Response to Reviewer 2 Comments

Manuscript title: Multivariate regression trees as an 'explainable machine learning' approach to exploring relationships between hydroclimatic characteristics and agricultural and hydrological drought severity

Author's general response:

The authors would like to thank the reviewer for thoroughly reviewing the manuscript. Your insightful and specific comments helped us to improve the manuscript's scientific quality. We are particularly grateful for your meaningful observations on the application of MVRT to this particular study and for providing constructive feedback on the manuscript's overall readability. We will apply multiple changes to incorporate the reviewer's suggestions. In the following, you will find the answers to the general and specific comments. Some of them required a particular action or change in the manuscript. The changes we will apply in the Revised Manuscript (RM) are in italics.

General **Comments**

1. I am wondering why the authors used SMDI and SSI to identify soil moisture/agriculture and streamflow droughts, respectively. These are two different methods. Why don't the authors use the Standardized Soil Moisture Index (SSMI) in order to have a comparable method with SSI since both are the standardized indices. I suggest to write a clarification of why the authors decide to use SMDI instead of SSMI.

We evaluated different drought indices to select the most appropriate for this study. The SSMI is an agricultural drought index derived from daily satellite data and applicable for short-term agricultural drought monitoring (and prediction) across large areas. In validating the SSMI, the index authors found a moderate correlation with the Palmer Drought Severity Index (PDSI), an effective index in determining long-term droughts. We concluded that SSMI was unsuitable for this study for two main reasons. First, the index is developed for short-term drought monitoring. Our study focuses on past drought events, particularly severe, long-lasting droughts. Second, there is no previous assessment of the index performance using simulated soil moisture as the input parameter.

On the other hand, SMDI was developed to use simulated soil moisture with SWAT as the input parameter. In addition, in the SMDI validation, the index authors found a good correlation with the PDSI. We agree with the reviver that SMDI and SSI apply different methods to estimate agricultural drought severity. Nevertheless, we considered that difference had no implications for this study. Despite the method to estimate the drought severity, both indices successfully represented the past drought events in the region. Additionally, they allowed us to determine the number of months for each drought category (moderate, severe, extreme) at each subbasin during the analysis period. That information was used to define the set of response variables to apply the MVRT technique.

2. Another I do not get the importance of PCA analysis in your study. Here the authors used the PCA to further confirm the key drivers of droughts obtained from the MVRT. However, more explanation in the text about the PCA results and how these confirm the MVRT results is lacking. For example, from the 11 variables, which variables have the higher explained variances, and how to read the loading factors in the sense of what positive and negative signs mean? From the MVRT, I can see that ET, precipitation, and percolation are key drivers for agriculture drought (correct me if I am wrong) and the key drivers for streamflow drought are precipitation and water yield.

The authors thank the reviewer for questioning the relevance of the PCA results. Before applying the MVRT, we used PCA to explore the dataset of explanatory variables. Our goal was to identify the most influential parameters of the dataset and discard non-influential parameters. The PCA results showed that all the parameters considerably influenced at least one of the PC retained; thus, for the MVRT technique, we used all the parameters initially selected. Reviewer's comment makes us reevaluate the PCA results' relevance since the technique application does not produce changes in the set of explanatory variables. We conclude that using PCA is a good strategy for explanatory variables exploration, but the outcome of the analysis is not relevant to the objective of this study. Accordingly, we will remove the PCA analysis in the RM.

Although the analysis is not included in the RM, we consider it essential to answer the questions posed. Regarding the first question, when applying PCA, explained variance indicates how much of the total variance in the dataset is "explained" by each principal component. In this case, the first component explained 36% of the total variance in the set of explanatory variables, the second 29% and the third 12%. The cumulative explained variance of the three principal components retained was 77%.

Regarding the second question, loading factors indicate which individual variables contribute the most to the principal components. The sign (+ or -) indicates whether a variable and a principal component are positively or negatively correlated. In this case, the first component was heavily influenced by precipitation, potential evapotranspiration, evapotranspiration, percolation, curve number and slope.

The reviewer's interpretation of the MVRTs is correct, and it is possible to confirm that all these individual variables heavily influenced at least one of the three components retained.

3. An explanation of why the authors used different CVRE, relative error, and EV values for agriculture and streamflow droughts is needed.

We highlight that CVRE, relative error, and EV values are given by the MVRTs explanatory power. The explanatory power refers to the proportion of the variance explained by the tree. Our values are different because the trees for agricultural and hydrological droughts have distinct explanatory power. Section 2.2.3 (Building the MVRT) presents the parameters definitions and the equations to calculate them. In Section 4.3 (Accuracy of the MVRTs), we discuss the accuracy of the trees and present possible causes of the different EVs obtained. The original sections mentioned are included below:

Cross-validation of the partitions and tree pruning

This cross-validation process was repeated several times for consecutive and independent divisions of the data into test groups. For each group, the mean and standard deviation of all CVRE were computed. The CVRE varied from 0 for perfect predictors to close to 1 for poor predictors (for large errors, CVRE may reach +∞). Among the mvpart function arguments, we used ten cross-validation groups (function argument, xval = 10) and 100 iterations (function argument xmult = 100). The tree was selected using interactive cross-validation (function argument xv = 'pick').

To choose the size of the tree that retained the most descriptive partition, we used the approach suggested by De'ath (2002). According to the author a tree with the smallest CVRE offers the best combination of explanatory power and interpretability. Once the tree was built, the proportion of explained variance (EV) was calculated as 1-〖RE〗_tree (tree relative error) (Cannon, 2012).

4.4 Accuracy of the MVRTs

The high EV (0.81) value reflects the good explanatory power of the tree built for agricultural drought. This confirms that the selected explanatory variables significantly influence the severity of agricultural drought.

Conversely, the explanatory power of the tree built for hydrological drought is not very high (EV = 0.48). This may be related to the inaccurate representation of groundwater contribution to the streamflow. Streams depend significantly on groundwater during droughts to maintain flow; nevertheless, groundwater *contribution to the streamflow was not included as a key drought driver in the MVRT, although it was in the list of explanatory variables. It is possible that the model's simplifications for the simulation of groundwater flow and storage did not adequately represent the groundwater contribution to the streamflow (Molina-Navarro et al., 2019). The lack of adequate information about this relevant factor hydrological drought may have compromised the MVRT's accuracy. Unexplained variability may also link to factors that influence hydrological drought but were not considered in the dataset of explanatory variables (e.g. abstractions such as water for irrigation, industry or human consumption).*

Specific Comments

1. P1L17: Maybe add the word "such as" -> ….model outputs, such as soil moisture and streamflow….

The authors thank the reviewer for the suggestion, but, after reflecting on it, we consider that the adverb "such us" is not suitable for this sentence, because we are not introducing examples. Instead, soil moisture and streamflow are the only two model outputs we used to calculate the drought indices.

