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Spatial Analysis and Visualization of Triadic Crop Variety Traits in Central America



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Abstract

A rapid increase in population, urbanization, and climate change has put huge pressures on all aspects of society, and in particular agriculture. These pressures lead to a massive demand of agriculture products which is increasingly difficult to meet due to climate change, or more specifically the challenges climate change introduces to farmers. Seeds for Needs is a global initiative from the Bioversity International Research Center which is aiming to help farmers adapt better to climate change through the use of agriculture biodiversity. The method employed by this Seeds for Needs initiative is called 'Tricot' (Triadic Comparisons of Technologies) and consists of a farm-specific comparisons between three randomly-assigned crop varieties (sampled from a large set) which are then also compared to local varieties. Numerous environmental datasets were linked in a spatially explicit way for each observation (e.g. elevation, temperature, and water balance), this was possible because all the farms were geo-located. These datasets were used to produce valuable information about the interactions between crop variety performance and crop growing environment. The method employed here included the Hargreaves method which calculated the necessary evapotranspiration, and ultimately the water balance. The Plackett-Luce statistical model was then used to predict crop varieties performance under different environmental situations using model based recursive partitioning of environmental covariates. As the data for these covariates were spatially explicit and continuous, all model results were able to be visualized by an interactive webpage which allowed farmers to assess appropriate crops for their particular farms.

Keywords: Tricot, environmental covariates, water balance, Hargreaves, Plackett-Luce model, recursive partitioning, interactive webpage

1. Introduction

A rapid increase in population, urbanization, and climate change has put huge pressures on all aspects of society, and in particular agriculture. The population growth leads to a massive demand of agriculture products which is increasingly difficult to meet due to climate change, or more specifically the challenges climate change introduces to farmers (e.g. temperature change, pest influx). As it is exceedingly difficult for agriculture to adapt to these new living environments, these challenges are ultimately threatening food safety and security worldwide (Van Etten et al., 2016). Therefore, in order to attain sustainable food security, satisfy huge food consumption and maximize farmers benefits under worsening conditions, a global initiative, *Seeds for Needs* initiated by *Bioversity International* appeared. This initiative has been carrying out experiments on a worldwide scale, with more than 14 participative countries. Within the context of the *Seeds for Needs* initiative, the purpose of this study is to perform spatial analysis on different crop varieties in the Nicaragua area and visualize their respective traits.

1.1 Background

Bioversity International is one of the research center of the CGIAR (Consultative Group for International Agricultural Research) consortium. It focuses on delivering scientific proof, management operations and policy options to be used worldwide for agricultural biodiversity preservation (Bioversity, 2016). As one of the initiatives from Bioversity international, *Seeds for Needs* works in 14 countries, throughout Africa, Asia, and Central America, to help farmers to better adapt to climate change by utilizing agricultural biodiversity. By introducing farmers to more crop varieties and strengthening their local seed systems, farmers could access more vital information to help them choose different crops or varieties that is more suitable for their conditions. As such, the aim of the *Seeds for Needs* initiative is to provide effective and cost-efficient methods for smallholder farming communities to resist and adapt climate change and to obtain more potential benefits (Zanzanaini, 2016).

The *Seeds for Needs* initiative employs a new approach called *Triadic Comparisons of Technologies* (or *Tricot*) which uses *crowdsourcing* concepts (Van Etten et al., 2016). In 2016, Van Etten *et al.* published a paper which introduced *Tricot* as a novel citizen science methodology. By the time of that paper, this method had been utilized in several counties in trials, including India, Nicaragua, Honduras and Ethiopia. In the trials, each farmer receives three different varieties and is trained on how to implement the experiment in terms of plot layout and management (Van Etten, 2018). After farmers plant the seeds, and as the crop grows, they have to evaluate which of these three perform the best and worst, following a list of requirements that they have developed together with the researchers. For example, farmer 1 might receive varieties A, B and C. Farmer 2 receives varieties A, B and D. Each farmer evaluates variety performance pairwise whether A is better than B or B is worse than C. The pairwise comparisons of the three varieties will also include one local crop variety, making for a total of 6 possible combinations to be evaluated by this method (i.e. A-B, A-C, B-C, A-local, B-local, and C-local). Farmers observe all varieties during the growing season after which they evaluate which 'new' varieties perform better (or worse) than the local variety. The pairwise comparisons within the varieties (three introduced and one local) for each farmer, and is known as a *partial ranking* or *incomplete ranking*.

Keep in mind that there is no standard local variety, meaning that their characteristics vary between farmers and locations, and that the 'new' varieties might not even be particularly suitable for their farms. The farmers report their observations to a local *Tricot* facilitator who is a contact person between the researchers and the participants via digital online platform (Steinke, Van Etten & Zelan, 2017).

The aforementioned *crowdsourcing* component of *Tricot* distributes large tasks into 'micro tasks', after which it retrieves and integrates the results in order to fulfil the original large task (Van Etten et al., 2016). In the context of the Seeds for Needs project, this approach also incorporates a digital platform (*ClimMob*) which enables citizen science initiatives (*Lichten et al.*, 2018). This platform designed by Bioversity International holds tools to assign, collect, and analyze the (large) crop data. This should not only make it easier for the researchers to prepare the packages of three different varieties that will go to the farmers, but also enables very rapid analysis of the results (Van Etten et al., 2016).

Many studies have demonstrated that participative approaches, where farmers are encouraged to share their knowledge and resources in exchange for information, to crop improvement is more effective than conventional approaches as it is mutually beneficial (Ashby et al., 2009). As they now effectively take on the role as citizen scientists, farmers plays an important role in every step in the *Seeds for Needs* project (Van Etten et al., 2016):

- Each farmer 'blindly' tests three varieties from a pool of up to 20 varieties;
- Each farmer plants these varieties amongst their local variety, treating them equally;
- During the entire crop growing period, each farmer observes and rates all (3 + 1) varieties multiple times based on several aspects. These include: vegetative characteristics, yield, and consumption-related traits (ranked relatively);
- Farmers report their observations via an online platform (*ClimMob*) on their mobile device;
- Researchers examine and analyze these observations using the aforementioned statistical models, and give the resulting information back to the farmers as feedback.

In comparison to other current methods, *Tricot* has some novel features. As stated by Van Etten (2016), 1) variety trials are blind which means that farmers are not aware of the exact varieties they are planting. This will eliminate any cognitive bias and potentially increase the farmer's motivation to finish the experiment. 2) Data is collected by farmer themselves through a digital platform. Digital data collection can help reduce reporting mistakes and accelerate the analysis process. 3) *Tricot* also utilizes complementary environmental data which, if spatially explicit, can generate valuable information about interactions between crop variety performance and their environments (Van Etten et al., 2016). Since all the data was geo-located, numerous environmental using a 'special' statistic model for data ranking. There are two statistical models that can be used to analyze farmer's partial ranking data. One is the *Bradley-Terry model* (Bradley and Terry, 1952), another one is the *Plackett-Luce model* (Plackett, 1975, Luce, 1959). The reason why these statistical models are special is because neither of them have been used frequently in agriculture studies (Van Etten et al., 2016). They can both be used to assess the probabilities of preferences for a certain variety in a triadic variety trial, using ranked comparisons (Van Tilborg, 2018).

1.1.1 Environmental Covariates

It is important to remember that environment plays an important role in crop performance, as stated by Miflin (2000). They also stated the following: "Crops are not creatures that stay in one place and are therefore at the mercy of the environment in which they find themselves. They have evolved complex genetic systems which enable them to adapt to the changes in the environment in order to complete their life cycle". Environment changes according to geography and seasonality, therefore a given variety will perform differently from place to place and season to season (Miflin, 2000). Farmers are concerned with the yield of the crop variety that grows in their fields. By quantifying the environmental situation for farmers, it can assist them to select the most suitable crop variety under their own crop planting environments.

As mentioned, one of the novel aspects of *Tricot* is that the trial data can be analyzed by combining complementary environmental data. Because the data is digitally collected, it is possible to locate these observations and link them with crop growing environment data from various sources, for example, soil type, elevation, humidity, wind speed, daily temperature and so on (Van Etten et al., 2016). By combining this information into appropriate statistical models, the *Tricot* approach could produce essential information about the interaction of crop performance and crop growth environment. This study will implement several essential environmental conditions into an appropriate statistical model as *environmental covariates* (in chapter 2.1 & 2.2). The results we get from said model are the different performances of varieties under certain environmental conditions.

In chapter 1.1.2, we will first address which statistical model will be used in this study and why, after which we will explain how to combine environmental covariates into this model.

1.1.2 Plackett-Luce model and Plackett-Luce tree

As indicated at the end of chapter 1.1, there are two statistical models that can be used to analyze overall crop performance for partial crop rankings, the Bradley-Terry model (Bradley and Terry, 1952) and the Plackett-Luce model (Plackett, 1975, Luce, 1959). They are two of several models developed for data ranking (Van Etten, 2018). The Bradley-Terry model was used for ranking overall crop performance in the first several years of the *Tricot* experiment. However, since the Plackett-Luce model is an extension of the Bradley-Terry model, which was recently made available in R, the *Tricot* method started using this Plackett-Luce model for the analysis of overall crop performance instead of the Bradley-Terry model. The reason for this replacement is that the Plackett-Luce model can involve more than two elements in one comparison (Turner et al., 2018). That is to say, when the three varieties are A, B and C, the Plackett-Luce model can rank all elements as A>B>C instead of A>B, B>C and A>C as is the case for the Bradley-Terry model.

In previous studies done by Fadda C, Van Etten (2018) and Van Tilborg (2018), the Plackett-Luce model was eventually used in both cases as it is able to deal with more observations in one comparison as compared to the Bradley-Terry model (Van Tilborg, 2018). As an extension of the Bradley-Terry model (Turner et al., 2018), the difference between the Plackett-Luce model and the Bradley-Terry model is that the latter uses a contest between two objects which gives a winner and loser, whilst the former can compare more than two elements in one comparison (Van Tilborg, 2018). In case of pairwise

comparisons, the Plackett-Luce model reduces to the Bradley-Terry model (Pfeiffer, 2012). The output of the Plackett-Luce model is the estimated worth parameter for each item that appears in the rankings. The worth parameters can represent the probability for each variety to be ranked as the best if it is constrained to sum to one (Turner, 2018, Van Tilborg, 2018). In our study, each observation that was collected from farmers included the relative ranking of three varieties and their individual comparison to the local variety. The ranking from each farmer can also be called partial ranking (Cook, Golany et al. 2007).

Numerous software implementations of the Plackett-Luce model exist for a variety of programming languages. Very recently, the *Plackett-Luce package* was made available for R (Turner et al., 2018). This package also provides a method based on the psychotree package, called the Plackett-Luce tree, which can partition the ranking by covariates values like random forests (optimal decisions) (Turner, 2018, Benini, 2019). The covariate values can be the attributes of the 'judge' that make the ranking, or the conditions under which the ranking is made (R documentation, 2018). Plackett-Luce tree is a recursive partitioning based on Plackett-Luce models. The partitioning is based on covariates. In this study, the environmental covariates mentioned in chapter 1.1.1 were used as the 'judge' which can assess the stability of the data with respect to each covariate. Based on these covariates, a Plackett-Luce model can automatically determine the ranking of subgroups using model-based partitioning.

