J. Hydrol. Hydromech., 69, 2021, 4, 456–466
DOI: 10.2478/johh-2021-0023
ISSN 1338-4333

sciendo Journal of Hydrology and Hydromechanics

Relation of influencing variables and weather conditions on rainfall partitioning by birch and pine trees

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Abstract: General weather conditions may have a strong influence on the individual elements of the hydrological cycle, an important part of which is rainfall interception. The influence of general weather conditions on this process was analysed, evaluating separately the influence of various variables on throughfall, stemflow, and rainfall interception for a wet (2014), a dry (2015), and an average (2016) year. The analysed data were measured for the case of birch and pine trees at a study site in the city of Ljubljana, Slovenia. The relationship between the components of rainfall partitioning and the influential variables for the selected years was estimated using two statistical models, namely boosted regression trees and random forest. The results of both implemented models complemented each other well, as both indicated the rainfall amount and the number of raindrops as the most influential variables. During the wet year 2014 rainfall duration seems to play an important role, correlating with the previously observed influence of the variables during the wetter leafless period. Similarly, during the dry year 2015, rainfall intensity had a significant influence on rainfall partitioning by the birch tree, again corresponding to the influences observed during the drier leafed period.

Keywords: Throughfall; Stemflow; Rainfall interception; Rainfall microstructure; Boosted regression trees; Random forest.

INTRODUCTION

The hydrological cycle is altering due to climate change, as differences in global redistribution of precipitation and variations in seasonal precipitation patterns are observed (Inglezakis et al., 2016). This results in a significant reduction of precipitation in some parts of the world, while major variations in the timing and amount of precipitation per dry and wet season are expected elsewhere (Peng et al., 2021). The pronounced differences between the wet and dry periods significantly alter the water yield and the local water balance, the ecosystem services, the water availability for vegetation, leading to changed occurrences of floods and droughts (Bezak and Mikoš, 2014; Hungate and Hampton, 2012; Xu et al., 2020).

In the context of climate change, the relationship between the water balance and vegetation in dry and wet periods is increasingly recognized. In this aspect, various influences of different vegetation systems were studied. Vegetation is an important component, determining the ecosystem services, which were recognised to help mitigate the intensity of extremely dry and wet conditions expected in the future (Peng et al., 2021). An important contribution to the ecosystem services is also presented by the forest ecosystem affecting the global carbon budget. The different response of a forest ecosystem in wet and dry periods was analysed by Xiao et al. (2020), who concluded that in the dry season the precipitation generated significantly positive effects to the cumulative CO_2 emissions, while the soil respiration rate was mainly influenced by the fine root biomass regardless the season. An analysis of historical data from the tree rings was performed by Gao et al. (2020), who observed that the growth of trees was improved by wetness, suggesting that tree growth is more sensitive to wetness than the forest coverage. Wetter conditions may, on the contrary, reduce the carbon flux and evapotranspiration in steppe ecosystems, for which Hao et al. (2008) reported that both timing and frequency of rainfall events during the growing season significantly alter the capacity of steppe vegetation to uptake CO_2.

Forest ecosystems and trees in general also significantly influence the hydrological cycle through the process of rainfall interception (Dohnal et al., 2014; Klamerus-Iwan et al., 2020; Xu et al., 2013). Precipitation reaching the vegetation surface is distributed among the intercepted rainfall, which is captured by the canopy and eventually evaporates back into to the atmosphere, throughfall, which is described as the precipitation reaching the ground by dripping from the canopy or falling directly to the ground through the gaps in the foliage, and stemflow, presenting the water flowing to the ground down the branches and stems (Levia and Germer, 2015; Sadeghi et al., 2020; Staelens et al., 2008; Xiao et al., 2000; Yue et al., 2021; Zabret et al., 2018). Rainfall interception is influenced by vegetation and meteorological characteristics. Vegetation characteristics considered are mainly tree characteristics, such as the tree height and surface area (e.g., projected tree canopy), smoothness and absorbance of the bark, leaf area index, canopy coverage, and canopy storage capacity (Dohnal et al., 2014; Klamerus-Iwan et al., 2020; Xu et al., 2013; Zabret, 2013). According to the differences among the tree species, the different response of rainfall partitioning was analysed (Honda et al., 2014; Schooling and Carlyle-Moses, 2015). As characteristics of some tree species (e.g., deciduous trees) are substantially influenced by the phenoseasons (presence and absence of leaves in the tree canopy), the rainfall partitioning in leafed and leafless period has also been frequently studied, mainly in relation to the meteorological conditions (Brasil et al., 2020; Levia and Germer, 2015; Mużyło et al., 2012; Su et al., 2019; Zabret et al., 2018). Meteorological characteristics on the contrary explain the characteristics of rainfall events, for example the rainfall amount, duration and intensity, air temperature and humidity, vapour pressure deficit and wind conditions (Andre et al., 2008; Staelens et al., 2008; Zabret and Šraj, 2019a). Although meteorological conditions are significantly associated with dry and wet periods, which influence the hydrological cycle, the influence of these two water-related conditions has been so far overlooked in the analysis of rainfall interception.

Rainfall interception is an important part of the hydrological cycle and is, due to the inclusion of trees, also one of the ecosystem services. The response of rainfall interception according to various influencing variables, type of rainfall events, and phenoseasons has been analysed; however, the process of rainfall interception associated with dry and wet periods has been neglected so far. As numerous researchers have observed the relationship between wet and dry periods and vegetation response to various natural processes, the main objective of the presented analysis is to investigate a possible influence of general weather conditions (e.g., wet and dry periods) on throughfall, stemflow, and rainfall interception. Extreme weather events are becoming more frequent due to climate change and the differences in water balance between dry and wet periods are increasing. As a result, the connections between climate variables and individual interception processes as well as the processes of the hydrological cycle are also different. There are not many studies with data sets long enough to capture wet and dry periods, therefore this is one of the important advantages of this study. Two statistical methods, namely boosted regression trees and random forest, were used to evaluate the influence of meteorological variables on rainfall partitioning components during wet, dry, and average years. Such statistical methods are seldom used for analysis of rainfall interception data, although the application of such methods can give us a new, different insight into the data and the connections between them. Additionally, the study of different tree species is very important in the field of interception, as these results cannot be generalized.

MATERIAL AND METHODS

Study site

The study site is located in the outskirt of the city of Ljubljana, Slovenia (46.04° N, 14.49° E). The area has typical sub-alpine climate with well-defined seasons and is characterized by Temperate oceanic climate (Cfb) according to the Köppen Climate Classification. The long-term analysis of the meteorological data was prepared taking into account the data collected at the Ljubljana Bežigrad meteorological station between years 1986 and 2016 (ARSO, 2020). The average air temperature for the area was equal to 10.5 °C. Generally, the lowest temperatures are observed during January (–0.1 °C on average), while the warmest is July (20.8 °C on average). The average long-term air temperature in winter was 0.8 °C, in spring and autumn 10.7 °C, and in summer 19.9 °C. The average amount of rainfall delivered per year in the analysed period was 1355 mm. The driest year was observed to be 2011, characterized by 998 mm of rainfall, while the wettest year was 2014, delivering 1851 mm of rainfall in total. The most rainfall is in general delivered during the autumn months (around 30% of total yearly rainfall), while winter is the driest period, also because snow precipitation is observed instead of rainfall in the colder part of the year.