2. P1L26: the authors may replace the word "brought on" with "caused"

We like the suggestion. The word will be replaced in the RM.

3. P2L46-50: Here the authors describe drought propagation. I suggest stating this clearly thus the readers understand what is drought propagation. Moreover, the authors also used the term propagation a few times in the next paragraph. The authors may also add a drought propagation study by Van Loon et al. (2012).

We like the suggestion. In the RM, we will indicate that we refer to drought propagation and will include the reference.

Remarkable progress has been achieved in understanding drought propagation through the hydrological cycle (Van Loon et al., 2012).

4. P3L66-68: Write the references (two studies) directly after the sentence.

In the RM, we will update the paragraph as shown below. Editor's suggestion will be included.

We have found two studies that employ machine learning to analyse the non-linear relationship between climate and basin processes and droughts (Konapala & Mishra, 2020; Valiya Veettil & Mishra, 2020).

5. P3L79-80: Same, write such as or the authors may re-write it as: “Soil moisture and streamflow obtained from the SWAT model are used to…….”

In the RM, we will update the paragraph as shown below. Editor's suggestion will be included.

> *To understand the relationship between the drivers of droughts and the individual categories of agricultural and hydrological droughts severity, this study employs a methodology that consists of three steps. The first is hydrological modelling. We used Soil Water Assessment Tool (SWAT) to simulate the hydroclimatic parameters required for analysing droughts and applying the MVRT approach. The Second is the analysis of droughts. SWAT outputs, soil moisture and streamflow, are used to calculate the drought indices Soil Moisture Deficit Index (SMDI) and the Standardized Stream Flow Index (SSI). Drought indices were utilised to identify the agricultural and hydrological drought events during the period of analysis and describe their severity. Finally, the MVRT approach is applied to assess the relationship between hydroclimatic characteristics (represented by the simulated parameters at each subbasin, see Table 2) and droughts severity categories (represented by the observed number of months for each drought severity category at each subbasin, see Table 3). The analyses for agricultural and hydrological droughts were conducted separately; thus, two MVRTs were obtained. A concrete application of this methodology is developed in the Cesar River basin (Colombia, South America).*

6. P3L80-81: The authors mention “other simulated hydroclimatic parameters….” -> mention them already.

The authors thank the reviewer for the suggestion; however, we consider mentioning all the parameters (11 in total) can affect the readability of the paragraph. Please note that they are already presented in Figure 2 (Flowchart of the methodology), and Table 2 explicitly describes each one of the hydroclimatic parameters used as explanatory variables. In the RM, we will refer to Table 2 (See answer to Specific Comment 5).

7. P3L86: I suggest restructuring section 2. Section 2 will be Study location and methods and thus section 2.1 will be study location and section 2.2 will be methods. Swap figures 1 and 2 accordingly. In the present form, the authors mention first the flowchart describing the data and method but then no explanation is followed. Study location is placed after this 1 sentence about data and method, and then section 2.2 back to method again.

The authors thank the reviewer for the suggestion since it improves the structure of the section. We will apply the following changes in the RM. The section title and subtitles will be updated. Section 2 is *Study location and methods*, and the subsections are 2.1 Case of study and 2.2 Methods. Section 2.2 includes *2.2.1 Hydrological modelling*, *2.2.3 Agricultural and hydrological drought analysis* and *2.2.3 Multivariate regression tree approach for evaluating the relationships between hydroclimatic characteristics and droughts severity.* Figures 1 and 2 are swapped according to the new section's order. The relevant sections will read as follows:

2 Study location and methods

2.1 Case study

Figure 1 presents the Cesar River basin's location, topography and land use. The basin is located between 72º53'W 74º04'W and 10º52'00'N 7º41'00''N latitude (Colombia). It extends for an area of 22,312 km2. The basin's topography is defined in three distinct climatic regions (Universidad del Atlantico, 2014). In the north is La Sierra Nevada de Santa Marta. This sector is characterised by steeply sloped mountains reaching up to 5,700 meters above sea level (masl). The temperature ranges from 3°C to 6°C, and the mean annual precipitation is 1,000 mm. In the east is La Serranía del Perijá. This mountainous area is an extension of the eastern branch of the Andes range. In this sector, the altitude ranges from 1,000 to 2,000 masl. The average temperature is 24°C, and the average annual precipitation varies from 1,000 mm to 2,000 mm. Lastly, the valley of the Cesar River and the Zapatosa marsh are in the west and south of the basin, respectively. The valley is characterised by flat topography and a complex system of marshes formed by the Cesar River floodplains and its confluence with the Magdalena River. The average temperature is 28°C, and the mean annual precipitation is 1,500 mm. At the basin, the annual rainfall pattern presents a dry season from December to April, followed by a rainy season from April to May. In the intermediate period from June to July, precipitation decreases. The main rainfall events occur between August and November.

The predominant land use is pasture, followed by agriculture (Universidad del Atlantico, 2014). The primary land use in La Sierra Nevada foothills is pastures for cattle farming. In La Serranía del Perijá, the high altitude areas are *covered by forests in very good condition; at the lower altitudes, the principal land use is agriculture, particularly subsistence crops. The Cesar River valley's soils are rich in nutrients, providing favourable conditions for agriculture. The riverbanks are covered by forest with low tree density.*

The Zapatosa marsh is recognised as one of the most important wetlands in the country, and considering the relevance of this ecosystem, it was declared a Ramsar site in 2018. Nevertheless, the region is threatened by the overexploitation of its forest resources and overfishing. In addition, climate change projections indicate that the basin's temperature may increase by 2.7°C, and precipitation may reduce by ten percent by 2070 (Universidad del Magdalena et al., 2017). Accordingly, multiple initiatives are oriented to improve water management and create resilience to hydroclimatic extremes (Ministerio de Ambiente y Desarrollo Sostenible (Colombia), 2015).

