Towards Tree-level Evapotranspiration Estimation with Small UAVs in Precision Agriculture
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Evapotranspiration (ET) estimation is important for precision agriculture, especially precision water management. Mapping the ET temporally and spatially can identify variations in the field, which is useful for evaluating soil moisture and assessing crop water status. ET estimation can also benefit the water resources management and weather forecast. As a new remote sensing platform, researchers are gaining interests in the potential of small UAVs in precision agriculture, especially on heterogeneous crops, such as vineyard and orchards. However, there are still challenges to develop reliable tree-level water stress detection method using UAV-based high-resolution images. Within this monograph, contributions are made to take steps closer towards tree-level ET estimation and water stress detection.

It is important to evaluate the methods for tree-level ET estimation and water status inference. Thus, in Chap. 5, the authors proposed a reliable tree-level ET estimation method using UAV high-resolution multispectral images. A framework was also established using a linear regression model between the NDVI and $K_c$ to estimate the actual daily ET. In Chap. 6, the authors developed a reliable tree-level water stress detection method using UAV-based high-resolution thermal images. The concept of complexity-informed machine learning (CIML) was proposed and its performance was proved on the classification of tree-level irrigation treatments. A convolutional neural network (CNN) model and its performance was also evaluated on the tree-level water status inference.

The roadmap of this monograph is shown in Fig. 1. In Chaps. 2 and 3, the authors reviewed the most commonly used ET estimation methods with small UAVs. In Chaps. 4 and 5, reliable tree-level ET estimation methods were developed using high-resolution UAV images. In Chap. 6, the authors evaluated the reliability of the UAV thermal camera on the individual tree water status inference. Finally, conclusions and future works are presented in the last chapter.
Fig. 1 Book roadmap

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|---------|------------|
| AI      | Artificial Intelligence |
| ANN     | Artificial Neural Network |
| ARS     | Agricultural Sciences Center |
| BRDF    | Bidirectional Reflectance Distribution Function |
| CIMIS   | California Irrigation Management Information System |
| CIML    | Complexity-Informed Machine Learning |
| CNNs    | Convolutional Neural Networks |
| CRP     | Calibrated Reflectance Panel |
| DEM     | Digital Elevation Model |
| DLS     | Downwelling Light Sensor |
| DN      | Digital Number |
| DNNs    | Deep Neural Networks |
| DOY     | Day of Year |
| DTD     | Dual Temperature Difference |
| ET      | Evapotranspiration |
| FOV     | Field of View |
| GPS     | Global Positioning System |
| GPU     | Graphics Processing Unit |
| HRMET   | High-Resolution Mapping of ET |
| ID      | Identity |
| IoLT    | Internet of Living Things |
| IR      | Infrared |
| JPG     | Joint Photographic Experts Group |
| LAI     | Leaf Area Index |
| LDA     | Linear Discriminant Analysis |
| MAE     | Mean Absolute Error |
| METRIC  | Mapping Evapotranspiration with Internalized Calibration |
| ML      | Machine Learning |
| MLP     | Multi-layer Perceptron |
| NDVI    | Normalized Difference Vegetation Index |
| NIR     | Near Infrared |
| Acronym | Description                                      |
|---------|--------------------------------------------------|
| NIST    | National Institute of Standards and Technology  |
| OSEB    | One Source Energy Balance                        |
| PA      | Precision Agriculture                            |
| PCA     | Principal Component Analysis                     |
| PDF     | Probability Distribution Function                |
| POTM    | Principle of Tail Matching                       |
| PPIML   | Plant Physiology-Informed Machine Learning       |
| QDA     | Quadratic Discriminant Analysis                  |
| RGB     | Red, Green, and Blue                             |
| RMSE    | Root Mean Square Error                            |
| RSEB    | Remote Sensing Energy Balance                    |
| SCN     | Stochastic Configuration Network                 |
| SEBAL   | Surface Energy Balance Algorithm for Land        |
| SGD     | Stochastic Gradient Descent                      |
| SVM     | Support Vector Machine                           |
| SWIR    | Short-Wave Infrared                              |
| TIR     | Thermal Infrared                                 |
| TSEB    | Two-Source Energy Balance                        |
| TSEB-PT | Priestley-Taylor TSEB                            |
| UAVs    | Unmanned Aerial Vehicles                         |
| UGVs    | Unmanned Ground Vehicles                         |
| US      | United States                                    |
| USDA    | United States Department of Agriculture           |
| VIS     | Visible                                          |
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Chapter 1
Introduction

1.1 What Is Evapotranspiration Estimation?

Evapotranspiration (ET) estimation is important for precision agriculture, especially precision water management. Mapping the ET temporally and spatially can identify variations in the field, which is useful for evaluating soil moisture [152, 167] and assessing crop water status [67]. ET estimation can also benefit the water resources management and weather forecast [163]. ET is a combination of two separate processes, evaporation (E) and transpiration (T). Evaporation is the process whereby liquid water is converted to water vapor through latent heat exchange [3]. Transpiration is the process of the vaporization of liquid water contained in plant tissues, and the vapor removal to the atmosphere [3]. The current theory for transpiration is constituted by the following three steps. First, the conversion of liquid-phase water to vapor water causes canopy cooling from latent heat exchange. Thus, canopy temperature can be used as a plant physiological indicator of ET. Second is diffusion of water vapor from inside plant stomata on the leaves to the surrounding atmosphere. Third, atmospheric air mixing by convection or diffusion transports vapor near the plant surfaces to the upper atmosphere or off-site away from the plant canopy. Usually, evaporation and transpiration occur simultaneously.