The study plot is part of a small urban park, located between educational and business buildings. The research plot itself spans over 600 m^2 and is covered with regularly mowed grass. In its western part there are two separated groups of trees, while in the east side there is a clearing. One group of trees in the southern part consists of birch trees (*Betula pendula* Roth.), which are on average 15.7 m high and have a total projected crown area of 17.9 m^2 and a diameter at breast height of 17.9 cm. Their branches grow upwards, and its bark is smooth and thin with a bark storage capacity estimated to be 0.7 mm (Zabret and Šraj, 2021). Birch is a deciduous tree species with distinct phenoseasons, which were determined according to the observations of the tree canopy at the field and complemented with leaf area index (LAI) measurements, using LAI-2200c Plant Canopy Analyzer (LI-COR). In general, the leafless phenoseason was observed between October and April, when LAI was on average 0.8 and the canopy storage capacity was 1.1 mm. The leafed phenoseason was observed between April and October, when LAI was equal to 2.6 and the canopy storage capacity increased to 3.5 mm. The group of the trees on the northern part of the plot are pine trees (*Pinus nigra* Arnold). They are on average 12.6 m high, have an average diameter at breast height of 19 cm, and a total projected crown area of 22.7 m^2. The bark surface is rough, the bark itself is thick and more absorbent with an estimated storage capacity of 3.5 mm. The branches are inclined downwards. As pine is a coniferous tree species, phenoseasons are not influencing the canopy characteristics to such an extent as in the case of birch trees. However, LAI in winter is 3.4 and the canopy storage capacity was estimated to be 2.7 mm, while in the summer time, LAI is 4.3 and the canopy storage capacity 2.9 mm.

Measurements

The components of rainfall partitioning have been measured at the study plot since the beginning of 2014 (Zabret and Šraj, 2021; Zabret et al., 2018). Measurements of throughfall and stemflow were performed under both groups of trees, while rainfall in the open was measured on the clearing at the study plot and at the nearby rooftop (Zabret, 2013; Zabret and Šraj 2019a; Zabret and Šraj, 2021). Values of other meteorological characteristics (wind speed and direction, air temperature and humidity) were obtained from the Ljubljana Bežigrad meteorological station (ARSO, 2020), which is because of its location representative for the whole Ljubljana basin (Nadbath, 2008).

Measurements of throughfall were performed both automatically and manually. Under each group of trees there were two fixed steel trough gauges (0.75 m^2) positioned from the tree trunk towards the edge of the canopy. One was equipped with a tipping bucket flow gauge (Unidata 6506G, 50 mL/tip) and a data logger (Onset HOBO Event), while the other one was connected to 10 L and 50 L polyethylene containers, which were manually emptied after each event. Under each group of trees there were also 10 funnel-type gauges (78.5 cm^2, 1-L capacity), manually emptied after each event and occasionally moved under the trees to capture the spatial variability of throughfall. These collectors were moved after every 20 events in a random pattern under the canopy. Throughfall values used in the analysis were determined as the weighted average according to all the collectors' area used.

Stemflow was measured per one tree from each group. The halved rubber collar was spirally wrapped around the tree trunk and attached with silicone and nails. In case of a pine tree the water was collected in a manually read 1-L container at the bottom of the tree, which was emptied at the same time as the throughfall collectors. In case of a birch tree, the stemflow was automatically recorded, as the hose from the collar was connected to a tipping bucket flow gauge (Onset RG2-M, 0.2 mm/tip) and a data logger (Onset HOBO Event).

Rainfall was measured at two locations, at the clearing approximately 10 m from the nearest tree canopy and at the nearby rooftop, approximately 45 m from the treetops. Rainfall at the clearing was measured with a tipping bucket rain gauge (Onset RG2-M, 0.2 mm/tip), connected to the data logger (Onset HOBO Event). Rainfall on the rooftop was measured with a disdrometer (OTT Parsivel), enabling also measurements of rainfall microstructure, i.e. raindrop diameter, raindrop velocity, and the number of raindrops. The measuring area of the disdrometer is 54 cm^2 and the measured data are allocated to one of the 32 drop diameter classes (ranging from 0.312 mm to 24.5 mm) and 32 velocity classes (ranging from 0.05 m/s to 20.8 m/s). The drop diameters smaller than 0.312 mm were assigned to the smallest drop diameter class, as they are outside the device's measurement range. The recorded time series data from the rain gauge and the disdrometer were used to identify the rainfall events (separated with at least a 4-hour dry period) and their characteristics (duration and intensity). The 4-hour dry period was selected to divide the events based on the observations of the rainfall and throughfall dynamics at the field, as during the wetter time of the year throughfall lasted for quite some time after the cessation of the rainfall. Shorter rainfall interruptions were captured as part of the defined events. The dry period was defined with an accuracy of 0.2 mm of rainfall (equal to the volume of the rain gauge tipping bucket).

The tree characteristics were determined in individual surveys. The photographs of the trees were taken at a required distance to avoid deformation of proportions and were used to determine the tree height, the area of the projected canopy, and the branch inclination. The diameter at breast height was calculated from the measured perimeter of the stem. The bark storage capacity was determined from the bark samples, extracted using a steel hole puncher, according to the procedure described by Perez-Harguindeguy et al. (2013). Phenoseasons were determined based on the regular measurements of LAI, performed with LAI-2200c Plant Canopy Analyzer (LI-COR) following the protocol for isolated trees (Li-COR, 2015). The canopy storage capacity was calculated from the observed rainfall and throughfall data according to the Leyton graphical method (Leyton et al., 1967).

Data analysis

Measured data of rainfall precipitation (P), throughfall (TF), and stemflow (SF), collected in years 2014, 2015, and 2016, were used in the analysis. Based on these data, the third component of rainfall partitioning, i.e. rainfall interception (I), was calculated for each event:

$$I = P - TF - SF \tag{1}$$

In the selected period, 413 rainfall events were observed in total, but not all of them were included in the analysis. Snow and sleet events were excluded in the initial phase, while during the further preparation of the data, the events without complete time series on rainfall, throughfall, and stemflow due to clogging of the measurement equipment were also excluded. Therefore 365 rainfall events were taken into account in the analysis, capturing 86% of the total rainfall, delivered in the analysed period. Additionally, the disdrometer was not operational due to a software error for a longer time period during 2015. Therefore, rainfall microstructure data were not included in the analysis for this year.

For the selected rainfall events, the influence of the variables describing general weather conditions was evaluated using two similar statistical methods, namely general boosted regression trees (BRT) and random forest (RF). Both models are based on the method of the regression trees, however the way of upgrading them differs for each method. Two methods were selected for the analysis as a combination of several methods allows the verification of the results of an individual method and enables a broader interpretation of the results. The regression tree model is designed by repeating the divisions of the influential variables and by adapting a simple prediction model for the target variable within each division. The result of the division process is shown graphically with a decision or regression tree (Loh, 2011; Zabret et al., 2018). As a target variable, throughfall (TF), stemflow (SF), and rainfall interception (I) were set. Each model was run six times per observed year (namely, 2014, 2015, and 2016), once per each target variable, taking into account all influential variables and also the variables without data on the rainfall microstructure due to the longer period without available data (year 2015 was excluded). The influential variables included in the analysis (Table 1) were the total rainfall amount per event (P_a), the average rainfall event intensity (P_i), the total duration of the rainfall event (P_d), the average air temperature (T), and the vapour pressure deficit (*VPD*) during an event, the average wind speed (W_s) and the direction (W_d) per event, the dry period duration before a rainfall event (*DryP*), the time when an event occurred, namely during the day, the night, or both (*DN*), the phenoseason (*Feno*), the average raindrop diameter (*DropD*), the velocity (*DropV*) per event, the median volume diameter of an event's raindrops (*MVD*), and the number of raindrops delivered per event (*DropNr*).

