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Relating canopy size of pecan (*Carya illinoinensis* (Wagenh.) K. Koch) trees to transpiration

by

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DECLARATION

I, Mhlonishwa Siboniso Zwane, hereby declare that this dissertation submitted at the University of Pretoria for the degree of Master of Science (Agric.) in Horticulture is my work and has never been submitted by me at any other university and that all reference material contained therein has been duly acknowledged.

Signed:

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ABSTRACT

The South African pecan (*Carya illinoinensis (Wagenh.) K. Koch*) sector is not exempt from water scarcity difficulties, so effective irrigation management techniques are required in pecan orchards to help growers maximize production with a limited water supply. One of the first steps in irrigation management is to have a means of estimating orchard water use (ET_c), which usually involves a modelling approach. Canopy size is a key determinant of water use when soil water is not limiting and is used together with prevailing weather conditions in many water use models. The FAO-56 approach, in which ET_c is calculated as a product of reference evapotranspiration and a crop coefficient (K_c)., is the most widely used method of estimating ET_c. Previous research in several fruit trees demonstrated a linear relationship between K_c or transpiration crop coefficients (K_t) and canopy size, indicating that K_c and/or K_t values, and ultimately ET_c or T, can be estimated from a measure of canopy size. It is therefore critical to capture canopy size accurately for future modelling exercises and irrigation scheduling in order to optimise yield, growth, and quality of pecan nuts. This study was therefore initiated to quantify the canopy size and water use of a mature pecan orchard at Innovation Africa@UP in Pretoria. Aerial photography was assessed as a means of providing accurate estimates of canopy cover in pecan orchards. Canopy cover estimates of trees in the orchard were compared using red green blue (RGB) images from above the canopy and the Canopeo app, which selects green pixels, with estimates of fractional interception of photosynthetically active radiation (FI-PAR), leaf area index and canopy cover calculated using the shaded area under the canopy. A sap flow technique was used to monitor transpiration rates in the orchards. Results suggest that canopy size can be accurately estimated with aerial photography as it is digitalized and can capture canopy size for large orchards faster. There was a good relationship between canopy cover determined using the Canopeo app and FI-PAR estimated using the ceptometer, with an R^2 value of 0.85. There was a poor relationship between canopy cover determined using the Canopeo App and LAI, with the lowest R^2 value of 0.56. The results support the hypothesis that the use of photographs captured from above the canopy and image analysis (Canopeo App which selects green pixels) can provide reliable estimates of canopy size, as compared to measurements of FI-PAR by the canopy and canopy cover calculated using the shaded area. Canopy development is influenced by thermal time, thereby

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the results from this study demonstrated dependency between growing degree days and leaf senescence. The regression between K_t and the different canopy size measures indicated a positive linear correlation, however, this relationship was not good enough to be used in deriving orchard specific values using canopy cover in pecans. The R^2 value for the relationship between canopy cover determined using the Canopeo App and K_t values was 0.66, whilst it was 0.7 for midday FI-PAR and $K_{t,}$ and 0.54 for canopy cover determined as the area on the ground shaded by the tree and $K_{t.}$ There was a poor correlation between K_t values and LAI measurements, as indicated by an R^2 value of 0.41. Despite the fact that this study revealed a poor correlation between K_t and the canopy size measured with Canopeo App, an attempt was made to use the relationship derived in one season to derive weekly K_t values for the 2020/21 season, but a poor relationship was found between measured and estimated T, yielding an R^2 value of 0.58. This underestimation was due to a peak in K_t values near the end of the season, which corresponds to the nut filling stage and a minor vegetative flush. Despite some shortcomings, the findings of this study can potentially benefit the pecan industry as the Canopeo App method provided good canopy cover estimates, when compared to widely accepted methods using very expensive equipment.

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LIST OF ABBREVIATIONS AND SYMBOLS

Symbol	Definition	Unit
Δ	Slope of saturation vapour pressure-temperature curve	
πr^2	Area of a circle	m^2
u_2	Wind speed	$m\ s^{-1}$
ρ_b	Wood density	$g\ cm^{-3}$
ρ_s	Density of water	$g\ cm^{-3}$
γ	Psychrometric constant	kPa°C^{-1}
A	Site altitude	m
A_x	Area of the shade	m^2
ACT	Automatic colour threshold	
AWS	Automatic weather station	
C_d	Denominator constant	
C_n	Numerator constant	
CO_2	Carbon Dioxide	
CRM	Coefficient of residual mass	
C_s	CO_2 concentration in the leaf boundary layer	
CU	Chill Units	
CV	Coefficient of variation	
C_w	Heat capacity of wood	$J\ kg^{-1}\ ^{\circ}C^{-1}$
D	The Willmott index of agreement	
DIA	Digital image analysis	
DPU	Daily Positive chill units	
E_s	Soil evaporation	mm
ET	Evapotranspiration	$mm\ d^{-1}$
ET_c	Crop evapotranspiration	$mm\ d^{-1}$
ET_o	Reference evapotranspiration for short grass	$mm\ d^{-1}$
ET_r	Reference transpiration for tall grass	$mm\ d^{-1}$
ET_{ref}	Reference evapotranspiration	
FDIPAR	Daily fraction of intercepted photosynthetic active radiation	
FIPAR	Fraction of intercepted photosynthetically active radiation	

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G	Heat flux density at the soil surface	MJ m^{-2} d^{-1}
GDD	Growing degree days	
HPV	Heat pulse velocity	m s^{-1}
I_o	Amount of incoming solar above the canopy	
IPAR	Intercepted PAR	µmol m^{-2} s^{-1}
K	Thermal diffusivity	m^2s^{-1}
K_c	Crop coefficient	
K_{cb}	Basal crop coefficient	
K_e	Evaporation coefficient	
K_t	Transpiration crop coefficient	
LAD	Leaf area density	m^2 m^{-3}
LAI	Leaf area index	m^2 m^{-2}
LIDAR	Light Detection and Ranging	
MAE	Mean absolute error	
M_c	Sapwood water content	g cm^{-3}
NWRS	National Water Resources Strategy for South Africa	
Pa	Atmospheric pressure	kPa
PCA	Plant canopy analyzer	
R^2	Coefficient of determination	
RGB	Red green blue	
R_s	Solar radiation	MJ m^{-2} day^{-1}
RSME	Root mean square error	
SAPPA	South African Pecan Nut Producers' Association	
SFD	Sap flux density	$cm^3cm^{-2}s^{-1}$
T	Time	seconds
T	Transpiration	mm d^{-1}
T_a	Air temperature	°C
TDP	Thermal dissipation	
V_c	Corrected heat pulse velocity	m s^{-1}
V_h	Heat pulse velocity	m s^{-1}
VPD	Vapour pressure deficit	kPa
$\Psi_{predawn}$	Predawn leaf water potential	MPa
Ψ_{stem}	Stem water potential	MPa

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w_d	Oven-dried wood mass	kg

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DISSERTATION OUTLINE

There are six chapters in this dissertation. Chapter 1 provides a general introduction that discusses the study's relevance and importance to the pecan industry, as well as the study's hypotheses, aims, and objectives. Chapter 2 examines the current literature on canopy size in pecans and fruit trees in general, as well as the methodologies for measuring canopy size. Experiments on canopy size and water consumption of fruit tree crops in general, as well as pecans in particular, are discussed in this chapter. It also covers the elements that affect tree transpiration as well as the methods for determining tree transpiration. The study's methodology and experimental site are described in Chapter 3. In the following two chapters, the hypothesis and objectives for the study are tested and discussed. The results of canopy size of pecan trees are provided in Chapter 4. The findings on the relationship between pecan water use and canopy size are presented in Chapter 5. Chapter 6 discusses the research's primary findings and contributions, as well as future research directions.

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CHAPTER ONE

GENERAL INTRODUCTION

Given the potential for rapid urbanization, increasing competition for water between irrigated agriculture, commercial and industrial uses, and already restricted water supplies, the lack of sufficient water is the most significant risk to sustainable fruit production in South Africa (Midgley and Lötze 2008, Dzikiti et al. 2018). Irrigated agriculture is reported to be one of the most inefficient water consumers, according to the new National Water Resources Strategy for South Africa (NWRS2 2013). Between 30 and 45 percent of the water allocated to this sector is lost due to leaks, inefficient irrigation scheduling, and/or other non-beneficial uses (operational spill and excess surface runoff). As a result, it is critical that the fruit industry has the tools and information it needs to optimize water use, while maintaining or increasing yields.

The pecan industry in South Africa is heavily reliant on irrigation, as most commercial orchards are located in the country's drier regions. Rapid expansion of the South African pecan industry has occurred in the last two decades, with planted areas increasing from an estimated 6770 ha in 2007 to between 33 500 and 39 000 ha in 2019 (Andre Coetzee, South African Pecan Nut Producers Association, personal communication). Although pecan production occurs in all the South African provinces (Figure 1.1) the majority of plantings are found in the Northern Cape, with an estimated 60% of all plantings occurring in this province. Conditions are ideal for pecan production in this region due to cold winters and long hot summers.

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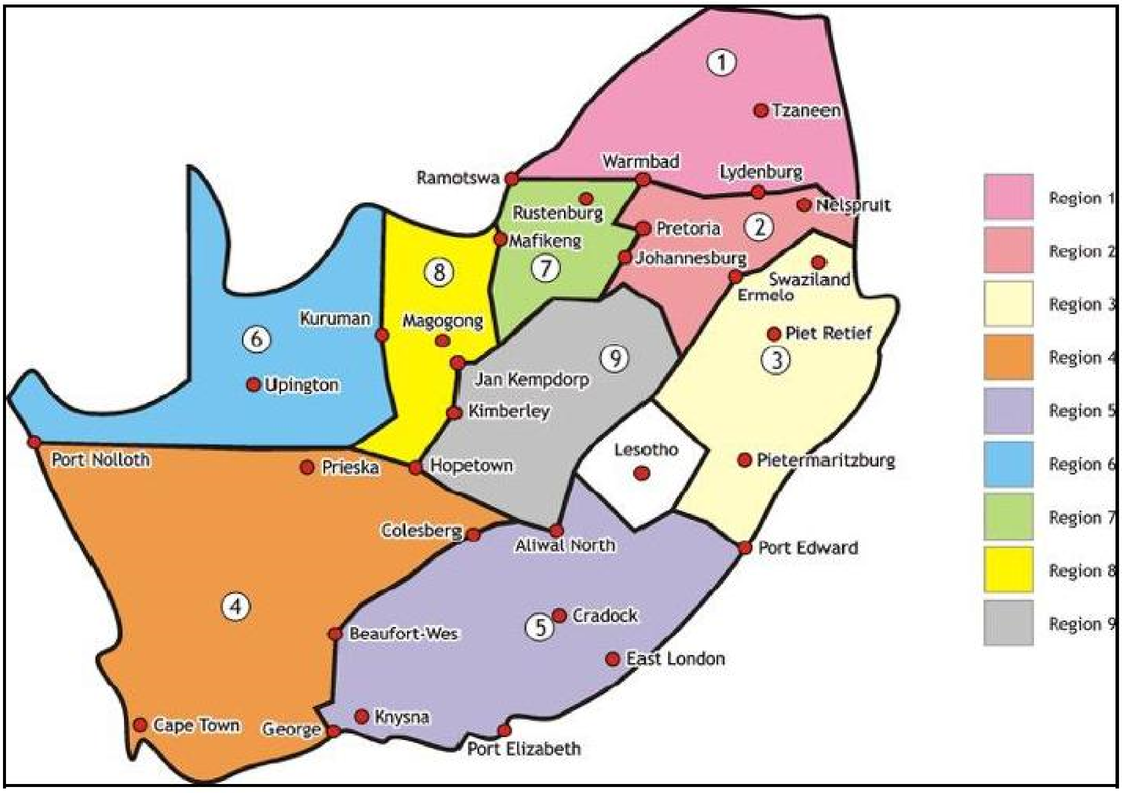

Figure 1.1 Different pecan nut production regions in South Africa (Hortgro, 2018).

The Northern Cape Province is, however, semi-arid and rainfall is often insufficient, failing to satisfy the water requirements of pecan trees. As a result, irrigation is required for optimal production in this region, as water stress impacts nut size and filling, leaf and stem growth, and yield (Wells 2015). The South African National Government has identified the need to increase the water use efficiency of fruit tree crops in the summer and winter rainfall zones of South Africa, where water stress is increasing (Roux 2006). Where the product produced per unit of water consumed by the crop is defined as water use efficiency. As a result, farmers are urged to manage irrigation water efficiently, and in order to do so, they must have accurate knowledge of water use in order to schedule irrigation to fit the crop's needs (Dragoni et al. 2005, González-Talice et al. 2012). Actual measurements of water use are not possible in commercial production and growers, therefore, rely on soil water content measurements or models which estimate water use to schedule irrigation. In order to model successfully and precisely, it is vital to know the variables that drive tree water use, such as solar radiation, relative humidity, wind speed, and temperature. In addition, the size of the canopy, the spacing and direction of the trees, the structure of the canopy, and the

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amount of water in the soil all have an impact on how much water is used in the orchard (Wullschleger et al. 1998, Li et al. 2002).

Water use of pecan trees is controlled mainly by the canopy size, coupled with environmental conditions and the intrinsic hydraulic conductance of the tree. As canopy size can vary from one orchard to the next, depending on the age of the orchard and the manner in which the trees are pruned, it is crucial to be able to have good estimates of canopy size in order to ensure good estimates of transpiration. As a result, a precise estimate of the canopy size of fruit tree crops at any time during the production cycle may aid in the establishment of precise crop water use estimates. This is particularly true for deciduous crops, where leaf area changes dramatically over a season. Despite the fact that there is widespread consensus that canopy size has a significant impact on tree water use (Cohen et al. 1987, Li et al. 2002, Green et al. 2003, Goodwin et al. 2006, Villalobos et al. 2009b, Mahohoma 2017), there is a lack of tools that can be readily employed by growers to determine canopy size with a good degree of accuracy. Available tools are typically expensive and can be complicated to use. Given how important canopy size is in controlling how much water is used, irrigation managers and researchers require a reliable and cost-effective method for assessing and monitoring the temporal and spatial changes in the canopy structure. Therefore, the focus of this study was to first assess the accuracy of using aerial imagery to quantify canopy size, as compared to scientifically accepted methods for determining canopy size from below the canopy. Secondly, it was to use this data to determine the relationship between canopy size and transpiration and transpiration crop coefficients (K_t) in pecan to improve modelling approaches. Finally, the data was utilized to determine the driving variables for canopy growth at the beginning of the season and canopy senescence at the end of the season, as well as the rate of change of transpiration and K_t values associated with these processes.

The aim of the study was to accurately estimate canopy size using fairly simple tools and relate these changes to transpiration and weather conditions, in order to allow for accurate estimations of pecan tree transpiration.

1.1 Hypotheses

1. The use of photographs captured from above the canopy and image analysis (Canopeo App which selects green pixels) can provide reliable estimates of

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canopy size, as compared to measurements of fractional interception of photosynthetically active radiation (PAR) by the canopy, canopy cover calculated using shaded area, and the estimation of leaf area index using gap fraction analysis.

2. The interaction between chilling and heating will be the main factors determining the rate of canopy development at the start of the season and therefore thermal time and chill unit accumulation can be used to predict the rate of canopy development. The decline of the canopy at the end of the season can be predicted with thermal time.
3. A positive linear relationship exists between canopy size and transpiration crop coefficients of unstressed pecans trees, and as a result, simple estimates of canopy cover can be used to derive transpiration coefficients for various orchards.

1.2 Aims and Objectives

The main aim was to accurately estimate canopy size using fairly simple tools and relate these changes to transpiration and weather conditions, in order to allow for accurate estimations of pecan tree transpiration.

The main objectives of the study were:

1. To compare canopy cover estimates of orchards using red green blue (RGB) images from above the canopy and the Canopeo app, which selects green pixels, with estimates of fractional interception of PAR, leaf area index and canopy cover calculated using shaded area.
2. To quantify changes in canopy size throughout the season in pecan orchards in relation to possible driving variables, including thermal time, in order to be able to predict canopy development.
3. To determine the transpiration of unstressed pecan trees and calculate transpiration crop coefficients in relation to canopy size over the season.

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CHAPTER TWO

LITERATURE REVIEW

2.1 Defining Canopy size

Canopy size can be defined as the scale, shape, orientation, and positional distributions of various plant organs, such as leaves, stems, branches, flowers, and fruits, which were described by Norman and Campbell (1989) as canopy structure. Solar radiation interception, scattering, and transmission, alongside gas and water exchanges in the canopy, are all determined by the canopy structure (Welles 1990). The role of canopy size in determining tree water use in pecan orchards has been demonstrated in several studies using various metrics of canopy size, that is canopy volume (Smith 2008), fractional interception of photosynthetic active radiation (PAR) by the canopy (Ibraimo 2018), destructive leaf area index (Torri et al. 2009) and remote sensing (Strahler et al. 1992). These authors emphasized the characterization of canopy size as a significant variable in monitoring and/or modeling water use, despite the fact that several canopy size descriptors were used. Surprisingly, given the importance of canopy size in connection to orchard water use, simple, easily applied, and cost-effective approaches for assessing canopy size in fruit trees remain elusive due to the considerable spatial and temporal variability of canopy structures (Norman and Campbell 1989, Welles 1990). This is a significant disadvantage because a correct estimate of canopy size at any given growth or production cycle in orchard crops could aid in making accurate irrigation modifications based on crop water demand.

The three approaches currently used to quantify canopy size attributes are direct, indirect, and allometric methods. Within-canopy metrics comprise leaf area (LA), angular distribution, and density, whereas whole-canopy measurements include area, shape, biomass, and volume. These measurements, which entail sample and cutting (Norman and Campbell 1989), can be disruptive, but they are commonly used validation techniques (Jonckheere et al. 2004). Indirect measurements are non-destructive and rely on models that take canopy light transmission into account under specified situations (Norman and Campbell 1989). Allometric methods estimate selected tree structural properties by using comparatively easily determined tree

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measurements (for example, tree height and stem diameter) and analytically developed equations to derive an estimation of canopy size (Jonckheere et al. 2004). These procedures are limited to the type of tree and parameter ranges for which the models were created.

2.2 Methods for determining canopy size

2.2.1 Remote sensing

Crop development and production must be monitored to understand the crop's reaction to the environment and agronomic approaches, as well as to develop successful fieldwork and/or remedial management programs (Peng et al. 2019). Two important indices of crop health and development are leaf area index (LAI) and biomass. Numerous crop growth and production predicting models incorporate LAI as a parameter (Kross et al. 2015). Physical and visual methods for estimating LAI in situ are labour-intensive and time-consuming, similar to destructive field approaches for biomass estimates. Furthermore, neither of these approaches gives a map of crop growth and biomass spatial variability (Kang et al. 2016, Yue et al. 2017). The introduction of sensors mounted on satellites, aerial vehicles, and tractors has assisted in obtaining vital information on site-specific properties, that can assist with management (for example, water, fertilizer, and other inputs), and the identification of biotic and abiotic stresses (Mulla 2013, Campos et al. 2019). Light detection and ranging (LiDAR) technology, for example, has evolved into a precise tool for measuring the canopy volume of fruit trees (Palleja et al. 2010). Over the last few decades, remote sensing technologies have also played a key role in cost-effective, non-destructive canopy structure mapping in forestry (Comeau et al. 1993).

Canopy size and biomass have been estimated using remote sensing data for a range of crops, including field crops, orchards and vine crops (Kalisperakis et al. 2015). Typically, such research establishes a regression or machine learning based method to measure LAI and/or biomass for a target field using a collection of reference data (for example, measured LAI and accompanying vegetation indices). Samani Majd et al. (2013) used Landsat 5 satellite data, aerial imagery, and orchard floor photographs to estimate the fractional canopy cover of pecan orchards. A high coefficient of

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determination (R^2 = 0.93) was found when ground-truthing the data against orchard floor photographs.

From soil preparation to harvesting, remote sensing has potential uses in practically every area of precision agriculture. The availability of high spatial resolution multi-temporal satellite data, as well as low-cost unmanned aerial vehicle and commercially available ground-based proximity sensors, has altered the face of precision agriculture. While most satellite data is freely accessible, processing them for real-world applications may necessitate a significant amount of technical knowledge and expertise. Image pre-and post-processing, for example, necessitates specialist expertise and software. Image resolution (spatial, spectral, and temporal); atmospheric, climatic, and weather variables; crop and field circumstances, and analysis approach all affect the accuracy of remote sensing (satellite, aerial, and unmanned aerial vehicle) data systems. Several applications have been developed for this purpose, which will be discussed below.

2.2.1.1 Canopeo

Canopeo is an image processing application written in the Matlab programming language (Mathworks, Inc., Natick MA) that analyses pixels based on the red to green (R/G) and blue to green (B/G) colour ratios, as well as an excess green index (Shepherd et al. 2018). Canopeo is also a free iOS and Android software developed by the Oklahoma State University App Centre as a high-speed method for determining fractional green canopy cover (FGCC) (Patrignani and Ochsner 2015). Canopeo's pixel categorisation strategy, which uses red to green and blue to green colour value ratios to separate green vegetation from non-green backgrounds, has been shown to be successful in distinguishing green vegetation from non-green backgrounds (Wang and Naber 2018). The result is a picture in which colour pixels are transformed to black and white, with white pixels representing the green region and black pixels representing the non-green area. Canopeo allows the user to preview the efficiency of the settings before initiating picture analysis, which is very beneficial when processing a large number of images or videos. The ability to set, evaluate, and adjust threshold R/G and B/G values for many test images, chosen from the set of images to be analysed, increases the user's trust in the threshold values (Patrignani and Ochsner 2015). Canopeo can also remove isolated green pixels from images to minimize noise.