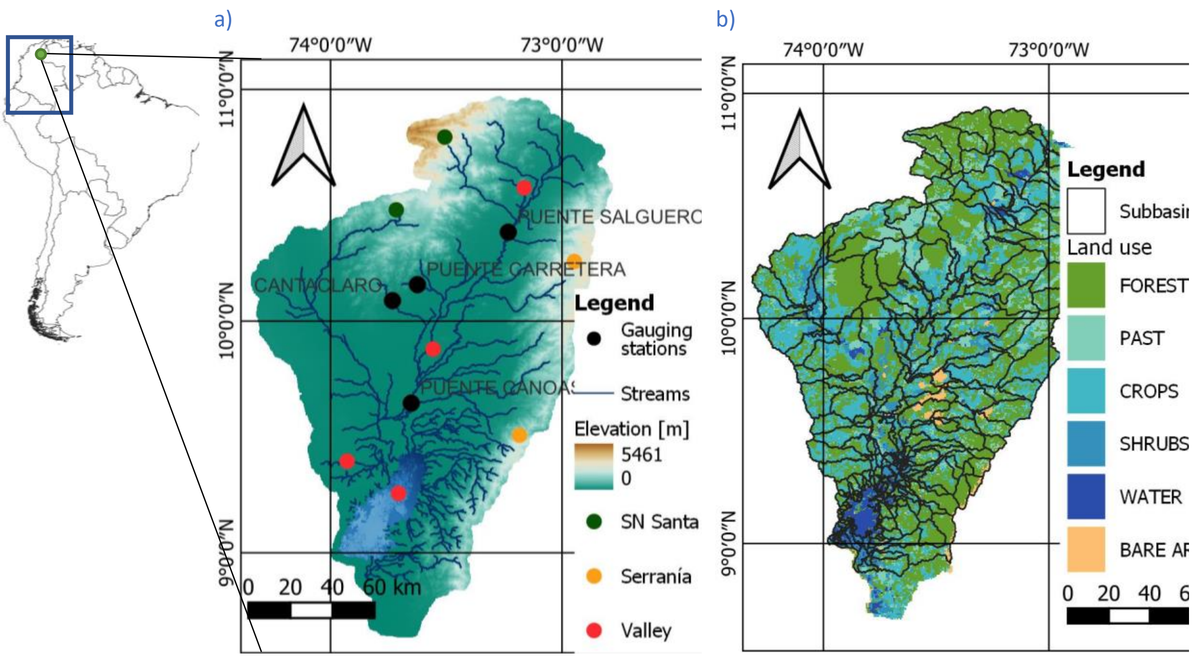

***Figure 1** Cesar River basin: a) topography and b) land use.*

2.2 Methods

Figure 2 illustrates the three steps methodology applied in this study. Section 2.2.1 describes the hydrological modelling, and 2.2.2 the drought analysis. Section 2.2.3 presents the application of the MVRT technique.

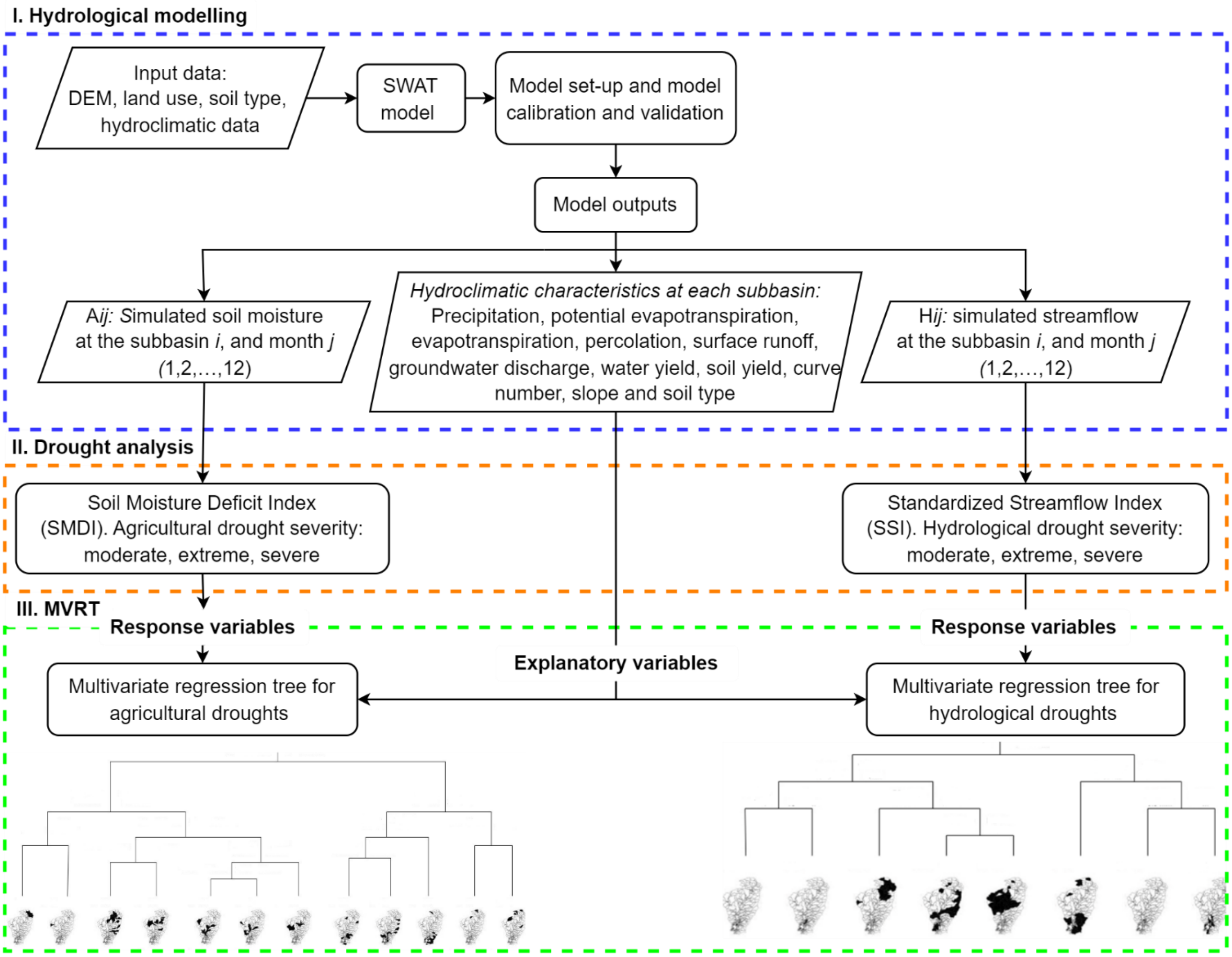

Figure 2 *Flow chart of the methodology*

8. P5L117: Figure 2. Please label this figure into 2a and 2b and refer these figures in the text above. I also strongly suggest the authors change the color label for Figure 2b. Using red color for water bodies, blue for grass, and black color for forest are not common. Change the color codes into the most commonly used colors to represent the land use.