1.2 Review previous studies

A number of studies related to the *Tricot* experiment have been completed (Van Etten et al., 2016, Steinke et al., 2017, Turner et al., 2018, Van Tilborg, 2018). In 2016, Van Etten et al. introduced the *Tricot* method for the first time. They outlined the origin and background of the *Tricot* method, stated the development of this method in detail and delineated the implementation of each step. They also demonstrated what statistical model can be used and which data was considered for analysis. The research of Steinke (2017) emphasized the advantages of using crowdsourcing concepts in the *Tricot* method. This combination not only produces research products in a robust and cost-efficient way, it also reduces requirements for logistics, farmer training, field visits and physical assets per participant. In the study by Turner et al. (2018), the Plackett-Luce method was implemented in R for the analysis of ranking data. This software package (Plackett-Luce) offers various methods for the handling of partial ranking data, disconnected items networks, and model visualization by means of the Plackett-Luce tree implementation.

In the study by Van Tilborg (2018), the goal was to enhance statistical analysis of the *Tricot* experiment in Nicaragua. She combined the Plackett-Luce model with environmental data to highlight the spatial variation amongst the observations and predicted the crop variety ranking performance under certain environmental conditions. In her analysis, she selected six environmental covariates which are altitude, slope, season, soil types, maximum night-temperature (Tnmax) and water balance. The current thesis is a follow-up study to Van Tilborg which continues investigating *'Which crop variety performs best under given environmental conditions?*' as proposed by Van Tilborg herself. Based on her recommendations and peer review, there are some other points of concern given this respective methodology that we will be taking a closer look at in the following paragraphs.

Water balance – Hargreaves VS Blaney-Criddle

Van Tilborg (2018) concluded that the water balance is a significant covariate for crop variety ranking. Water balance showed strong influence on the crop variety ranking which she concluded using a Plackett-Luce tree model. She also suggested that the Blaney-Criddle method she used to calculate evapotranspiration for the water balance could be replaced by the Hargreaves (Hargreaves & Samani, 1985) method to potentially provide more accurate results (Van Tilborg, 2018). In contrast to Van Tilborg (2018), researchers at Bioversity International found that the water balance did not show any apparent influence on crop variety ranking. Therefore, in this study, the 'recommended' water balance method by using Hargreaves evapotranspiration equation is used to calculate water balance in order to inspect whether the water balance influences crop performance.

Water-stress indices

Van Tilborg (2018) used daily water balance indices per growth stage (4 in total) and used them as environmental indicators, partly because it is practically infeasible to input daily water balance into the Plackett-Luce model. However, there are a multitude of ways you can express water balance (or derivatives thereof) that contain different facets of the crop water status (Van Etten et al., 2018). Examples of derivatives are: consecutive drought days in every crop growing stage, consecutive precipitation days and so on. In this study, we create two water-stress indices, consecutive drought days and consecutive water deficit days, to assess whether these water-stress indices (creates based on water balance) have impact on crop performance ranking.

Geo-graphic visualization

Van Tilborg (2018) utilized fixed pie charts to visualize the ranking results for various environmental conditions, which are determined by their location. These charts give considerable insight to what environmental covariates are important for what crop, but they are not spatially explicit. You could argue that deeper insights of the results can be achieved by a more geo-spatial depiction of the results, as most data on covariates is both spatially explicit and continuous.

Kraak (2004) concluded that an interactive and dynamic map will guide and assist the user in solving geospatial problems. Map can be functioned as an interface to the wealth of data though the Web (Kraak, 2004). In this study, an interactive web application was made and will be shown in chapter 2.1 & 3.4.

1.3 Research questions

As mentioned, we will focus on data from Nicaragua - one of the pilot countries from the *Seeds for Needs* initiative. The selected study object in Nicaragua is the common bean. Since it is an important crop in Nicaragua, it is more likely to be accepted by local farmers (Van Etten et al., 2016). The dataset collected from the Nicaragua area contains 888 observations from an equal number of farms. Each observation contains a relative ranking of the varieties (three introduced and one local) for each farmer. Environmental conditions vary across the regions where the experiments were conducted, and ultimately affect the performance and ranking of all varieties.

The goal of the *Tricot* experiment was thus to not only get partial rankings from each farmer, but to understand complete rankings under given environmental conditions. If quantified, farmers can now use this information to select crop varieties that are expected to thrive on their particular farms.

Therefore, we want to know that "Under a given certain environmental conditions, what crop varieties **perform best**"? This is the main research question of this study which is the same with Van Tilborg (2018). However, we will take a closer look at the remaining issues in her study and the suggestions from peer reviews. Here are the four research questions we will answer in this follow up study.

- 1. What is the impact of changing the evapotranspiration model on the water balance
- 2. Which environmental covariates are meaningful to crop variety scoring?
- 3. To what extent do crop variety scores under identified environmental conditions correspond with reported variety traits?
- 4. In what way can the analysis results be interactively visualized?

The overall structure of this study takes the form of 5 chapters, including this introduction chapter which mainly explained the background of this study. Chapter 2 is concerned with the methodology used for this study which has two sections, data statement and data analysis. Throughout the data analysis section, some necessary theory underpinning the research will also be laid out. The third chapter presents the findings for each research question. The fourth chapter includes a discussion of the implication of the findings. Finally, the last chapter gives a brief summary of this study and its recommendation for future research into this area.

2. Methodology

This chapter comprises two sections. Section 2.1 briefly describes the datasets and the study object (i.e. common bean) in the study area. Next, section 2.2 illustrates methods for water balance calculation, model application, results validation and outcome visualization. This section is separated into 4 subsections following the order of research questions.

2.1 Study area and data

The data for this study was provided by the *Seeds for Needs* initiative as part of the Tricot experiment and depicted a subset of western Nicaragua, located between -86.07° and -85.19°W and the parallels 12.66° and 13.47°N, as shown in Figure 1(Van Etten et al., 2018). In this experiment, there were 888 smallholder farmers who cooperated as citizen science volunteers for the testing of varieties (depicted as blue dots in *Figure 1*). They tested 10 common bean varieties during three growing seasons (*Table 1*) from September 2015 until January 2017. Each farmer received three different randomly-assigned varieties. After planted them for the duration of the whole growing season, the farmers compared those received crop varieties with their own local variety. They assessed the performance of these varieties on yield, overall performance and relative performance, against their local crop variety (Bioversity, 2016). *Appendix 1* shows all the data sources involved in this study. Since elevation is the only continuous spatial data in this study, it was used as a background map as shown in *Figure 1*.

Growing Season			Time Period		
Primera			End of May to beginning of August		
	Prostrera			nd of September to end	of December
Apante			Middle of December to end of March		
10 common bean varieties					
ALS 0532-6	INTA Centro Sur	INTA Ma	atagalpa	INTA Rojo	PM2 Don Rey SJC
BRT 103-182	INTA Ferroso	INTA F	Precoz	INTA Sequia,	730-79

Table 1 Growing seasons in Nicaragua and 10 common bean varieties

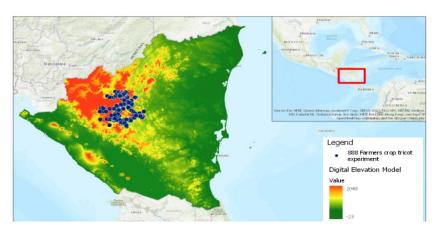


Figure 1 Study Area: Locations of Tricot experiment (blue dots) in Nicaragua with digital elevation model (DEM) background

2.2 Data analysis

This section lists all the procedures in the order of research questions. First of all, the water balance was calculated using the Hargreaves evapotranspiration formula (Hargreaves & Samani, 1985). Next, several indices were created based on water balance from step 1. These indices were calculated as part of the environmental covariates in the Plackett-Luce model. Then, after inputting all the environmental covariates into the Plackett-Luce model, section 2.2.3 mainly validates its results by comparing the predicted traits with real world traits. Finally, section 2.2.4 illustrates the design of an interactive web application for the visualization of results. The workflow is shown in *Figure 2*.

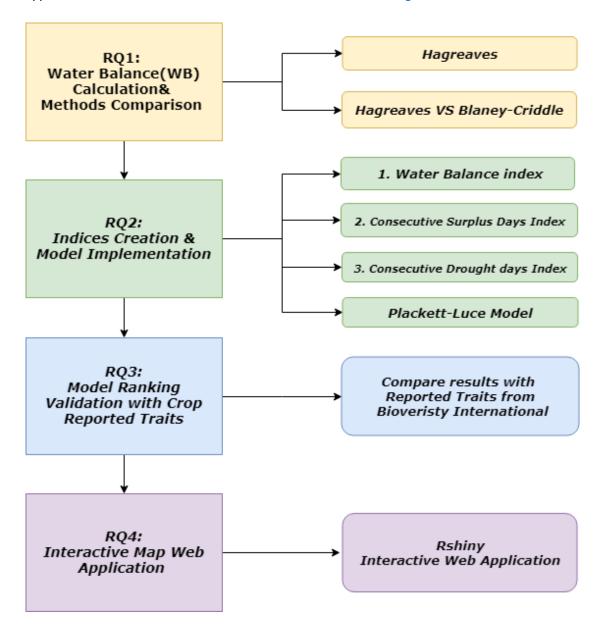
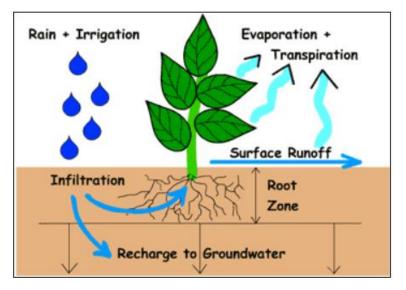


Figure 2 Flowchart of the methodology

2.2.1 Water balance

As an essential input for crops, water relates to plant growth, development and production. Both excess of water and water shortage could cause severe impediment to a successful harvest. In order to understand how water distributes in plants, Ritche (1981) simulated a soil water balance model by means of *Equation 1*:

Equation 1



Soil Water Balance = Water In - (Water Out + Change)

Figure 3 Soil Water Balance (source: Nullet 2016)

As we can see in *Figure 3*, *Water In* implies all water added on to the surface. It includes precipitation and artificial watering (i.e. irrigation). *Water Out* includes evaporation, transpiration, surface runoff(R), and recharge to the groundwater (RG). *Change* represents continuously changing of soil moisture storage in the root zone (Nullet, 2016). Evaporation and transpiration in this study were assumed as potential evaporation and potential transpiration. In summary, *Equation 1* can be translated by *Equation 2* (Nullet, 2016):

Equation 2

Soil Water Balance = (Rainfall + IR) - (Evaporition + Transpiration + R + RG + SM)

However, due to a lack of data, the proposed methodology in this study suffered from some limitations in the calculation of soil water balance. In this research, all precipitation was assumed to be effective rainfall, it means all water was simply used by crop growth. Surface runoff, recharged to the ground water and soil moisture storage were all ignored in this study. Also to be noted, no irrigation was taken into account because varieties tests in the experiment are rainfed (Van Tilborg, 2018). Therefore, in this study all the *Water In* is considered to be precipitation, and all the *Water Out* is considered to be evaporation and transpiration. As a result, the "simplified" soil water balance equation can be expressed by *Equation 3*:

Equation 3

Soil Water Balance = Rainfall – (Evaporition + Transpiration)

Evaporation is a process where water escapes as vapour from open water sources such as soil surface, leaves surface and plant stem (Brouwer & Heibloem, 1986). When water escapes to the atmosphere as vapour through leaves and stem, this process is called *transpiration*. Crop requires water to finish evaporation and transpiration. These two processes are usually also called *evapotranspiration* (*ETc*) (Brouwer & Heibloem, 1986).