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The user-adjustable noise reduction setting in Canopeo determines the bare minimum number of four-connected pixels that every binary picture region must have to avoid being eliminated (Patrignani and Ochsner 2015).

Whilst the Canopeo application has been tested in field crops, there are no reports available of it being assessed in tree crops. In soybean, Shepherd et al. (2018) compared canopy cover estimated with Canopeo with PAR interception measured with line quantum sensors. The two approaches were shown to have a substantial positive connection (R^2 = 0.94; $p < 0.01$). Büchi et al. (2018) also discovered a link between canopy cover of cover crops measured with Canopeo and visual canopy cover evaluations. In a lucerne pasture, yield was determined using the Canopeo application (Jáuregui et al. 2019) as the amount of biomass accumulated was proportional to the percentage of ground cover, with an overall goodness of fit of 0.77.

There are both benefits and drawbacks to using Canopeo to measure canopy cover. Canopeo is a more efficient way to calculate canopy cover percentages, and it can be done in the field. Canopeo's sensitivity for defining green pixels can be fine-tuned by adjusting its settings. This function helps produce precise readings, although it is difficult to discern dark green plants regardless of the modification (Shepherd et al. 2018). The Canopeo app does not distinguish between crops and weeds, which is a significant flaw in this technique.

2.2.1.2 ImageJ

ImageJ is a free digital image analysis (DIA) software package that was initially designed for medical research (Schindelin et al. 2015). It can process any image format with full-function colour and grey-scale processing. The software is free to use, runs on any operating system, is user-friendly, and can perform a wide range of imaging modifications. It also boasts a sizable and well-informed user base. The application supports all image manipulations, including reading and writing image files, operations on individual pixels, image areas, full images, and volumes.

In a study by Su et al. (2020) ImageJ was successfully used characterise apple tree canopies. The study used ImageJ to process images captured by an RGB-D camera and estimated the canopy size of apple trees. In another study by Guo et al. (2019) aerial images of apple orchards were captured using an unmanned aerial vehicle

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(UAV) equipped with a digital camera. The images were then processed using three image analysis techniques including ImageJ to estimate the tree canopy cover. The results showed that all three techniques were able to accurately estimate the tree canopy cover, with thresholding and ImageJ being more accurate than manual interpretation. However, the authors noted that the accuracy of the different techniques varied depending on the characteristics of the orchard, such as the density and height of the trees.

For researchers who need to process many photos, ImageJ is an excellent option. In addition, in ImageJ, colour thresholds are applied with quick visual feedback to the user. ImageJ makes it easier to save and export processed photos and calculated cover data by reducing the number of steps required (Xiong et al. 2019). The main limitation of this application is that image quality can have an impact on measurement accuracy. Brightness and evenness of illumination, contrast, resolution, geometry, colour accuracy, and colour discrimination of an observed image are all factors that determine quality. Getting the best image quality requires not just having the best equipment available, but also making the right photographic decisions. The overall quality of a photograph is influenced by the correct use of exposure, lighting techniques, and post-processing procedures. Also, ImageJ demands some basic computer literacy, as well as the installation of a Java version that is compatible with ImageJ (Schindelin et al. 2015).

2.2.1.3 SigmaScan Pro

SigmaScan Pro 5, an invention of Systat software (company), is another commonly used automatic colour threshold (ACT) software package in agronomy (Chicago, IL, US). This computer software requires hue (from 0 to 360) and saturation (from 0 to 100) values from the user (Purcell 2000). This package has been employed to examine canopy cover and light interception in soybean (Purcell 2000), percent grass coverage (Richardson et al. 2001, Karcher and Richardson 2003), and grass colour (Karcher and Richardson 2003). This software has the potential to be substantially faster than other software, with high-resolution photographs taking up to 30 seconds to process (Barbedo 2013). Traditionally, only a few photographs were taken to represent study plots, however, new technology is producing a growing interest in

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high-resolution spatial and temporal plant development monitoring, resulting in massive datasets that require quicker image processing methods.

This application allows you to choose up to eight different colours for “healthy” tissue, which improves accuracy and precision. SigmaScan's portability and flexibility for on-site use are further enhanced by its availability on a mobile platform. This application, however, is not compatible with iOS. Another potential drawback of SigmaScan is the image analysis requires a black background. However, improvements to the application's programming could enable in-situ canopy cover estimation (Hietz 2011).

2.3 Ground Based measurements

2.3.1 Leaf Area Index (LAI)

One of the most important parameters for canopy architecture is LAI. The leaf area index is a measure of canopy density, described as half the total area of the green leaf (on one side of the leaf) per unit of soil surface covered by the plant (Jonckheere et al. 2005). The LAI in conjunction with sunlight interception can be used to analyse canopy productivity (Fischer 2011). It's a critical variable in analysing plant biological and physiological activities including photosynthesis, respiration, and transpiration because it's a vital indicator of canopy size (Welles and Cohen 1996).

There are two types of procedures for estimating LAI, which include direct (for example, leaf area harvest, and leaf litterfall) and indirect methods (for example, optical techniques and application of allometry) (Gower et al. 1999). Methods that directly measure leaf area belong to the first category, while methods that derive LAI from more easily quantifiable parameters belong to the second group (Fassnacht et al. 1994, Gower et al. 1999). Although direct approaches for estimating LAI are more precise and reliable, they can be time-consuming, tedious, and destructive in commercial orchards (Liu et al. 2013). As a result, the method is unsuitable for use in commercial orchards, where disruptive sampling is generally prohibited. As a result, the most practical strategy for estimating LAI in orchards is to use indirect techniques, notably non-contact optical techniques. Indirect approaches use data from another variable to determine leaf area. They are usually speedier and more flexible to automation (Jonckheere et al. 2004).

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Two types of commercial instruments indirectly measure LAI: (1) those that utilize gap fraction analysis and (2) those that employ gap size distribution analysis. By comparing differential beam and/or diffuse solar radiation measurements above and below a canopy, the gap analysis calculates LAI depending on the proportion of sky that is not obscured by the canopy elements. To estimate canopy LAI indirectly, the following devices and procedures have been utilized: (1) hemispherical photographs (Bonhomme 1972, Ducrey 1975), (2) PAR line quantum sensors (Sunfleck Ceptometer, Decagon Devices, Pullman, Wash., USA), (3) canopy beam transmittance measurements (Demon; CSIRO, Canberra; Assembled Electrics, Yagoona, New South Wales, Australia), and (4) plant canopy analyser LAI-2200. The LAI-2200 plant canopy analyser (LICOR, Lincoln, NE, USA) is a practical, effective, and hence extensively used optical approach for determining LAI (Welles and Norman 1991). The gap analysis approach has a key flaw in that the leaves are supposed to be spread randomly throughout the canopy, which is not always the case.

When contrasted to direct measurements, the indirect measurements tend to underestimate LAI (Gower and Norman 1991, Sampson and Allen 1995, Gower et al. 1999, Barclay and Trofymow 2000, Mason et al. 2012) and therefore require correction (Bréda 2003). This is often performed through the use of a correction model generated from a comparison of direct (reference) and indirect estimations (Chen and Cihlar 1996, Stenberg 1996).

2.3.2 Leaf Area Density (LAD)

The canopy leaf area density (m^2 leaf area per m^3 canopy volume) is a three-dimensional measurement that takes into consideration the total leaf area, as well as its spatial distribution within a specific canopy volume or location (Gladstone and Dokoozlian 2003). Leaf area density represents one-sided LA per unit volume of the canopy and can provide more detail about the vertical structure of the canopy than LAI measurements (Hosoi and Omasa 2006). Ground indirect measures, including the point-quadrant approach, can be applied to determine the LAI and LAD. When the spatial distribution of leaves is vital for representing the transmission and interception of solar radiation, LAD has been effectively employed in radiation interception models. The point-quadrant approach, which entails placing a probe into the canopy and determining contact frequency, was used by Wilson (1963) and Hosoi and Omasa

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(2006) to estimate LAD. Although this is a valid method, its usage in orchard crops is limited as it is time consuming and, as leaves are removed completely from a predetermined volume to determine leaf area within that volume, it is destructive in nature. Destructive methods can often not be used in commercial orchards (Wilson 1963). This limits not just its employment in commercial orchards, but also its practical application outside of academia, as farmers often prefer the most practical (easier and less laborious) technique for estimating and/or measuring canopy size.

The advantage of employing contact frequency to estimate LAD is that it eliminates the need for theories about leaf spatial distribution, shape, or size. Leaf area density can also be determined indirectly with less time-consuming commercial instruments based on the gap fraction approach (the probability of solar radiation passing through a given canopy). Beer's Law of solar energy transmission through a turbid medium is used in this procedure (Sanz et al. 2013). The LI-COR LAI-2200 Plant Canopy Analyzer and cameras with fisheye lenses are examples of this. However, as proven in some fruit canopies, such as citrus canopies, these approaches may require certain assumptions that may not reflect localised variation in leaf area distribution (Cohen et al. 1987). Furthermore, the gap fraction method's inability to differentiate the spatial distribution of leaves from that of non-photosynthetic tissues can have a considerable impact on the accuracy of LAD estimations (Hosoi and Omasa 2006).

2.3.3 Canopy volume

For physiological and environmental research, canopy volume is a crucial canopy parameter (Nemani and Running 1989). Light penetration into the plant canopy, and consequently leaf photosynthesis and evapotranspiration, is influenced by canopy volume. The impact of climate conditions (Innes 1988), insect plague (Landsberg 1989), and nutritional deficits (Hunter et al. 1991) on tree health have also been estimated using canopy volume. Conventionally, the canopy volume of fruit trees has been calculated by manually measuring the canopy diameter parallel and perpendicular to the tree row close to the ground, as well as canopy height after removing the height of the bare stem. By making assumptions about the canopy's geometry, different geometric equations are then employed to compute the canopy volume (Wheaton et al. 1995). However, using canopy volume as a metric of canopy density can lead to mistakes, especially in studies of radiative transmission and water

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consumption. This is because manual measurements are, in most cases, an abstraction of the canopy that does not account for the leaf area density (Mõttus et al. 2006). Also, some fruit trees grow a dense canopy at the outer edges, resulting in non-homogeneous leaf distribution and a rapid decline in LAD closer to the stem (Cohen et al. 1987). Sanz et al. (2018) used canopy volume to estimate leaf area of apple, pear, and vine. The findings of the logarithmic regressions were very significant, with R^2 values of 0.85, 0.84, and 0.86 in the apple, pear, and vine, in that order. With these findings, the first assumption to their research, that canopy volume is a good variable for estimating the leaf area, was confirmed.

2.4 The influence of chilling and heating units on canopy development of pecans.

After reviewing the methods of estimating canopy size, it is important to touch base on what controls the speed of bud break and leaf growth in pecans, as it is a deciduous tree whose leaf area changes over the season. In the present study, the focus is on factors determining the rate of canopy growth from bud break, as well as the major driving factors for canopy senescence as the trees enter dormancy. In general, temperate perennial crops that grow in seasonally limited temperate climates require chilling temperatures in order to commence development and flowering in the spring (Saure 1985). They go through a dormancy phase that prevents them from growing until they have been exposed to sufficient cold winter temperatures (chilling), which typically occurs in spring and results in bud break. Lack of chilling can result in a variety of problems, including poor flower quality, abscission of flower buds, protraction of the flowering phase, and reduced fruit set (Abbott 1962, Erez 1971, Jackson et al. 1982). In addition, in tropical and sub-tropical climates, a lack of sufficient winter chill results in prolonged dormancy, which leads to deficient flowering, strong apical dominance, and nonsynchronous development patterns, resulting in low yields (Cook and Jacobs 1999).

Chilling and heating play a part in canopy development in spring in pecans. Heat units are a method of estimating plant growth and development during the growing season. The underlying idea is that development occurs only when the temperature rises above a certain minimum development threshold or base temperature. Waite (1925) was the first to propose that pecan buds need to be exposed to cold to break their

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dormancy and grow regularly. When pecans are grown in areas with insufficient chilling hours, it appears that foliation is delayed, fruit drop is increased, and yield is decreased (Van Horn 1941, Nasr and Hassan 1975). The temperature threshold for pecan chilling requirement is generally considered to be between 0°C and 7°, with most cultivars having a chilling requirement of around 400 to 1000 hours below 7°C during the winter dormant period. Chilling hours required to break dormancy in different pecan cultivars include 500 for ‘Desirable' and ‘Mahan,' and 600 for ‘Stuart’, according to McEachern et al. (1978). Whilst Amling and Amling (1980), proposed 300 to 400 chilling hours for ‘Mahan,' ‘Success,' ‘Desirable,' and ‘Schley,' and from 700 to 1000+ for ‘Stuart' (Amling and Amling 1980).

All of this suggests that temperature plays a critical role in predicting canopy growth. Apart from chilling units, another role player is thermal time (heat units) which is a value calculated by adjusting local temperature data with threshold temperatures, and it can be applied to better depict how temperature affects tissue development than minimum/maximum temperature values (Yin et al. 1995). According to a number of studies on deciduous fruit/nut tree growth, development is a function of heat unit accumulation, (for example, pistachio, peach, apple) (Stanley et al. 2000, Marra et al. 2001, Zhang et al. 2015). The use of heat units to estimate plant development is thought to be more accurate than using calendar days (Darbyshire et al. 2014). Costa et al. (2021) used deep learning convolutional neural networks to construct an accurate measurement method of pecan nut development during the growing season and to correlate these changes to thermal time. They reasoned that connecting pecan nut seasonal growth and development to temperature could help with crop production scheduling and irrigation management. The rate of development changed as the number of heat units increased. Development had distinct growth curves, expanding slowly until they reach 1,200 heat units, but then growing quickly from 1,200 to 2,000 heat units.

2.5 Factors influencing growth and crop water use

Surface runoff, deep percolation, evaporation from the soil surface, as well as transpiration from the cover crop that grows between the tree rows, and transpiration from the crop's leaves all contribute to water loss in the orchard. The largest losses are caused by evaporation and transpiration, which are referred to collectively as

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evapotranspiration (ET) (Allen et al. 1998). The focus of this study, however, will be on the transpiration component. Both environmental conditions and plant characteristics, such as canopy size, crop rooting characteristics, and resistances to water movement within the plant, influence transpiration rates (Allen et al. 1998a). Management options in orchards are also likely to influence transpiration rates, particularly the level of irrigation and irrigation scheduling, which ultimately determine soil water content.

2.5.1 Tree Factors

Crop water use is influenced by a variety of factors. Crop type, variety, and stage of development affect internal resistances to water movement, crop height, surface roughness, albedo, and crop root characteristics (Allen et al. 1998a). As the crop matures, the ground cover, crop height, and leaf area will change, and the amount of water consumed by trees for a particular crop will vary over time. Canopy size, which impacts the amount of energy intercepted by the tree and transpiration rates, is one of the most critical elements influencing orchard water use. Canopy size varies greatly, and it is the main reason for the variation in transpiration rates from tree to tree within the same orchard and from orchard to orchard (Kang et al. 2017). The water requirements of young orchards with sparse canopies will differ from those of mature trees with dense canopies. It is also unclear if different cultivars will experience differences in water use rates, which may necessitate different water management strategies. Dzikiti et al. (2018) demonstrated the important role of canopy size in determining water use in apple orchards and were able to show that careful management of the canopy could reduce the water use of mature apple orchards.

Attempts have been made in olives (Testi et al. 2004), apples and pears (Auzmendi et al. 2011, Girona et al. 2011), peaches (Ayars et al. 2003b), almonds (Espadafor et al. 2015), and grapevines (Williams and Ayars 2005) to find a relationship between easily measurable canopy size descriptors and water use. According to these studies, fractional interception of solar radiation is the most important canopy size descriptor. This is due to the fact that canopy radiation interception is directly related to crop growth and water use, which is a topic of great interest to many agricultural scientists (Westling et al. 2018). Importantly, transpiration is influenced not only by the amount

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of available solar radiation intercepted but also by how this energy is distributed within the canopy.

2.5.2 Environmental factors

Environmental factors will have an impact on pecan water use because they produce a driving force for water transportation out of the plant. Environmental factors impacting water use include solar radiation, relative humidity or vapour pressure deficit (VPD), temperature, and wind speed. The energy needed to evaporate water is provided by solar radiation absorbed by the leaves, and the rate of transpiration is largely determined by the vapour pressure gradient between the sub stomatal cavity and the boundary layer surrounding the leaf. Solar radiation has different impacts depending on the amount of solar energy accessible (which varies as a result of geography, meteorological conditions such as clouds, and time of year) and the fraction intercepted by the canopy (Jones et al. 1985). Stomata are also induced to open in the morning as solar radiation increases, allowing carbon dioxide (CO_2) uptake and hence photosynthesis to begin. As a result, water is lost through the stomata, and transpiration begins. The water holding capacity of the air is greater on warm, dry, sunny days than on cool, humid, and cloudy days, so the potential driving force for transpiration will be greater on those days.

Another key limiting environmental element for plant physiological processes and activities is soil water deficit, which is projected to worsen as climatic conditions change (Galeano et al. 2019, Bhusal et al. 2020). Water stress is known to cause a wide range of plant reactions, from cellular metabolism to crop growth rates, resulting in lower biomass, yield, and quality in crops (Yang et al. 2016). In pecans, when the root system detects a lack of accessible water, the leaf stomata are signalled to lengthen their closure periods (Smith and Huslig 1990). Stomatal closure is one of the earliest responses to water stress, allowing plants to reduce photosynthetic activity and hence reduce transpiration.

Furthermore, high air temperatures (>30°C) restrict physiological processes (can reduce photosynthesis by up to 70%) and thus the growth of some deciduous tree species, such as pistachios and walnuts, however, a similar limitation was not found for pecans (Andersen 1994). An increase in temperature can also lead to increased evapotranspiration, which results in a substantial increase in the water needs of the

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crops. Pecans heating requirement for budbreak in the spring is determined by how much chill is accumulated (Sparks 1993). As a result, the impact of air temperature on physiological processes, growth, and the length of the growing season could influence transpiration regulation.

2.5.3 Management factors

Orchards management has a big impact on orchard ET. The planting system, which comprises both tree arrangement in orchards (planting distances and row orientation) and tree canopy training (tree shape and height) are essential aspects in orchard management that affect transpiration by affecting the quantity of solar radiation intercepted by the canopy (Willaume et al. 2004). Pecan orchards are usually pruned every year to improve radiation interception through the canopy, as a result, the amount of leaf area and solar energy intercepted by the canopy decreases, lowering transpiration (T). The change in T is usually determined by the intensity of canopy reduction.

To get a faster return on investment, several fruit tree enterprises are relying more and more on high planting densities. This will increase orchard water demand as compared to lower density plantings, especially when the trees are young and have not yet filled their designated space. However, when orchards develop and create a hedgerow, the difference between low and high density plantings may become insignificant, with canopy cover dictating the majority of the difference (Trentacoste et al. 2015). However, research in several orchard crops found that trees planted with narrower spacing had higher root densities, but contradicted results on the effect of plant densities on crop ET.

2.6 Pecan water use

Crop water use, expressed as crop evapotranspiration (ET_c), is the total amount of water lost in vapour form by a crop as a result of soil evaporation (E_s) and plant transpiration (Allen et al. 1998a). Rainfall and/or irrigation should be used to replace all the water lost through ET in agricultural crops to obtain maximum production (Kool et al. 2014). As a result, understanding the two processes involved in ET is critical for better water management in irrigated agricultural systems, such as orchards. Direct measurements of ET_c are costly and time consuming, and the complexity of most

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agricultural vegetation makes indirect estimation methods difficult (Kool et al. 2014). Regardless of these drawbacks, these methods have generated significant information on the water use of pecan orchards in South Africa and elsewhere (Miyamoto 1983, Sammis et al. 2004b, Ibraimo et al. 2016).

Pecans require more irrigation water to maximize yield than many other crops (Sammis et al. 2004b) and have a higher water use than most row crops (Andales et al. 2000). Despite the fact that pecans are a major crop in several nations, including South Africa (INC, 2011), most pecan research has been conducted in the United States. Pecan water use varies throughout a single season, according to the different development stages, and over the orchard's life, depending on canopy size. Canopy size provides an explanation for the different results concerning annual, monthly, and daily water requirements of pecan trees in different regions. Figure 2.1 illustrates the pecan development stages. Wells and Conner (2007) noted two crucial stages of pecan development that necessitate adequate water. The first stage occurs early in the season, around November in South Africa, during nut sizing; enough moisture at this period results in large nut size. The second stage occurs later in the season when pecan kernels develop, and this ensures that the kernels are fully filled. Water requirements increase until the shuck splits, allowing the shuck to open.