Table 1. Influential variables included in the analysis.

Variable	Abbreviation	Unit
Rainfall amount per event	P_a	mm
Average rainfall event intensity per event	P_i	mm/h
Total duration of the rainfall event	P_d	h
Average air temperature during the event	T	°C
Average vapour pressure deficit during the event	*VPD*	kPa
Average wind speed during the event	W_s	m/s
Average wind direction during the event	W_d	°
Dry period duration before the rainfall event	*DryP*	h
Time when the event occurred, namely during the day, the night, or both	*DN*	–
Phenoseason	*Feno*	–
Average raindrops diameter of the drops, observed during the event	*DropD*	mm
Average raindrops velocity of the drops, observed during the event	*DropV*	m/s
Median volume diameter of an event's raindrops	*MVD*	mm
Number of raindrops delivered per event	*DropNr*	–

The BRT method combines two algorithms, regression trees and boosting (Elith et al., 2008), which improve the efficiency of an individual model and provide a better understanding of the results with additional factors. Boosting is based on the assumption that the average of many raw predictions, which are upgraded after every single repetition, will result in a better final model. The sequential approach of the step-by-step method iteratively adjusts and improves the model based on a set of training data (Elith et al., 2008). Due to the larger number of model runs, it is also possible to estimate the impact of an individual variable on the design of the model and thus on the target variable. Friedman (2001) presented an equation that can be used to estimate the relative influence (RI) of each variable included in the BRT model. The RI is based on how many times a variable has been selected in the model to divide the regression tree. The number of selections is weighted by the square of the model improvement rate as a result of each split and expressed as an average with respect to all generated regression trees (Friedman and Meulman, 2003). The RI is adjusted so that the sum of the RI values of all considered variables equals 100, making the higher values directly indicating a greater influence of the variable.

The BRT models were implemented using the "gbm" package (Ridgeway, 2020) in R software (R core team, 2020). In the initial phase we determined the arguments of the model, using 75% of the whole data set for training and 25% of the data for testing of the model, implementing 50 iterations for each set of the arguments and calculating the RMSE value of predictions from all iterations. When adjusting the model, various number of regression trees (15000, 1500, and 500) and values of the shrinkage parameter (0.001, 0.01, 0.05) were applied. According to the results, the final BRT models were estimated, taking into account the Gaussian distribution, 1500 trees, a shrinkage parameter of 0.01, and 5 cross-validation folds.

Random Forest (RF) is an ensemble-learning algorithm, which merges the concepts of regression trees and bagging (Breiman, 2001). Bagging is a procedure enabling growing of regression trees from different subsets in order to avoid highly correlated predictors. This algorithm relies on random selection of trees to describe the reliable relationship between the target and the influential variables. Cases are randomly selected from a data set, a random sample is used to design an individual regression tree, and predictions are formed for the remaining cases. The model repeats this process several times. Randomness is additionally ensured by imposing different randomly selected sets of influential variables on each division. This is possible due to random and repeated selection of individual target values and influential variables (Breiman, 2001). For each variable the variable importance measure is also estimated (Breiman et al., 2018). The variable importance gives the total decrease in node impurities from splitting on the variable, averaged over all trees. In case of regression, as presented here, it is measured by the residual sum of squares.

The RF models were built in R software (R core team, 2020), using package "RandomForest" (Breiman et al., 2018). In the first phase of the model establishment, we divided the data set into a training (75%) and test (25%) set. The model arguments were selected one by one, applying numerous iterations for each of the 30 models. For the number of variables randomly sampled as candidates at each split (mtry), the values between 10 and 40 were tested, using the "tune" function. The maximum number of terminal nodes of the trees (maxnode) was applied for the values between 5 and 30, while the number of the trees to grow (n.trees) was tested for values between 250 and 5000. For these two arguments the best value was selected according to the RMSE and R^2 values of the iteration results.

RESULTS

The analysed data on rainfall partitioning were collected during the years 2014, 2015, and 2016. These years were hydrologically quite distinct, as according to the long-term average annual precipitation, 2014 was recognised as a wet, 2015 as a dry, and 2016 as an average year. During 2014 we registered 167 events, delivering 1575 mm of rainfall. For this year, the total rainfall amount (1841 mm) was 36% larger than the average long-term yearly rainfall amount of 1355 mm measured at the Ljubljana-Bežigrad meteorological station. On the contrary, in 2015, we recorded 85 events, delivering 931 mm of rainfall. The total delivered rainfall (1106 mm) was 18% smaller than the long-term average rainfall amount per year (1355 mm). Furthermore, the year 2016 was similar to an average one, as we observed 113 rainfall events delivering 1139 mm of rainfall. Through the entire year, 1317 mm of rainfall was measured, which is comparable to a long-term average precipitation of 1355 mm at the Ljubljana-Bežigrad meteorological station. Although during the dry year 2014 the largest number of the rainfall events were recorded, they on average delivered the smallest amount of rainfall per event (9.4 mm) and on average lasted for the shortest time (5.7 h), but were on average the most intense (2.1 mm/h) (Figure 1). The average rainfall intensity and duration of rainfall events during the years 2015 and 2016 were similar (average intensity of 1.4 mm/h and 1.5 mm/h, respectively and average duration of 8.0 h and 8.1 h, respectively); however, the events in the dry year 2015 delivered on average more rainfall (11.0 mm) than the events in the average year 2016 (10.1 mm per event on average).

Comparing the climate conditions in the considered years only slight differences were observed for the wind characteristics, vapour pressure deficit, and air temperature. However, a noticeably shorter dry period between the events was observed in the wet year 2014 (40 h on average) comparing to the years 2015 and 2016 (58 h and 56 h, respectively). The rainfall events characteristics in the considered years also differ according to the rainfall microstructure. The size of the rainfall drops was significantly different ($p < 0.001$) during the wet year 2014 comparing to the years 2015 and 2016, as in the year 2014 an average raindrop diameter was equal to 0.85 mm and *MVD* was equal to 1.79 mm, while during the years 2015 and 2016 the drop diameter on average accounted to 0.67 mm and 0.62 mm and *MVD* to 1.51 and 1.44 mm, respectively. However, the larger raindrops resulted in the smaller number of drops per event, as the lowest number of raindrops was on average detected in the wet year 2014 (Figure 1).