Crop water requirements relies on many factors such as crop type and growth stage. The same crop type grown in a different climatic environment will have different water needs. A standard or reference crop was introduced as a tool to determine water needs of crops (Brouwer & Heibloem, 1986). The evapotranspiration of grass was chosen as **reference evapotranspiration** (*ETo*). For the calculation of evapotranspiration (*ETc*) for different crops, it is simply a multiplication of the **crop factor** (*Kc*, i.e. the relationship between reference grass crop and the actual crop) with the reference evapotranspiration (*ETo*). This multiplication is shown in *Equation 4*:

Equation 4

$$ETc = ETo * Kc$$

The unit of *ETo* and *ETc* is usually expressed in millimetres per period of time, for example, mm/day, mm/month, or mm/season (Brouwer & Heibloem, 1986). In this study, water balance was calculated on daily bases. *Kc* varies per crop type, crop growing stage and climate. In order to find the crop factor of a certain crop, it is necessary to identify the total length of growing season and length of each growing stage. This information for the common bean (dry), as documented by Brouwer (1986), is shown in *Table 2*.

Growth stage and	Initial stage	Crop development	Mid-season stage	Late-season stage
period(110 days)	(20 days)	stage (30 days)	(40 days)	(20 days)
Crop factor	0.35	0.70	1.10	0.30

 Table 2 Common Bean Growing Period and Crop Factor of Each Stage

The total growth length of the common bean is between 90-110 days (Brouwer & Heibloem, 1986). This study used 110 days for all calculations which is in line with the previous study done by Van Tilborg (2018).

Before we can answer research question 1, it is necessary to compute the water balance. However, according to *Equation 3*, *ETc* should be calculated first. Since there are many methods to obtain *ETo*, it also means that *ETc* could be acquired in multiple ways. Shahidian (2012) offers an in-depth evaluation of these equations, for example, Thornthwaite (1948), Blaney-Criddle (1950), Hargreaves and Samani (1982), Priestly-Taylor (1972), Makkink (1957), Penman (1948), modified Penman (Doorenbos and Pruitt, 1977) and FAO PM (Allen et al., 1998). He claimed that equations which are only based on a single or reduced number of weather parameters for computing *ETo* are more suitable than the Penman-Monteith method (i.e. a global standard for estimating *ETo*). They are more easily used in practice because of their lower parameter requirements, cost effectiveness and relative accuracy.

In the previous study performed by Van Tilborg (2018), she used the Blaney-Criddle method to calculate *ETo*. However, based on literature study and Van Tilborg's own recommendation, this research decided to use the *Hargreaves* method to calculate *ETo* and apply it in the water balance. The difference and relation between these two methods (Hargreaves and Blaney-Criddle) will be illustrated later in chapter 3.1.

The equation for **Hargreaves** (ETo) is shown in *Equation 5* (Hargreaves & Samani, 1985). It is a simple method with low parameter requirements and relatively high accuracy. Only daily maximum temperature (*maxTemp*) and minimum temperature (*minTemp*) values are required (Hargreaves & Allen, 2003).

Equation 5

$$ET_0 = 0.0023 R_a (TC + 17.8) \sqrt{TR}$$

Where

- TR is the difference of maximum daily temperature (*maxTemp*) and minimum daily temperature (*minTemp*) (°C/day);
- Ra is extra-terrestrial radiation (mm/day);
- **TC** is average daily temperature (°C/day).

Data sources for daily temperature data and precipitation data can be seen in Appendix 1. RStudio, an integrated development environment for the R programming language, supports a package called 'sirad'. The function called *extrat* can calculate *extraterrestrial solar radiation* (Ra) (Bojanowski, 2013). Solar radiation incident outside the earth's atmosphere is called extraterrestrial radiation. The *extrat* function only needs the day number of the year (Julian day) and the latitude in radians as input. The unit of extraterrestrial solar radiation (Ra) in *extrat* function in R is MJ/m^2 . It needs to be transformed from MJ/m^2 to mm ($MJ/m^2 = 0.408$ mm) (Ramírez et al., 2011). The function returns three values. In this study, only the daily sum of extra-terrestrial radiation value was considered. *ETo* was calculated for each observation (in total 888 observations) per day for the entire growing season (110 days).

After calculating the *ETo*, the next step is to compute daily *evapotranspiration (ETc)* in *Equation 4*. The difference between daily precipitation and evapotranspiration is the daily water balance which was depicted in *Equation 3*. If a water balance value is positive, it means that the surface has gained a water surplus, or in other words, there is more precipitation than crop water requirement. If this is not the case, it means that the surface is suffering water deficit (Mason, 2015). This water balance (both positive and negative) inform us of the crop water status. In order to identify the differences between the Hargreaves and Blaney-Criddle methods, water balance values for all the observations for the entire growing season were used to quantify the correlation (if any) between these two methods. This result is presented in chapter 3.1.

2.2.2 Index Creation and Model Implementation

In this study, we generated three indices from the water balance as demonstrated in *Table 3*. Each index was also calculated per crop growing stage. Therefore, there are 5 sub-indices under each index.

Index	1. Accumulated	2. Consecutive days with	3. Consecutive days with
	Water Balance	water deficit (Drought	water surplus (Surplus
		days index)	days index)
phase		 Initial stage 	
		Develop stage	
	Mid-season stage		
		Late season stage	ý
		Total growth sease	on

Table 3 Indices computed from water balance

These indices were created based on a daily water balance. As introduced in chapter 2.1, the length of entire growing season for the common bean (dry) is 110 days. The entire growing season consists of four stages. For index 1, we calculated the summation of daily water balance for each growth stage and the total growth season. Each sub-index as an indicator could indicate water status at every growth stage. The second and third indices were also constructed from daily water balance. For index 2, the number of consecutive water deficit days in each stage were counted. It basically computed the number of consecutive days with negative water balance in each stage and over the entire growing season. More than three days of continued positive or negative water balance values were seen as consecutive drought or surplus days. Index 3 used the same method with index 2, the only difference here is that it counted the number of positive water balance value at each stage. Thus, these three indices (actually 15 sub-indices because they are calculated for four crop phases) were used as input for the Plackett-Luce model together with other environmental covariates. Later in this report, these indices will be called *water balance index, drought days index,* and *surplus days index*.

After the water balance-based indices were created, the Plackett-Luce model was initiated. As highlighted in Chapter 1.3, the Plackett-Luce model has several advantages over the other ranking model. In Rstudio, a package called "*PlackettLuce*" can handle full or partial ranking. The main function in the package is the *PlackettLuce* function which requires a standard data form to fit the model. This package also provides the function "pltree" for the fitting of a *Plackett-Luce tree*. These trees partition the rankings by the conditions under which the rankings were made. There are functions to prepare ranking data in order to a fit Plackett-Luce model and Plackett-Luce trees. In our study, the 888 observations in our dataset were first transformed into specific forms that Plackett-Luce models can interpret as shown in the code provided by Turner (Turner et al., 2018). Then a *pltree* function was utilized for the fitting of Plackett-Luce trees. A Plackett-Luce tree is constructed via the following steps(Turner et al., 2018):

- 1. Fit a Plackett-Luce model to the full data.
- 2. Assess the stability of the worth parameters with respect to each available covariate.
- 3. If there is significant instability, split the full data by the covariate with the strongest instability and use the cut-point with the highest improvement in model fit.
- 4. Repeat steps 1-3 until there are no more significant instabilities, or a split produces a sub-group below a given size threshold

As stated by Brouwer (1986): 'Crop growth depends not only on rainfall, but also on other climatic factors (most notably sunshine and temperature) and non-climatic factors such as the availability of suitable soils.' In our study, water availability was represented by water-stress indices since water-stress stands for differences between rainfall and crop evapotranspiration. Night maximum temperature was chosen as an environmental indicator mainly because beans are sensitive to night temperatures, especially those higher than 18 °C (CIAT, 2015). Elevation not only affects temperature but also humidity, solar radiation and wind speed. It can play an important role in the health and growth of plants. Humidity, wind speed, soil type and many other environmental variables also influence crop performance. However, due to the limited availability of data, the only covariates used for partitioning were elevation, Tnmax (night maximum temperature), water-stress index (water balance index, drought day index, surplus day index). Each of the last three indices that were mentioned contain 5 sub-indices as shown in *Table 3.* Therefore, 17 covariates in total were eventually inputted to the Plackett-Luce model. In chapter 3, we will display the results of the associative Plackett-Luce trees.

2.2.3 Interpretation of model results

To investigate to what extent the traits predicted by the PL model correspond to real-world crop traits, we compared the predicted traits with the information provided by Bioversity International (*Table 4*).

Variety	Maturity Abiotic Tolerance
ALS 0532-6	Tolerant to high temperature
BRT 103-182	Tolerant to high temperature
INTA Centro Sur	Tolerant to high temperature and drought
INTA Ferroso	Tolerant to drought
INTA Fuerte Sequía	Tolerant to high temperature and drought
INTA Matagalpa	Susceptible to high temperatures
INTA Precoz	Tolerant to high temperature and drought
INTA Rojo	Tolerant to high temperature and drought
PM2 Don Rey	Tolerant to drought
SJC 730-79	Tolerant to high temperature and drought
	•

Table 4 Crop characteristic (source: Bioversity International, 2018)

As shown in *Table 1* and *Table 4*, most of the varieties are tolerant to either high temperature or drought, or both. However, only the variety INTA Matagalpa is susceptible to high temperature. It means INTA Matagalpa will not perform well when temperature is relatively high. It is worth exploring the relation of model output with real-world trait varieties. For example, to check whether varieties with a high temperature tolerance actually show better performance than the variety which is vulnerable to high temperature.

2.2.4 Geographic Visualization

Interactive visualization could provide a manner of exploring high-dimensional data that links features to the underlying details, allowing for different views of the data. Interactive graphs offer great opportunities to make connections across diverse data types (Broman, 2015). In this study, the performance of 888 geo-related observations in complex environments are visualized by means of an interactive map. We use the Shiny application from Rstudio, which is able to create online interactive maps. As Potter (2016) suggests "There are many advantages in using Shiny as a visualization tool. They can be interactive, dynamic, user-friendly, visually appealing and publicly accessible via the web". Shiny supports replotting of tables and figures automatically without having to refresh the web page (Jahanshiri & Shariff, 2014). When users change their text inputs or check box selection, the results will immediately be reflected in the form of figures, texts or tables. These features enable both rapid exploration of model results and true real-time decision making.

Each Shiny app consists of two components: a user-interface script (ui.R) and a server script (server.R). Users operate using the user-interface. These operations as input are set to trigger an event which are sent and handled by the server. After this execution, the results are presented to the user via the user interface (*Figure 4*). In this study, a web application is designed where users can select their environmental covariates of interest, such as elevation and maximum night temperature. According to these selections, a pltree model is executed on the server side. The user interface allows users to visualize the observations on map along with ranking information. The Plackett-Luce tree is also displayed, allowing for users to gain a deeper insight in the model.

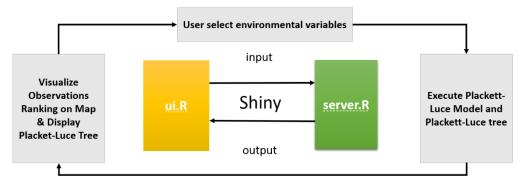


Figure 4 Shiny Web Application Flowchart

In this thesis work, the main user interface is composed of five blocks. The framework is shown in *Figure 5*; the first section is a ranking information map for crop varieties that is integrated with geospatial data. This geospatial data can be selected in section 2. Since the Plackett-Luce tree is able to partition the rankings under certain environmental conditions, we provide a function where users can select these environmental covariates and apply them real-time to a server-side Plackett-Luce model. For example: elevation, water stress indices, and maximum night temperature. All the trials were conducted in different environments, which play essential roles in crop performance.