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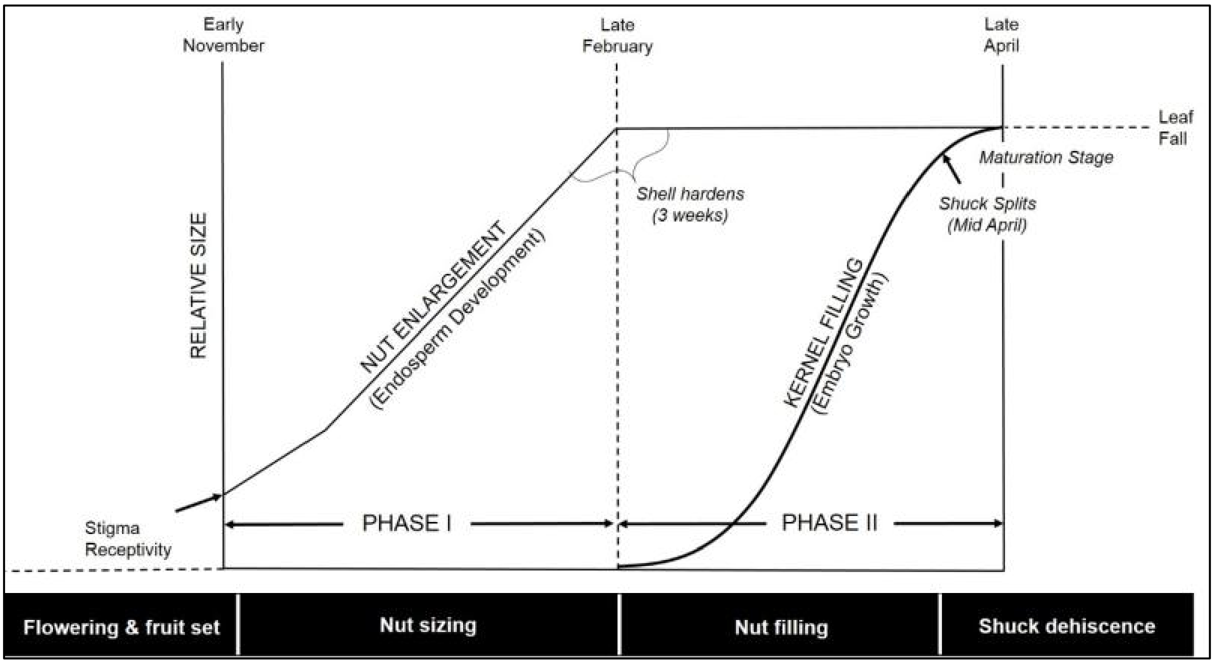

Figure 2.1 Different phenological stages of pecan nut growth and development which impacts water requirements (adopted from Byford and Herrera (2005) and adjusted to South African conditions).

Researchers have used a range of approaches to estimate and model the ET of pecan trees. In South Africa, Ibraimo et al. (2016) conducted research in the Gauteng Province to estimate water use and a six-stage crop coefficient curve approach for a mature pecan orchard that was established in 1975 was proposed. For the three seasons, seasonal ET ranged from 985 to 1050 mm, whereas reference evapotranspiration (ET_o) ranged from 944 to 1034 mm. The 6 stage crop coefficient (K_c) curve developed from measured data over three seasons in mature pecan trees is shown in Figure 2.2 (Ibraimo et al. 2016), which is in contrast to the four-stage, generic crop coefficient curve described in FAO-56 (Allen et al. 1998),.

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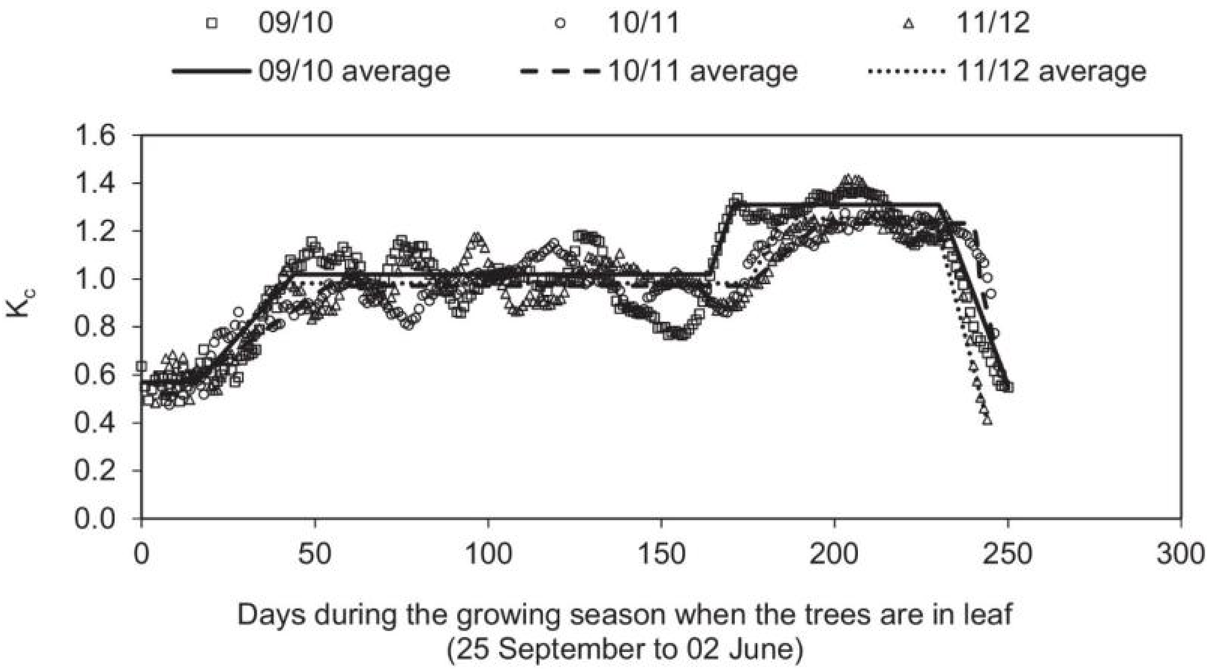

Figure 2.2 Crop coefficient (K_c) curve for a 'Choctaw' pecan orchard at Cullinan over 3 seasons of data (Ibraimo et al. 2016).

In another study, Miyamoto (1983) estimated water use of seven commercial pecan orchards in the El Paso – Las Cruces area in New Mexico, United States of America. Yearly water consumption ranged from 1000 to 1300 mm for mature trees in this study. In the same area, Thomson (1974) had previously stated that water use ranges from 680 to 1000 mm per season. The water requirement of pecans in different regions of South Africa is shown in Table 2.1.

Table 2.1 Water requirement per South African regions (adapted from SAPPA https://www.sappa.za.org/wp-content/uploads/2018/11/sappa-water-requirement-per-production-area.)

Region	**Annual requirement (m^3 ha^{-1})**	**Maximum daily requirement (L $tree^{-1}$ day^{-1})**
Eastern region	**10 000**	**460**
Central region	**12 000**	**600**
Western region	**15 000**	**800**

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2.7 Estimation and modelling of evapotranspiration of fruit trees

A variety of techniques can be used to determine how much water is used in orchards. This includes hydrological methods (lysimetry and soil water balance-based methods), micrometeorological methods (Bowen ratio, eddy covariance, and scintillometry), remote sensing (remote sensing energy balance and satellite-based crop evapotranspiration models by means of vegetation indexes), and plant physiology methods (sap flow methods and whole tree chamber systems). These approaches are often complex and difficult to implement, and they may necessitate a great deal of experimentation (Allen et al. 2011). Furthermore, the majority of these methods, such as micrometeorological approaches, are typically costly, time-consuming, and require specialized staff (Allen et al. 2011). Despite these drawbacks, these methods have provided valuable information on the water needs of numerous fruit trees, as stated by Ibraimo et al. (2016), Rana et al. (2005), Villalobos et al. (2009a), Villalobos et al. (2013), and Mahohoma (2017). The three most common sap flow methods are i) heat pulse velocity (HPV) (Green and Watson 1989, Burgess et al. 2001), ii) thermal dissipation (TDPs) (Granier 1985), and iii) heat balance (Sakuratani 1981). All of these methods are simple to automate and have been shown to be durable and dependable enough to be used in the field for long periods of time (Dragoni et al. 2005). Heat pulse velocity methods have been used in pecans (Steinberg et al. 1990, Ibraimo et al. 2016). This is primarily due to the fact that HPV techniques are less expensive, require less power than thermal dissipation and heat balance techniques, which necessitate constant heat and thus require more power (Forster 2017), and are well suited for automatic data collection (Vandegehuchte and Steppe 2013). The key drawback of using HPV methods to estimate sap flow and, ultimately, transpiration in woody plants is that they are invasive. Furthermore, under low sap flux densities and reverse flows, some heat pulse velocity techniques are prone to errors (Kume et al. 2007.

While various field measurement techniques can be used to obtain information on orchard water requirements, their practical implementation is fraught with uncertainty and requires considerable experimentation (Allen et al. 2011). As a result, ET simulation models provide a cost-effective method of estimating crop water needs for irrigation management. These models estimate ET from readily available meteorological data for a variety of species, and some can distinguish between beneficial (transpiration) and non-beneficial water use (evaporation losses). Simple

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empirical approaches and complex mechanistic approaches are two examples. Simple, empirical approaches are easier to parameterize, but they are often site-specific, whereas mechanistic approaches can be more commonly transferred if the necessary input parameters are well determined (Leenhardt et al. 1995). In order for these models to be adopted by growers, input data requirements should be kept to a bare minimum, and clear procedures for determining the appropriate input variables should be available (Searcy et al. 2003).

2.7.1 Crop coefficient approach

Standard crop coefficients (K_c) are calculated as the ratio of crop evapotranspiration (ET_c) to reference evapotranspiration (ET_o) (Doorenbos and Pruitt 1977, Allen et al. 1998a, Allen and Pereira 2009). If ET_o explains almost all changes caused by weather, it is generally believed that K_c can be transferred between regions and climates. Therefore, K_c is the comparative proportion of ET_o, which mainly depends on the amount, type, and condition of the vegetation. There are two approaches to the crop coefficient method: single and dual crop coefficient. The former combines ET_c and ET_o into a single coefficient, while the latter divides K_c into a basal crop coefficient (K_{cb}) and an evaporation coefficient (K_e). The K_{cb} embodies transpiration when the soil surface is dry, but the soil water content in the root zone is sufficient to maintain full transpiration (Allen et al. 1998a). By observing the stringent definition of K_{cb}, Villalobos et al. (2013) recommended the use of transpiration coefficient (K_t) if transpiration was measured directly with sap flow techniques. Equation 1 gives the procedure for computing ET_c using the dual coefficient method.

$$\mathbf{ET_c} = (\mathbf{K_{cb}} + \mathbf{K_e}) \times \mathbf{ET_0} \quad \textbf{(1)}$$

While these methods have been demonstrated to be reliable in a range of annual crops, they have also been found to be very site-specific in perennial orchard crops, where crop coefficients change depending on variety, rootstock, tree spacing, canopy cover, microclimate, and irrigation method (Naor 2006). Allen et al. (1998a) compiled typical K_c values for a variety of irrigated fruit orchards using both the FAO-56 Penman-Monteith single and dual K_c methodologies. Tabulated values are based on a sub-humid climate with a minimum relative humidity (RH_{min}) of 45 % and a moderate wind speed of 2 m s^{-1} for uniformity (Lakso 2003, Ferreira et al. 2012).

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Crop coefficients have been used successfully to determine the water use of a wide range of crops, including pecans. Wang et al. (2007) successfully determined crop coefficients in open canopy orchards of 'Western Schley' under the assumption that canopy cover influences K_c. In another study, seasonal evapotranspiration in a mature pecan orchard was measured using an energy balance eddy covariance system (Sammis et al. 2004b). The crop coefficients varied from 0.2 to 1.1, which was lower than the previous maximum pecan crop coefficient of 1.4 reported by Miyamoto (1983). Using remote sensing to estimate fractional cover, Samani et al. (2011) calculated monthly K_c values for three pecan orchards.

However, these values can vary quite widely for a crop as they are influenced by factors such as cultivar, orchard orientation, plant spacing, training method, irrigation method, and soil management.

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CHAPTER THREE

MATERIALS AND METHODS

3.1 The experimental site

The experiment was conducted in a pecan orchard at the Hatfield Experimental Farm of the University of Pretoria (recently renamed Innovation Africa @UP), South Africa (25°44' 55.85 S, 28°15'23.88 E, 1372 m above sea level) from March 2018 to June 2020. For validation purposes, data from the 2020/21 season was also used. The site lies in the country's summer rainfall region, which is marked by high-intensity, short-duration rain events interspersed with sunny spells. Pretoria has a semi-arid subtropical climate with long, hot summers (September to April) and brief, cold winters (from May to August). The annual rainfall averages 670 mm, with mean daily temperatures ranging from 9.7 to 21.2 °C. During the winter, frost is possible (Alemayehu et al. 2009). The pecan orchard consisted of two cultivars, 'Western Schley' and 'Wichita', which were grafted onto 'Ukulinga' rootstocks and planted in alternate rows (Figure 3.1). These trees were planted in a north-south orientation in 2006, meaning they were 12 years old at the start of the experiment. The orchard was approximately 3.4 ha and consisted of two planting densities i.e., 10 x 10 m and 5 x 10 m. Irrigation in the orchard was done using three lines of pressure compensated drippers per tree row, which were spaced 0.6 m apart and delivered 1.6 L h^{-1}. The orchard forms part of a water stress trial, where water stress was implemented at different phenological stages in various blocks. The irrigation for the control was scheduled according to readings from soil water sensors and measurements of predawn leaf water potential and midday stem water potential.

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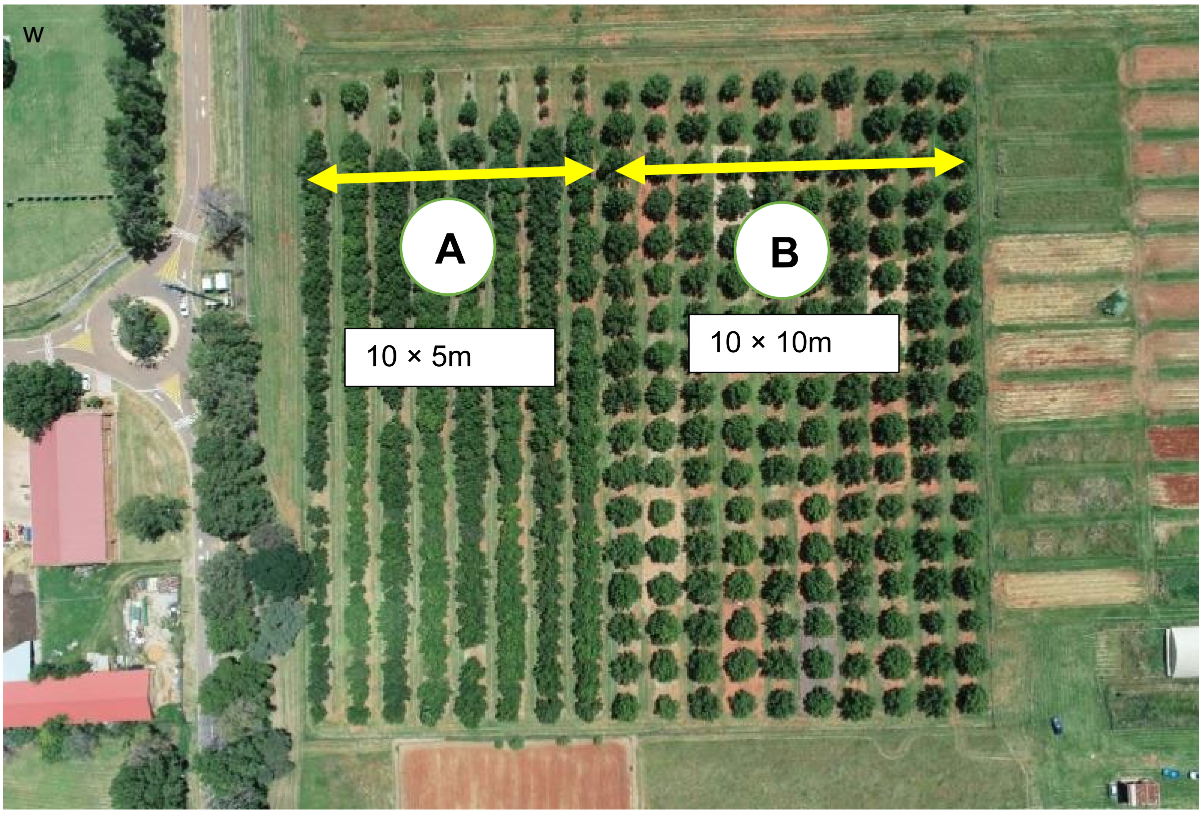

Figure 3.1 Aerial photograph of the pecan orchard at Innovation Africa @UP, showing the A) 5 x 10 m layout and the B) 10 x 10 m layout.

3.2 Measurements

3.2.1 Aerial photography and image analysis

Aerial red-green-blue (RGB) photographs were acquired using a Phantom 3 drone. For all replications, the drone was flown weekly at midday and at a height of 15 meters above the ground. The photos were processed and analyzed with the Canopeo image analysis tool, which was written in the Matlab computer language (Mathworks 2005) and used RGB colour values (Figure 3.2). The images were edited to depict each tree's specific 100 and 50 m^2 area, depending on the planting density. Canopeo was utilized to independently process the canopy photos. The Canopeo software does not have the ability to handle batches of photographs and each image was processed separately, however, each image took less than 10 seconds to process. The resulting image shows a binary image with white pixels, which can be changed using a slider bar based on the built-in, default colour threshold criteria.

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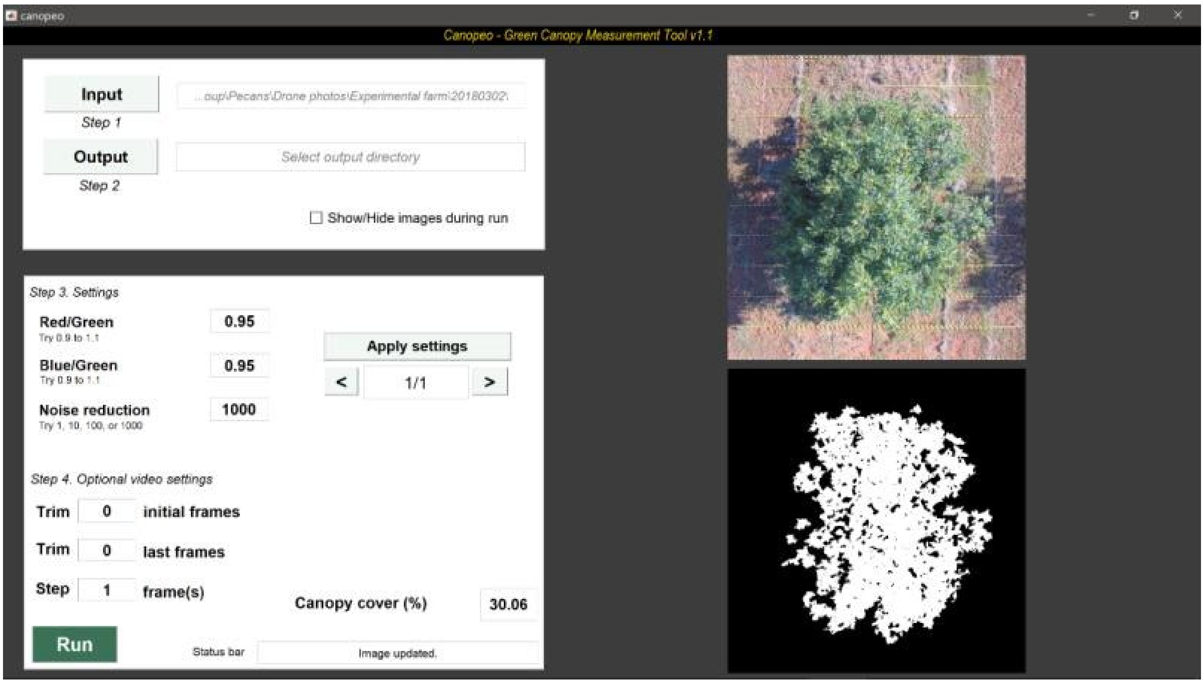

Figure 3.2 The Canopeo image analysis tool to determine canopy cover from RGB images.

3.2.2 Fractional interception of photosynthetically active radiation by the canopy

Fractional interception of photosynthetically active radiation (PAR) of the experimental trees was measured weekly at midday utilizing a Decagon AccuPAR LP-80 ceptometer (Decagon Devices now known as Meter, Pullman, WA, USA). Two measurements were taken in the open next to the orchard (to simulate above canopy measurements), and 110 measurements (in the low density orchard) and 60 measurements (in the high density orchard) were taken below the canopy. Photosynthetically active radiation was sampled below the canopy across and within the row at pre-determined 1 m intervals (covering the complete area assigned to one tree) as shown in Figure 3.3. A 10 x 10 m (in the low-density orchard) and a 5 x 10 m (in the high-density orchard) grid was laid out in all the sampling trees. Data collection was only performed under clear-sky days. The fraction of PAR intercepted by the canopy (I_c) was calculated as follows:

$$\mathbf{Ic} = \mathbf{1} - \frac{\mathbf{I}}{\mathbf{Io}} \qquad \textbf{(2)}$$

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Where I_o is the incident radiation, I is the radiation transmitted below the canopy which was calculated by averaging the readings below the canopy.

Figure 3.3 The measurement of fractional interception of PAR (FI-PAR) and the grid used to collect the data.

Fractional interception of PAR was also measured with ten 0.9 m long SQ-311-SS line quantum sensors (Apogee, North Logan, USA) installed permanently in the orchard under a single tree that was well-watered (Figure 3.4). An additional line quantum sensor was installed in an open area adjacent to the orchard to measure incoming above PAR. The sensors were connected to a datalogger (CR3000, Campbell Scientific, Logan, Utah, USA) and data was logged on the hour, every hour.

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Figure 3.4 Installation of quantum sensors in the orchards, as well as wiring the CR3000 datalogger.

3.2.3 Canopy cover calculated using shade.

Canopy cover was also determined by measuring the shaded area under the tree at midday. The diameter of the shade was measured at different points using a measuring tape and these values were then averaged to get one diameter value. In the pecan orchard, the shade was usually circular in shape and therefore the shaded area was estimated using the formula for the area of a circle as follows:

$$\textbf{Area of a circle} = \pi r^2 \qquad \textbf{(3)}$$

Where r is the radius (m).