We will label Figure 2 as suggested and change the color map into the most commonly used colors to represent land use. See answer to Specific Comment 7.

9. P6L143: Maybe reverse the abbreviations and full names. I suggest to write the full name first and then the abbreviation.

The new text will read as follows:

Based on expert judgment and the available literature (Arnold et al., 2012; Transactions of the ASABE (American Society of Agricultural and Biological Engineers), 2018), the following SWAT parameters were used in the calibration *and validation process: baseflow alpha factor (ALPHA_BF), effective hydraulic conductivity in main channel alluvium (CH_K), SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), groundwater delay (GW_DELAY), threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), deep aquifer percolation fraction (RCHRG_DP), threshold depth of water in the shallow aquifer for percolation to the deep aquifer to occur (REVAPMN) and available water capacity of the soil layer (SOL_AWC).*

10. P8L195: Please write the minimum threshold. Is it 30%?

Indeed, the threshold is 30%. The paragraph will be updated in the RM.

SMDI and SSI were calculated monthly using the simulated soil water and streamflow values at each subbasin. The drought events during the period of analysis were then identified. A drought (agricultural or hydrological) event was assumed to occur in the basin when a number of subbasins (covering at least 30 % of the basin's total area) were in a moderate drought state for at least two consecutive time steps (i.e. in this study month).

11. P9L198: PCA analysis. Please describe in this section that the authors only used the first order until the third order only.

Please see answer to General Comment 2.

12. P9L215: MVRT method. Some explanations why the authors only used this single method are encouraged.

We agree with the reviewer that the introduction and methodology do not explicitly present the reasons for choosing the MVRT approach and how the technique capabilities are exploited in this study. Accordingly, two changes will be included in the RM. First, we will update the introduction indicating that drought severity categories (moderate, severe and extreme) are the three response variables modeled with the MVRT and summarising the technique capabilities relevant to the study, as shown below: We present the updated version of the introduction (There are no changes in the first two paragraphs of the introduction).

Projections indicate that drought frequency, severity and duration are expected to increase globally in the twenty-first century (UNDRR, 2021). Upcoming soil moisture drought scenarios predict statically significant, large-scale drying, especially in scenarios with strong radiative forcing in Central

America and tropical South America United States Department of Agriculture (Lu et al., 2019). A similar trend is predicted for hydrological drought severity. This is expected to increase by the end of the twenty-first century, with regional hotspots in central and western Europe and South America, where the frequency of hydrological drought may increase by more than 20 % (Prudhomme et al., 2014). The intensification of drought characteristics (in combination with other factors) could force the migration of up to 216 million people by 2050 (The World Bank, 2021), increase wildfire risk and tree mortality, and negatively affect regional air quality, among other ecosystem impacts (Vicente-Serrano et al., 2020).

It is essential that we better understand drought drivers if we are to foster preparedness and resilience to projected drought events. Remarkable progress has been achieved in understanding drought propagation through the hydrological cycle (Van Loon et al., 2012). Drought occurs due to climatic extremes, which may be enhanced or alleviated by region characteristics and anthropogenic influence (Hao et al., 2022; Seneviratne et al., 2012; Tijdeman et al., 2018). Typically, droughts are triggered by atmospheric circulation and weather systems that combine to cause lower precipitation and/or higher than normal evaporation in a region (Destouni & Verrot, 2014; Sheffield & Wood, 2011a). Reduced precipitation leads to a decrease in soil moisture, causing agricultural drought. When soil moisture depletion is high, it is restored in the wet season, thus reducing subsurface flow and groundwater recharge and giving rise to hydrological drought (Iglesias et al., 2018). Regional characteristics such as soil type, stratigraphy, elevation, slope, vegetation cover, drainage networks, water bodies and groundwater systems play a relevant role in response to the climate anomalies that affect drought propagation and contribute to different levels of agricultural and hydrological drought (Sheffield & Wood, 2011a; Zhang et al., 2022). Equally important, human interventions in the hydrological cycle (e.g. reservoirs, water diversion, deforestation, over-pumping groundwater, overgrazing, urbanisation) can reduce water supplies, triggering *a drought situation or exacerbating a climate-driven drought (Rangecroft et al., 2019; Wang et al., 2021).*

Drought planning also uses research progress on drought characterisation. Various methodologies for drought characterisation exist, using drought indices is widespread (Zargar et al., 2011). Drought indices are computed numerical representations of drought severity (Hao & Singh, 2015; Keyantash & Dracup, 2002). Severity refers to the departure from the normal of an index. Generally, severity is divided into different categories (e.g. moderate, severe, extreme), providing a qualitative assessment of the drought state in a region during a given period. Drought indices (and their categories) are crucial for tracking or anticipating drought-related damage and impacts (WMO & GWP, 2016).

Despite remarkable progress achieved in understanding the drought-generating process and drought characterisation, there is still a need for studies that assess the complex interplay between the different drivers of droughts and how their combined effect influences drought characteristics (e.g. duration, severity, intensity) (Valiya Veettil & Mishra, 2020). Previous studies focus on the influence of one driver (Margariti et al., 2019; Mastrotheodoros et al., 2020; Shah et al., 2021; Xu et al., 2019), and some of the methodologies applied cannot adequately address the non-linear relationship between climate, basin processes and droughts (Peña-Gallardo et al., 2019; Saft et al., 2016; Van Loon, 2015).

We have found two studies that employ machine learning to analyse the non-linear relationship between climate and basin processes and droughts (Konapala & Mishra, 2020; Valiya Veettil & Mishra, 2020). Valiya Veettil et al. (2020) used a classification and regression tree (CART) to identify the variables influencing drought duration. Since CART allows one output variable (drought duration), the authors applied the technique three times to evaluate the variables influencing short-term, medium-term and long-term drought events. Meanwhile, Konapala et al. (2020) used a random forest (RF) algorithm to identify the climate and basin parameters influencing the characteristics (duration, frequency and intensity) of three different drought regimes (long duration and *mild intensity, moderate duration and intensity, short duration and high intensity). As the core of RF is a decision tree that allows one output variable (in this case, each characteristic of each drought regime), the authors repeated the procedure for each drought regime and characteristic. Both studies focused on drivers of hydrological drought and were developed in the continental United States.*

Mentioned research shows the potential of machine learning techniques for drought-related analysis; nevertheless, there is still a need for testing a technique capable of simultaneously assessing the influence of different drought drivers on the individual categories of drought severity. Commonly used in the field of ecology to relate independent environmental conditions to populations of multiple species, Multivariate Regression Tree (MVRT) arises as a suitable technique for this purpose. MVRT is a supervised clustering technique that links explanatory variables to multiple response variables while maintaining the individual characteristics of the responses. Significantly, the technique does not assume a linear relationship between explanatory and response variables. Furthermore, it allows for the so-called "interpretable machine learning" algorithms that make decisions and predictions understandable to humans (Molnar, 2022). MVRT interpretably is a relevant attribute for drought researchers and planners since the method allows them to identify the parameters influencing severe (or mild) drought conditions.