Section 3 shows the resulting Plackett-Luce tree, while the crop ranking table is shown in section 4. In addition, this web application also displays the following data: information of the Bioversity International research center, the instruction of the *Tricot* experiment, the results from this study, reference literatures, and the data sources (section 5). These components along with the spatial analysis, can provide users with a full picture of the *Tircot* experiment.

Title			
Menu Item • Tricot visualizer • Background • Data exploration • Reference • Data source	Map Ranking information with geo- spatial data		Plackett-Luce tree
		Section 1	Section
	Covariates selection:		Ranking information
	 Option 1 Option 2 Option 3 Option 4 		
Section 5		Section 2	Section

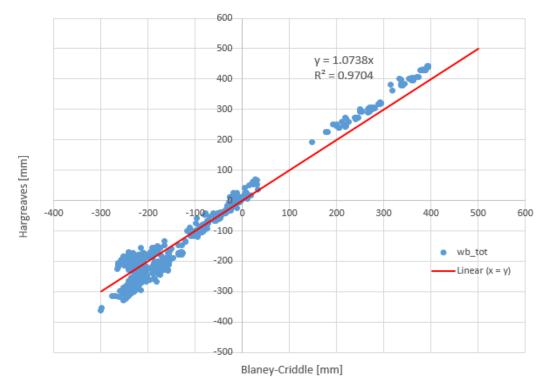
Figure 5 Web application framework

3. Results

The following sections show and describe the results in the order of the research questions.

3.1 Differences between Hargreaves and Blaney-Criddle

In order to find out how Hargreaves and Blaney-Criddle methods could impact water balance results, both methods were applied. In this section, water balances according to these two methods were calculated for the entire crop growing season. In *Figure 6*, the blue dots represent water balance values at entire growing period. The red line represents x = y trendline where Hargreaves water balance value equals to the one from Blaney- Criddle method. The X and Y axis are the Blaney-Criddle and Hagreaves water balance values, respectively. The points are mainly located close to the X = Y trendline. This means that Blaney-Criddle estimates were similar to the water balance value obtained with the Hargreaves method during the entire growth perios. The correlation coefficient (r^2) was 0.9704. It measured the strength of association between the Hargreaves water balance and the Blaney-Criddle water balance.



water balance summation for entire growing period

Figure 6 Water balance comparison at entire growing period for Hargreaves and Blaney-Criddle method

3.2 Environmental indicators used in the Plackett-Luce model

There are several essential factors which influence crop performance. They were used as environmental covariates for the Plackett-Luce model and recursive partitioning. The rankings can be read from line graph in Plackett-Luce tree, such as *Figure 7*. Covariates in this study were divided in to three categories: water-stress indices, Tnmax and elevation. *Table 5* below shows all the covariates and their corresponding Plackett-Luce tree result. *Figures 11* to *18*, illustrate results for each situation. As can be seen, *Figure 11* corresponds with most of water-stress indices which produced no splits in the Plackett-Luce tree model. In other words, when any of environment covariates (covariates 1 to 12) varies, crop variety performance will not be influenced in this case. However, three out of fifteen water-stress indices (covariates 13, 14, 15) did produce splits in Plackett-Luce model. When environmental covariates include elevation or Tnmax, it also splits Plackett-Luce model under different environmental situations.

Environmental covariates	ID	Covariates	Figure number
	1.	Water balance index - initial stage	
	2.	Water balance index - development stage	
	3.	Water balance index - mid season stage	
	4.	Drought days index - initial stage	
	5.	Drought days index - develop stage	
	6.	Drought days index – mid season stage	
	7.	Drought days index – late season stage	Figure 7
Water- stress indices	8.	Drought days index – entire growth season	
	9.	Surplus days index - initial stage	
	10.	Surplus days index - develop stage	
	11.	Surplus days index – late season stage	
	12.	Surplus days index – entire growth season	
	13.	Water balance index – late season stage	Figure 8
	14.	Water balance - entire growth season	Figure 9
	15.	Surplus days index – mid season stage	Figure 10
	16.	Water balance index & drought days index &	Figure 11
		surplus days index	
	17.	Maximum night temperature (TNmax)	
Tomov	18.	Maximum night temperature & Water balance	Figure 12
Tnmax		index & drought days index & surplus days index	
	19.	Elevation	Figure 13
Elevation	20.	Elevation & Water balance index & drought days	
		index & surplus days index	Figure 14
	21.	Elevation & Maximum night temperature	
	22.	Input all covariates	

Table 5 Model covariates used in the Plackett-Luce tree analysis with corresponding figure numbers result

Note: In following Plackett-Luce tree figures, nodes in every line graph from left to right represent 11 varieties (Figure 7 to 14). The order will not change with situations.

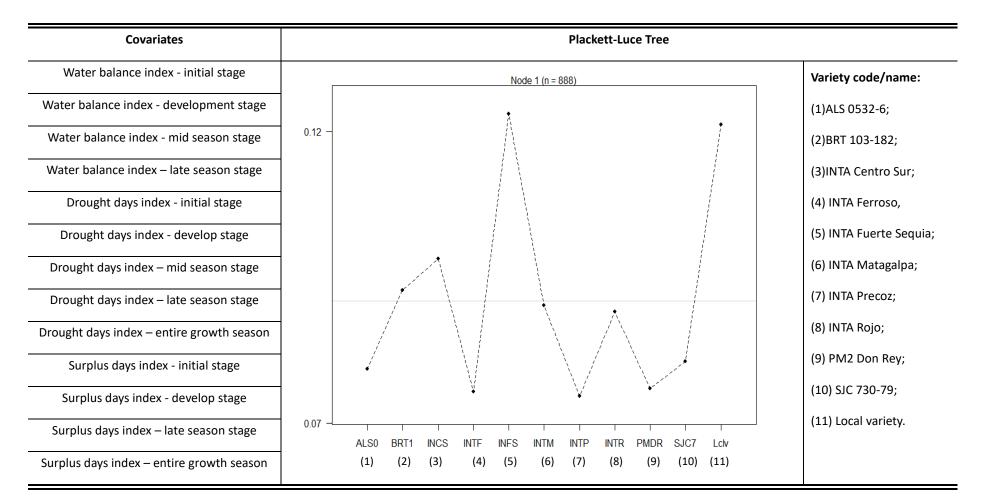


Figure 7 Variety scores without splits

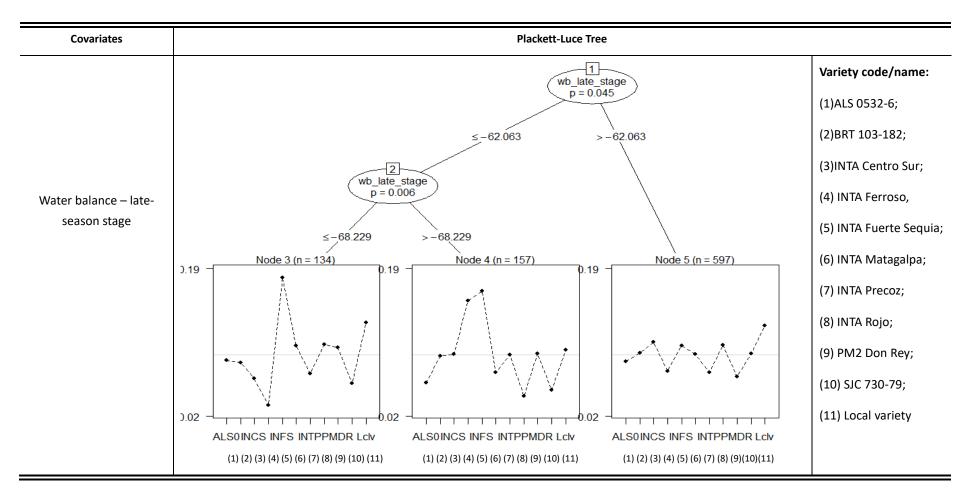


Figure 8 Variety scores when water balance (at late season stage) as covariate

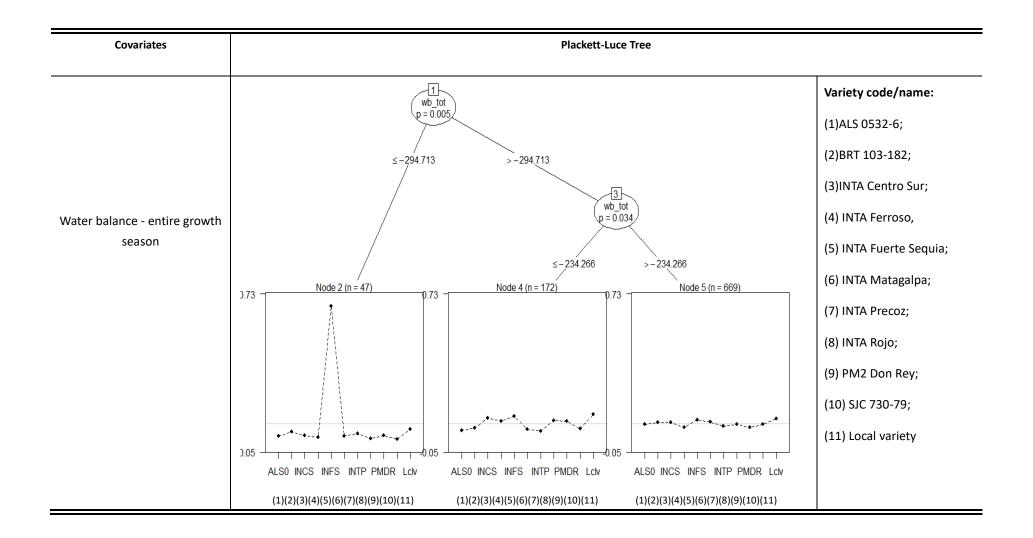


Figure 9 Variety scores when water balance (over entire growth season) as covariate