Upon finding the area of the shade, canopy size was calculated based on the area assigned to the tree in the orchard (100 m^2 for the low density orchard and 50 m^2 for the high density orchard) for both densities, as:

$$\textbf{Canopy size} = \frac{A_x}{100} \qquad \textbf{(4)}$$

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$$\textbf{Canopy size} = \frac{\mathbf{A_x}}{\mathbf{50}} \tag{5}$$

Where A_x is the area of the shade (m^2).

These values were compared with canopy size values determined by fractional interception of PAR (ceptometer measurements), leaf area index (LAI) and the Canopeo app (aerial photography).

3.2.4 Estimation of Leaf Area Index (LAI)

Indirect LAI measurements were taken using a LAI 2000 Plant Canopy Analyzer (PCA, Li-Cor, Lincoln, NE, USA). The PCA is a device that measures how much light a fish-eye lens captures. Five concentric light-detecting silicon rings (with central zenith angles of 7°, 23°, 38°, 53°, and 68°) were employed to sample five concentric sky sectors. The LAI was estimated using an inversion model that compared the transmittances calculated simultaneously for each sky sector and measured above and below the canopy (PCA Operating Manual, Li-Cor, 1991). Measurements were taken with the same instrument in each orchard. In all of the sampling trees, a measurement cycle comprised of two reference measurements and ten below-canopy readings. Reference measurements were taken in large clearings or open areas near the experimental orchard at the beginning and end of each cycle. The instrument's fish-eye lens was covered with a 90° aperture view cap to ensure that the reference measurements were not influenced by the trees around the clearings or by the operator (Li-Cor 1992). All measurements were collected at the same level (between 1 and 1.5 m above ground) and in diffuse light, with the sun at or below the horizon, to avoid confounding brilliantly illuminated leaves with canopy gaps (Li-Cor 1992). To avoid abrupt and transitory changes in sky conditions between reference and below-canopy observations, cloudless or uniformly overcast days were also chosen.

3.2.5 Meteorological measurements

The meteorological data was provided by an automatic weather station (AWS) on the farm, which was located within 300 m of the orchard. The weather parameters that

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were recorded were wind speed, solar radiation, temperature, relative humidity, and rainfall The FAO-56 technique was used to calculate daily reference evapotranspiration (ET_o) and vapour pressure deficit during the measurement period (Allen et al. 1998a). Reference evapotranspiration was calculated using the following equation:

$$\mathbf{ET}_r = \frac{0.408\Delta(\mathrm{R_n} - \mathrm{G}) + \gamma\left(\frac{\mathrm{C_n}}{\mathrm{T_a}} + 273\right)\mathrm{u_2}(\mathrm{VPD})}{\Delta + \gamma(1 + \mathrm{C_d}\mathrm{u_2})} \quad \textbf{(6)}$$

Where ET_r is the standardized reference evapotranspiration (mm d^{-1} for daily time), Δ is the slope of the saturation vapour pressure-temperature curve (kPa°C^{-1}), R_n is the net radiation at the crop surface (MJ m^{-2} d^{-1}), G is the heat flux density at the soil surface (MJ m^{-2} d^{-1}), T_a is the mean daily temperature (°C) at 1.5-2.5 m height, u_2 is the mean daily wind speed at 2 m (m s^{-1}), VPD is the vapour pressure deficit (kPa), γ is the psychrometric constant (kPa°C^{-1}), C_n and C_d are the numerator and the denominator constants which change with the reference type and time steps (Pereira et al. 2015). The different values for C_n and C_d are shown in Table 3.1

Table 3.1 Values for C_n and C_d coefficients for calculating reference evapotranspiration on an hourly or daily basis (Pereira et al. 2015). ET_o is for the short grass reference surface and ET_r is for the alfalfa reference surface.

Time step	ET_o		ET_r		Units for ET_{ref}	Units for R_n and G
	C_n	C_d	C_n	C_d		
Hourly during daytime	37	0.24	66	0.25	mm h^{-1}	MJ m^{-2} h^{-1}
Hourly during night-time	37	0.96	66	1.7	mm h^{-1}	MJ m^{-2} h^{-1}
Daily	900	0.34	1600	0.38	mm d^{-1}	MJ m^{-2} d^{-1}

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3.2.6 Transpiration measurements

Transpiration (T) was measured using the heat ratio method (Burgess et al. 2001). In the 10 m × 10 m plot, sap flow was measured in four 'Wichita' trees. To account for radial variation in sap flux within the conducting sapwood, four probe sets, each consisting of a heater probe inserted into a 2.5 mm brass collar and two type-T copper-constantan thermocouples embedded in 2 mm PFTE tubing, were installed radially into the stem of the tree at different depths. The depths were chosen based on stem size to ensure that each probe set represented an equal amount of conducting sapwood. Thermocouples were put equidistantly upstream and downstream of the heater probe (4.65 mm). Vaseline was applied to the probes to make insertion easier and to ensure good contact with the xylem vessels as shown in Figure 3.5.

Figure 3.5 Installation of the sap flow equipment on the experimental farm.

Heat pulse velocities were recorded every hour using a CR1000 datalogger and an AM16/32B multiplexer (Campbell Scientific Inc., Logan, Utah, USA). Following the approach indicated by Burgess et al. (2001), heat pulse velocities were converted to transpiration volumes. The heat pulse velocity (V_h) was computed as per the equation created by Marshall (1958):

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$$V_h = \frac{k}{z} \ln \frac{V_1}{V_2} 3600 \tag{7}$$

Where z is the distance (4.65 mm) between the heater and the thermocouples, V_1 and V_2 are temperature rises at the same points upstream and downstream of the heater probe, k is the fresh wood thermal diffusivity (2.5 x 10^{-3} cm^2 s^{-1}) and 3600 converts seconds to hours. Correction of wounding was done using Burgess et al. (2001)'s numerical model as follows:

$$V_C = bV_h + cV_h^2 + dV_h^3 \tag{8}$$

where V_c the corrected heat pulse velocity, V_h is the heat pulse velocity and b, c and d are the correction coefficients to adjust for wound width x calculated as follows:

$$b = 6.6155x^2 + 3.332x + 0.9236 \tag{9}$$

$$c = -0.149x^2 + 0.0381x - 0.0036 \tag{10}$$

$$d = 0.0335x^2 - 0.0095x + 0.0008 \tag{11}$$

Wound widths were determined by chiselling a sample of wood from where a probe was inserted and measuring the width of the wound at its widest point. This was done for one probe set per tree. The wound widths were measured using Vernier callipers. Sapwood area was determined by allowing the tree to take up a solution of safranin injected into the tree and taking core samples with an incremental borer above the point of insertion to determine the length of stained sapwood tissue and therefore sapwood area.

Sap flux density was then computed from an equation by Marshall (1958), which was later modified by Barrett et al. (1995):

$$V_s = \frac{V_s \rho_b (c_w + m_c c_s)}{\rho_s c_s} \tag{12}$$

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where C_w =1200 J kg^{-1} ˚C^{-1} and C_s = 4182 J kg^{-1} ˚C^{-1} are respectively the heat capacities of wood and water at a temperature of 20 ˚C, m_c sapwood water content, ρ_b the wood density (g cm^{-3}) and ρ_s the density of water (g cm^{-3}).

Other parameters essential to convert heat pulse velocities to transpiration volumes comprised wound width, sapwood density (ρ_b), the water content of the sapwood (m_c), and the area of conducting sapwood. The wound widths were measured at four positions across the length of the wound created by sensor implantation using Vernier callipers. The mean values of the wound widths were 2.95 mm with a standard error in the mean (SEM) of ±0.11 mm. The density of the sapwood was calculated as per Burgess et al. (2001):

$$\rho b = \frac{wd}{vf} \quad (13)$$

where wd is the oven-dried wood mass (kg) and vf is the volume (m^3) of the freshly excised sample of wood. The volume of the sample of wood was determined by immersing the sample in water and applying the Archimedes principle. Sapwood water content was calculated as per Burgess et al. (2001):

$$m_c = \frac{wf - wd}{wd} \quad (14)$$

where wf is the fresh mass of a freshly excised wood sample from three trees alongside the sample trees.

The area of conducting sapwood was determined by injecting safranin solution into the scion above the rootstock. Wood cores were then extracted a short distance above the dye injection location with the use of an incremental stem borer, approximately 40 min after the dye injection began. The conducting sapwood was visible on the cores by the methylene stain, and as a result, the heartwood was also observed. Wounding correction was also performed as illustrated in figure 3.6.

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Figure 3.6 Wound correction was performed by peeling the bark, then measured the wound diameters in order to convert heat pulse velocity into sap flux density and sap flow.

Water use measurements were compared with canopy size measurements to evaluate if changes in canopy size using aerial photography and image analysis can be used to adjust transpiration crop coefficients (K_t). The K_t values were determined from measured tree T as the ratio between transpiration (mm d^{-1}) and ET_0 (mm d^{-1}) as:

$$\mathbf{K_t = \frac{T}{ET_o}} \qquad \textbf{(15)}$$

where K_t is the transpiration crop coefficient, T is transpiration estimated from sap flow measurements and ET_o is reference evapotranspiration. Weekly crop coefficients were calculated from weekly totals of measured daily orchard transpiration and ET_o.

3.2.7 Thermal time

Daily minimum and maximum temperature data were obtained from the automatic weather station on the Hatfield Experimental Farm. Thermal time was calculated using

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daily minimum and maximum temperatures and a base temperature of 15.5ºC (as reported by Miyamoto (1983) for pecans) using the formula:

$$\mathbf{GDD} = \frac{\mathbf{Tmax} + \mathbf{Tmin}}{\mathbf{2}} - \mathbf{15.5°C} \tag{16}$$

Where GDD is growing degree days.

This measurement was used to assess if the temperature is a major driver of canopy development and canopy decline by comparing GDD against the fractional cover.

3.2.8 Chill unit accumulation

Chill units were calculated from May to August, for the 2018/19, 2019/20 and 2020/21 seasons .The daily positive chill unit model of Linsley-Noakes et al. (1995) was used to calculate chill unit accumulation according to Table 3.2. The AWS on the Hatfield Experimental Farm' provided hourly weather data for the two seasons. Daily values were accumulated and if the value was less than 0, the value for the day was assumed to be 0.

Table 3.2 Chill units associated with specific hourly average temperatures (Richardson et al. 1974).

Temperature (˚C)	Unit h^{-1}
<1.4	0
1.5 – 2.4	0.5
2.5 – 9.1	1
9.2 – 12.4	0.5
12.5 – 15.9	0
16.0 – 17.9	-0.5
>18	-1.0

3.2.8 Leaf water potential

Water status of the trees was assessed through the measurements of midday leaf water potential on the middle tree of the well-watered trees in the 4 replications every

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5–6 days. Two leaves were cut off the tree from inside the canopy as close to the trunk as possible, and four from all cardinal points outside the canopy and put in a pressure chamber (model 3005, Soil moisture Equipment Co., Santa Barbara, CA) immediately after cutting. Measurements were taken at midday between 12:00 and 14:00.

Likewise, pre-dawn and midday stem leaf water potential were determined using the same procedure. However, for midday stem water potentials leaf samples were selected from the inside of the canopy only, enclosed in a plastic bag and were covered with aluminium foil for a period of 30 – 60 minutes before being picked. This was to stop the leaves from transpiring and allowing them to equilibrate to the water potential of the stem before water potential was determined (Scholander et al. 1965). The purpose of this measurement was to evaluate plant water status and then use this measure to confirm that the plants were unstressed since leaf water potential measures the integrated effect of soil, plant, and atmospheric conditions on water availability within the plant itself.

3.2.9 Model performance

The Willmott index of agreement (D), mean absolute error (MAE), root mean square error (RMSE), coefficient of residual mass (CRM), and coefficient of determination were used to evaluate the model's performance (R^2). The index of agreement is a measure of the degree to which the model predictions (observed vs. estimated) are accurate (Willmott 1981), whilst MAE, RMSE and CRM are residual based measures that give a quantitative estimate of the deviation of the modelled outcome from the observed data set (Abraha and Savage 2010, Bellocchi et al. 2011). The coefficient of determination (R^2) is a correlation measure which describes the goodness-of-fit of a model. According to Bellocchi et al. (2011), R^2 and D values range between 0 and 1, which demonstrates the worst and best model performance values respectively. The Mean absolute error ranges from 0 to infinity, with 0 denoting the best model performance. The coefficient of determination (R^2) and D should be more than 0.8, and MAE (stated as a percentage) should be less than 20% for these statistical indices. Positive and negative numbers imply underestimation and overestimation of the model, respectively. The CRM optimal value is zero. The statistical indices computation algorithms are listed below.

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$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathbf{Pi} - \mathbf{Oi})^2}{\mathbf{n}}} \quad \textbf{(17)}$$

$$\mathbf{MAE} = \frac{\left(\frac{1}{n}\right)\sum_{i=1}^{n}|\mathbf{Pi} - \mathbf{Oi}|}{\mathbf{O}} * 100 \quad \textbf{(18)}$$

$$\mathbf{D} = 1 - \frac{\sum_{i=1}^{n}(\mathbf{Pi} - \mathbf{Oi})^2}{\sum_{i=1}^{n}(|\mathbf{Pi} - \mathbf{Oi}| + |\mathbf{Oi} - \mathbf{O}|)^2} \quad \textbf{(19)}$$

$$\mathbf{CRM} = 1 - \frac{\sum_{i=1}^{n}\mathbf{Oi} - \sum_{i=i}^{n}\mathbf{Pi}}{\sum_{i=1}^{n}\mathbf{Oi}} \quad \textbf{(20)}$$

Where Pi and Oi are the estimated and measured values of the fraction of PAR interception; n is the number of observations (pairs of data both estimated and measured values), and O is the mean of the measured values.

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CHAPTER FOUR

CANOPY SIZE AND CANOPY DEVELOPMENT OF PECAN TREES

4.1 Introduction

Quantifying the canopy size of trees in orchards is important for several management practices, which include scheduling of irrigation and determining spray volumes for pesticides and foliar application of nutrients. Using estimates of canopy size to determine orchard specific crop coefficient (K_c) values has been demonstrated by Allen et al. (1998) and Allen and Pereira (2009), whilst other studies have shown very good relationships between K_c values and fractional interception of photosynthetically active radiation (PAR) (Ayars et al. 2003b, Girona et al. 2011). The quantification of canopy size and development in non-homogeneous agricultural systems including orchards, vineyards, and woods is a difficult undertaking (Pilau and Angelocci 2015). This is due to the complex canopy structures. As a result, it is the reliable and relatively cheap estimation of canopy size that has proven problematic. However, finding a balance between simplicity and accuracy in quantifying canopy size is still an area of debate for many researchers (Green et al. 2003).

Numerous tools for direct and indirect measurement of canopy size were described by Goel and Norman (1990). Major drawbacks of direct methods are errors in spatial sampling and the measurements are often time consuming and have specific labour requirements. In addition, for fairly accurate estimates, expensive equipment was required, which require time consuming measurements. Furthermore, Tu et al. (2019) indicated that visual canopy assessments are often subjective and can be inconsistent. The introduction of precision agriculture in modern orchards is severely hampered by these shortcomings. There is therefore a lack of tools that can be readily employed by growers to determine canopy size with a good degree of accuracy. Given the importance of the canopy size in determining water use, irrigation managers and researchers require a reliable and cost-effective method for assessing and monitoring the temporal and spatial changes in the canopy structure. The use of remote sensing and digital image processing may offer a solution to this dilemma.

In this chapter, it was hypothesised that the use of photographs captured from above the canopy and image analysis (Canopeo App which selects green pixels) could

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provide reliable estimates of canopy size, as compared to measurements of fractional interception of PAR by the canopy, canopy cover calculated using shade, and the estimation of leaf area index from below the canopy using gap fraction analysis. To test this hypothesis canopy cover was determined from aerial photographs of the orchard using the Canopeo App and compared to direct ground estimates of canopy size.

4.2 RESULTS

4.2.1 Canopy cover estimated using Canopeo application.

From weekly estimates of canopy cover using the Canopeo App, it was evident that there was rapid canopy development following bud break in September 2018 in both the low density and high density orchards, with canopy cover doubling in the second week of measurements (Figure 4.1 A and C). Canopy cover in the low density orchard became stable towards the middle of November 2018 reaching 0.46, as shoot growth slowed down (Figure 4.1 A). However, canopy cover in the high density orchard continued to increase until March 2019 when maximum canopy cover (0.66) was reached (Figure 4.1 B). Canopy cover gradually decreased in both orchards from March 15, as leaf senescence started, and the trees entered dormancy. Using this method, leaf senescence was observed to start in mid-March 2019 in the low density and on April 10 in the high density, lasting up until June when the trees were leafless. The most rapid leaf senescence was observed in the months of March and April. In the second season, canopy development was rapid soon after budbreak in September 2019. However, the maximum canopy cover (0.52 and 0.71), determined using the Canopeo App, was slightly higher in 2019/20 as opposed to the 2018/19 season. Unfortunately, due to the COVID-19 level 5 lockdown, the start of leaf senescence and the rate thereof could not be determined in the second season, as manual measurements during this time were not possible. The maximum canopy cover was 0.52 and 0.71 (Figure 4.1 AB) for the consecutive seasons in the low density orchard, with a maximum of 0.66 and 0.71 (Figure 4.1 CD) in the high density orchard. Importantly, very low canopy cover values, which were close to zero, were recorded at the beginning and end of the season when the trees were leafless. Looking at the figure below, there seemed to be a continual growth of the canopy, caused by new canopy flushes, as pecans can have more than one growth flushes.

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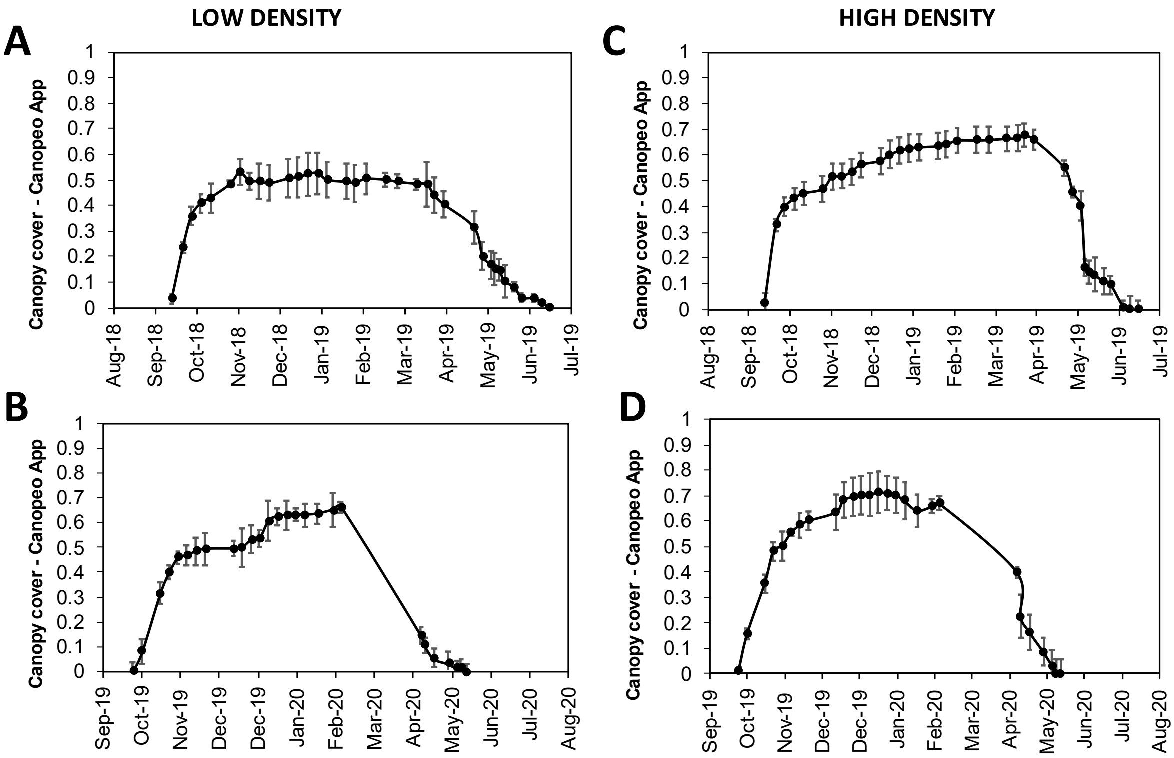

Figure 4.1 Estimates of pecan canopy cover using the Canopeo App during the A and C) 2018/2019 season and B and D) the 2019/2020 season, for 'Wichita' trees in A and B) the low density orchard (10 x 10 m planting) and C and D) the high density orchard (10 x 5 m planting). All measurements were for 'Wichita' trees. Each data point represents an average of four trees ± standard deviation indicated by the vertical error bars. The missing data in the 2019/2020 season from March to the end of April was a result of the level 5 COVID-19 lockdown.

4.2.2 Fractional interception of photosynthetically active radiation (FI-PAR) determined using a ceptometer

Figure 4.2 depicts results of PAR intercepted by pecan trees (FI-PAR) on clear sky days for two consecutive growing seasons (2018/2019 and 2019/2020) at the Innovation Africa@UP. The results follow a similar trend to canopy cover determined from aerial photographs and the Canopeo App, with FI-PAR rapidly increasing in spring and declining in autumn (Figure 4.2). At the start of the 2018/2019 season, FI-PAR was 0.07 in the low density orchard and 0.05 in the high density orchard. As the canopy developed, FI-PAR reached a maximum value of 0.42 in January 2019 in the low density orchard and 0.52 in February in the high density orchard. Canopy size

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remained relatively constant in both orchards from November to late March 2019, when the trees started losing leaves. At the end of the season (June 2019), when the trees were leafless the fraction of intercepted PAR was 0.08 in the low density and 0.05 in the high density. In the 2019/20 season, the highest FI-PAR value being 0.59 in March in the low density orchard and 0.57 in February in the high density orchard. Missing data from March 2020 was because of the global pandemic, as mentioned above. This made it impossible to track the starting date of canopy senescence. At the end of the season, FI-PAR was found to be 0.08 and 0.04 for the low density and high density orchards, respectively.