1.2 Challenges and Opportunities

Many approaches have been developed to estimate ET. Typically, there are direct and indirect methods. For direct methods, ET can be determined by water balance [169]:

\[ ET = P + I - D - R - S, \]  

(1.1)
where $P$ (mm day$^{-1}$) is precipitation, $I$ (mm day$^{-1}$) is irrigation, $D$ (mm day$^{-1}$) is drainage, $R$ (mm day$^{-1}$) is runoff, and $S$ (mm day$^{-1}$) is the soil moisture storage. These direct ET methods, however, are usually point-specific or area-weighted measurements and cannot be extended to a large scale because of the heterogeneity of the land surface. The experiment equipment is also costly and requires substantial expense and effort, such as lysimeters, which are only available for a small group of researchers. For indirect methods, there are energy balance methods [82] and remote sensing methods [6]. For energy balance methods, Bowen ratio [7, 43] and eddy covariance [104] have been widely used in ET estimation. However, they are also area-weighted measurements. Remote sensing techniques can detect variations in vegetation and soil conditions over space and time. Thus, they have been considered as one of the most powerful methods for mapping and estimating spatial ET over the past decades [73, 141]. Remote sensing models have been useful in accounting for the spatial variability of ET at regional scales when using satellite platforms such as Landsat and ASTER [4, 13, 75, 118]. Since the satellite was being applied [95], several remote sensing models have been developed to estimate ET, such as Surface Energy Balance Algorithm for Land (SEBAL) [6, 13], Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) [5], the Dual Temperature Difference (DTD) [115], and the Priestley-Taylor TSEB (TSEB-PT) [63]. Remote sensing techniques can provide information such as normalized difference vegetation index (NDVI), Leaf Area Index (LAI), surface temperature, and surface albedo. Related research on these parameters has been discussed by different researchers [74, 103, 124].

As a new remote sensing platform, researchers are more and more interested in the potential of small UAVs in precision agriculture [33, 47, 145, 174], especially on heterogeneous crops, such as vineyard and orchards [180, 182]. UAVs overcome some of the remote sensing limitations faced by satellite. For example, satellite remote sensing is prone to cloud cover; UAVs are below the clouds. Compared with the satellite, UAVs can be operated at any time if the weather is within operating limitations. The satellite has a fixed flight path; UAVs are more mobile and adaptive for site selection. Mounted on the UAVs, lightweight sensors, such as RGB cameras, multispectral cameras, and thermal infrared cameras, can be used to collect high-resolution images. The higher temporal and spatial resolution images, relatively low operational costs, and the nearly real-time image acquisition make the UAVs an ideal platform for mapping and monitoring ET. Many researchers have already used UAVs and lightweight sensors for ET estimation, as shown in Tables 1.1 and 1.2. For example, in [116], Ortega-Farías et al. implemented a remote sensing energy balance (RSEB) algorithm for estimating energy components in an olive orchard, such as incoming solar radiation, sensible heat flux, soil heat flux, and latent heat flux. Optical sensors were mounted on a UAV to provide high spatial resolution images. By using the UAV platform, experiment results show that the RSEB algorithm can estimate latent heat flux and sensible heat flux with errors of 7% and 5%, respectively. It demonstrated that UAV could be used as an excellent platform to evaluate the spatial variability of ET in the olive orchard.
Table 1.1 ET estimation using UAV platforms