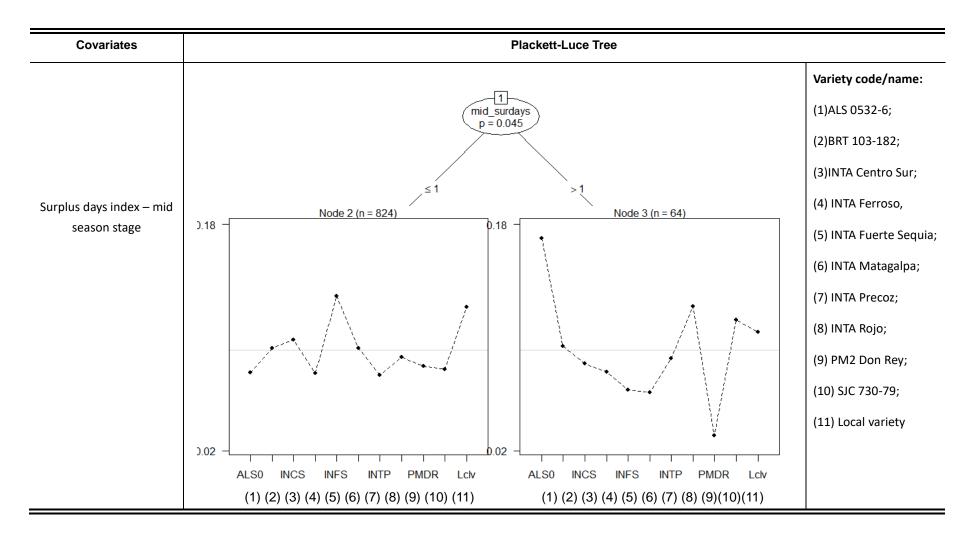


Figure 10 Variety scores when surplus days index (mid season stage) as covariate

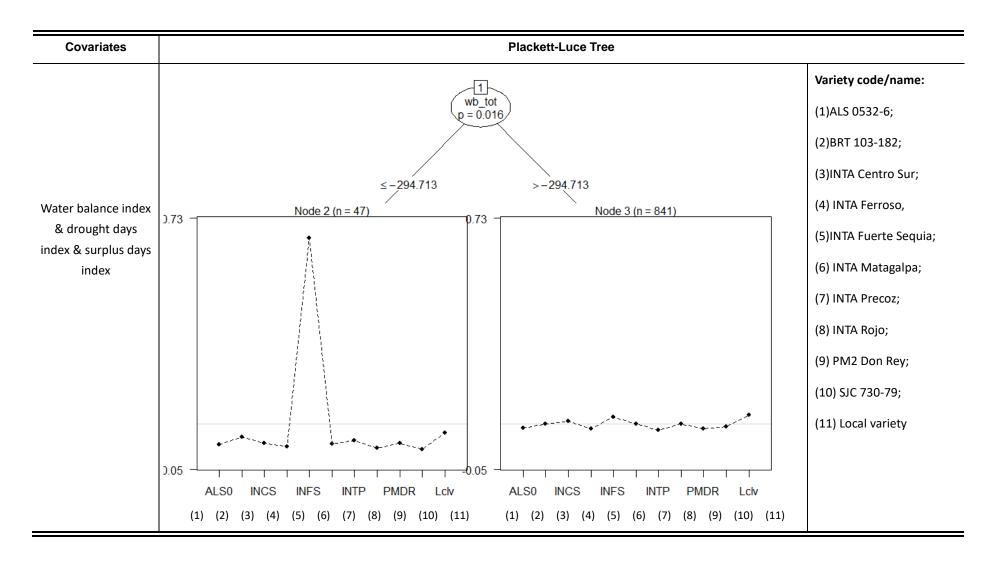


Figure 11 Variety scores when all water-stress indices (Water balance index & drought days index & surplus days index) as covariates

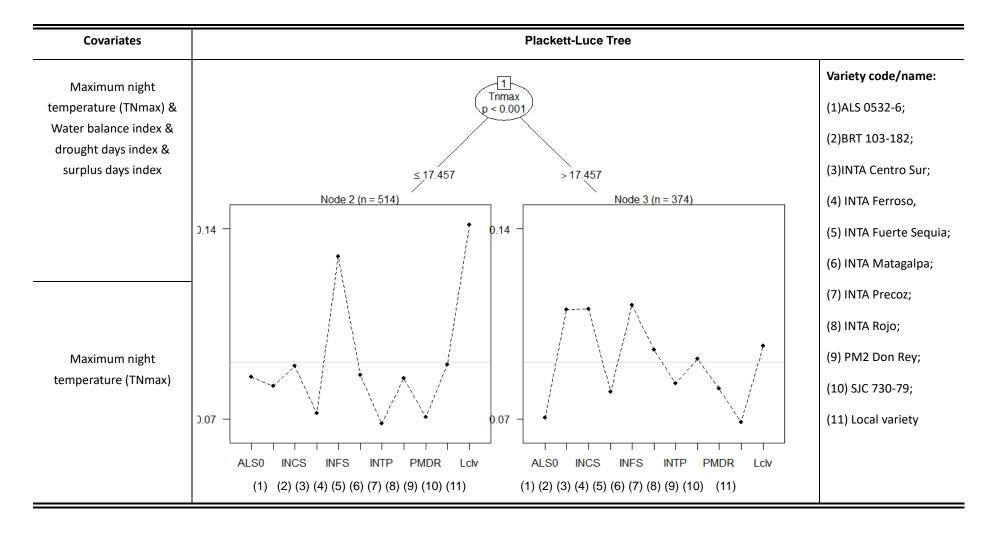


Figure 12 Variety scores when Maximum night temperature (TNmax) & Water balance index & drought days index & surplus days index as covariates

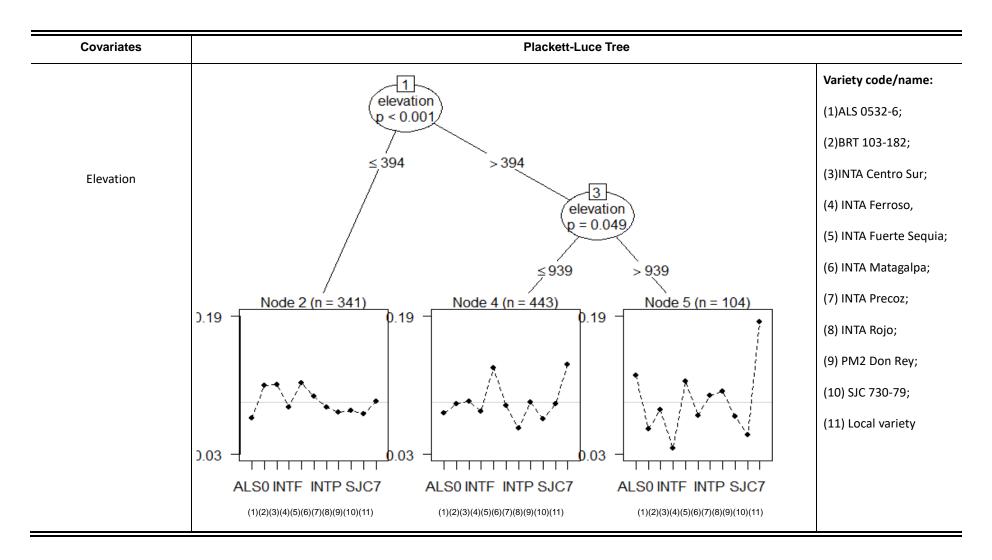


Figure 13 Variety scores when elevation as covariate

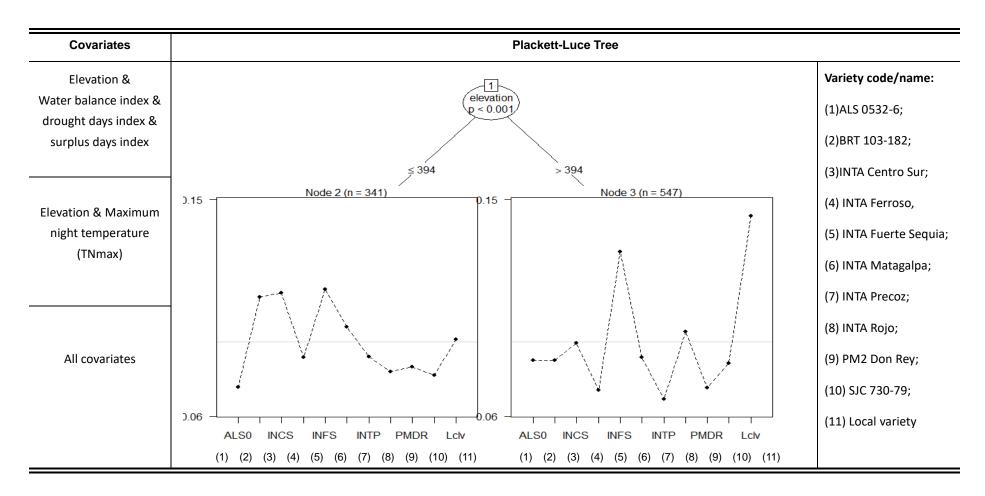


Figure 14 Variety scores when (Elevation & Water balance index & drought days index & surplus days index), (Elevation & Maximum night temperature (TNmax)),

All covariates as covariates

3.3 Model results validation with reported crop traits

The results for research question 3 were aiming to answer to what extent the rankings for each situation corresponds with crop real traits. *Table 4* illustrates that crop real traits considered in this study were summarized in to two aspects, drought and temperature. Since elevation and temperature have inverse relationships, temperature will also change when elevation varies, the results acquired from elevation covariates are also meaningful in results interpretation.

Figure 15 is a star rating for all varieties under different elevation, temperature and water-stress situations. This star rating is based on ranking results obtained from the Plackett-Luce model. The best variety has 5 stars, it decreases a half star for each time when the variety was ranked as one place lower. The worst performance was rated as an empty star. There are many interesting ranking results in *Figure 15*. As we can see, INTA Fuerte Sequia, as a drought and high temperature tolerant variety, it always has good performance when the environment is dry. When water surplus occurs during crop mid-season stage, INTA Fuerte Sequia has poor performance compare to other varieties. This symptom is in line with the reported traits of INTA Fuerte Sequia (*Table 4*). Another interesting example is variety SJC 730-79 which reported that it can tolerant to high temperature and drought. However, in *Figure 15* we can see that SJC 730-79 performed as the 3rd best when Tnmax is lower than 17.5°C, it ranked as the worst variety when Tnmax is higher than 17.5 °C. This shows a disagreement of Plackett-Luce tree ranking result and reported trait.

	Elevation							Maximum night temperature(Tnmax)											Water-stress																
Varieties Splits											2 1 1 1									WB late season stage															
	<= 394 m				>	= 394	ł m			<=	17.4	57°C			>=	17.4	57°C			<= -{	58.22	9 mr	m	>-6	8.22	9& <	<= 62.	.063		>=6	2.063	3 mm	1		
(1)ALS 0532-6;	☆					☆	☆				☆	☆	☆			\$					☆	☆	\$			☆					☆	\$			
(2)BRT 103-182;	☆	☆	☆	☆		☆	☆	\$			☆	☆				☆	☆	☆	☆		☆	☆				☆	☆				☆	☆	☆		
(3)INTA Centro Sur;	☆	☆	☆	☆	\$	☆	☆	☆	☆		☆	☆	☆	☆		☆	☆	☆	☆	13	☆					☆	☆	☆	☆		☆	☆	☆	☆	\$
(4) INTA Ferroso,	☆	☆				\$					☆					☆					☆					☆	☆	☆	☆	☆	☆				
(5) INTA Fuerte Sequia;	☆	☆	☆	☆	☆	☆	☆	☆	☆	\$	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	\$	
(6) INTA Matagalpa;	☆	☆	☆	☆		☆	☆	☆			☆	☆	☆			☆	☆	☆			☆	☆	☆	13		☆	13				☆	☆			
(7) INTA Precoz;	☆	☆	\$			☆					☆					☆	☆				☆	13				☆	☆	\$			13				
(8) INTA Rojo	☆					☆	☆	☆	☆		☆	☆				☆	☆	1			☆	☆	☆	☆		☆					☆	☆	☆	☆	
(9) PM2 Don Rey	☆	13				☆					13					☆	13				☆	☆	☆			☆	☆	☆	\$		☆				
(10) SJC 730-79	13					☆	13				☆	☆	☆	☆		☆					13					13					☆	☆	1		
(11) Local variety	☆	☆	☆			☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	13		☆	☆	☆	☆	13	☆	☆	☆	☆		☆	☆	☆	☆	☆

		Water-stress																												
Varieties Splits		wb_tot												surplus midseason stage									Other water-stress							
		<= 294.713 mm >294.713 & <= 234.266					1.266	>234.266 mm										>=1			covariates									
(1)ALS 0532-6;	☆	\$				\$					☆	☆				☆	13				☆	☆	☆	☆	☆	☆	☆			
(2)BRT 103-182;	☆	☆	☆	☆		☆	☆				☆	☆	☆	13		☆	☆	☆	☆		☆	☆	☆			☆	☆	☆	13	
(3)INTA Centro Sur;	☆	☆	\$			☆	☆	☆	☆		☆	☆	☆			☆	☆	13			☆	☆				☆	☆	☆	☆	
(4) INTA Ferroso,	☆					☆	☆	13			23					☆					☆	\$				13				
(5) INTA Fuerte Sequia;	☆	☆	☆	☆	☆	☆	☆	☆	☆	1	☆	☆	☆	☆	\$	☆	☆	☆	☆	☆	☆					☆	☆	☆	☆	☆
(6) INTA Matagalpa;	☆	☆				☆					☆	☆	☆	☆		☆	☆				13					☆	☆	☆		
(7) INTA Precoz;	☆	☆	☆	\$		☆					☆					☆	☆	☆	13		☆	☆	\$			☆				
(8) INTA Rojo	13					☆	☆	☆	1		☆	☆	13			13					☆	☆	☆	☆	\$	☆	☆	13		
(9) PM2 Don Rey	☆	☆	☆			☆	☆	☆			☆					☆	☆	☆			☆					☆				
(10) SJC 730-79	☆					☆	\$				☆	13				☆					☆	☆	☆	☆		☆	☆			
(11) Local variety	☆	☆	☆	☆	1	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	☆	1	☆	☆	☆	\$		☆	☆	☆	☆	1

Figure 15 Star rating of covariates performance under different environmental covariates

3.4 Interactive webpage

Figure 16 through *Figure 19* show sections of the main user interface of interactive web application. As stated in the *Methodology* chapter, the main interface consists of five sections. The full interface is shown in *Figure 19*. The underlying code and general instructions for usage has been made public by means of a Github repository, its associative link can be found in Appendix 2.

