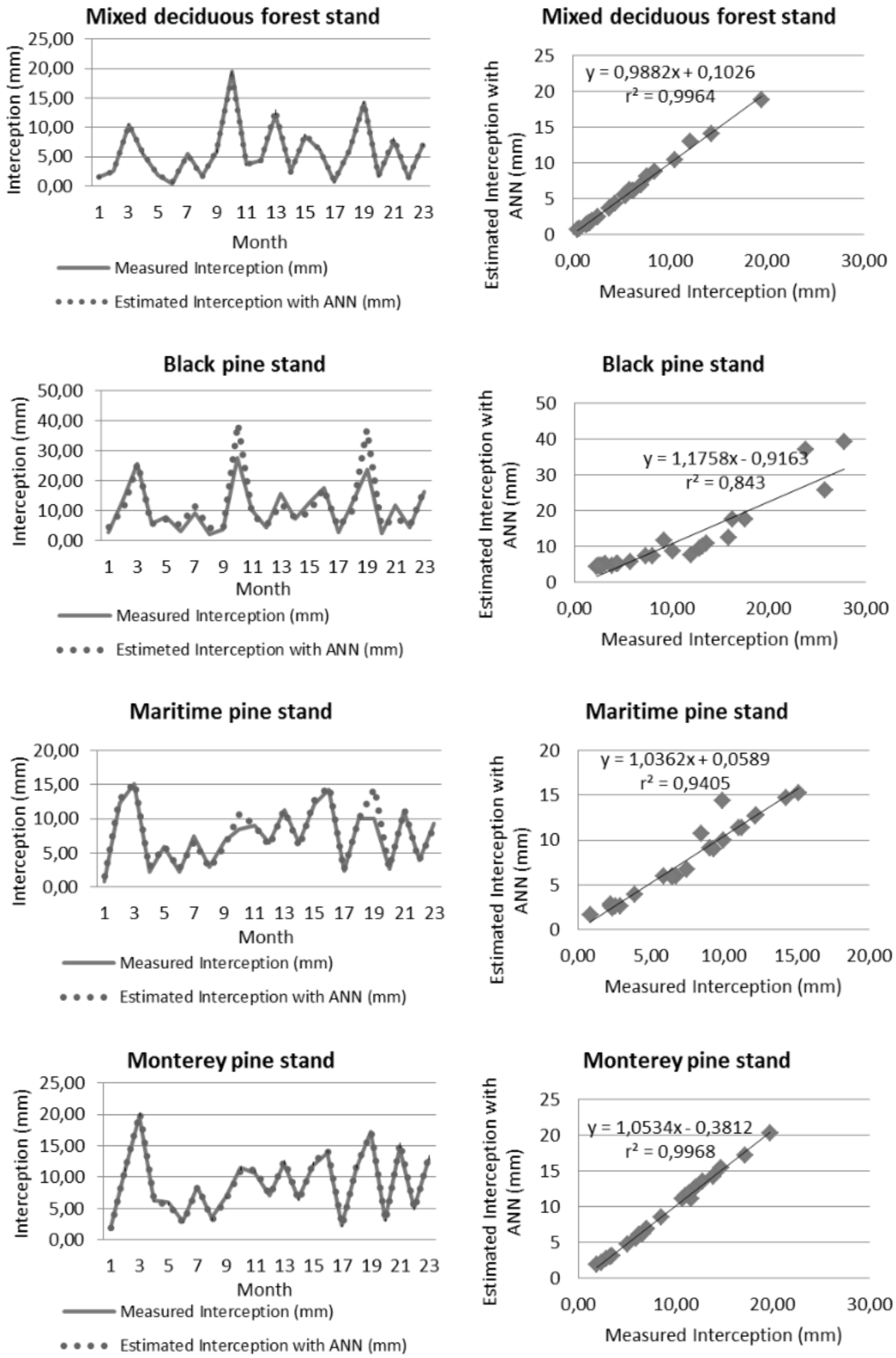

Figure 4 Comparison of the estimated interception values from the model with the measured values from different stands

considerable amount of time and effort for the watershed planner. It can be manifested with this study, the advantage of ANN structure is a useful tool in the application to the estimation of interception in the critical area. Models presented in this study could feasibly be used for stands with similar features. The results indicate that ANN-based model values were estimated very closely to measured values in different stands. In other words, if throughfall and open space precipitation values are known, these models provide the researcher with the opportunity to estimate interception amounts in ecosystems of stands that have similar qualifications. Therefore, throughfall and precipitation are sufficient parameters of stand to estimate the rainfall interception. But Ahrends and Penne (2010) reported that the diameter at breast height and the crown cover fraction were the most important stand characteristics for estimating the interception. According to Croton and Norton (2001), there are a very close relationship between leaf area index (LAI) and rainfall interception. However, the throughfall have already very close relations with canopy cover or interception (Marin and Sevink, 2000; Bryant et al., 2005). This research has demonstrated that throughfall and precipitation can be sufficed with an ANN based model to estimate rainfall interception. This enables to be used to estimate the interception of different forest stand on precipitation events without using stemflow records of trees.

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