The values of rainfall partitioning components were quite similar for the years 2014 and 2016, while some deviations are observed for the values measured in 2015, when higher values of throughfall and stemflow proportions according to the rainfall in the open were observed (Figure 2). In general, over all three observed years, throughfall under the birch tree was on average equal to 53% (± 34%), average stemflow was 1.2% (± 2.5%), and average rainfall interception was 46% (± 35%). Throughfall under the pine tree was on average lower than under the birch tree, resulting in 27% (± 26%) of rainfall in the open, while stemflow accounted for only 0.03% (± 0.10%) and the rainfall interception by the pine tree on average presented 73% (± 26%) of rainfall in the open.

Influence of the rainfall event characteristics on throughfall

Both of the applied models, namely BRT and RF, indicate that throughfall under the birch trees is influenced by the larger number of variables than throughfall under the pine trees, regardless the year (Figure 3). Throughfall (TF) under the birch trees in the wet year 2014 was the most dependent on the rainfall amount (P_a) and intensity (P_i), rainfall duration (P_d), and the average vapour pressure deficit (*VPD*) during the rainfall

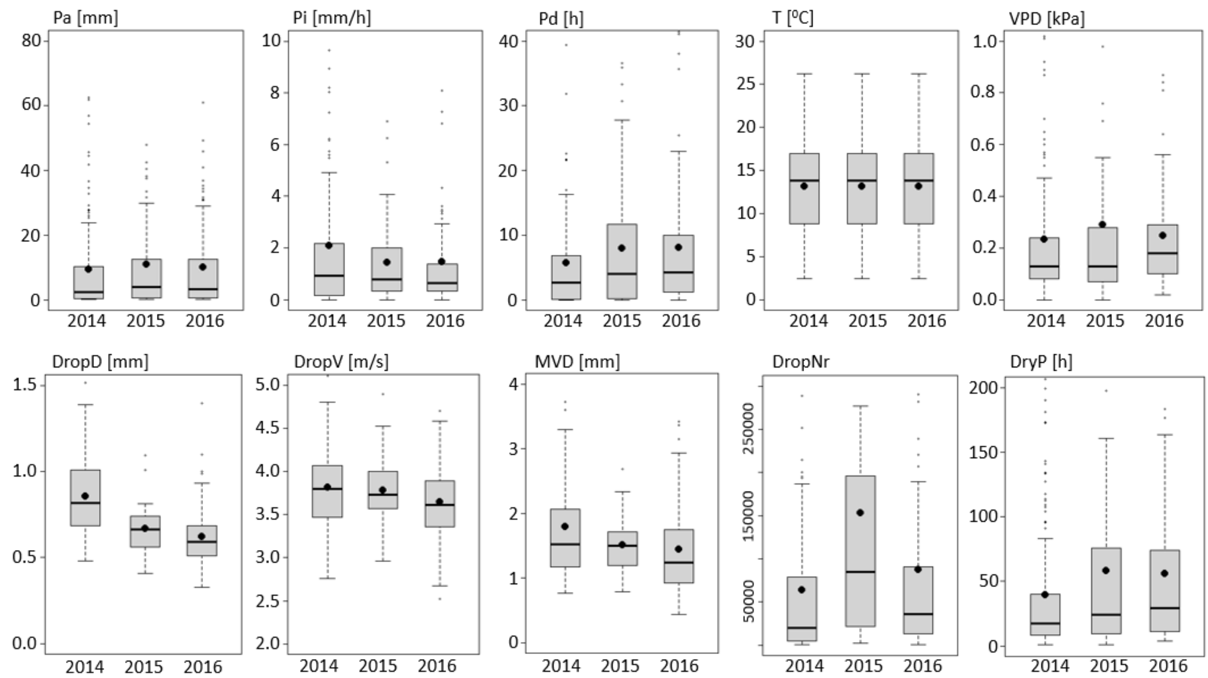

Fig. 1. Boxplots of considered rainfall event characteristics for each analysed year.

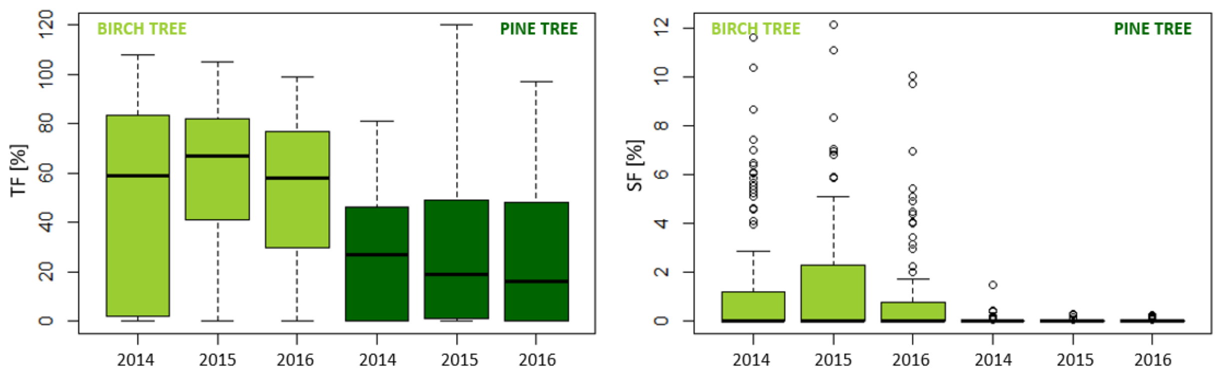

Fig. 2. Measured throughfall (TF) and stemflow (SF) by birch and pine trees per rainfall event according to the observed year.

event (Figure 3). Rainfall amount and intensity demonstrated between 18% and 20% of relative influence (RI) each by both applied methods, while RI for the first four most influential variables exceeded 60% in total. However, when taking into account also the variables describing the rainfall microstructure, the number of raindrops (*DropNr*) became the most influencing variable, indicating the amount of throughfall by birch in the wet year 2014.

For the throughfall under the birch trees during the dry year 2015, both models assigned a similar relative influence of almost 30% to rainfall intensity, indicating this variable as the most significant in addition to the rainfall amount. The BRT model also recognized air temperature and vapour pressure deficit as the influential variables with RI of 10%, while the random forest model assigned more than 8% of RI to rainfall duration and wind speed (W_s) (Figure 3).

The data collected during the average year 2016 showed a significant influence of the rainfall amount only, as it represented almost 40% of RI according to the BRT model and more than half of the total RI expressed by RF model. More than 9% of RI was assigned also to wind speed and vapour pressure deficit according to the BRT method and to air temperature and wind speed according to the RF model. In case of data for 2016, the inclusion of rainfall microstructure variables does not affect the order of the influencing factors (Figure 3). As the most influencing variable, the rainfall amount is still recognised by both applied models, however the second most influencing variable, having a similar value of RI, is the number of raindrops. In this case both variables together represent 45% and 60% of RI according to the BRT and RF model, respectively.

The number of influencing variables according to the dominant value of the relative influence in the case of throughfall under the pine tree is more straightforward (Figure 3). Rainfall amount was recognized to be the most influencing variable regardless the year, with an average RI between 43% (RF for 2014) and 82% (RF for 2016). Both models also recognized the influence of rainfall intensity and duration on throughfall by pine trees in 2014, while in 2015, more than 8% of RI was assigned to wind speed. In 2016, in addition to the rainfall duration air temperature was the second most influencing variable with RI larger than 5%. None of the rainfall microstructure variables exceeded more than 6% of RI, regardless the applied model or the year observed in case of throughfall under the pine trees.