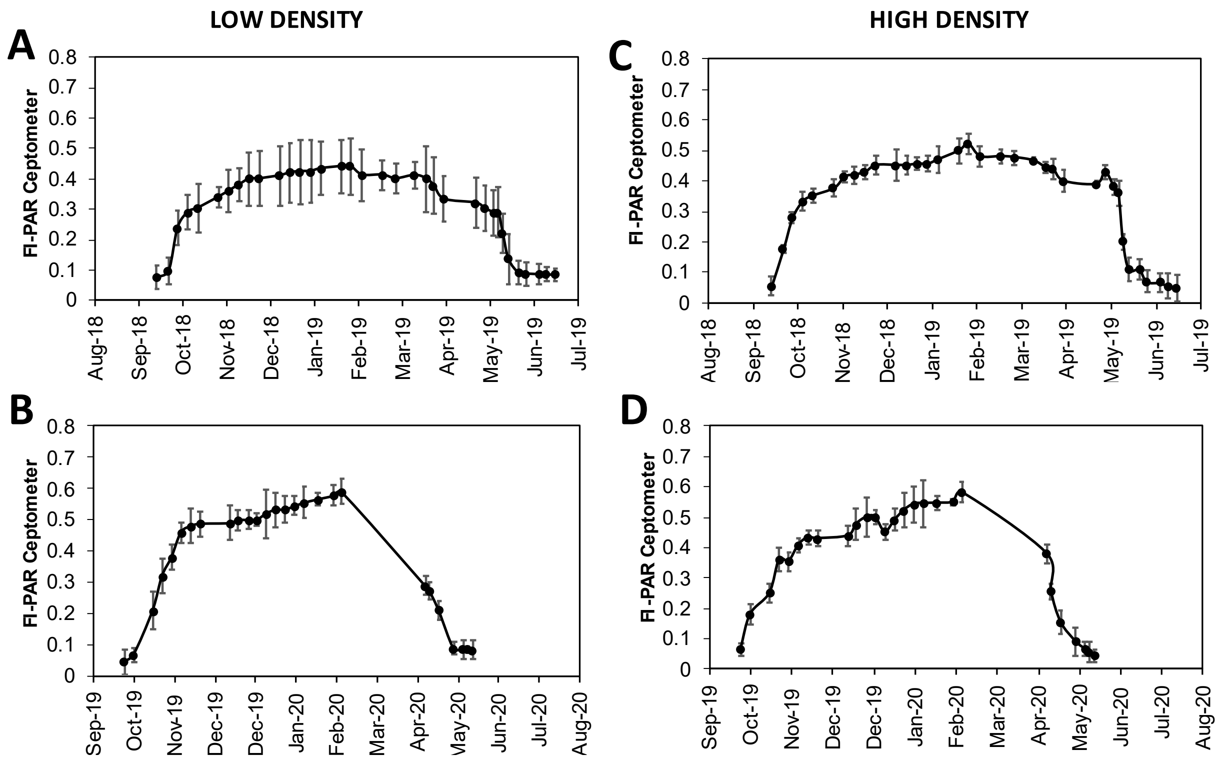

Figure 4.2 Fractional interception of photosynthetically active radiation (FI-PAR) during the A and C) 2018/2019 season and the B and D) 2019/2020 season, for 'Wichita' trees in the A and B) low density and C and D) the high density orchards. Each data point represents an average of four trees ± standard deviation indicated by the vertical error bars. The missing data in the 2019/2020 season from March to the end of April was a result of the level 5 COVID-19 lockdown.

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4.2.3 Leaf area index determined using the LAI2000

Figure 4.3 shows the LAI for both planting densities in the two seasons. In the 2018/2019 season, data collection only started on October, due to the unavailability of the LAI2000 at the start of the season. In October, the LAI was 2.3 $m^2 m^{-2}$ in the low density orchard and 2.4 $m^2 m^{-2}$ in the high density orchard. From this point LAI increased steadily with maximum values (5.2 $m^2 m^{-2}$ for the low density orchard and 6.4 $m^2 m^{-2}$ for the high density) reached in January and remained fairly constant until the end of April (Figure 4.3 A and C) for the 2018/2019 season. A decline in LAI was observed late in April for both planting densities, which was a month later than the decline in canopy cover result using the Canopeo App. When the trees were leafless at the end of the season, values of 0.9 $m^2 m^{-2}$ and 1.2 $m^2 m^{-2}$ were obtained for the low density and high density orchards, respectively. During the two growing seasons, the LAI for both densities rapidly increased from budbreak stage to the nut filling stage and decreased drastically towards the late growth stage with a major drop when the plants were losing leaves, signalling that dormancy was approaching. Budbreak couldn't be tracked in the first season, as mentioned in chapter 3, whereas in the second season it occurred from 26 September for both orchards. The average leaf area index for trees in the high density orchard ranged from 2.97 $m^2 m^{-2}$ in spring (October) to 6.4 $m^2 m^{-2}$ in summer (December), to 1.4 $m^2 m^{-2}$ in late autumn (May - leafless). In the 2019/2020 season the maximum values of LAI were 6.1 $m^2 m^{-2}$ in the high density orchard (Figure 4.4 B) and 5 $m^2 m^{-2}$ in the low density orchard (Figure 4.3 D). The decline in LAI started in May 2020, with values of 0.95 $m^2 m^{-2}$ and 1.2 $m^2 m^{-2}$ in June for the low density and high density orchards, respectively. This decline was abrupt.

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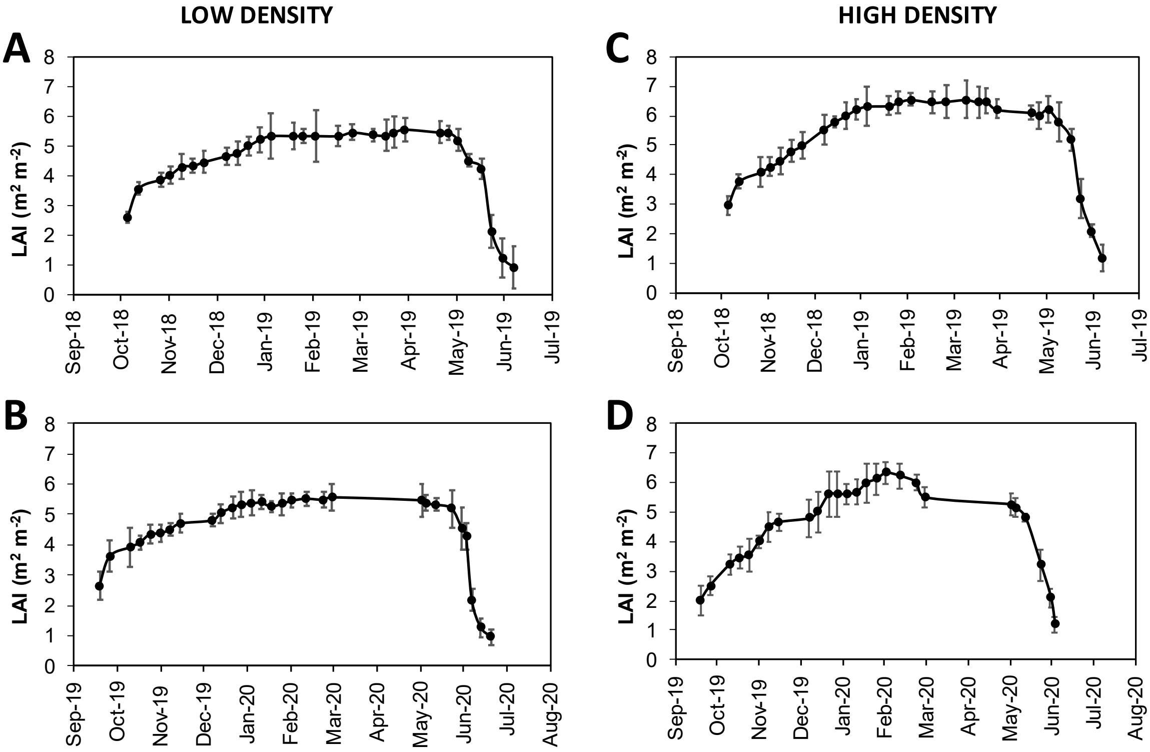

Figure 4.3 Average leaf area index (LAI) ± standard deviation for the A and C) 2018/2019 season and the B and D) 2019/2020 season, for 'Wichita' trees in the A and B) low density and C and D) the high density orchards. Each data point represents an average of the four trees ± standard deviation indicated by the vertical error bars. The missing data in the 2019/2020 season from March to the end of April was a result of the level 5 COVID-19 lockdown.

4.2.4 Canopy cover calculated using shaded area.

At the start of the season in spring), the angle of the sun at solar noon (referred to as solar declination), was lower than in the middle of summer. For this reason, the size of the shade at solar noon will be influenced by the time of year, with the highest values found during the summer solstice, when the sun is directly above. The canopy cover calculated by estimating the shaded area under a tree at solar noon increased from 0.01 in September 2018 reaching the highest value of 0.59 in February 2019 (Figure 4.4 A). As illustrated in Figure 4.4 the values increased immediately after bud break to February and decreased linearly starting from May which coincided with leaf senescence and leaf drop. Leaf senescence lasted for about 2 months. In the

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2019/2020 season, canopy development started in mid-September, growing linearly until reaching a maximum value of 0.55 in mid-January. Due to the COVID-19, it was not possible to capture the start of leaf senescence in the second season.

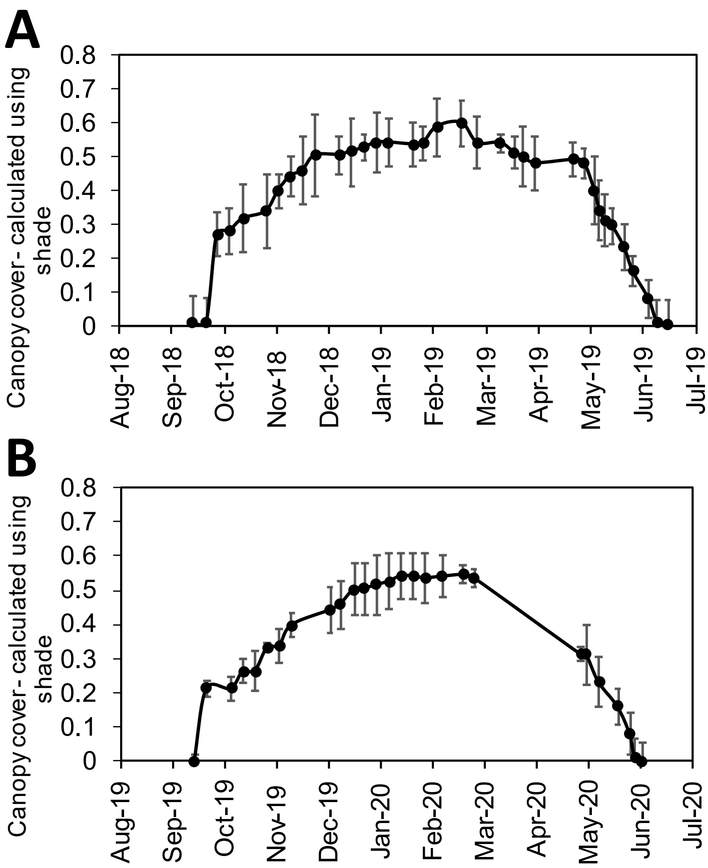

Figure 4.4 Canopy cover calculated as the fraction of shaded area by the canopy at solar noon for 'Wichita' trees in the low density orchard for (A) the 2018/2020 season and (B) the 2019/2020 season. Each data point represents an average of four trees ± standard deviation indicated by the vertical error bars. The missing data in the 2019/2020 season from March to the end of April was a result of the level 5 COVID-19 lockdown.

4.2.5 Hourly estimation of radiation interception (Quantum sensors)

The measured hourly FI-PAR is shown in Figure 4.5 for four different dates in 2019. The results showed a diurnal pattern in PAR interception by the tree, that is represented by an inverted bell-shaped curve, with high interception in the morning and afternoon, and the lowest interception at midday. Based on data collected from different stages of canopy growth, it was evident that the diurnal trend of FI-PAR

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remained unchanged over time during a growing season, however, the magnitude changed. In March 2019, the midday FI-PAR was found to be 0.45. As early as 06h00, the canopy intercepted the 90% of incoming PAR. This decreased as the day progressed reaching the lowest value (45%) at solar noon and starting to increase again towards the end of the day. In May 2019, leaf senescence had already started and at the start of the day the canopy intercepted 60% of incoming PAR, dropping to 30% at midday and again increasing towards the end of the day. Bud break was observed on 26 September in the 2019/2020 season, with the canopy intercepting 30% on incoming PAR in the morning, reaching 10% at midday. In November, when significant canopy growth had occurred, the canopy intercepted 59% of incoming PAR, reaching 35% at midday.

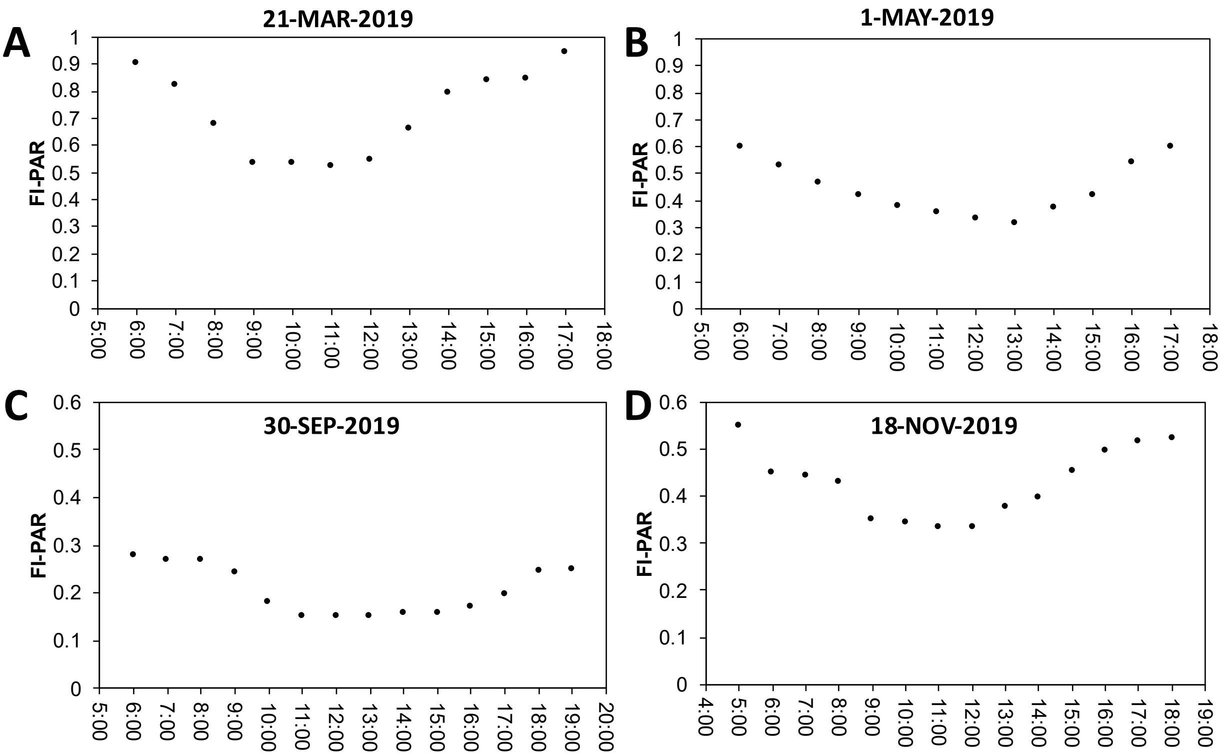

Figure 4.5 Diurnal variation of hourly fractional interception of photosynthetically active radiation (FI-PAR) for a 'Wichita' tree in the low-density orchard for different dates (A, B, C and D). Data was collected using logging quantum sensors installed in 2019. Solid circles represent measured FI-PAR.

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4.2.6 Daily estimation of PAR interception (Quantum sensors)

Measurements of daily fractional interception of PAR (FDIPAR) are shown in Figure 4.6. Unfortunately, these sensors were not always available for measurements in the pecan orchard, hence the missing data. Also, during the COVID-19 lockdown level 5 it was impossible to change batteries for the logger, resulting in missing data. Shortly after installing the sensors in the orchard in 2019 values of FDIPAR were starting to drop as leaf senescence had begun (Figure 4.6 A). Values decreased linearly from 0.62 in mid-March, reaching 0.15 in June when the trees were completely leafless. The sensors were again installed at the beginning of the 2019/2020 season (Figure 4.6 B), when bud break occurred in September. The FDIPAR values were 0.15 at the start of the season when the canopy had just started developing. The canopy steadily increased as the season progressed, with the highest FDIPAR value (0.46) found in mid-November. Even though it impossible to determine the start of leaf senescence, due to the COVID lockdown, the trend in FDIPAR followed the trend of the other methods employed. Figure 4.6 C shows FDIPAR for the 2020/2021 season. At the beginning of the season, FDIPAR was 0.18, reaching a maximum of 0.71 in February during the nut sizing stage. The rapid canopy development lasted from end of September to 15 December. The canopy started to senesce in late March becoming leafless in June. The rate of canopy decline was rapid, from 25 March to 6 June. There was missing data from December to early February as the sensor in the open was stolen.

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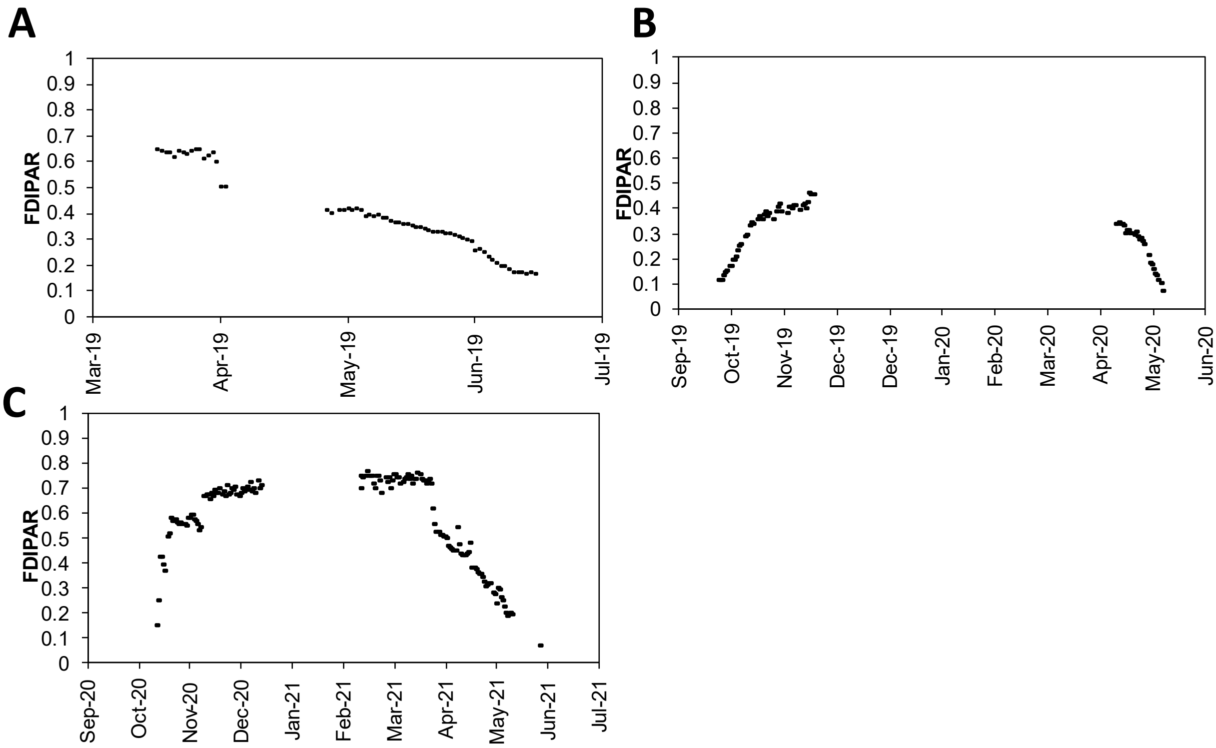

Figure 4.6 Daily fractional interception of photosynthetically active radiation (FDIPAR) measured using line quantum sensors under a single 'Wichita' tree in the low density orchard. Measurements were collected during the A) 2018/2019, B) 2019/20 and C) 2020/21 seasons. The missing data was due mainly due to sensor availability, and the level 5 COVID-19 lockdown when batteries could not be replaced.

4.2.7 Comparison of the different methods for determining canopy size

There was a good relationship between the Canopeo app and FI-PAR estimated using the ceptometer, with an R^2 value of 0.85 and a slope of 0.7 (Figure 4.7 A). The slope suggests that estimates of canopy cover by the Canopeo App were slightly higher than estimates using a ceptometer. Whilst there was good agreement between the measurements at high values of canopy cover, there was poor agreement between the two methods of estimation at low canopy cover (<0.4). The linear regression between the Canopeo App and the estimated area shaded by the canopy resulted in a slightly lower R^2 value of 0.70 (Figure 4.7 B), with greater disagreement between measurement methods at low canopy cover values (<0.4). The poorest relationship was found between canopy cover determined using the Canopeo App and LAI, with an R^2 value of 0.56 (Figure 4.7 C). Once again there was a strong disagreement

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between the two measurement methods when LAI was low, but even at higher LAI values there were discrepancies. There was a strong linear relationship between FI-PAR determined using a ceptometer and the estimated area of shade under a canopy, with an R^2 value of 0.83 (Figure 4.7 D). The relationship in Figure 4.7 D was shown to illustrate the ability of canopy cover determined by estimating the shaded area by the canopy to provide accurate estimates of canopy cover. This method was tested as it is cheaper and easier for a grower to perform than measurements requiring expensive equipment.