In section 1 (*Figure 16*), the background map is the digital elevation map of Nicaragua. Elevation has strong correlation with temperature and water stress, it is also the only "unchanging" spatial data in this study that can be visualized on the map since the uncertainty of precipitation and temperature every year. As a result, digital elevation model was used as background map in this web application. In the Plackett-Luce model, elevation showed splits at 394 meters and 939 meters. Based on that, the digital elevation model was classified in to three colours. Green area represents elevation above 939 meters, red area stands for elevation between 394 and 939 meters, yellow correspond to the elevation that lower than 394 meters. If user interested in crop variety ranking under different elevation, they can first select "elevation" in the checkbox (*Figure 17*), then click any of the three blue location markers, the top three crop varieties under that situation will show on the popup.

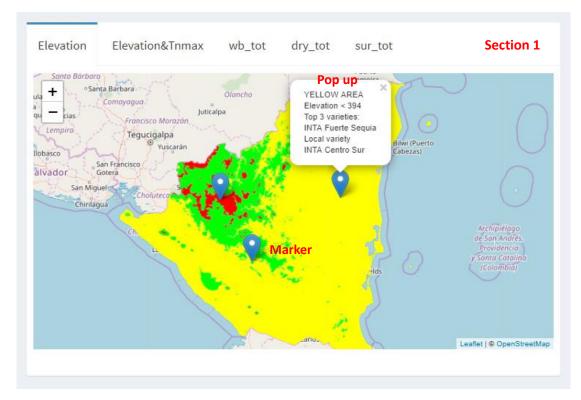


Figure 16 interactive web application (section 1)



Figure 17 interactive web application (section 2)

Section 2 (*Figure 17*) supports user selects multiple covariates for Plackett-Luce model. The results of Plackett-Luce tree and complete ranking were displayed in section 3 and 4 (*Figure 18, Figure 19*). They will change interactively based on user's selection. The ranking information that corresponds with each split can be seen in section 4.

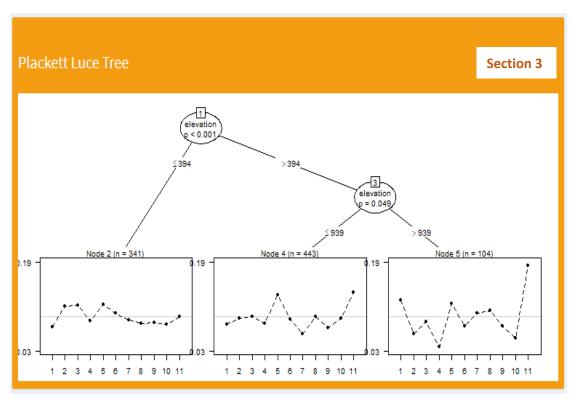


Figure 18 interactive web application (section 3)

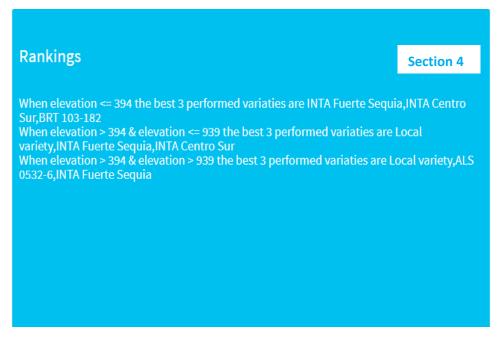


Figure 19 Interactive web application (section 4)

The fifth section on the main user interface is shown in *Figure 20*. There are 5 tab menus in section 5. It includes *Tricot Visualizer menu, Background* of Tricot experiment, *Data Exploration* of Plackett-Luce tree and *Bioversity International* website. Sources of all the reference literatures and datasets used in this study can be found under "*Support*" menu. Section 1 to 4 are displayed under *Tricot Visualizer* menu.

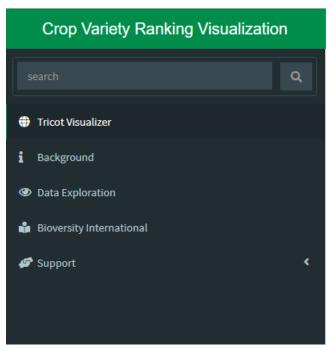


Figure 20 Interactive web application (section 5)

Crop Variety Ranking Visualization

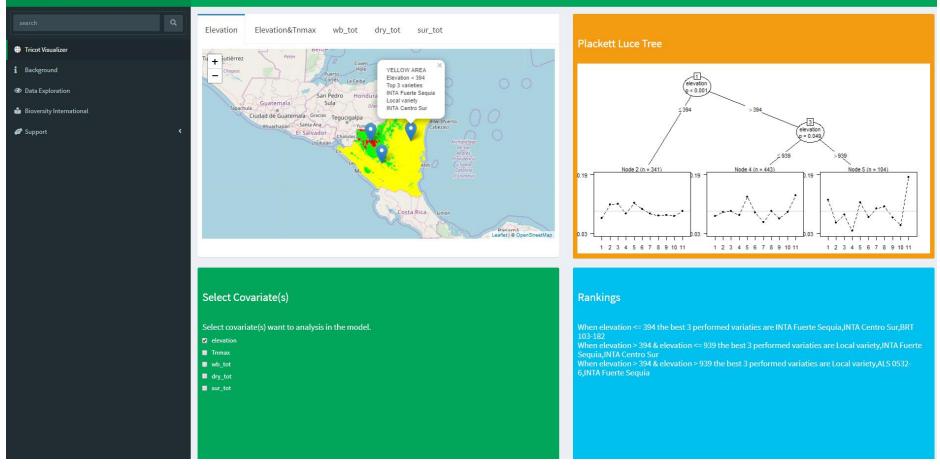


Figure 19 Interactive map webpage (main user interface)

4 Discussion

The overall objective of this study is to identify which crop variety has the best variety score (performance) under a given environmental situation. In this chapter, the results are discussed in the same order of the research questions.

4.1 Differences between Hargreaves and Blaney-Criddle

It is important to emphasize that *elevation*, *Tnmax* and three water-stress indices (i.e. *water balance index, drought days index*, and *surplus days index*) were used as environmental covariates in this study. As they are major influential factors for crop variety performance, they were also used to 'judge' the subsequent rankings. We placed an emphasis on the creation of water-stress indices. All the water–stress indices were created from the daily accumulated water balance. The two methods that were used to calculate this underlying water balance (i.e. Hargreaves and Blaney-Criddle) were compared in order to answer research question 1 (*Figure 6*). Considering the unavailability of full weather data as required by Penman–Monteith FAO 56 (*PMF-56*) which is considered the best way to determine reference evapotranspiration (*ETo*), the Blaney-Criddle and Hargreaves methods were used as they require less parameters while still providing accurate results (Tabari et al., 2013; George et al., 2002; Allen et al., 1998).

In *Figure 6*, it can be seen that Hargreaves and Blaney-Criddle produced similar water balance values. The square root of the correlation coefficient (r^2) was used to quantify the correlation between these two methods. The results showed an R^2 of 0.9704 which indicates that slightly more than 97% of water balance values fall on the X = Y trend line, and are thus highly correlated. In other words, most of the water balance values calculated from the Hargreaves method are identical to the values from the Blaney-Criddle method. However, due to the environmental complexity of the study area and the sparse resolution of the input data for the Hargreaves and Blaney-Criddle methods, it cannot be claimed that they would produce similar results universally.

Many researchers have indicated that the determination of a suitable method for the estimation of potential evapotranspiration can vary wildly per region, due to their seasonal climate and weather factors (Durgam & Sastri, 2015; George et al., 2002). In 2018, Durgam et al. also concluded that there are regional differences that influence the estimation of potential evapotranspiration. For example, in their study, daily weather data was collected from three stations at three different agro-climatic zones in Chhattisgarh state, India. The potential evapotranspiration was estimated using six different methods: *Modified Penman, Hargreaves, Christiansen, Blaney–Criddle, Turc* and *FAO Penman-Monteith* method. The results from these methods were compared to the result from the Open Pan evaporation method. The conclusion from that study was that the *Christiansen* method performed well at all 3 stations, with *FAO Penman-Monteith, Blaney-Criddle,* and *Modified Penman* closely followed behind it respectively at different stations. Likewise, in the case study of Ronad et al. (2016), he used the same reference evapotranspiration methods as Durgam (2018).

On the contrary, *Blaney-Criddle* was concluded as the most suitable method for their selected site. In the study of Tukimat (2012), the *Makkink* method was determined to be the most suitable method in Muda Irrigation Scheme which located in Kedah north of Malaysia, and followed by *Turc* method (Tukimat, Harun, & Shahid, 2012). So even though Hargreaves and Blaney-Criddle produced comparable water balance value with regards to our study area, this does not necessarily mean that these two methods always produce similar results.

4.2 Environmental indicators used in Plackett-Luce model

Every water-stress index contains five corresponding indices (four related to crop growth stages and one concerning the entire growing season), to be used as environmental covariates (along with elevation and Tnmax). There are 22 covariates in total which were considered for the Plackett-Luce tree model (*Table 5*). The combinations of covariates are: covariate 16 (three water-stress indices), covariate 18 (Tnmax with three water-stress indices), covariate 20 (elevation with water-stress indices), covariate 21 (elevation with Tnmax shown), and covariate 22 (all seventeen individual covariates combined).

Water-stress indices

The water balance index produced 3 splits at crop *late season stage* in the Plackett-Luce model (*Figure* 8). This implies that the performance of crop varieties is directly influenced by water balance deficits (at varying values). There are several possible reasons that may cause different variety performances at the *late season stage*, one of them is temperature. The common bean grows well at temperatures ranging from 15°C to 27°C with maxima up to 29.5°C (Salcedo, 2016). In our dataset, the average temperature for each crop growth stage of all observations were:

Crop growing stage	Initial	growth	Develop	growth	Mid-season	Late season stage
	stage		stage		stage	
Average temperature	25.1 °C		25.2 °C		26.0 °C	27.2 °C
Average precipitation	47.6 mm		82.0 mm		53.3 mm	19.2 mm

Table 6 Average temperature and precipitation per growing stage for 888 observations

It can be seen from *Table 6* that the late season stage had the highest average temperature of the entire growing season. It was slightly higher than 27 °C - the optimum temperature for common bean (Salcedo, 2016). More importantly, there were 67% observations that suffered from temperatures higher than 27 °C - during the late season stage. In addition, 2.3% of the observations grew above 29 °C, and only 32% of observations actually grew under the optimum temperature. Another possible explanation is precipitation. The common bean is a drought resilient crop and the ideal growing condition for it is 350–500 mm rainfall during the growing season (Salcedo, 2016). However, in *Table 6* the actual average precipitation for all observations over the growing seasons was 204 mm (sum up average precipitation for each stage). The splits at the late stage that did not occur in other growing stages might be caused by these unusual temperatures and precipitations.