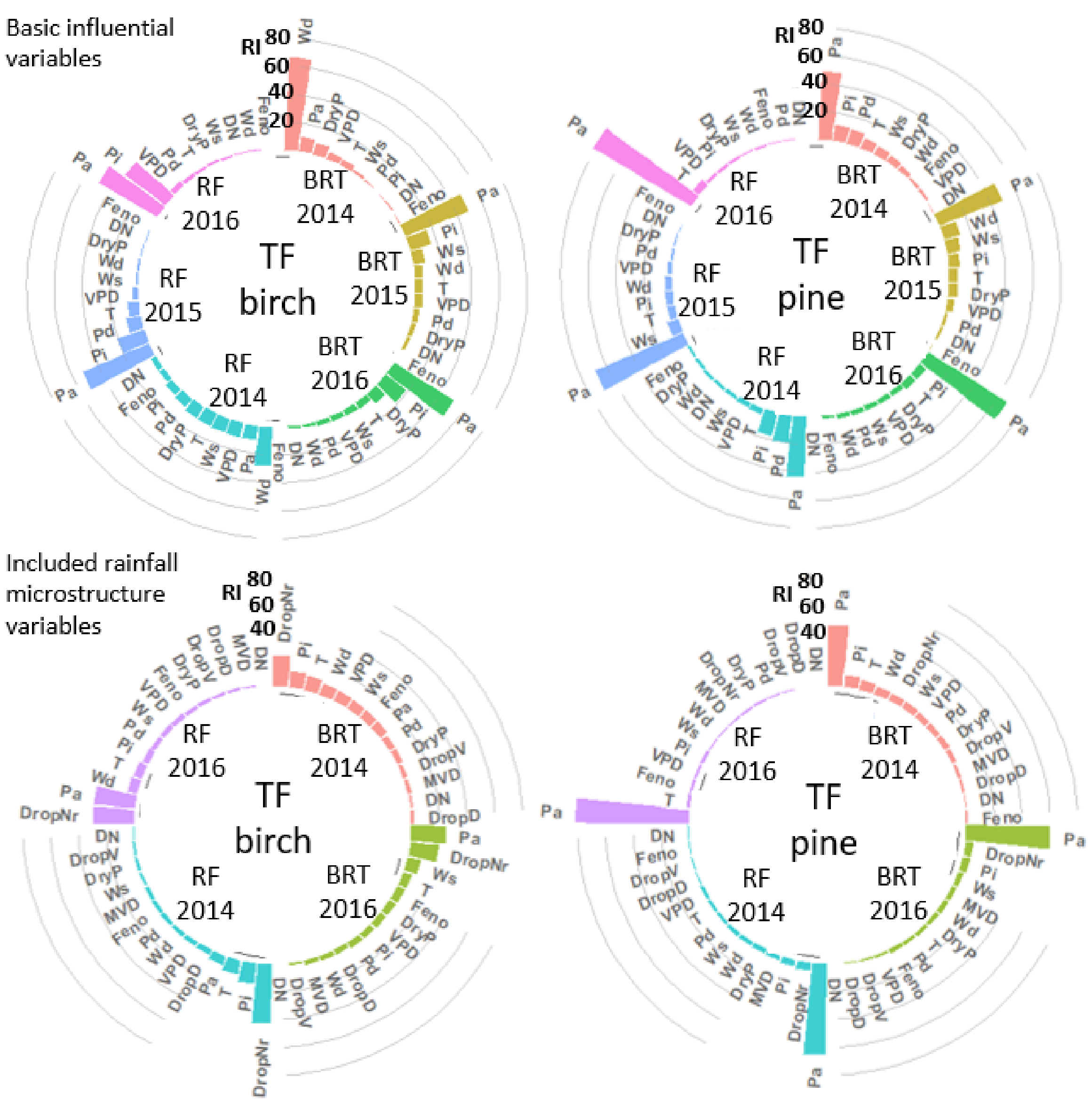

Fig. 3. Relative influence (RI) of the considered variables for throughfall (TF) by the birch and pine trees according to the observed years, evaluated by the boosted regression trees (BRT) and random forest (RF) models.

Influence of the rainfall event characteristics on stemflow

Similarly as throughfall, stemflow is in general the most influenced by the rainfall amount (Figure 4). Stemflow (SF) by the birch tree was the most characterized by the rainfall amount regardless the year as the RI for this variable ranged between 35% (RF, year 2014) and 61% (RF, year 2015). Stemflow by the birch tree in the wet year 2014 and the average year 2016 was also highly influenced by the rainfall duration, which had the second highest RI in both years, regardless the model used.

On the contrary, in the dry year 2015 stemflow by the birch tree was affected by a larger number of variables (Figure 4). The BRT model indicated that in addition to the rainfall amount, stemflow by the birch tree is also influenced by rainfall intensity, wind speed, vapour pressure deficit, and rainfall duration, as RI for all mentioned variables was larger than 9% (Figure 4). However, according to the RF model, the value of RI higher than 10% was estimated for the dry period duration and air temperature.

When taking into account also the rainfall microstructure characteristics, the rainfall amount is still one of the most influencing variables, combined with the number of raindrops. Stemflow in the wet year 2014 is still the most influenced by the rainfall amount, while the number of raindrops and *MVD* were also recognized as more influential. However, for stemflow in 2016, the number of raindrops together with the rainfall amount and duration were recognized as the variables with the highest RI (together accounting for 59% according to the BRT and 82% according to the RF model).

The amount of stemflow by the birch trees was similarly influenced during the years 2014 and 2016, however for the pine trees similarities can be observed between the years 2015 and 2016 (Figure 4). Stemflow by the pine trees during 2014 was the most influenced by wind direction, followed by the rainfall amount. In case of the BRT model these two variables resulted in RI of 77%, while in case of the RF model, the influencing variables with RI of more than 10% are also vapour pressure deficit, wind speed, and air temperature.

When also including the rainfall microstructure variables, the influence of wind direction is minimized, as rainfall amount, duration, and the number of raindrops in combination with *MVD* (estimated by the BRT model) and air temperature