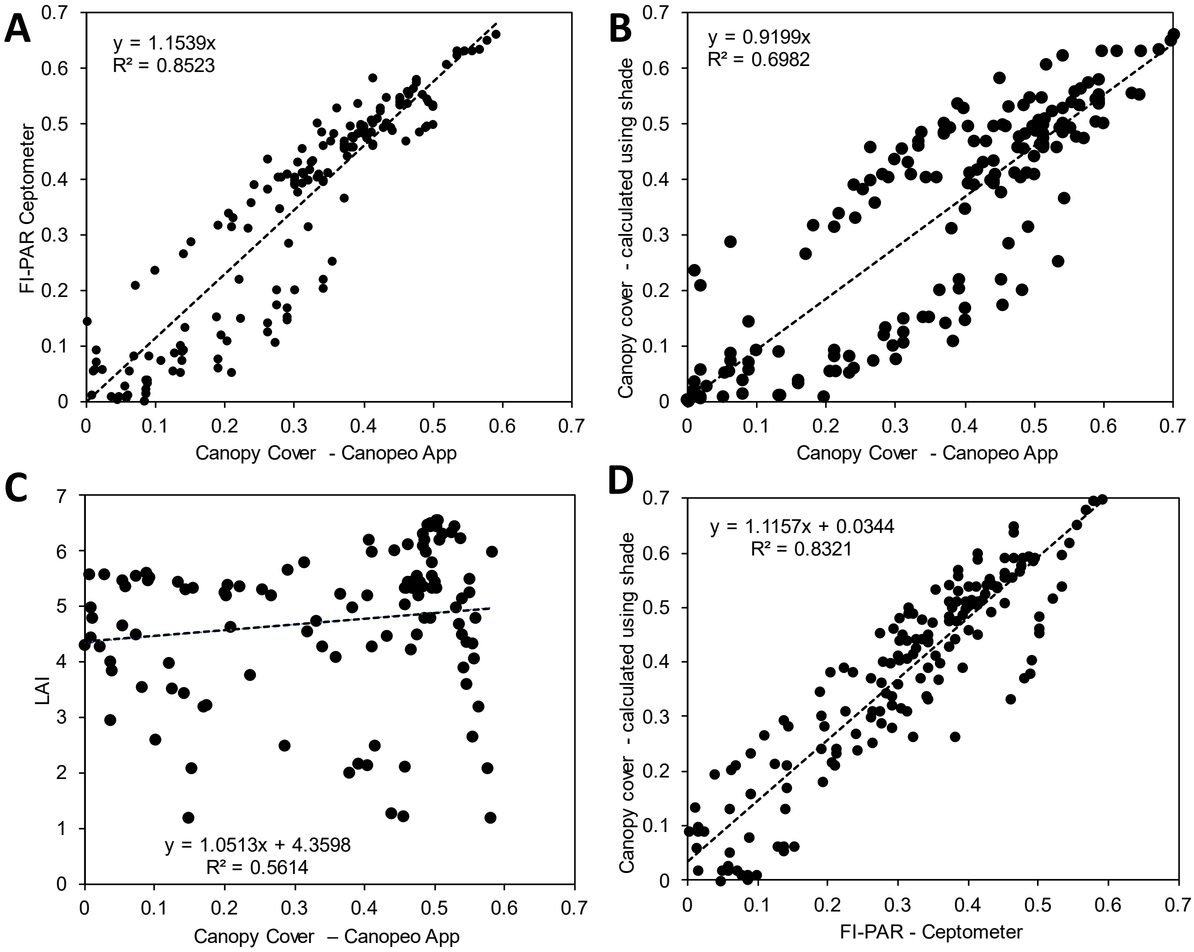

Figure 4.7 Correlation between (A) fractional interception of PAR (FI-PAR) determined using a ceptometer and canopy cover determined using the Canopeo App from aerial images, (B) canopy cover determined as the shaded area and using the Canopeo App, (C) LAI determined using a LAI2000 plant canopy analyser and canopy cover determined using the Canopeo App and (D) FI-PAR determined using a ceptometer

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and canopy cover determined using the shaded area. Data from both the 2018/2019 and 2019/2020 seasons in the low density orchard were combined for the analysis.

DISCUSSION

This study assessed the use of photographs captured from above the canopy and image analysis (Canopeo App which selects green pixels) to provide reliable estimates of canopy size over the season, with the main intention of being able to estimate water use of specific orchards. A reliable method that accurately quantifies the green leaf area over a season is needed because If canopy size is overestimated, water use will also be overestimated and vice versa.

In general, FI-PAR (ceptometer) compared well with the canopy cover determined using the Canopeo App especially in the middle of the season when the canopy was almost fully developed. However, for periods with low canopy cover, at the beginning of the season and when leaf senescence starts, there were discrepancies, causing significant scatter when the two methods were compared. During these periods the ceptometer measurements of FI-PAR tended to be higher than the Canopeo estimates of canopy cover. Such discrepancies may be explained by the fact that measurements of FI-PAR using a ceptometer cannot distinguish between leaves and branches, and this could have contributed to the higher values of FI-PAR at the beginning and end of the season. As a result, this method likely overestimates canopy size when the leaf area is very low. The use of a ceptometer to measure radiation interception in a sampled square grid can be inaccurate as it relies on the uniformity of leaf area in a 10 m x 10 m square, therefore if the canopy exhibits high foliage clumping, the instrument can overestimate FI-PAR (Johnson et al. 2010). This suggests that a critical number of samples must be taken to avoid the risk of overestimating FI-PAR, particularly under low LAI conditions, resulting in very laborious measurements. Furthermore, the PAR sensors on the ceptometer are sensitive and a slightly incorrect positioning of the instrument may lead to measurement errors. As the efficiency of the four different canopy-measurement approaches were directly tested in this study, it was clear that the ceptometer technique took the longest to complete measurements. It took more than one hour to carry out field measurements in the eight sample trees, whereas acquiring images for a 3-ha area took less than 15 minutes, whereafter the

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analysis could be performed at any time and took approximately more or less a minute per image.

The comparison of canopy cover using the Canopeo App and LAI, as noted with FI-PAR, revealed significant scattering at the start and end of the season, which was most likely because the method for measuring LAI does not distinguish between leaves and branches, which in turn causes the LAI to be overestimated when leaf area is low. Therefore, the weak correlation between the two measurements could be a result of such inaccuracies. Although commercial sensors for the indirect determination of LAI, such as the LAI-2000 plant canopy analyzer (Li-Cor, Inc., Lincoln, NE), have shown good performance, especially in homogeneous canopies (such as field crops), leaf area index measurements in fruit tree orchards are associated with a degree of error (Welles and Norman 1991, Villalobos et al. 1995, Welles and Cohen 1996). Significant inaccuracies are common when there are huge gaps in the vegetation (e.g., developing row crops, tree plantations) or when the leaves are not placed randomly. Measurements of the LAI2000 are technical and large user errors can result if not performed properly.

The Canopeo App gave a fairly good correlation when tested against the canopy shade method, as this yielded an R^2 value of 0.70. This relationship was, however, only good when the canopy had fully developed, otherwise significant scatter was observed at the start and the end of the season. Canopy shade diameters were measured using a tape measure and the last branch was considered to determine the lengths in the current study, which proved to be a useful method. The shade of the trees was calculated with the principle that any amount of solar energy that is obscured or reflected by vegetation is defined as shade. When the trees were leafless, a zero value was assumed, bearing in mind that the manner in which the shaded area was determined did not take into account canopy porosity. This method relies on solar angles as well as mathematical calculations based on an assumption of the canopy shape. This is the biggest limitation because porosity variations are a priority to assess a correct leaf area distribution in the canopy. This method lends itself more to evergreen orchards. Verma et al. (2016) in Eucalyptus and Castillo-Ruiz et al. (2016) in olive trees came to similar conclusions. These authors claimed that utilizing basic tape-measure or manual procedures to monitor canopy structures (dimensions) in orchards can be inaccurate, especially as the canopy expands into an irregular shape.

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This method is most suitable for the middle of the season when the canopy cover is at a maximum not at the start and end of the season.

Aerial photography needed careful calibration of the drone in order to get good quality pictures of the canopy. Aerial photography also necessitates a significant amount of time to evaluate the photographs after they have been collected in the field to determine their quality and reliability. It is a simple affair to set the drone and capture an image of the canopy overhead once the analysis program and camera have been calibrated. It took a few seconds to get results from the Canopeo App. Remote sensing may become a more popular and appropriate method for estimating canopy cover in the future as it is less laborious yet gives out appropriate results. An important limitation for this method is that it cannot differentiate crops from ground cover which can lead to overestimation of canopy cover. For accurate estimates the area within the tree row should be kept clean of other vegetation such as weeds.

CONCLUSIONS

A simple method (Canopeo application) to estimate canopy size was tested in this study to track the canopy development of pecan trees over two seasons. From the present study, it can be concluded that the use of photographs captured from above the canopy and image analysis (Canopeo App which selects green pixels) can provide reliable estimates of canopy size, as compared to measurements of fractional interception of photosynthetically active radiation (PAR) by the canopy, canopy cover calculated using shaded area, and the estimation of leaf area index using gap fraction analysis. Recognizing the fact that the Canopeo App followed the same trend in estimating canopy size when compared with existing methods suggests that it can be a powerful tool for growers in a wide range of commercial orchards, as it selects green pixels of a canopy. Therefore, from a practical standpoint, orchard managers could estimate canopy size throughout a season using this application. It is important to highlight that the measurements of FI-PAR, LAI, and canopy shade are invaluable methods for estimating canopy size but can tend to overestimate during the start and the end of the season, whereas the Canopeo App analyses and classifies green pixels in the canopy. Also, measurements of FI-PAR using a ceptometer and LAI are typically expensive, labourious, and can be complicated to use while the Canopeo App is a

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cost-effective and less labourious method for assessing and monitoring the temporal and spatial changes in the canopy structure.

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CHAPTER FIVE

CANOPY SIZE IN RELATION TO THE WATER USE OF PECAN TREES

5.1 INTRODUCTION

South Africa is mainly characterized by arid and semi-arid climates, thus irrigation is important for crop production in many parts of the country (Bennie and Hensley 2001, Maccarty 2001). Poor irrigation water management and dry spells (drought) are some of the main factors influencing the decline in food production and yields in the world (Jovanovic and Stikic 2012). In water-limited regions, it is becoming more important to have good estimates of water use and its components to manage water resources better (Kool et al. 2014). These estimates are increasingly important for irrigation system design, for government authorities to give out fair water use licenses and for growers to make decisions on possible expansion of their operations. Water use or evapotranspiration (ET) of agricultural systems consists of two main components, which is the combined water loss in vapour from a crop through evaporation from the soil (E_s) and through plant transpiration (T) (Allen et al. 1998a). Transpiration is related to productivity; therefore, it is important to understand the factors determining transpiration rates to ensure that transpiration can be maximised in production systems. With a thorough understanding of the governing factors, an appropriate modelling approach can also be chosen that will allow the extrapolation of measured data to a wide range of conditions. This kind of information is increasingly important to the pecan industry in most parts of South Africa, as these areas are often subjected to recurrent drought, which is predicted to intensify in the future (Clark 2020). Providing good estimates of water use for different regions and orchards is, therefore, key to the future sustainability of the pecan industry.

One of the most extensively used models to estimate crop water use is the crop coefficient approach of Allen et al. (1998a). This model has gained popularity due to its relatively simple approach, which still provides robust estimates of ET. This approach involves estimating crop ET by multiplying the reference evapotranspiration (ET_o) by a single crop coefficient (K_c). Crop ET estimates based on this method represent ET rates under well-watered, optimal management conditions (Allen et al. 1998a). Through the determination of crop coefficients, comparisons of water use of

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different orchards in different regions are possible, as crop coefficients normalise tree water use for weather, by dividing evapotranspiration by ET_o. However, in order to obtain orchard specific crop coefficients an adjustment needs to be made for canopy size. Several authors have suggested a relationship between canopy cover and crop coefficients, with good relationships found between midday canopy light interception and crop coefficients in peaches (Johnson et al. 2000, Ayars et al. 2003b), grapevine (Williams and Ayars 2005) and apple (Auzmendi et al. 2011), just to mention a few. Such a relationship may provide a simple method for estimating orchard specific K_c or transpiration crop coefficient (K_t) values using easily obtainable canopy size measurements.

Ibraimo et al. (2016) evaluated a pecan specific model, where K_c values of a mature pecan orchard ($K_{c\text{-}ref}$) are adjusted for canopy cover and local conditions, using an empirical K_c – growing degree day (GDD) relationship, to determine orchard specific K_c values based on canopy size. The relationship between GDD and K_c values derived by Sammis et al. (2004b) in New Mexico were used to adjust K_c values for the pecan orchard in Cullinan and were found to perform adequately. However, the ability of this simple empirical relationship to predict K_c values in some of the hotter production regions was questioned and therefore a more reliable method for determining how canopy growth differs with climate needs to be determined. As local temperatures are predicted to impact budbreak and the rate of canopy growth at the start of a season (Sparks 1993), it may be possible to determine the rate of development using chill unit accumulation during winter and GDD at the start of the season. In addition, the start of leaf senescence and the rate of leaf abscission at the end of the season may also be predicted through the determination of thermal time (Kim et al. 2020). This would allow the crop coefficient curve for pecans to be adjusted for different growing regions based on measurements of temperature in a region.

Consequently, the main objective of this chapter was to determine the relationship between K_t values and canopy size, determined using a number of different methods and if canopy growth at the start of the season and senescence at the end of the season can be predicted with thermal time or GDD. It was hypothesised that a positive linear relationship would exist between canopy size and transpiration crop coefficients of unstressed pecans trees, and as a result, simple estimates of canopy cover could be used to derive transpiration coefficients for various orchards. It was also

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hypothesised that the interaction between chilling and heating would be the main factors determining the rate of canopy growth at the start of the season and therefore thermal time and chill unit accumulation can be used to predict the rate of canopy development. In addition, it was proposed that the decline of the canopy can be predicted with thermal time because it is closely linked to the accumulation of heat units by the plant.

Full details of the materials for each measurement used in this chapter are provided in chapter 3.

5.2 RESULTS

5.2.1 Weather Variables

Weather variables driving crop ET were monitored at the site for the duration of the study. Hourly values were aggregated into daily averages for the period of May 2018 to August 2020 (Figure 5.1). The site experiences summer rainfall, with 500 mm measured in the 2018/19 season and 753 mm in the 2019/20 season. With canopy measurements starting in September in the 2018/19 season, the month of February in that season saw the most rain (123 mm). The temperatures in the orchard ranged from hot in the summer to cold in the winter. In the 2018/19 season, the lowest temperature was 0.19°C on 3 July 2018, and the highest was 36°C on 26 December 2018. The sentence has been rewritten and reads as follows: In the 2018/19 season, the maximum daily total solar radiation values peaked at 31.28 MJ m-2 day-1 in December 2018. The lowest maximum daily total solar radiation was recorded (14 MJ m-2 day-1) in June 2019. In the second season, the month of December received the highest rainfall (278 mm). The lowest recorded temperature was -0.04°C on 3 July 2019, and the highest was 35°C on 21 October 2019. The average daily solar radiation increased from 14 MJ m^{-2} day^{-1} in June 2019 to 31.4 MJ m^{-2} day^{-1} in December 2019.

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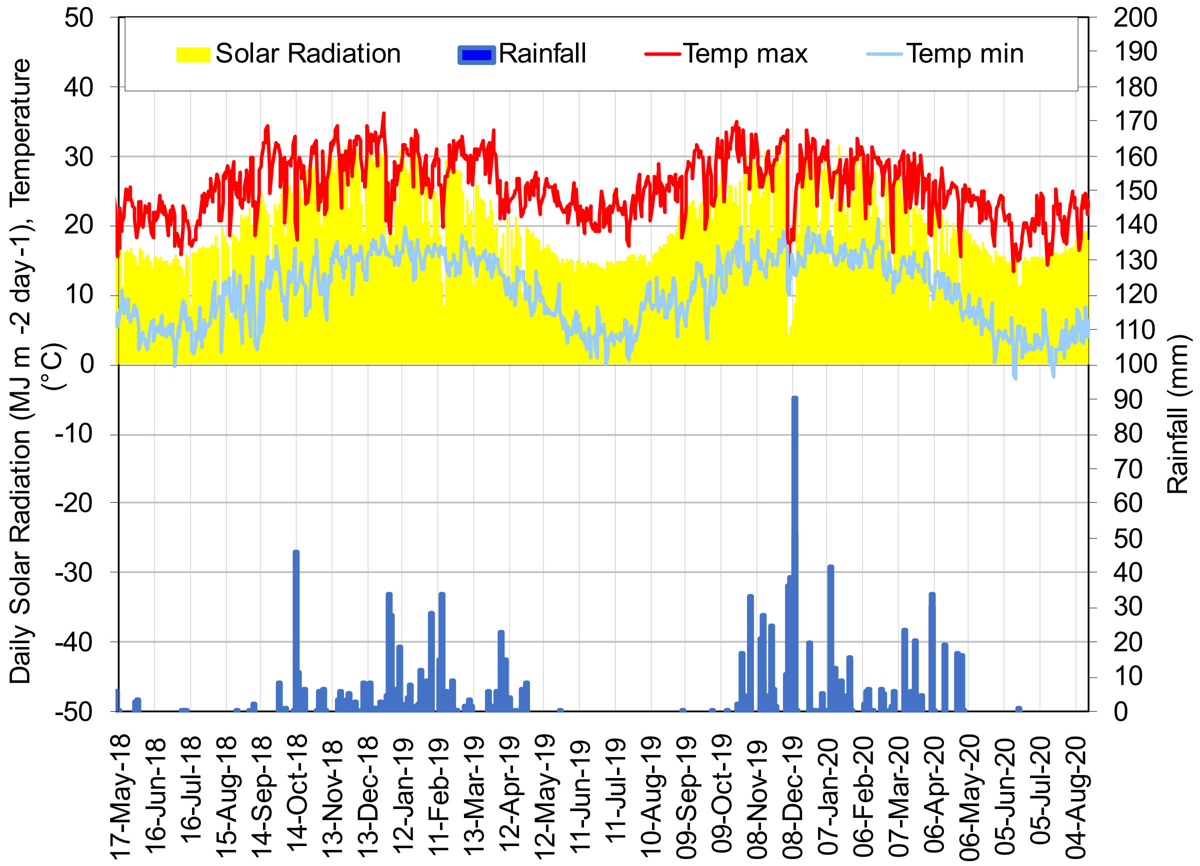

Figure 5.1 Daily values of maximum and minimum temperatures (°C), solar radiation (MJ m^{-2} day^{-1}), and rainfall (mm) at the site from 17 May 2018 until 4 August 2020.

Despite differences in rainfall and ET_o between the two seasons, applied irrigation was very similar for the two seasons Chameleon water sensors (https://via.farm), which determine soil matric potential which was used to schedule irrigation, with each event typically occurring for an entire day (Table 5.1).

Table 5.1 Total irrigation volume, ET_o and rainfall for the two seasons of the study from September to June in the two seasons.

Season	Rainfall (mm)	Irrigation (mm)	ET_o (mm)
2018/19	500	215	1429
2019/20	753	220	1363

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5.2.2 Predawn and Midday stem water potentials

Predawn leaf water potentials and midday stem water potentials for the well-watered trees in the two measurement seasons are shown in Figure 5.2. In the 2018/19 season, predawn leaf water potentials ($\Psi_{predawn}$) varied between -0.21 and -0.61 MPa, with an average of -0.32 MPa over the season. In the 2019/20 season, predawn leaf water potentials ($\Psi_{predawn}$) varied between -0.12 and -0.36 MPa, with an average of -0.26 MPa. In the 2018/19 season, midday stem water potential (Ψ_{stem}) varied from -0.4 to -1.08 MPa, with an average of -0.7 MPa. While in the 2019/20 season, midday stem water potentials (Ψ_{stem}) varied from -0.36 and -0.82 MPa, with an average of -0.56 MPa. It can be observed that in the first season, in November, there was a decline in both the predawn leaf water potentials (-0.6 MPa) and midday water potentials (-1.1 MPa) which was caused by a breakdown in the irrigation system in the orchard. This period of slight stress lasted approximately three weeks.