To understand the relationship between the drivers of droughts and the individual categories of agricultural and hydrological droughts severity, this study employs a methodology that consists of three steps. The first is hydrological modelling. We used Soil Water Assessment Tool (SWAT) to simulate the hydroclimatic parameters required for analysing droughts and applying the MVRT approach. The Second is the analysis of droughts. SWAT outputs, soil moisture and streamflow, are used to calculate the drought indices Soil Moisture Deficit Index (SMDI) and the Standardized Stream Flow Index (SSI). Drought indices are utilised to identify the agricultural and hydrological drought events *during the period of analysis and describe their severity. Finally, the MVRT approach is applied to assess the relationship between hydroclimatic characteristics (represented by the simulated parameters at each subbasin, see Table 2) and droughts severity categories (represented by the observed number of months for each drought severity category at each subbasin, see Table 3). The analyses for agricultural and hydrological droughts were conducted separately; thus, two MVRTs were obtained. A concrete application of this methodology is developed in the Cesar River basin (Colombia, South America).*

Second, in the methodology, we will update the introductory paragraph of the Section 2.2.3 and will include a paragraph describing the reasons considered in the selection of the technique, as follows:

MVRT is an extension of a regression tree (Breiman, 2001), but it differs in that it allows for multiple outputs (see De'ath, 2002). It allows the recursive split of a quantitative response variable (predictand, output) controlled by a set of numerical or categorical explanatory variables (predictors, input). The technique approach yields a set of non-linear models, each a piece-wise linear regression model (of zero order). An MVRT result is a tree whose terminal groups (leaves) of instances (input-output vectors) comprise subsets of instances selected to minimise the within-group sums of squares. Each successive split is given by a threshold value of the explanatory variables (Borcard et al., 2018). MVRT applies to dataset exploration, description and prediction (De'ath, 2002). In this study, explanatory variables are the hydroclimatic parameters at each subbasin, represented by the average value of each parameter during the analysis period (1987 to 2018). The number of months observed at each drought severity category (Categories are given by the drought indices) are the response variables. The analyses for agricultural and hydrological droughts were conducted separately; thus, two MVRTs were obtained.

Four technique attributes are relevant to this study. First, MVRT can capture the non-linear interactions between the parameters influencing droughts and their severity. Second, the technique can handle numerical and categorical hydroclimatic parameters influencing drought severity (explanatory variables).

Third, MVRT's capability to handle multiple outputs allowed us to evaluate the influence of the hydroclimatic parameters on moderate, severe and extreme drought conditions simultaneously (response variables). The drought indicators give these three categories to represent the drought severity. Simultaneous analysis of different drought categories provides a comprehensive understanding of the drought-generating process and the factors influencing severe (or mild) drought conditions. Fourth, MVRT results can be easily visualised and interpreted. The resulting tree structure provides a clear representation of the relationship between the drivers of droughts and the severity of agricultural and hydrological droughts.

13. P10L234: value -> values

We regret this mistake. The error will be corrected in the RM, as shown below:

To select the set of explanatory variables, we used the outcomes of previous studies on governing drivers of droughts (Sheffield & Wood, 2011a; Zhang et al., 2022). Table 2 describes the eleven parameters selected as the potential drivers of droughts. The used values correspond to the parameters' average in the analysis period (1987 to 2018). The averages were computed using the SWAT model outputs at each subbasin. We used the dominant category at each subbasin for the curve number, the slope, and the soil type (categorical variables).

14. P10L2242-243: I am wondering why the authors use the total number of months for each drought category and not monthly. By doing this then the response variables are only 1 total number of SM drought month and 1 total number of streamflow drought month? I thought the input variables for both explanatory and response are monthly data or at least yearly data.

This comment makes us realize that the introduction and the methodology could be more precise, which is an excellent opportunity to improve the paper. First, please note that this study's objective is to evaluate the relationship between droughts' drivers and the severity of agricultural and hydrological droughts. Generally, severity is divided into different categories (e.g. moderate, severe, extreme), providing a qualitative assessment of the drought state in a region during a given period. Drought categories are crucial for tracking or anticipating drought-related damage and impacts. The MVRT approach is applied to assess the relationship between hydroclimatic characteristics (represented by the simulated parameters at each subbasin) and droughts severity categories (represented by the observed number of months for each drought severity category at each subbasin). Regarding the reviewer's question, the response variables (in this case, the drought severity) were not aggregated in one category because the MVRT allowed us to evaluate the relationship between the hydroclimatic parameters and the severity of the drought while maintaining its individual categories. In our study, the explanatory variables are the hydroclimatic parameters at each subbasin, represented by the average value of each parameter during the analysis period (1987 to 2018). The months observed at each drought severity category (The drought indices give categories) are the response variables.

Therefore, we will update the RM in two sections:

- The introduction, as shown in response to Specific Comment 12.
- The methodology, improving the description of the sets of explanatory and response variables.

Set of explanatory variables

To select the set of explanatory variables, we used the outcomes of previous studies on governing drivers of droughts (Sheffield & Wood, 2011a; Zhang et al., 2022). Table 2 describes the eleven parameters selected as the potential drivers of droughts. The used values correspond to the parameters' average in the analysis period (1987 to 2018). The averages were computed using the SWAT model outputs at each subbasin. We used the dominant category at each subbasin for the curve number, the slope, and the soil type (categorical variables).

Set of response variables

We used the drought analysis outcomes to define the response variables (Table 3). Following the methodology presented in 2.3, we identified the agricultural and hydrological drought events during the analysed period. After identifying the drought events, we counted the months for each drought severity category at each subbasin. The observed months for each one of the three drought categories were used as response variables. The analyses for agricultural and hydrological droughts were conducted separately; thus, two sets of response variables were obtained.