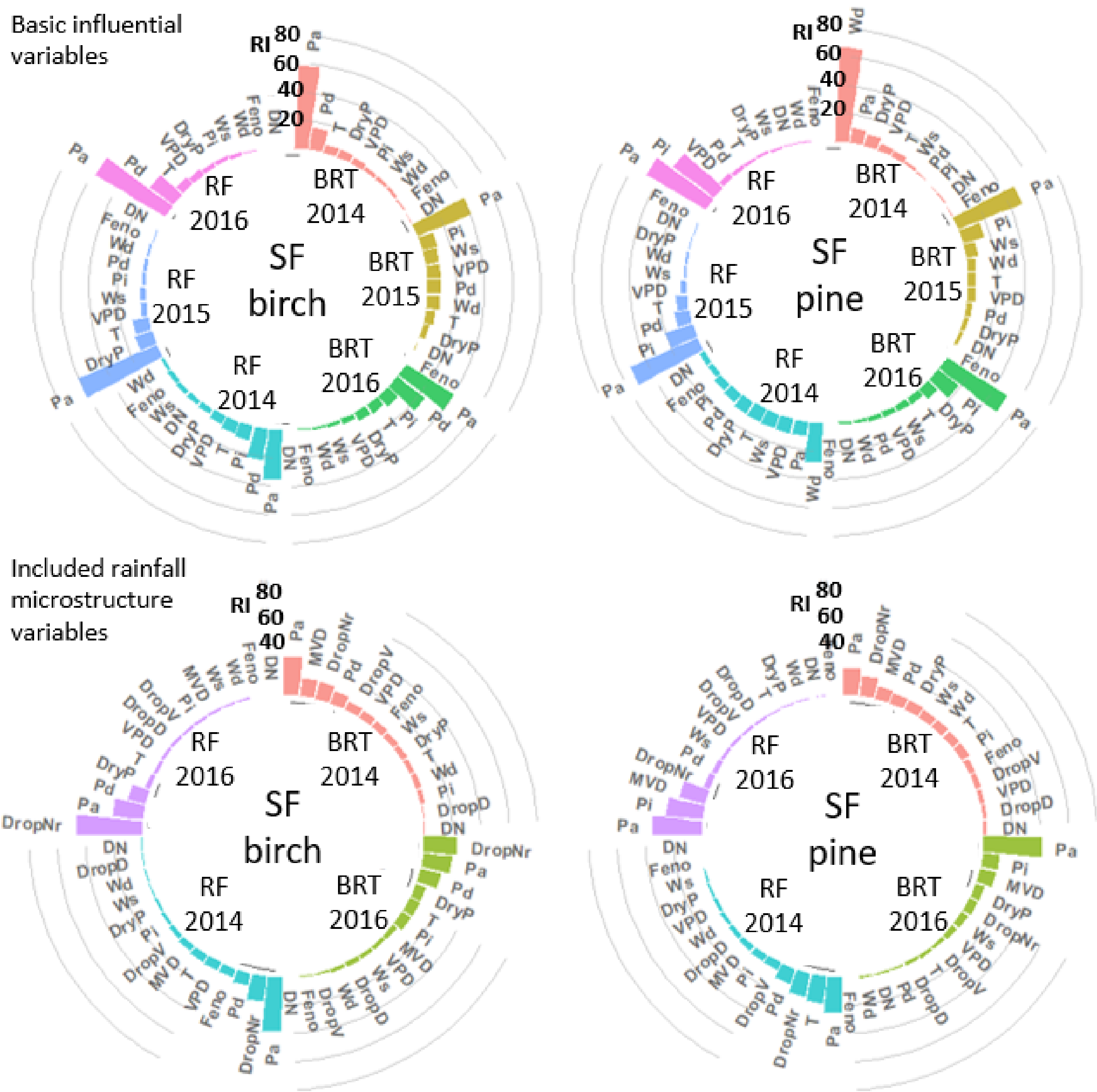

Fig. 4. Relative influence (RI) of the considered variables for stemflow (SF) by the birch and pine trees according to the observed years, evaluated by the boosted regression trees (BRT) and random forest (RF) models.

(estimated by the RF model) resulted in RI higher than 50%. Stemflow by the pine trees in 2015 and 2016 is significantly influenced by the rainfall amount and intensity, as regardless the model or the year, these two variables present between 64% and 85% of RI. The substantial influence of the rainfall amount and intensity is also retained when introducing the rainfall microstructure influence. In this case, as the second most influencing variable with RI larger than 10% both models recognised *MVD*.

Influence of rainfall event characteristics on rainfall interception

Rainfall interception (I) is calculated as the difference between the measured values, i.e. rainfall amount in the open, throughfall, and stemflow (Eq. 1). Therefore, as the amount of throughfall is much larger than stemflow, this is the value that mainly determines the proportion of intercepted rainfall, resulting in similarly evaluated influencing variables as throughfall (Figure 3).

Rainfall interception by birch and pine trees is the most influenced by the rainfall amount, which has the highest values of RI according to both models. In case of the birch trees the values of RI for the amount of rainfall ranged between 22% and 63%, while in case of the pine trees they were even higher, ranging from 47% to 83%. Comparing these values to RI estimated for throughfall, the values were a bit larger in case of the birch trees, while for the pine trees they were kept in a similar range.

Rainfall interception of the birch trees was in the wet year 2014 also significantly influenced by the rainfall duration and intensity, while in the dry year 2015 it was mainly influenced by rainfall intensity and in the average year 2016 by vapour pressure deficit (according to the BRT model) and air temperature (according to the RF model). In case of the pine trees the results were also very similar to the ones for the throughfall; in 2015 and 2016 only the rainfall amount played a significant role in the process of rainfall interception, while in the wet year 2014 also rainfall intensity and duration demonstrated RI values larger than 10% (Figure 5).