Another possible explanation for the model splits in the late season stage might be that the combination of unusual temperatures and precipitation do provide a suitable environment for diseases, which could spread in the common bean. There are several diseases that tend to spread at warm temperatures and low or high humidity, these include: *Ashy stem Blight, , Fusaruim Root Rot, Curly Top, Golden Mosaic and Bald head* (Hagedorn & Inglis, 1986). The appearance of large differences in crop variety ranking at late season stage might also be explained by the fact that crop varieties have different disease resistance abilities. Some of the varieties might have stronger diseases resistance than others.

Another notable result was the Plackett-Luce tree, as depicted in *Figure 9* and *Figure 11*. As we can see on the first split of *Figure 9*, INTA Fuerte Sequia showed exceptionally better performance than all the other varieties when severe water deficit occurs during the entire growing season. Similarly, INTA Fuerte Sequia also showed good performance when the value of surplus days index was below 1 (*Figure 10*). When consecutive water surplus days occurs less than once per growth stage, INTA Fuerte Sequia showed the best performance. In other words, in case of water deficit, INTA Fuerte Sequia was ranked better than all the other varieties, including the local ones. This finding corroborates the conclusion of Janick (2008) who states that the currently most desirable drought resistance traits is indeed the INTA Fuerte Sequia which was released in Nicaragua. On *The Integrated Breeding Platform (IBP)* official website, it is also claimed that "*INTA Fuerte Sequia is a small red seeded variety that is recommended for zones with limited water (less than 200mm) in Nicaragua.*"(IBP, 2015).

We can see that INTA Fuerte Sequia had superior performance when covariates only include the waterstress indices. However, it should not simply be concluded that the water-stress indices are meaningful for crop variety ranking. Except INTA Fuerte Sequia, all the other varieties in *Figure 9* and *Figure 11* presented comparable rankings. Especially in the middle and rightmost branches of *Figure 9*, we can see that in total 841 observations (node 4: 172, node 5: 669) showed indistinguishable rankings when the environmental covariate is the water balance index for the entire growing period. Simply put, the water-balance index at the entire growing period does not have a strong influence on crop variety rankings. In *Figure 10*, the water surplus index splits the model into two branches at mid-season stage. It is interesting to see that variety ALS 0532-6 was ranked differently when consecutive water surplus situation happened more than once or less than once. On the rightmost branch we can see that variety ALS 0532-6 has the best performance than all the other varieties when water surplus occurred. Since crops are most susceptible to diseases in humid environments (Buruchara. 2010), variety ALS 0532-6 is implied to exhibit stronger disease resistance than other varieties.

Elevation and Tnmax

Other environment conditions such as maximum night temperature and elevation appeared to be more meaningful for the differentiation of performances of the evaluated crop varieties. With Tnmax and all water-stress indices used for the Plackett-Luce mode (covariates 18), it can be seen that the model only showed splits for different Tnmax values. In other words, Tnmax affected the ranking more than individual water-stress indices. The same was found for elevation; none of the water stress indices had an apparent influence on the crop ranking when they were considered together with elevation. Elevation was found to be the most effective environmental indicator when all seventeen covariates (covariates 22) were included in the Plackett-Luce model (*Figure 14*). It is in line with the fact that the majority of environmental factors which effects tree growth vary with changes in elevation, since the changes of elevation also impact the air temperature and wind speeds (Worrell, 1987).

4.3 Model results validation with reported variety traits

Table 4 lists the reported-traits of all evaluated bean varieties (except for the local varieties). *Figure 15* summarizes variety ratings under different environment based on the Plackett-Luce model results from *Figure 7* to *Figure 14*. By comparing the information in said figure and table, it is possible to assess to what extent variety rankings actually correspond to claimed crop features.

(1) ALS 0532-6: Tolerant to high temperature

ALS 0532-6 had quite low rankings in almost all assessments, except for the situation when consecutive water surplus days happened more than once at mid-season stage (*Figure 10*). As a high temperature tolerance variety, it has the second worse performance when Tnmax was higher than 17.5 °C (*Figure 12*). It is important to know that the variety rankings are relative ranked to each other. It means that even though variety ALS 0532-6 has low ranking at high temperature, it does not indicate that ALS 0532-6 is not tolerant to high temperature, the reason might be that all the other varieties are also high temperature tolerance and can perform better than ALS 0532-6.

(2) BRT 103-182: Tolerant to high temperature

BRT 103-182 ranked as the 3rd best variety in both cases when elevation was lower than 394 meters, also Tnmax was higher than 17.5 °C (*Figure 12* and *Figure 13*). It had better performance than ALS 0532-6 even though they both have high claimed temperature tolerance.

(3) INTA Centro Sur: Tolerant to high temperature and drought

INTA Centro Sur has high temperature resistance variety, it has the 2nd best performance when elevation lower than 394 meters. It is also the 2nd best one when Tnmax higher than 17.5 °C (*Figure 12* and *Figure 13*). As a drought resistance variety, it was ranked as the 3rd worst when late season stage water balance extremely deficit (water balance at late season stage <= - 62.063mm). However, it was the 2nd best when water balance shortage was slightly better (water balance at late season stage > - 62.063mm) (*Figure 8*).

(4) INTA Ferroso: Tolerant to drought

Variety INTA Ferroso had poor performance in almost every situation. It is always ranked as 2nd or 3rd worst one. However, particularly good performance was found when the late season stage water balance deficit was between 68.009 mm and 62.063 mm (*Figure 8*).

(5) INTA Fuerte Sequía: Tolerant to high temperature and drought

INTA Fuerte Sequía had outstanding ranking in almost every case. The only situation that it dropped from the 1st or 2nd place was when the late season stage water balance deficit was less than 62.063 mm. In that case it was listed as the 4th best variety. This variety was found to have superior performance when water deficit at late season stage (*Figure 8*). The possible reason was explained in chapter 4.2.

(6) INTA Matagalpa: Susceptible to high temperatures

Being the only variety which was claimed to be sensitive to high temperature, it had the same ranking no matter the value of Tnmax. It showed no difference in ranking when temperature changed. However, we cannot claim that INTA Matagalpa was not sensitive to temperature, because the rankings are relative to the other assessed varieties (*Figure 12*).

(7) INTA Precoz: Tolerant to high temperature and drought

INTA Precoz ranked as the worst variety when temperature lower than 17.5 °C, and ranked as the 5th worst when temperature higher than 17.5 °C. The ranking improved with temperature increase (*Figure 12*). It performed as the 4th best variety when the entire season water balance was less than 294.7mm. Compare to INTA Precoz's ranking under other situation, it shows better performance in extremely water balance shortage (*Figure 9*).

(8) INTA Rojo: Tolerant to high temperature and drought

Inta Rojo has interesting ranking when water balance index at late season stage. When water balance less then -68.2mm or higher than -62.1mm, it was found to be the 3rd best variety in both situations. However, when water balance was between -68.2mm and -62.1mm, it was ranked as the worst variety (*Figure 8* middle branch). INTA Rojo had plain ranking when Tnmax changed (*Figure 12*). The ranking was around 6th and 7th.

(9) PM2 Don Rey: Tolerant to drought

When considering the water balance covariates for the entire growing season, PM2 Don Rey turned out to be the 5th best variety when the accumulated water balance was less then -294.7mm or between - 294.7mm and -234.3mm. Even though PM2 Don Rey is claimed to be a drought tolerant variety, it performed the worst when water balance deficit less than 234.2mm (*Figure 9*).

(10) SJC 730-79: Tolerant to high temperature and drought

Although SJC 730-79 is claimed to be tolerant to high temperature and drought, it was found to be the 2^{nd} worst when elevation lower than 394m, and the worst variety when Tnmax was above 17.5 °C. It surprisingly showed inferior ranking in most cases except when Tnmax lower than 17.5 °C (*Figure 12*).

(11) Local variety:

The local variety (11) unsurprisingly exhibits good performance in every situation. The local variety varied from farmer to farmer. Because each farmer has his/her own rich experience and field practice, the most suitable variety was selected for the local circumstances. Therefore, it is reasonable to expect that the local variety (11) had relatively good performance (*Figure 13* rightmost branch and *Figure 12* left branch).

4.4 Interactive webpage

To investigate large, complex and multivariate datasets, a more interactive process can lead to a faster answer to a given problem (Dykes, 1997). In this study, ranking information is presented to users through an interactive webpage which can dynamically generate ranking information on-demand for specific selected covariates. When a user navigates to the website, in the first section (Figure 16), there is an interactive colored DEM map of Nicaragua. When user select elevation as their covariates of interest, the DEM map can be classified based on Plackett-Luce model results of a split on elevation. In other words, the map based on splits value classify digital elevation map in to 3 classes and they were colored individually on the map. When users click on any of the markers, they visualize (by 'pop-up') the ranking information of the area that users are interested in. Every popup marker in each classified area summarizes the ranking information in that region. The prototype web application shown in *Figure 21* can interactively select interested environmental covariates in section 2 and execute them in the Plackett-Luce model. Crop variety ranking then can be automatically visualized on the environmental map. Also, users can easily identify which varieties are feasible for analysis from section 2. Only elevation and maximum night temperature could be used as background map data because both the crop growing seasons and the water-stress indices are not spatially continuous and so cannot easily be depicted on a map.

Another advantage of building an interactive web application is that people can visualize the result without the knowledge of R programming or the Plackett-Luce model. It needs low level skills to read and operate the web map. There is a potential that in the future, without reading feedback sheet from Bioversity International, farmers could visualize the result on their own mobile device in an interactive way.

4.5 Review of previous study

Compared to the previous study from Van Tilborg (2018), there were several different conclusions in this follow up research. Van Tilborg (2018) concluded that "the most explanatory varieties were the water balance during initial stage, the elevation and TNmax during the initial stage". In our study, we got similar a conclusion with elevation and Tnmax, as they had strong effects on crop variety performance. However, we did not get obvious proof that the water balance at initial stage played an important role in crop variety performance differences. Therefore, we took a closer look at the data from Van Tilborg and found that there might be a data miss-ordering that happened in that study which leads to that different conclusion. The dataset processed in both studies is the original dataset which was provided by Bioversity International. It includes the location for each observation. However, when we were checking data from Van Tilborg, we noticed that the all locations were matched with the wrong environmental data. For example, there is only one observation that was planted at 9/10/2019(m/d/y) at location 85.73 W, 12.81N. In the dataset of Van Tilborg shows that specific observation is located at -85.56W, 13.46N. If a location was wrongly matched with observation, it would not be possible to extract correct climate data for that observation. We suspect that this initial error might have propagated through the rest of the observations, which unfortunately results in the observations no longer corresponding to the underlying data (especially when observations are far apart).

Furthermore, the researchers from Bioversity international also did not find that any stage of water balance could influence crop varieties performance as much as elevation or TNmax which is in line with the results we obtained in this study (Van Etten, personal communication).

4.6 Limitations

The water balance in this study was calculated by a simplified and incomplete water balance equation. Even though it was an important part of this research, it was impossible to compute the water balance value accurately because of the unavailability of surface water runoff data, soil water storage capacity, solar radiation, and the lacking of accurate precipitation data. Precipitation was downloaded from Daily Global Rainfall data with 0.05° * 0.05° (5km * 5km) spatial resolution which is way too course for water balance calculation in farm scale. The other two water-stress indices would also be inaccurate since all

the other water-stress indices were generated based on water balance index.