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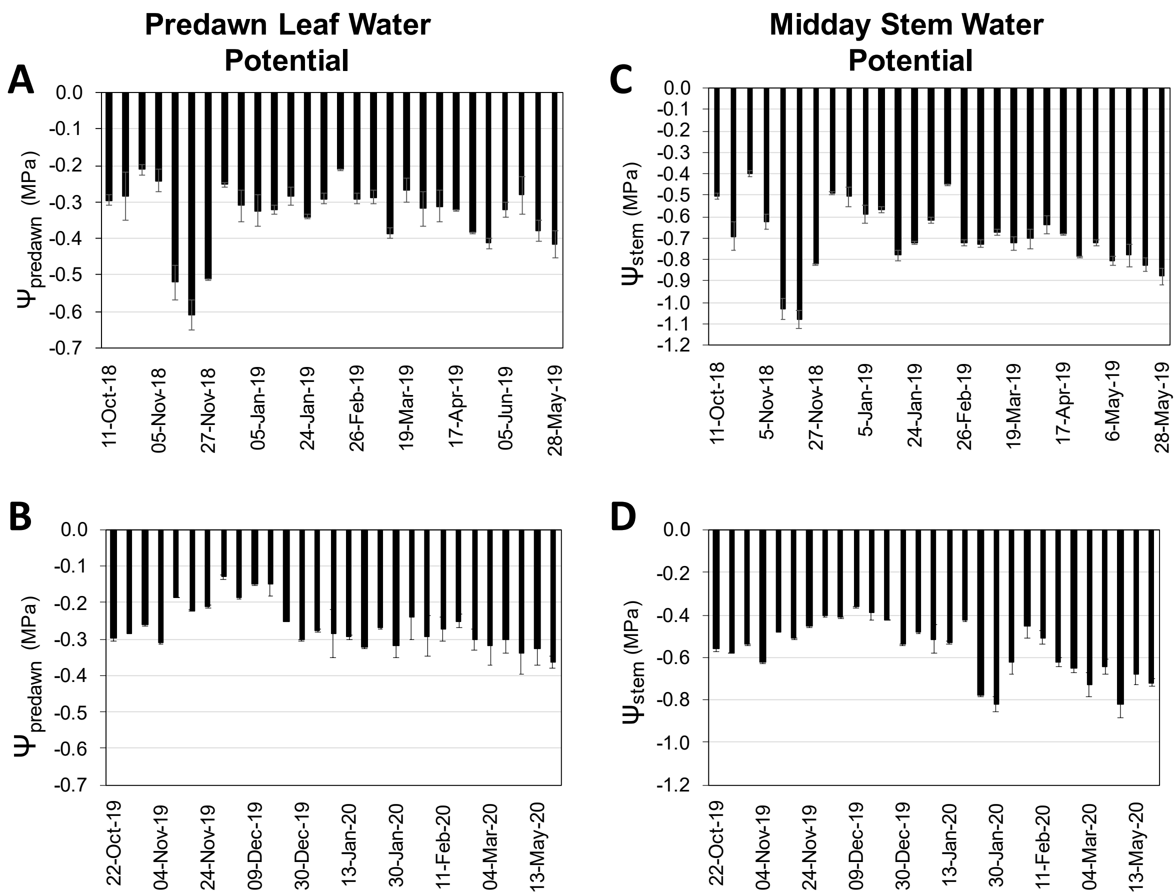

Figure 5.2 Predawn leaf water potentials ($\Psi_{predawn}$, A and B) and midday stem water potentials (Ψ_{stem}, C and D) for the 2018/19 (A and C) and 2019/20 seasons (B and D) for well-watered trees. Each data point represents an average of four trees ± standard deviation indicated by the vertical error bars. (Measurements were made by Mr Seluleko Kunene).

5.2.3 Daily positive chill unit accumulation

The daily positive chill unit model of Linsley-Noakes et al. (1995) was used to calculate the accumulation of chill units in the 2018/19, 2019/20, and 2020/21 seasons, as illustrated in Figure 5.3. The calculation started on 1 May, as there were no chill units accumulated before that date for the three seasons. In 2018, the first chill units (0.5 DPU) were accumulated on 6 May, in 2019 it was on 27 May (2 DPU), and in 2020 on 7 May (0.5 DPU). In the 2018 winter 226 DPU were accumulated, 282 DPU in the 2019 winter, and 614 DPU in the winter of 2020/21 (Figure 5.3). The accumulation of DPU ended earlier in the 2018/19 season, followed by the 2019/20 season. In the third

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season, DPU accumulation continued until August. Chill unit accumulation ended on 15 July 2018, 29 July 2019 and 24 August 2020 for the three respective seasons.

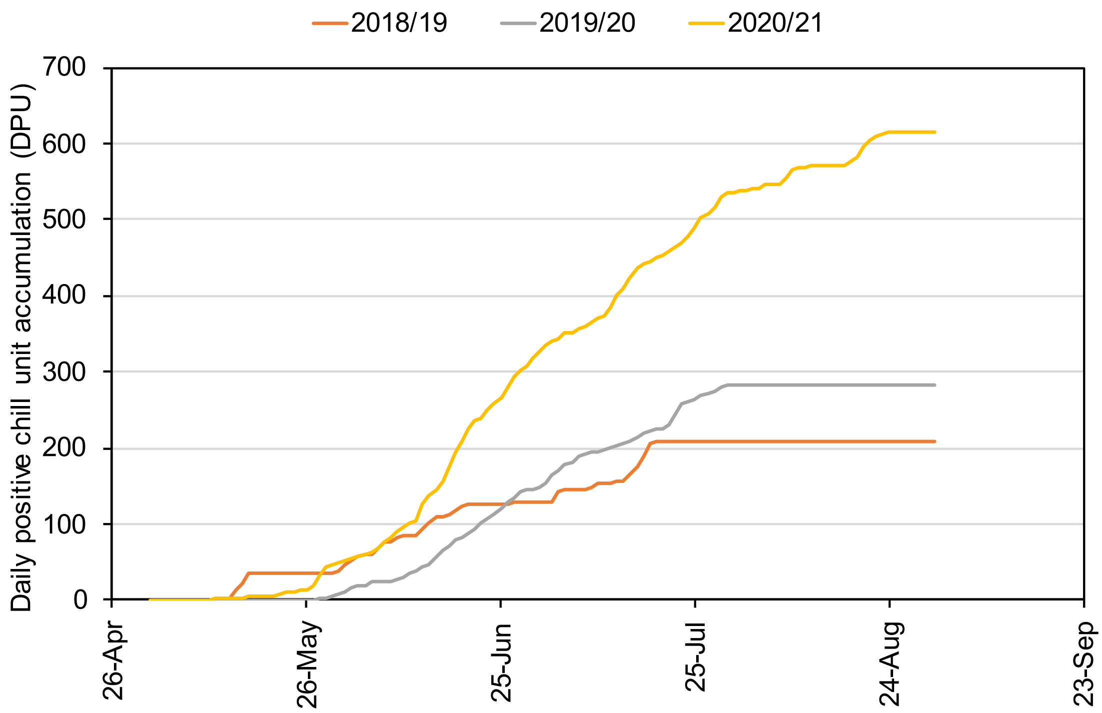

Figure 5.3 Daily positive chill unit accumulation (DPU) for the period from May to August at the Hatfield Experimental Farm (Innovation Africa@UP) for three measurement seasons (2018/19, 2019/20 and 2020/2021).

5.2.4 Effect of thermal time on the rate of canopy development

The accumulation of growing degree days (GDD), or thermal time, at the study site was determined for the 2018/19, 2019/20, and 2020/21 seasons, using a base temperature of 15.5 °C as defined by Miyamoto (1983) (Figure 5.4). Thermal time started accumulating on 31 July 2018, 4 August 2019, and 19 September 2020. In the 2018/19 season, a total of 1414 GDD were accumulated by 24 May 2019, whereafter there was no further increase in GDD. In the 2019/20 season, 1324 GDD were accumulated by 27 April 2020 and in the 2020/21 season, 1145 GDD were accumulated by 29 April 2021.

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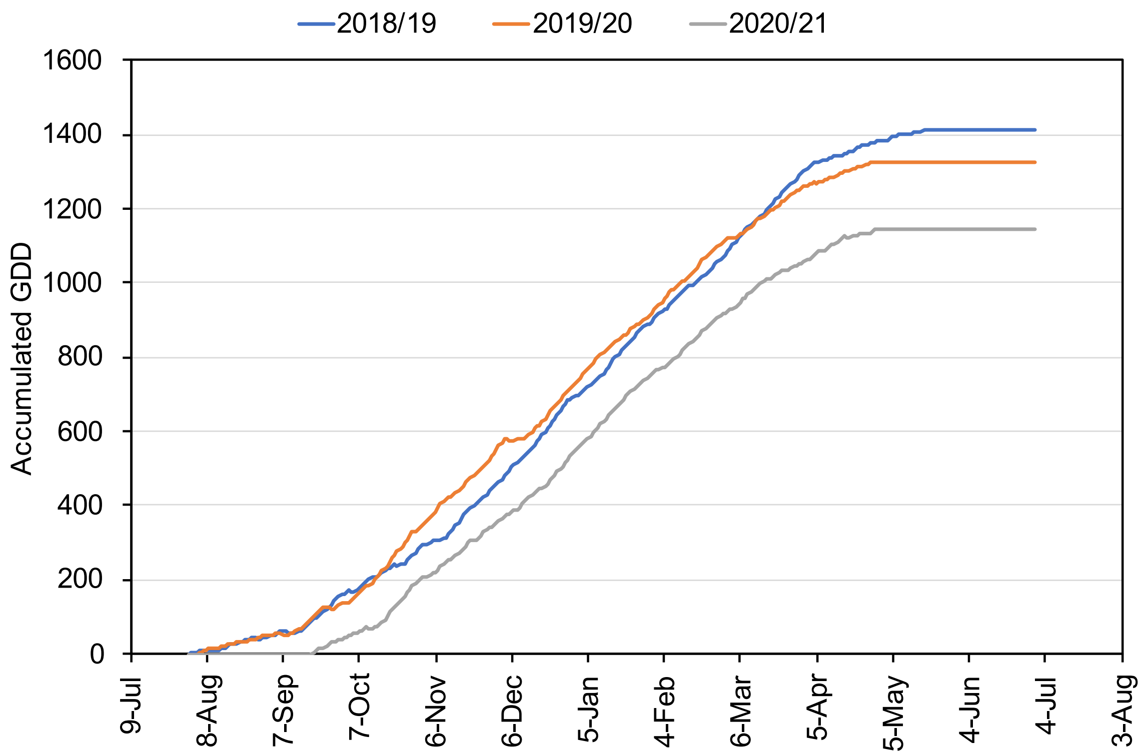

Figure 5.4 Growing degree day (GDD) accumulation from 30 July to 30 June for the 2018/19, 2019/20, and 2020/21 seasons. Growing degree days were calculated using a base temperature of 15.5 °C for pecans as suggested by Miyamoto (1983).

The results of thermal time on canopy development show that as soon as GDD started to accumulate, canopy size also started to increase (Figure 5.5). In the first season, soon after bud break when canopy cover was 0.03, GDD were 94.2. In the middle of the season when the canopy cover was stable, at 0.52, the GDD was 844. When leaf senescence began, GDD was 1200, levelling off to 1400 at the end of the season when the trees were leafless. In the second season, after bud break when the canopy cover was at 0.08, GDD was 122. Mid-season when the canopy cover was at 0.63, GDD was 800. Due to lockdown restrictions, it was impossible to monitor the exact date for the beginning of leaf senescence, but GDD reached a maximum of 1324 when the trees were leafless. In the third season, after bud break, the canopy cover started off at 0.01 and GDD was 24, increasing to 765 mid-season. When leaf senescence began, the canopy cover was at 0.71 and GDD was 854 and reached 1145 at the end of the season. As a result of this total GDD for different phenological stages for each season varied quite considerably. The figure also shows the occurrence of the different phenological stages for each season. The flowering and fruit set stage occurred first

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in 2018/19 season, followed by the 2020/21 season and last was the 2019/20 season. This figure also demonstrates that thermal time is not the greatest measure to differentiate phenological stages.

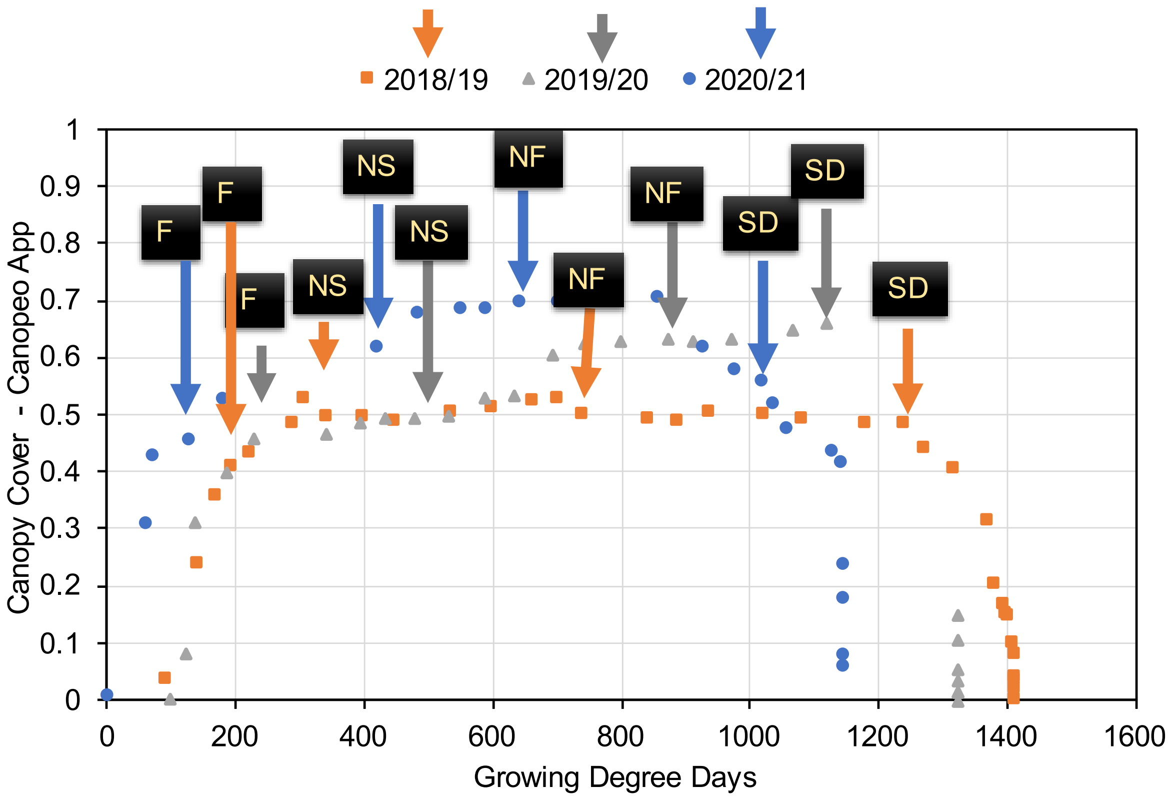

Figure 5.5 The relationship between accumulated growing degree days and changes in canopy cover measured with the Canopeo App in the 2018/19, 2019/20 and 2020/21 seasons. Growing degree days were calculated using a base temperature of 15.5 °C for pecans as suggested by Miyamoto (1983). The missing data in 2020 is due to level 5 lockdown COVID restrictions. Each data point represents an average value of weekly canopy cover for four well-watered measurement trees. (F, Flowering and fruit set; NS, nut sizing; NF, nut filling and SD, Shuck dehiscence.

5.2.5 Effect of canopy size on transpiration

5.2.5.1 Seasonal transpiration crop coefficients

The seasonal dynamics of K_t values exhibited a similar pattern in both seasons (Figure 5.6). In the first season, transpiration crop coefficients started to increase on 31 August 2018 (2018/19 season), which corresponded to budbreak. These values increased

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until the end of October and then reached a plateau until the end of February, when there was another linear increase in values until a maximum of 0.27 was reached on 4 May 2019. After this point, K_t started to decrease, which corresponded to the start of leaf senescence. During the dormancy period which started on 6 June 2019, the K_t values were low, as transpiration has stopped. Again, K_t values started to increase with budbreak on 12 September 2019 and followed a similar pattern to the previous season. A maximum K_t value of 0.34 occurred on 7 May 2020. After this point, leaf senescence begun, and K_t values started to decrease and reached a minimum value in the middle of June 2020.

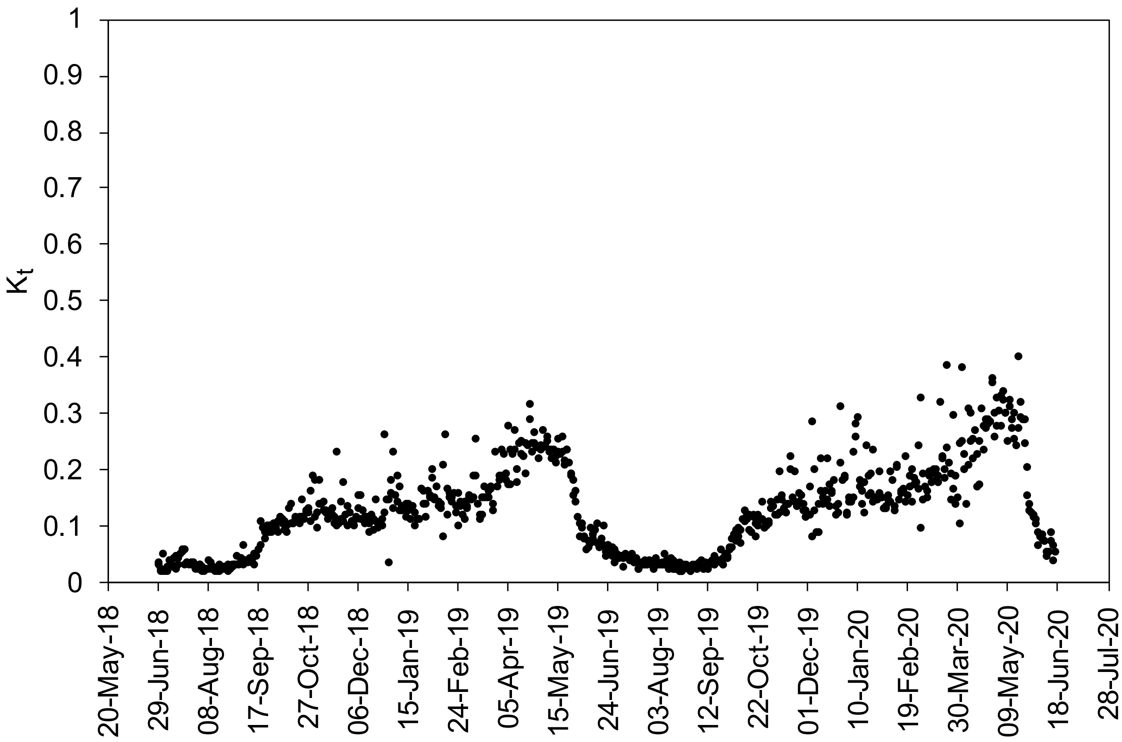

Figure 5.6 Daily transpiration crop coefficients (K_t) for a well-watered tree for the 2018/19 and 2019/20 measurement seasons.

5.2.5.2 Effects of canopy size on transpiration crop coefficients

Regression analysis demonstrated a positive linear relationship between canopy size and K_t values based on the various methods for determining canopy size (Figure 5.7). According to the R^2 values obtained from the regression analyses, canopy cover determined using the midday FI-PAR measured with the Ceptometer exhibited the

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strongest correlation with K_t (Figure 5.7 A), as compared to the other canopy size descriptors. The observed R^2 value for the Canopeo App was 0.66, whilst it was 0.7 for midday FI-PAR measured with the Ceptometer and 0.54 for canopy cover determined as the area on the ground shaded by the tree. There was a poor correlation between K_t values and LAI measurements, as indicated by an R^2 value of 0.41. Looking at the four graphs, it can be seen that there was a significant scattering when the canopy cover was close to its maximum. This shows that the relationship between K_t values and canopy size (from the four different canopy descriptors) was inconsistent when canopy cover was fairly high.

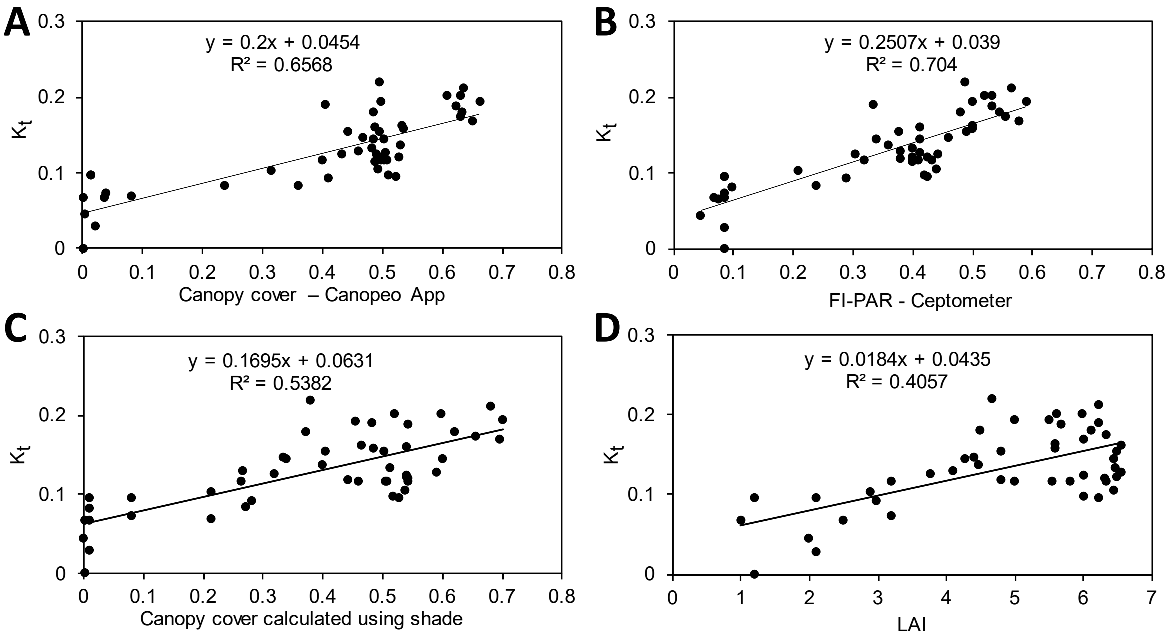

Figure 5.7 Relationship between transpiration crop coefficients (K_t) and measured values of (A) canopy cover estimated using the Canopeo App, (B) midday FI-PAR measured with a Ceptometer, (C) canopy cover calculated using shaded area at midday, and (D) orchard LAI for a well-watered tree. Each point represents the weekly K_t in the week of the measurement of canopy size for the 2018/19 and 2019/20 seasons from one measurement tree.