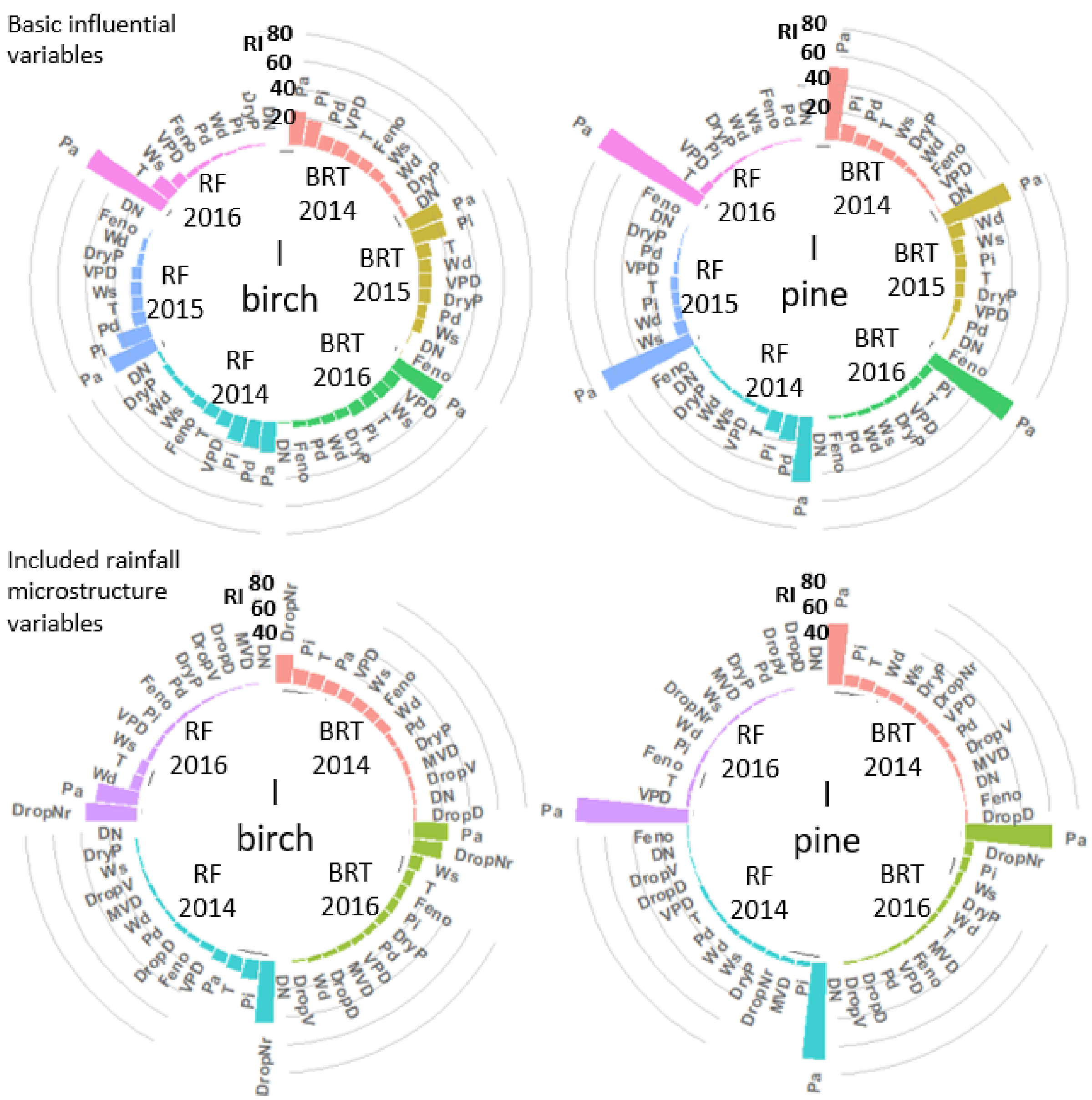

Fig. 5. Relative influence (RI) of the considered variables for rainfall interception (I) by the birch and pine trees according to the observed years, evaluated by the boosted regression trees (BRT) and random forest (RF) models.

The results of both applied models considering also the rainfall microstructure are also similar to the results of throughfall data analysis (Figure 3). In case of the birch trees, the number of drops was recognised as a variable with the highest influence among the newly introduced variables, while in case of the pine trees for none of these variables the estimated RI exceeded 6% (Figure 5).

DISCUSSION

Although the two methods are very similar as they are both based on the principle of regression trees, there is one main difference if we consider the method associated with the regression trees (boosting and bagging). This is also reflected in the estimation of the most influential variables and their RI values. A comparison of the results by the two models shows that in general, the RI values of the variables estimated by the RF model are higher than those estimated by the BRT model (Figures 3–5). Therefore, the number of the variables for which the RI value exceeds the threshold value is larger when taking into account results of the BRT instead of the RF model. Thus, the combined analysis of the two methods allows for a more comprehensive evaluation of the results, as the RF model indicates the most influencing variables, while the BRT model highlights also the other possible variables with meaningful influence.

The results demonstrate that throughfall, stemflow, and rainfall interception by birch and pine trees were the most influenced by the amount of rainfall, which has been repeatedly recognized as the factor most influencing the rainfall partitioning components in general also in other studies (e.g., Levia and Germer, 2015; Staelens et al., 2008; Su et al., 2019; Zabret et al., 2018). In case of both considered tree species, rainfall duration seems to play an important role mainly during the wet year 2014, while rainfall intensity had a significant influence on rainfall partitioning by birch trees during the dry year 2015. This observation seems to correlate well with the results presented by Mużyło et al. (2012), who observed a significant influence of rainfall duration on throughfall in a deciduous forest, especially during the leafless season. The leafless season is usually characterized by more precipitation and generally wetter months, which may be equivalent to the hydrologically wetter year of 2014, in which a more pronounced influence of rainfall duration was observed in this study (Figures 3–5).

As the wetter year 2014 can be correlated with the wetter leafless phenoseason, the drier year 2015 is expected to be associated with the drier leafed period. Therefore, the influence of rainfall intensity on rainfall partitioning in the drier year 2015 is initially unexpected. Rainfall intensity was actually recognized as one of the most influential variables in previous studies, but its effect was observed for winter throughfall (Xiao et al., 2000), rainfall interception in the leafless period (Zabret et al., 2018), and rainfall interception in a wet year (Zabret and Šraj, 2019b). However, for a beech tree, Staelens et al. (2008) reported significant influence of rainfall intensity on stemflow, especially during the leafed period resulting in a decrease in the stemflow amount due to splashing of droplets intercepted by the canopy and forming throughfall instead of stemflow. Additionally, a more evident influence of rainfall intensity was estimated by both applied models for birch rather than for pine trees (Figures 3–5). A different influence of rainfall intensity on tree species with distinct vegetation properties was already observed in other analyses (e.g., Sadeghi et al., 2020; Siegert and Levia, 2014; Zabret et al., 2018). Birch trees have a smoother bark surface and more flexible leaves compared to the rougher and more absorbent bark of pine trees and its compact needles, therefore the process of splashing of intercepted droplets may be more intense in the canopy of the birch trees.

The relative influence, estimated by the BRT and RF models, shows that throughfall under the birch trees is determined by a larger number of influencing variables. In addition to the rainfall amount, duration, and intensity, also air temperature and vapour pressure deficit (*VPD*) were assigned with values of RI larger than 8%. Air temperature and *VPD* are closely connected to the season of the year, corresponding also to the phenoseasons, and are especially significant for a deciduous birch trees (Zabret et al., 2018). Therefore, the significant RI values of air temperature and *VPD* may indirectly indicate the influence of phenoseasons on throughfall by birch, which is larger in the leafless period, characterized by lower air temperature and lower *VPD* values (Andre et al., 2008; Brasil et al., 2020; Mużyło et al., 2012; Šraj et al., 2008; Zabret and Šraj, 2018; Zabret et al., 2021). However, the relation between the influence of phenoseasons and meteorological variables on rainfall partitioning has already been recognized as a very complex one (e.g., Andre et al., 2008; Mużyło et al., 2012; Zabret and Šraj, 2021). When analysing the influence of air temperature and *VPD* on throughfall by the birch tree, the results are similar among the years (Figure 6). Throughfall is in general decreasing with increasing air temperature, which was observed also by Staelens et al. (2008). Warmer months of the year are also characterized with a fully leafed canopy, also decreasing the throughfall, while a higher air temperature increases the evaporation, which may also lead to a decrease in throughfall (Šraj et al., 2008; Xiao et al., 2000). However, the response of