15. P11L251: What are these two groups?

The new sentence will be clearer:

The data partitioning consisted of three steps. First, for each explanatory variable were generated all possible partitions of the sites (subbasins) into two groups.

16. P13L292: Figure 3. I suggest to write the alphabet a, b, c, and so on at the top of the figure. Moreover, please use different colors for observed and simulated for better visibility.

Agreed.

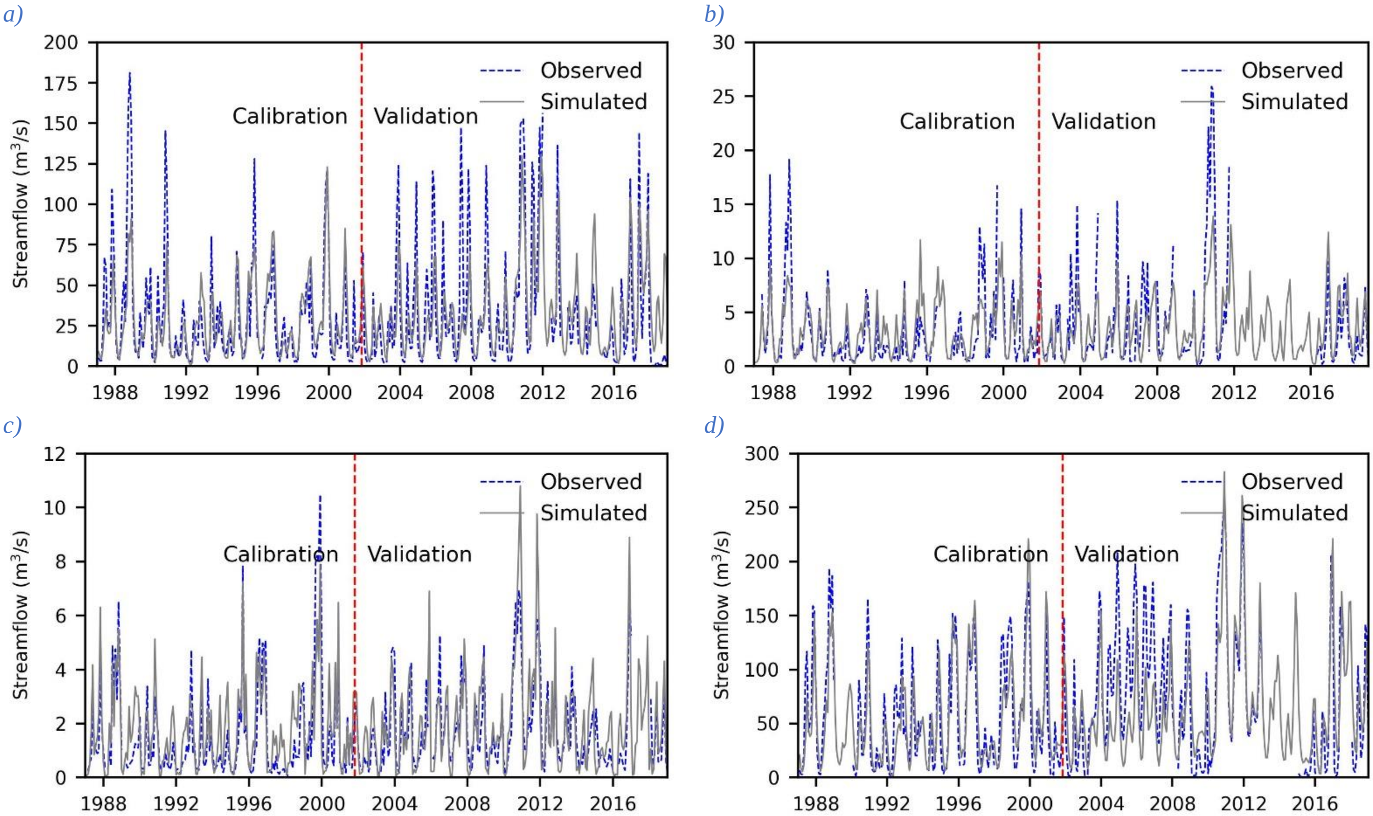

Figure 3 *Monthly calibration and validation for streamflow at: a) Puente Salguero, b) Puente Carretera, c) Cantaclaro and d) Puente Canoas.*

17. P13L296: The authors may re-write the sentence into "……of the parameters, which are the curve number, slope, and soil type at…..

We will edit paragraph in the following way:

Figure 4 a to h presents the average value of the numerical hydroclimatic drivers of droughts at each subbasin. The average was calculated using the hydrological model's outputs during the simulation period (1987 to 2018). Figure 4 i to k presents the categorical drivers: the curve number, slope and soil type. The dominant category at each subbasin is shown in Figure 4 i to k. The dataset of explanatory variables was created from the values presented in Figure 4.

18. P14L300: Figure 4. Please describe the soil types. What is soil type a, b, c, and d? I could not find it everywhere.

We regret this mistake. The soils type definition and the corresponding reference will be included in the Table 2.

Table 1. *Explanatory variables used in MVRT*

Hydroclimatic parameter	***Abbreviation***	***Unit***	***Definition***
Precipitation	*PRECP*	*mm*	*Average precipitation at each subbasin*
Potential evapotranspiration	*PET*	*mm*	*Average potential evapotranspiration at each subbasin*
Evapotranspiration	*ET*	*mm*	*Average actual evapotranspiration at each subbasin*
Percolation	*PERC*	*mm*	*Average percolation past the root zone*
Surface runoff	*SURFQ*	*mm*	*Average surface contribution to the streamflow at each subbasin*
Groundwater	*GRWQ*	*mm*	*Average groundwater contribution to the streamflow at each subbasin*
Water yield	*WYLD*	*mm*	*Average amount of water that leaves the subbasin and contributes to the streamflow at each subbasin*
Sediment yield	*SYLD*	*metric tons/ha*	*Average sediment from the subbasin transported into the reach*
Curve number	*CN*	–	*Dominant curve number at each subbasin*
Slope	*SLP*	–	*Dominant slope at each subbasin*
Hydrologic soil group	*STY*	–	*Dominant hydrologic soil group (A, B, C, and D) at each subbasin. The U.S. Department of Agriculture (USDA) classify soils in four hydrologic groups based on the soil's infiltration characteristics. Properties of each soil type can be found in USDA (2007)*

19. P16L316: PCA. Please see my general comment.

Please see answer to General Comment 2.

20. P17L347-348: Please re-write this sentence: "This leaf contains no instance of severe…" It is unclear what do the authors mean with no instance? Also, write Figure 9b after the sentence.