5.2.6 Thermal time and transpiration crop coefficients

In the first season, the values of K_t start to increase on 31 August, increasing steadily as thermal time also increased. As soon as accumulated thermal time reached a maximum level and no further accumulation of GDD occurred, K_t values started to

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drop, caused by leaf senescence. The same trend was observed in the second seasons of measurements, but the initial increase in K_t started at a higher value of accumulated GDD and accumulated GDD in the 2019/20 season reached a maximum level earlier than in the previous seasons.

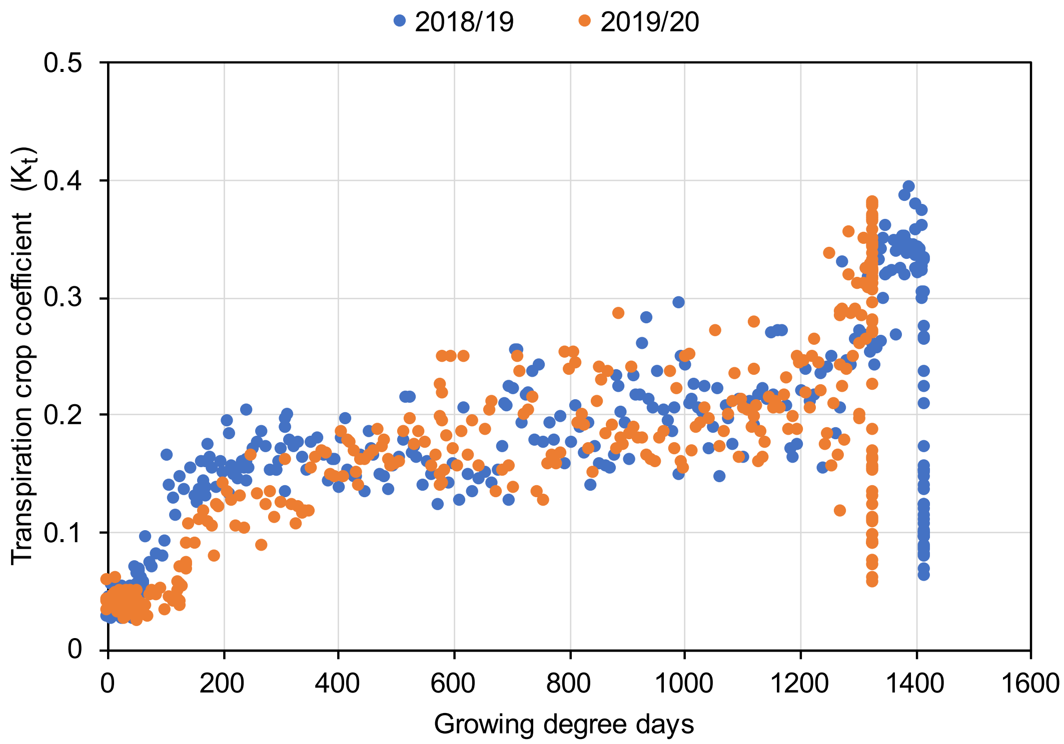

Figure 5.8 The effect of accumulated growing degree days on the daily transpiration crop coefficient values (K_t) for the 2018/19 and 2019/20 measurement seasons. Growing degree days were calculated using a base temperature of 15.5 °C for pecans as suggested by Miyamoto (1983). Each data point represents a daily K_t for a well-watered tree.

5.2.7 Estimation of transpiration from the relationship between canopy cover and transpiration crop coefficients.

The ability to use the regression equation (y = 0.2x + 0.0454), obtained when regressing K_t values against canopy cover determined using aerial images and the Canopeo App, to predict K_t values throughout a season was tested in the 2020/21 season. Weekly canopy cover values from the 2020/21 season were used in the regression equation above to derive weekly K_t values. These weekly K_t values were

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then used with daily ET_o estimates for the 2020/21 season to calculate a daily transpiration value. When the measured and estimated daily T were compared against calendar days (Figure 5.9 B) a clear underestimation of T from the beginning of the season until January and from mid-February to the end of the season was evident. However, from January to mid-February the model seemed to perform fairly well. Overall, model performance was not acceptable, as indicated by the statistical indices of R^2 0.56 and a D of 0.64 (Figure 5.9 A). Furthermore, the RMSE, MAE and CRM values (0.22, 0.018 and 0.42 respectively) were out of the acceptable range.

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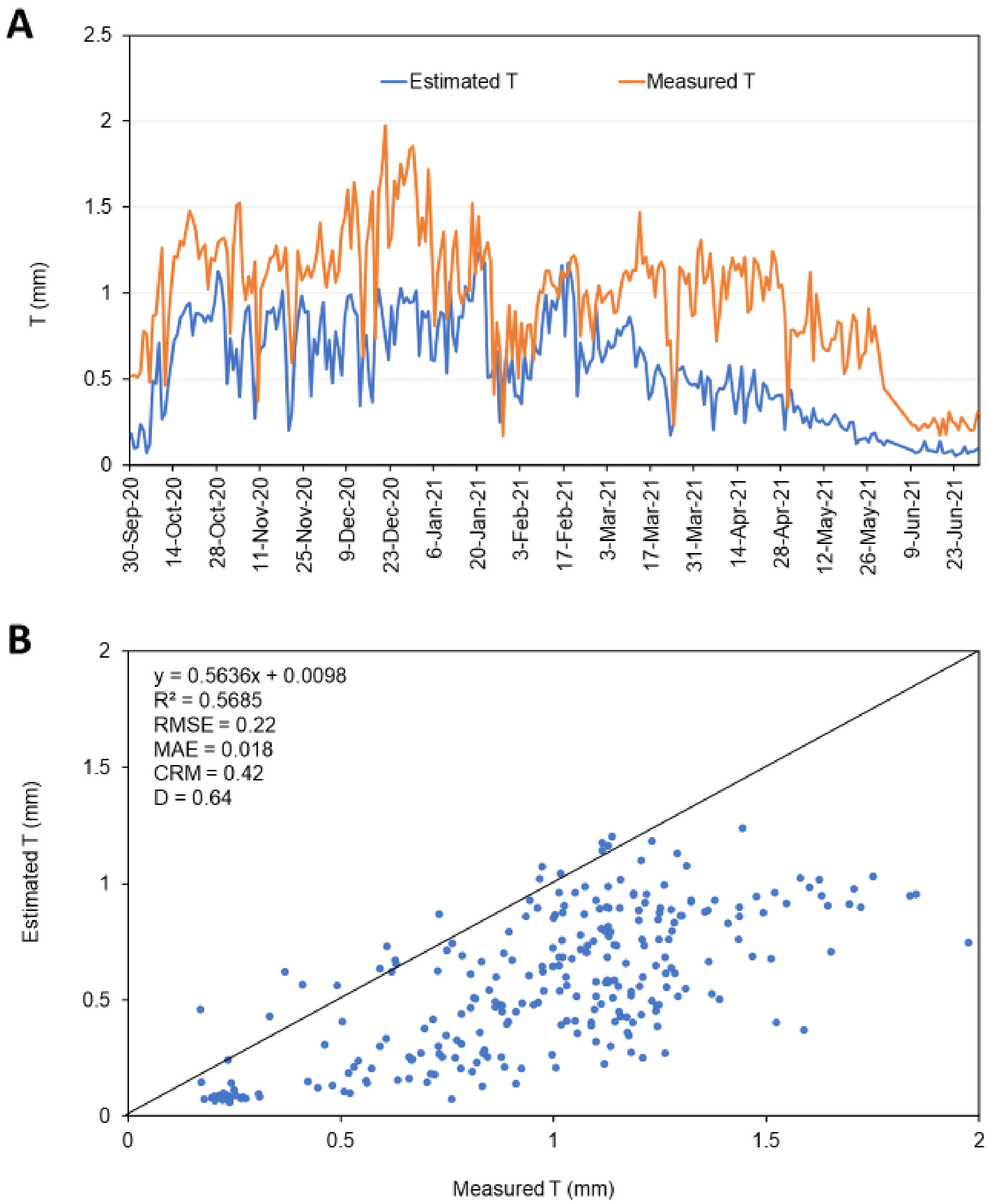

Figure 5.9 Comparison between measured transpiration (T) and estimated daily T for the 2020/21 season in the pecan orchard. (A) is measured and estimated T plotted against calendar days and (B) is the correlation between measured and estimated T. The solid line represents a perfect agreement (1:1 line).

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Accumulated estimated and measured transpiration is shown in Figure 5.10. The total accumulated measured T was found to be 262 mm while the total accumulated estimated T was found to be 150 mm, which shows a 112 mm difference. This figure illustrates the underestimation of transpiration by the model.

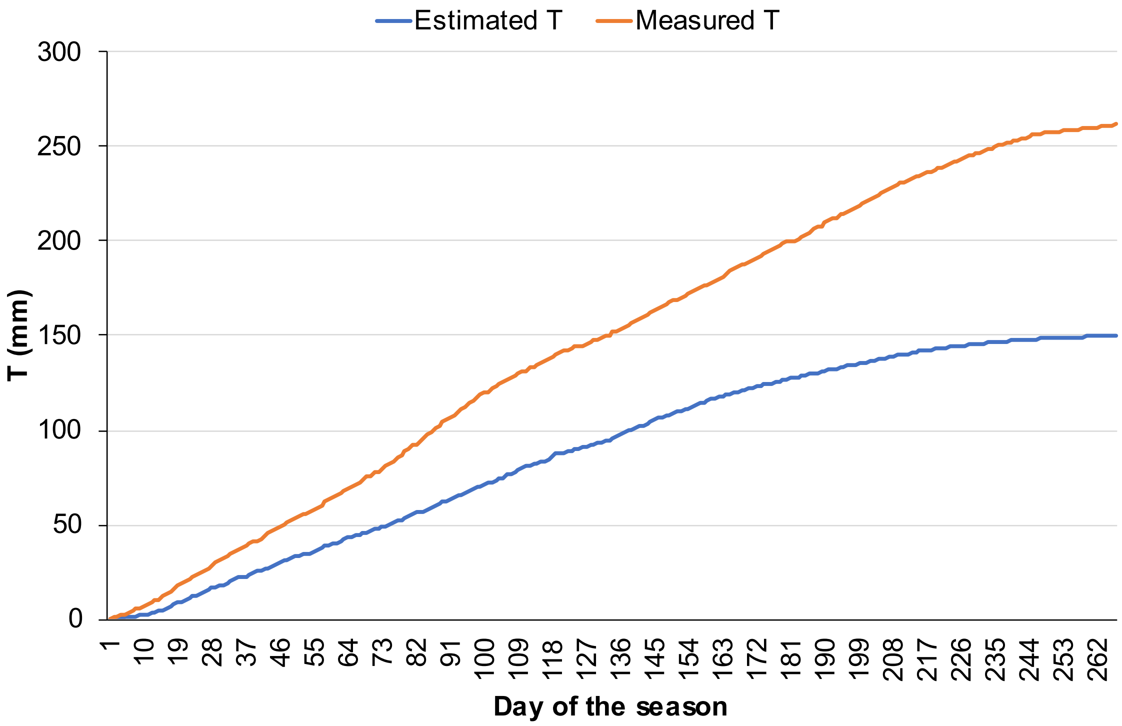

Figure 5.10 Accumulation of measured and estimated transpiration during the 2020/21 season.

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DISCUSSION

The weather variables during the course of the trial demonstrated that conditions regarding temperature and solar radiation were satisfactory for pecan production and unlikely to have a negative impact on production. The rainfall totals for the 2018/19 season were 500 mm and 753 for the 2019/20 season, with total ET_o being 1429 and 1363 mm respectively. The seasonal total water requirements for pecan orchards are estimated to be between 673 and 1000 mm for the region (Ibraimo et al. 2016). Although rainfall in the second season was below the optimum range for pecan production, the irrigation supplied was adequate to meet the needs of the pecans trees. The two measurement seasons received sufficient chilling in winter and heating in spring as these two factors play a part in the timing of bud break in pecans (Sparks 1993). The minimum temperatures in the winter of the two seasons were sufficient for the trees to reach the necessary chilling units. In pecans, temperatures between 0 and 7°C are ideal for chilling, while temperatures below 0°C and above 13°C are ineffective for dormancy (Tuzcu et al. 1991, Erez 1994, Arora et al. 2003). Spring temperatures were optimal for heating. According to Sparks (1989), chill and heat determine the time of canopy development and nut maturity, thus colder springs can delay nut maturity.

In this research trial, the measurement trees were largely unstressed, considering that for the majority of the study Ψ_{stem} fell above the threshold of -0.90 MPa for mild stress (Othman et al. 2014). The average predawn values were -0.48 and -0.49 MPa respectively. For the majority of the time, predawn leaf water potentials were -0.32 MPa in the first season and -0.26 MPa in the second season, indicating that water stress was unlikely to be a limiting factor in both seasons, except in November 2018 when there was an issue with the irrigation system and values went up to -0.6 MPa for predawn leaf water potential and 1.1 MPa for midday stem water potential. On average, in the two seasons, midday stem water potentials were -0.40 and -0.85 MPa, respectively, signalling that the trees were not stressed.

The results from this study demonstrated a fair relationship between GDD and leaf senescence. Also, chill units play a major role in canopy development as budbreak occurred after optimal chill units were accumulated, and leaf senescence began after the trees had reached full maturity according to thermal time.

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The accumulated chilling units reported in this study (226 DPU, 282 DPU and 614 DPU) for the three seasons, with Sparks (1993) reporting that pecan budbreak does not have a critical requirement for either chilling or heating and, instead, is under the interactive control of heating and chilling. The influence of higher DPU can lead to poor uniformity in bud break in the following season. In the third season, bud break occurred at lower GDD than the first two seasons due to the higher DPU accumulated in the winter of 2021. When accumulated GDD were plotted with canopy size, it was observed that leaf senescence started when GDD were no longer accumulating. The relationship between GDD and Kt was found to be relatively weak, as the model proposed by Sammis et al. (2004a) was deemed unsuitable for most regions. Consequently, it was determined that thermal time cannot reliably predict crop coefficients in Pretoria.

The relationship between canopy size and K_t (R^2 = 0.65) values of unstressed pecans trees was fair and did not exceed 0.8 as De Jager (1994) reported that the acceptable R^2 should be above 0.8. Except for LAI, R^2 values were above 0.5 for the relationship between the other measured of canopy size and K_t. Moreover, K_t values varied with changes in canopy size throughout the season. There was also a peak in K_t values near the end of the season, which corresponds to the nut filling stage and a minor vegetative flush. This is consistent with previous work in Cullinan (Ibraimo et al. 2016), which identified a six-stage crop coefficient curve for pecans rather than the four-stage FAO 56 generic curve. This is due to the fact that pecan trees may have more than one cycle of shoot growth in a single season (Wells and Conner 2007). The relationship between canopy descriptors and K_t presented in this study were particularly poor. The canopy cover measured by the Canopeo App yielded a poor correlation with K_t (R^2 = 0.66). According to Girona et al. (2011), using midday fractional interception of PAR can cause certain issues. These authors discovered a non-linear link between midday interception and crop relative water consumption in their three-year study, which they attributed in part to the structure of the canopies in the fruit trees analyzed. When comparing canopies of different structures, they determined that radiation interception at noon may not be a good indicator of canopy size. They contended that differences in canopy properties such as porosity could have a significant impact on the light interception. This explains why the correlation of K_t and Canopeo was preferred in this study over midday FIPAR measurements. Even

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though the relationship between K_t and canopy size in pecans has not been substantiated, this relationship has been studied in other fruit trees (Ayars et al. 2003a, Williams and Ayars 2005, Villalobos et al. 2009a, Marsal et al. 2013, Espadafor et al. 2015).

Despite the fact that this study revealed a poor correlation between K_t and the canopy size measured with Canopeo App, an attempt was made to derive weekly K_t values for the following season (2020/21). A poor relationship was found between measured and estimated T, yielding an R^2 value of 0.58, which shows the inability of the method. This relationship does not always hold true to pecans as K_t values remain high late in the season, as during this stage little evidence of stomatal closure during conditions of high evaporative demand in summer flush leaves was reported by Anderson and Brodbeck (1988).

CONCLUSIONS

Pecan budbreak is controlled by the interactive control of chilling and heating. Once enough chill units have been met, budbreak occurred. Once chilling is completed, the heat requirement is set, interactively. According to the findings of this study, there is a poor link between canopy size and K_t values with missing data during level 5 COVID19 lockdown playing a part thus, Additional measurement of canopy size needs to be done to improve this. With increased interest in digital horticulture and precision agriculture, the use of the Canopeo App in estimating canopy size could be optimized and can be very important in water use models. There appeared to be an underestimation of transpiration when using K_t values estimated from canopy size. These findings were fair as they were below the acceptable R^2 range suggested by De Jager (1994) of >0.8. In addition, D, MAE and RMSE were all below the acceptable range. Overall, the model underestimated transpiration by over 111 mm. In pecans, canopy size estimates are key, but other factors such as canopy conductance needs to be considered, in order to be able to estimate pecan transpiration with a model. More studies should be conducted under a range of climates, orchard ages, and management practices to evaluate the relationship; and test the applicability and identify potential areas for improvement.

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CHAPTER SIX

GENERAL CONCLUSION

Pecans are considered an important cash crop in South Africa, contributing 7% to the world's pecan production. This industry has demonstrated massive growth since 2010. Pecan production is widespread in South Africa, with plantings in all nine provinces, with major production in the Northern Cape. Importantly, most of the pecan production areas are under irrigation, since these areas are classified as semi-arid, with limited and seasonal rainfall. As a result, the availability of sufficient water is important for the pecan industry's long-term viability and expansion. Due to global water shortages and increased competition across other industries, the agriculture industry is under pressure to use allocated water more efficiently for long-term sustainability. To improve irrigation water management measures, such as irrigation scheduling, accurate quantification of crop water use is essential.

To address the essential issue of measuring or estimating water in pecan trees, various methodologies have been explored. In most cases, farmers choose the FAO-56 dual crop coefficient because it is the most convenient and practical technique for determining water requirements. This is because the farmer just needs weather data and an appropriate K_c to estimate water use of their orchard. However, weather data is not always available to farmers, depending on a range of factors such as region, technological infrastructure, and costs. By providing a relevant and practical approach to deriving orchard specific K_t values for pecans, the current study tested a potential way to help farmers estimate water requirements of pecan orchards. This was done by firstly examining the most practical way of estimating canopy size. Secondly, the link between various canopy size measurements and water use was examined. This was done by evaluating the relationship between different measures of canopy size (i.e., leaf area index, FI-PAR, canopy shade and Canopeo App) and K_t values. The aim of evaluating this approach was to potentially provide farmers with an easier way of estimating K_t and ultimately transpiration in orchards where measurements were not available. This data is critical for growers to better understand how much water is transpired by crops for effective management of limited water resources.

With canopy cover data being critical for estimating water use, chapter 4 compared canopy cover estimates of a pecan orchard using red green blue (RGB) mages from

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above the canopy and the Canopeo App, which selects green pixels, with estimates of fractional interception of PAR, leaf area index and canopy cover calculated using shaded area. Based on the results, consistent correlations were observed between the Canopeo App and the other methods, except for leaf area index which produced a poor correlation. The findings potentially can contribute to the pecan industry as the Canopeo App method provided good canopy cover estimates when compared to widely accepted methods, signalling that it can be a trusted canopy descriptor. This method reliably separates the tree's branches from leaves, resulting in a realistic estimate of canopy coverage. Considering that LAI and Ceptometer methods take into account branches and leaves, estimates of transpiring leaf area can be inaccurate. Estimating canopy size with the Canopeo App overrides some of these limitations. This Canopeo App can also be more useful to farmers due to the shifts from laborious measurements to technology in agriculture since, it is less time consuming than doing actual measurements and less costly. It is less laborious because it allows a large number of images to be recorded and processed in a short space of time, reducing the tedium of manual measurements.

In Chapter 5, the objective was to firstly quantify changes in canopy size throughout the season in pecan orchards in relation to possible driving variables, including thermal time, in order to be able to predict canopy development. A fair relationship was found between GDD and leaf senescence as the canopy started to decline as soon as GDD reached a maximum as temperatures were dropping. However, there was a poor relationship between GDD and K_t. This evaluation indicated that thermal time cannot be used to to adjust the crop coefficient curve for different climatic regions. Secondly, an objective was to determine the transpiration of unstressed pecan trees and calculate transpiration crop coefficients in relation to canopy size over the season. The findings of this study revealed that there is a poor link between K_t and measured canopy size measurements, as the relationship between K_t and canopy size was inconsistent. Real-time estimation of crop water consumptive is complex and often beyond the reach of individual farmers due to the diversity of pecan tree ages, spacing, density, and management practices, pruning, and growth dynamics on a farm. Samani et al. (2011) stated that canopy cover and water availability are both important factors for determining K_c values. A direct estimation of K_t from measurements of canopy cover may be too simplistic for pecans and the approach presented by Samani et al.

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(2011), where K_c values were scaled according to a maximum K_c for a mature orchard should be further evaluated for South African orchards.

Future work needs to be done where the Canopeo App method is tested in orchards of different ages to test its capability. Furthermore, it should be tested in orchards with no ground cover in order to reduce errors associated with noise caused by green ground cover underneath the canopies. More research is needed in summer rainfall locations, which differ to the climate in the Gauteng province to have a fuller picture of how these orchards use water in order to conserve scarce water supplies.

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