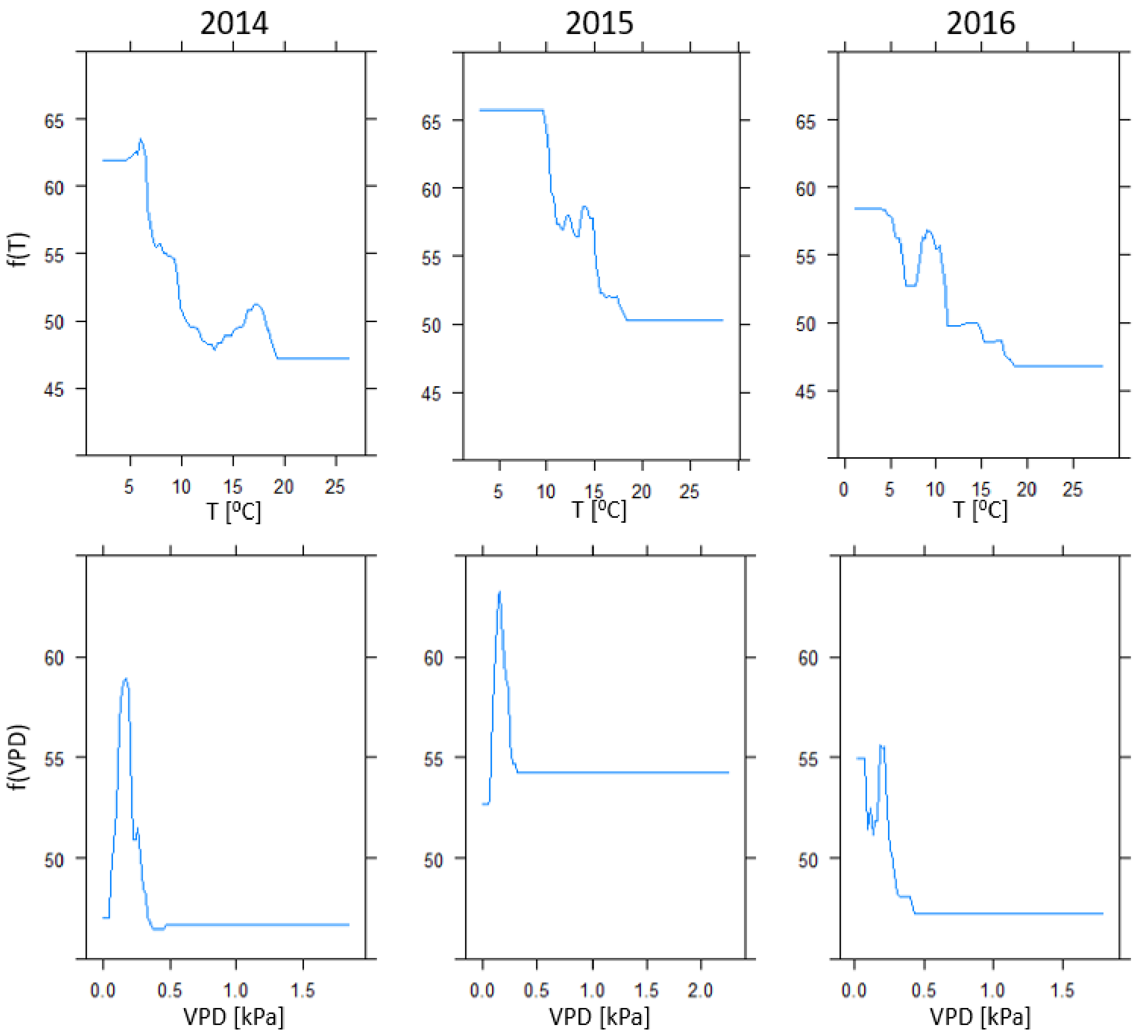

Fig. 6. Partial dependence plots of the influence of air temperature (*T*) and vapour pressure deficit (*VPD*) on throughfall (TF) by birch trees during the considered years.

throughfall according the *VPD* values is similar for the years 2014 and 2015, as lower *VPD* up to 1.5 kPa increases throughfall under the birch tree, while larger values of *VPD* decrease the amount of throughfall (Figure 6). The data collected in 2016 show a bit different response of throughfall according to the *VPD* values up to 2 kPa, while larger *VPD* values decrease throughfall under birch trees as well.

Pine tree's stemflow was influenced by more variables compared to throughfall. In addition to the rainfall amount, which mainly determines stemflow under both tree species, rainfall intensity and rainfall duration also had an important influence on stemflow under the pine and birch trees, respectively. The significance of rainfall duration on stemflow by the birch tree was also recognised in the analysis of the stemflow response (Zabret and Šraj, 2021), as well as in the analysis of predicting the stemflow of a birch tree using the regression trees (Zabret et al., 2018). Although rainfall intensity was recognised as a less influential variable in the case of throughfall under the pine trees, it seems to have a larger influence on its stemflow. Results of both implemented models (BRT and RF) indicate RI values larger than 15% for rainfall intensity in the years 2015 and 2016 (Figure 4). This is consistent with the results of the BRT model applied to stemflow data of a leafed phenoseason (Zabret et al., 2018), which also indicates some similarities in meteorological influences during the leafed phenoseason and the drier hydrological year.

Introduction of variables specifying the rainfall microstructure into the analysis expressed significant influence of the number of rain drops on throughfall and rainfall interception by the birch trees. The number of raindrops as well as the mean volume diameter (*MVD*) were estimated to have considerable influence on stemflow in case of both considered tree species. However, no influence of these variables on throughfall under the pine trees was observed, as throughfall under the pine trees was still the most influenced by the amount of rainfall, which provided more than half of the RI according to the other considered variables. A more noticeable influence of rainfall microstructure on throughfall by birch than by pine trees was also confirmed in previous study (Zabret et al., 2018), in which a similar comparison of data with BRT models per phenoseason showed the influence of *MVD* on throughfall by pine trees only in the leafless season, while the number of raindrops had a significant role in regulating throughfall under the birch trees regardless the phenoseason. This might be connected to the distinct characteristics of the foliage of the considered tree species, i.e. leaves of the birch trees and needles of the pine trees. The different interaction of needles and leaves to the rain drops and their characteristics has been already reported by other researchers (e.g., Holder, 2013; Nanko et al., 2016; Zabret et al., 2017; Zabret et al., 2018).

CONCLUSIONS

The rainfall partitioning process is part of the hydrological cycle, for which changes are expected due to more pronounced precipitation patterns, resulting in more intense wet and dry periods. Accordingly, the influence of meteorological factors on throughfall, stemflow, and rainfall interception during a wet, a dry, and an average year was analysed. Two similar statistical methods based on the regression tree approach were applied, namely boosted regression trees and random forest. The comparison of the results showed that the methods are complementary, since the BRT model indicates numerous variables with relevant influence and the RF model highlights the variables with the highest influence.

The variables with the highest influence expressed by both models were the rainfall amount and the number of raindrops. The comparison of the influential variables indicates to some extent the correlation between the wet period and the leafless season, as well as between the dry period and the leafed season. For example, rainfall duration had a high relative influence on rainfall partitioning by both tree species mainly in the wet year 2014, while researchers already reported its influence in the leafless season. Stemflow by birch trees was also strongly influenced by air temperature and vapour pressure deficit, which are dependent on the season of the year, which is also consistent with the phenoseason. However, the results of the models also indicate significant differences in the response of the two tree species. The influence of rainfall intensity, the number of raindrops, and the median volume diameter was more pronounced in the case of the birch trees, while it was negligible in the case of the pine trees. This observation coincides with the conclusions of previous studies, i.e. that raindrops behave differently when interacting with needles or leaves.

The presented analysis mainly confirms all previous observations made by other researchers about the different influences on the rainfall partitioning process by distinct tree species. However, a new insight into the impact of wet and dry period is presented, indicating that during a longer wet period the trees behave similarly as in the leafless period and during the longer dry period the rainfall interception process is similar as that in the leafed period. Nevertheless, additional analysis, taking into account multiple wet and dry periods as well as data for these periods for other tree species and other locations with different microclimatic characteristics, should be implemented in order to understand this aspect in more detail.

Acknowledgements. The work was founded by the Slovenian Research Agency (ARRS) through research program P2-0180.

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Received 28 May 2021
Accepted 5 August 2021