Instance refers to "months". The paragraph will be updated in the RM to prevent the reader's confusion.

In this leaf, there are no months in the extreme drought category.

21. P18L374: Figure 8. Please mention a, b, c, d, and so on are the number of n in each decision tree. Same for all figures. The figure caption should be self-explanatory and detailed.

In the RM, Figures 7 and 8 captions will indicate that the tree leaves are named from a to l, and the variable n refers to the number of subbasins clustered at each terminal group. In the Figures 9 and 10 captions, we will indicate that the tree leaves are named from a to h, and the variable n refers to the number of subbasins clustered at each terminal group.

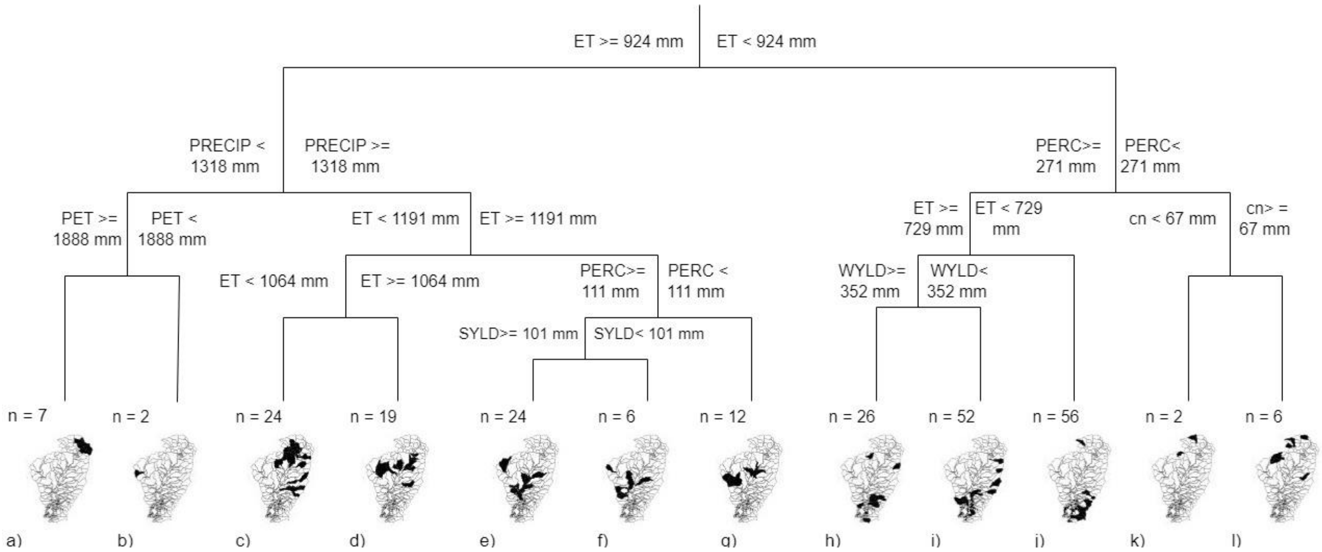

Figure 4 *MVRT of hydroclimatic drivers of agricultural droughts at the Cesar River basin, and spatial distribution of the subbasins clustered at each leaf. Tree leaves are named from a to l and n indicates the number of subbasins clustered at each leaf.*

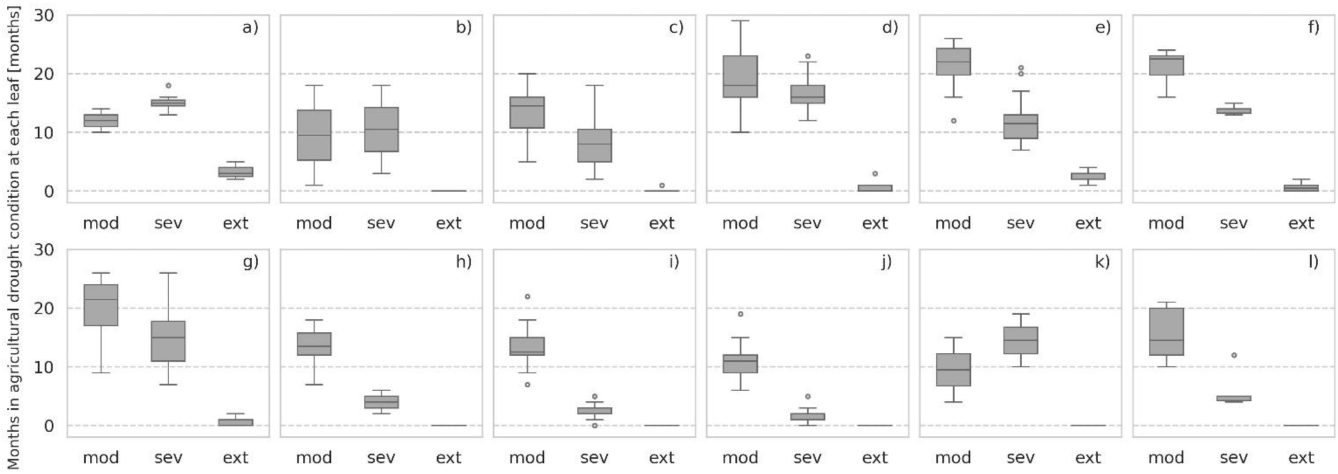

Figure 5 *Number of months in agricultural drought categories (moderate, severe, extreme) at each leaf. Tree leaves are named from a to l.*