As a limited demo application, it still needs huge improvements with regards to functionality and performance before being made available to the public. First, the web page takes a long time to update the results. Depending on the number of selected varieties, the server side may take more than 3 minutes to provide the data to be displayed on the webpage. However, running the Plackett-Luce model in Rstudio, takes considerably less time. Unfortunately, the problem could not be solved in time. Secondly, the interface can be more interactive and the platform could be holds as crop portfolio. Ideally, each farmer is assigned a farm code which represents the code of their farm. Farmers could then select their own farm on the map based on their farm code. Then the information of each farm could be provided along the map, functioning as a crop portfolio of sorts. Farmers could be enabled to read the location of their farm, elevation, daily average temperature, daily water balance, soil type information and the recommend variety in that particular farm.

5 Conclusion and Recommendation

5.1 Conclusion

The following conclusion were drawn from the results of this study.

- 1. The Hargreaves and the Blaney-Criddle methods showed very similar results for the water balance calculations. However, since reference evapotranspiration varies from place to place and from season to season, there is no guarantee that these methods would always produce similar results.
- 2. Elevation was the most meaningful environmental indicator in this study, as it significantly impacted the variety ranking. It was followed by maximum night temperature. Maximum night temperature showed splits at 17.5 °C which is closely in line with the known common bean sensitivity to high night temperature (18 °C). Water-stress indices had the least influence on crop variety ranking.
- 3. Not all variety performs correspondingly to the reported traits, some even showed opposite traits. However, it is clear that the INTA Fuerte Sequía did exhibit outstanding performance in most of dry environments as expected from its reported traits. The local varieties also performed extraordinarily well which was to be expected as they are essentially cultivated for those particular farms.
- 4. The interactive web application prototype may be an appropriate way to visualize the result. Through the interactive webpage, the ranking information is dynamically generated on-demand for specific interested covariates from users (without requiring programming skill and/or the knowledge of the underlying of statistical models). Combining ranking information and spatial data was realized in this webpage. However, this prototype application still suffers from technical difficulties (e.g. speed up the code) and data unavailability for environmental covariates.

5.2 Recommendation

Throughout this research, we have mainly focussed on the water stress covariates as part of the recommendation by Van Tilborg (2018) where she emphasized their importance to crop performance. However, other covariates might also prove to be highly influential on said performance (e.g. soil type and season, of which data was made available). Our recommendation for further analyses of tricot data would include a closer look at different environmental covariates which might give them new insights of crop characteristics. By accessing this knowledge, it will assist farmers to select the most suitable varieties to fit climate change for their particular farms.

Some suggestions with regards to the web application are also provided here for further research. One of the important practical applications is that users could upload their own regional data. This web application could automatically visualize the ranking, via Plackett-Luce tree, or even a spatial map to gain information. Moreover, considerably more work needs to be done to make the code work more efficiently. Gillespie and Lovelace (2016) suggested many ways on how to make R code more efficient. For example, profvis is a tool that gives a profile of how each function spends time.

After figuring out which part of scripts slows down the processing, more accurate optimization needs to be completed to speed up the code (Chang 2016). One of the solutions for speeding up the code is parallel processing. In an article of Dancho (2016), he mentioned that for a long-running R scripts, parallelized code can save substantial amounts of time. R by default only uses one processor (i.e. core.) when running scripts. However, PC nowadays mostly have multiple cores that are underutilized. Therefore, parallel processing takes advantage of this by splitting the work across the multiple cores for maximum processor utilization (Dancho 2016). Dancho (2016) also confidently claimed that parallel processing could have a significant improvement on processing time. The package for parallelizing R code is called multidplyr. The associated workflow and function scripts can be found in Appendix 2.

References

(IBP), T. I. B. P. (2015). The Integrated Breeding Platform. *The IBP Breeding Management System Version 3.0.9*. Retrieved from https://www.integratedbreeding.net/breeding-management-system".

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. *Fao, Rome, 300*(9), D05109.

Ashby, J., Ceccarelli, S., Guimarães, E., & Weltzien, E. (2009). Plant breeding and farmer participation.

Bailey, T. C., & Gatrell, A. C. (1995). Interactive spatial data analysis (Vol. 413): Longman Scientific & Technical Essex.

Bioversity (2016) Seeds for Needs – Emerging evidence on triadic comparisons of technologies (tricot). Internal report Bioversity international.

Bojanowski, J. S. (2013). sirad: Functions for calculating daily solar radiation and evapotranspiration. URL http://sirad. r-forge. r-project. org/. R package version, 2.0-9.

Bradley, R., & Terry, M. (1952). Rank Analysis of Incomplete Block Designs: I. The Method of Paired Comparisons. Biometrika, 39(3/4), 324-345. doi:10.2307/2334029

Broman, K. W. (2015). R/qtlcharts: interactive graphics for quantitative trait locus mapping. Genetics, 199(2), 359-361.

Brouwer, C., & Heibloem, M. (1986). Irrigation water management: irrigation water needs. Training manual, 3.

Buruchara, R. A., Mukaruziga, C., & Ampofo, K. O. (2010). Bean disease and pest identification and management.

CIAT. (2015.). Developing beans that can beat the heat. Cali, Colombia: International Center for Tropical Agriculture (CIAT.). 12p.

DURGAM, U., & Sastri, A. (2015). Comparison of the Values of Potential Evapotranspiration Estimated through Different Methods and their Relationship. Trends in Biosciences, 3489.

Dykes, J. A. (1997). Exploring spatial data representation with dynamic graphics. Computers & Geosciences, 23(4), 345-370.

George, B. A., Reddy, B., Raghuwanshi, N., & Wallender, W. (2002). Decision support system for estimating reference evapotranspiration. Journal of irrigation and drainage engineering, 128(1), 1-10.

Hagedorn, D. J., & Inglis, D. (1986). Handbook of bean diseases. Publication-University of Wisconsin, Cooperative Extension Service.

Hargreaves, G. H., & Allen, R. G. (2003). History and evaluation of Hargreaves evapotranspiration equation. Journal of Irrigation and Drainage Engineering, 129(1), 53-63.

Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. Applied engineering in agriculture, 1(2), 96-99.

Jahanshiri, E., & Shariff, A. R. M. (2014). Developing web-based data analysis tools for precision farming using R and Shiny. Paper presented at the IOP Conference Series: Earth and Environmental Science.

Janick, J. (2008). Plant breeding reviews (Vol. 30): John Wiley & Sons.

Lichten, C. A., Ioppolo, B., d'Angelo, C., Simmons, R. K., & Morgan Jones, M. (2018). Citizen Science.

Mason, J. A. (2015). Physical geography: The global environment: Oxford University Press.

Nullet, D. (2016). THE NATURAL ENVIRONMENT Geography 101 Online. Kapiolani Community College Geography, 12. Retrieved from https://laulima.hawaii.edu/access/content/group/2c084cc1-8f08-442b-80e8-ed89faa22c33/book/toc/toc.htm.

Paradis, E., Claude, J., & Strimmer, K. (2004). APE: analyses of phylogenetics and evolution in R language. Bioinformatics, 20(2), 289-290.

Reddy, P. C. P. (1999). A comparison of triadic and dyadic methods of personal construct elicitation. Journal of Constructivist Psychology, 12(3), 21853-264.

Ronad Basanagouda F. and Jangamshetti Suresh H., (2016) Identification of Suitable Method for Crop Water Assessment by Estimating Evapotranspiration-A Case Study. International Journal of Agriculture Sciences, ISSN: 0975-3710 & E-ISSN: 0975-9107, Volume 8, Issue 48, pp.-2020-2023.

Ramírez, V. H., Mejía, A., Marín, E. V., & Arango, R. (2011). Evaluation of models for estimating the reference evapotranspiration in Colombian Coffee Zone. Agronomía Colombiana, 29(1), 107-114.

Salcedo, J. M. (2016). Regeneration Guidelines Common bean. Bioversity International,, Regional OfcefortheAmericas,Cali,Colombia.Retrievedfromhttps://www.genebanks.org/resources/publications/beans-eng/.

Steinke, J., & Van Etten, J. (2016). Farmer experimentation for climate adaptation with triadic comparisons of technologies (tricot): a methodological guide.

Steinke, J., Van Etten, J., & Zelan, P. M. (2017). The accuracy of farmer-generated data in an agricultural citizen science methodology. Agronomy for sustainable development, 37(4), 32.

Shahidian, S., Serralheiro, R. P., Serrano, J., Teixeira, J., Haie, N., & Santos, F. (2012). Hargreaves and other reduced-set methods for calculating evapotranspiration (pp. 59-80). InTech.

Tabari, H., Grismer, M. E., & Trajkovic, S. (2013). Comparative analysis of 31 reference evapotranspiration methods under humid conditions. Irrigation Science, 31(2), 107-117.

Tukimat, N. N. A., Harun, S., & Shahid, S. (2012). Comparison of different methods in estimating potential evapotranspiration at Muda Irrigation Scheme of Malaysia. Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS), 113(1), 77-85.

Turner, H. L., Van Etten, J., Firth, D., & Kosmidis, I. (2018). Modelling rankings in R: the PlackettLuce package. arXiv preprint arXiv:1810.12068.

Van Etten, J., Beza, E., Calderer, L., Van Duijvendijk, K., Fadda, C., Fantahun, B., . Mengistu, D. K. (2016). First experiences with a novel farmer citizen science approach: Crowdsourcing participatory variety selection through on-farm triadic comparisons of technologies (tricot). Experimental Agriculture, 1-22.

Van Etten, J., de Sousa, K., Aguilar, A., Barrios, M., Coto, A., Dell'Acqua, M., . . . Steinke, J. (2018). Replication data for: "Crop variety management for climate adaptation supported by citizen science" [Crop/Field data]. Retrieved from: https://doi.org/10.7910/DVN/4ICF6W

Van Tilborg. (2018). Spatial Analysis and Visualization of Triadic Crop Variety Trialsin Central America. Wageningen University&Research, 53. MSc thesis

Worrell, R. (1987). Geographical variation in Sitka spruce productivity and its dependence on environmental factors.

Zanzanaini 2016, Farmer involved in the Seeds for Needs initiative, India, Bioversity International, accesses 22 February 2019, https://www.bioversityinternational.org

Appendix 1

Table 7 Data sources

Name	Time range	Area	Download Link			
Daily precipitation[mm/day]	2015/09/10 - 2017/04/30	Nicaragua administration	<u>CHIRPS-2.0</u> Nicaragua administration			
Extra-terrestrial solar radiation [MJm-2]	365 days in a year	Latitude:12.66 S; -13.47S	<u>Extrat(day,lat)</u>			
Maximum daily temperature[°C/day]	2015/09/10-	Latitude: Min:-88.5 S; Max:-83.0 S	Temperature			
Minimum daily temperature[°C/day]	2017/04/30	Longitude: Min:10.5 E; Max:14.0 E	(max-temperature & min-temperature at 2 meters)			
Digital Elevation Model[m]	None	Latitude: Min: 90 S; Max: 85 S Longitude: Min: 10 E; Max: 15 E	<u>SRTM data</u>			

Appendix 2

The underlying code and general instructions for usage of interactive webpage: https://github.com/mengzhangg/crop_ranking_app (public Github repository)

The package for parallelizing R code (multidplyr). The associated workflow and function scripts can be found under this public GitHub repository <u>https://github.com/hadley/multidplyr</u> (Hadley, 2015. Retrieved on April, 10, 2019).