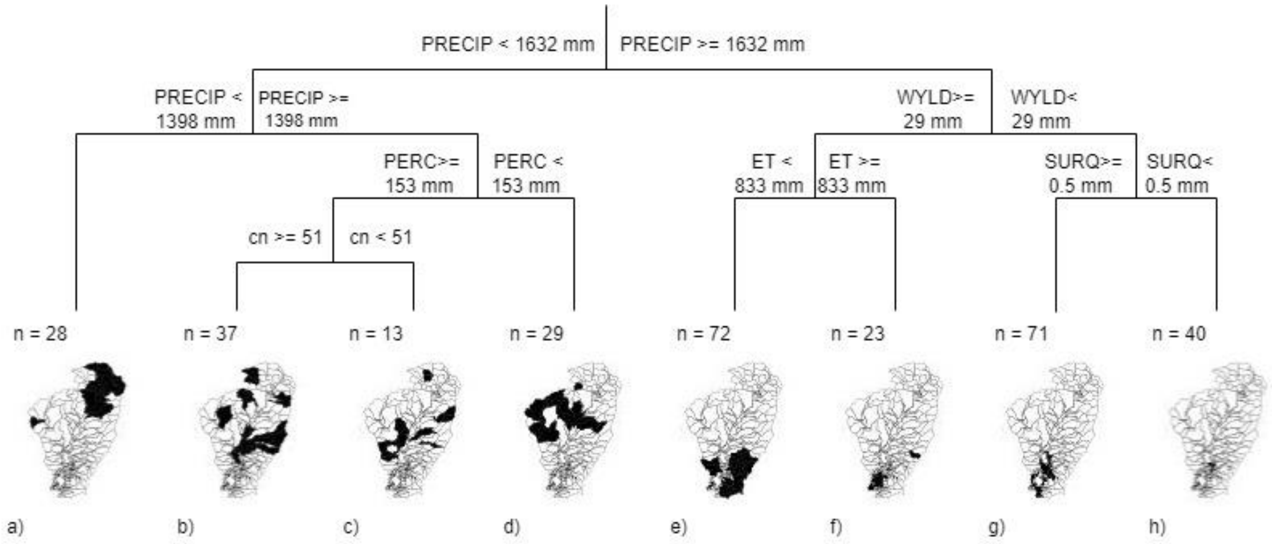

__Figure 6__ MVRT of hydroclimatic drivers of hydrological drought at the Cesar River basin, and spatial distribution of the subbasins clustered at each leaf. Tree leaves are named from a to h and n indicates the number of subbasins clustered at each leaf.

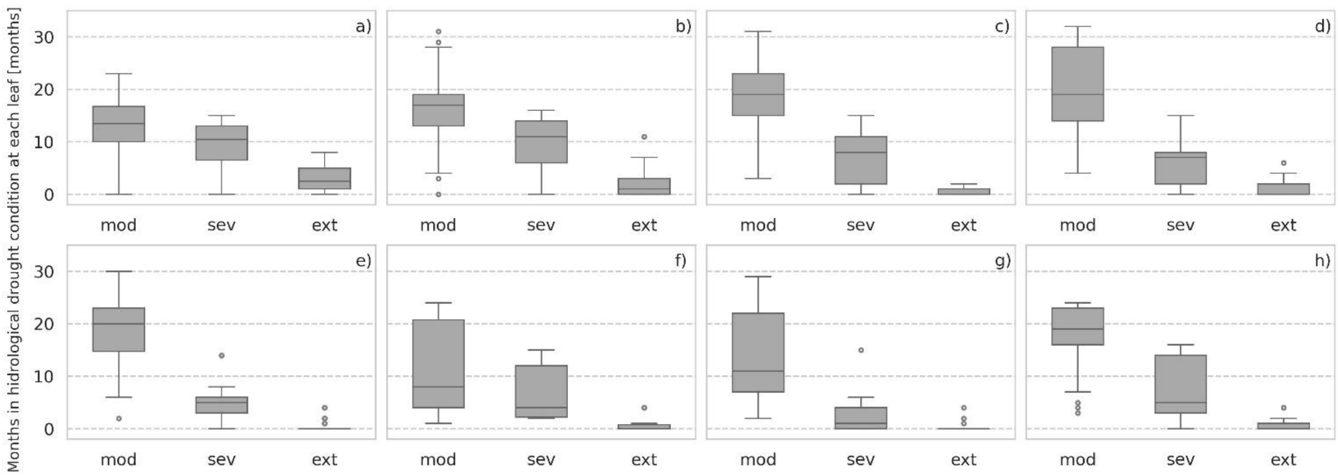

__Figure 7__ Months in agricultural drought categories (moderate, severe, extreme) at each leaf. Tree leaves are named from a to h.

22. P20L411: I see that the MVRT has higher (g) and lower (h) than 0.5 mm.

Indeed, we double-checked the value, and the runoff threshold at the third level of split surface is 0.5 mm. We will improve the explanation in the RM for the tree's leaves, *g* and *h*, as follows:

> *The subbasins in terminal group g experienced the lowest median number of months for all hydrological drought categories (Figure 10g). The selected drought drivers and thresholds indicate that surface runoff contributes to the streamflow, and the amount of water that leaves the subbasins is limited. Both characteristics reduced their exposure to hydrological drought. It can be*

explained by the subbasins' proximity to the marsh (which acted as a natural control), the low slope in the area (which reduced streamflow velocity) and the presence of water bodies (which collected and stored runoff during the rainy season) may have enhanced the water retention capacity in these areas. The observed moderate exposure of these subbasins fits the results of earlier analyses, which found that wetlands exert significant impacts on the alleviation of hydrological drought severity when direct evaporation from the water body does not significantly reduce water storage (Wu et al., 2023). Thus, the present findings indicate that the water storage capacity of the Zapatosa marsh can compensate for the increased evaporation that occurs during drought events, thereby alleviating hydrological drought severity upstream.

The hydrological drought conditions in the subbasins clustered at leaf h were mild, despite water yield values below 29 mm (Figure 10h). Negligible surface runoff values indicated that in leaf h, rainfall is either stored in the soil profile, lost by evapotranspiration or percolates in an area of minimal baseflow contribution to streamflow. This limits the amount of water reaching the streamflow and enhances the severity of hydrological droughts, compared to leaf g.

23. P22L476: Please mention the selected drivers.

Selected drivers will be included in the RM.

Conversely, the MVRT also showed that in terminal groups b, c and d, hydrological drought severity was linked to the inefficient partition of precipitation. Selected drivers (precipitation, percolation and curve number representing land use) are widely recognized as predominant drivers of hydrological droughts (Iglesias et al., 2018; Stoelzle et al., 2014; van Lanen et al., 2013; van Loon, 2015).

24. P23L484: The authors stated "previous studies". Please mention those studies.

We have reformulated the paragraph as follows:

The present selection of the curve number at the third level of split suggests that hydroclimatic parameters and human activities influence hydrological droughts; however, the influence of both drivers is uneven. This is consistent with previous studies concluding that hydroclimatic parameters are more influential (Jehanzaib et al., 2020; Saidi et al., 2018).

25. P24L524: What do the authors mean with eleven out of nine potential drivers? Usually 9 out of 11 and not vice versa.

We really regret this mistake. It is 9 out of 11. However, we have removed this paragraph as discussed in the response to General comment 2.

26. P25L555: Here the authors mention other ML techniques. This is the reason I suggest the authors to describe why the MVRT was selected compared to others.

Agreed. See our comprehensive answer to Specific Comment 12