| Study sites                                      | UAV platforms  | Sensors                                      | Method | Crops                      | References |
|-------------------------------------------------|----------------|----------------------------------------------|--------|----------------------------|------------|
| Ames, Iowa, USA                                 | eBee Ag        | Sequoia, Canon S110 thermoMAP camera         | SEBAL  | Corn and soybean           | [100]      |
| Scipio, UT Lodi, CA, USA                       | AggieAir       | Canon S-95 ICI thermal camera                | METRIC | Vineyard                   | [38]       |
| Pinto Bandeira city Rio Grande do Sul State, Brazil | AIBOTIX       | Nikon Coolpix A camera                      | METRIC | Vineyard                   | [34]       |
| HOBE agricultural site, Denmark                | Q300, QuestUAV | Optris PI 450                                | TSEB   | Barley                     | [63]       |
| Lodi, CA, USA                                  | Cessna TU206   | ImperX Bobcat B8430 ThermaCAM SC640          | TSEB   | Vineyard                   | [168]      |
| Lodi, CA, USA                                  | AggieAir       | NA                                           | TSEB   | Vineyard                   | [106]      |
| Pinto Bandeira Serra Gaucha, Brazil            | AIBOTIX Hexacoptero | Nikon Coolpix A camera                  | TSEB   | Vineyard                   | [99]       |
| Lodi, CA, USA                                  | NA             | NA                                           | TSEB   | Vineyard                   | [107]      |
| Pencahue Valley Región del Maule, Chile        | NA             | Mini MCA-6 EasIR-9                           | TSEB   | Olive                      | [116]      |
| Bushland, Texas, USA                           | AggieAir       | Kodak1 thermal infrared model 760            | TSEB   | Sorghum and corn           | [20]       |
| Petit-Nobressart, Luxembourg                   | MikroKopter OktoXL | Samsung ES80 Optris Pi 400               | TSEB   | Grassland                  | [17]       |
| Lodi, CA, USA                                  | Cessna TU206   | ImperX Bobcat B8430 ThermaCAM SC640          | OSEB   | Vineyard                   | [168]      |
| Petit-Nobressart, Luxembourg                   | MikroKopter OktoXL | Samsung ES80 Optris Pi 400               | OSEB   | Grassland                  | [17]       |
| Tatura, Victoria, Australia                    | DJI S1000      | A65 and RedEdge-M                            | HRMET  | Peach, nectarine, and corn | [118]      |
| Sensor                | Function                  | Resolution                  | Weights | Spectral bands                        | Accuracy                     |
|----------------------|---------------------------|-----------------------------|---------|---------------------------------------|------------------------------|
| RedEdge-M            | Multispectral             | 1280 x 960 pixels           | 231.9 g | Blue, green, red edge, near infrared (NIR) | 8.2 cm/pixel at 120 m        |
| MAPIR survey 3       | Multispectral             | 4608 x 3456 pixels          | 76 g    | 375-650 nm                            | 4.05 cm/pixel at 60 m        |
| Mini MCA-6           | Multispectral             | 1280 x 1024 pixels          | 700 g   | 375-650 nm                            | 4.05 cm/pixel at 150 m       |
| Tetramap ADC lite    | Multispectral             | 2048 x 1536 pixels          | 200 g   | 375-650 nm                            | 5 cm/pixel at 100 m          |
| Sequoia              | Multispectral             | 4608 x 3456 pixels          | 72 g    | 450-1000 nm                           | 3.3 cm/pixel at 60 m         |
| Tetracam ADC lite    | Multispectral             | 2048 x 1536 pixels          | 72 g    | 450-1000 nm                           | 3.3 cm/pixel at 60 m         |
| Canon S110           | Near infrared             | 4096 x 3072 pixels          | 198 g   | 0.9-1.7 μm                            | ±1 °C                        |
| ICI SWIR 640 P       | Shortwave infrared        | 640 x 512 pixel             | 130 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| ICI 9640 P           | Thermal infrared          | 640 x 480 pixel             | 37 g    | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Vue Pro R 640   | Thermal infrared          | 640 x 480 pixel             | 74.5 g  | 7.5-13 μm                             | ±1 °C                        |
| FLIR Pi 450          | Thermal infrared          | 640 x 480 pixel             | 72 g    | 7.5-13 μm                             | ±1 °C                        |
| Optris Pi 400        | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Pi 450          | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Pi 400          | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Pi 400          | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Pi 400          | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |
| FLIR Pi 400          | Thermal infrared          | 640 x 512 pixel             | 134 g   | 7.5-13 μm                             | ±2 °C or ±2%                 |

**Table 1.2** Multispectral and thermal infrared sensors on UAV platforms
In the next section, the authors will discuss the research philosophy and methodology behind the ET research. The authors were motivated by the following section for individual tree-level ET estimation with small UAVs in precision agriculture.

1.3 Smart Big Data in Precision Agriculture: Acquisition and Advanced Analytics

1.3.1 What Is Smart Big Data in Precision Agriculture?

Big data technology, such as Internet of Things (IoT) and wireless sensors, enables researchers to solve complex agricultural problems [139]. By applying the sensors in the field, farmers can track valuable data for farm management, such as soil moisture, wind speed, air temperature, humidity, and so on. The amount of the data can be huge and challenging to process timely. How to make the big data “smarter” becomes necessary. Thus, the concept of smart big data analysis is proposed in this monograph. Smart big data in agricultural applications is an interdisciplinary research topic that is related to the extraction of meaningful information from data of plant physiology, drawing techniques from a variety of fields, such as UAV image processing, deep learning, pattern recognition, high-performance computing, and statistics. The big data can then be filtered and becomes smart big data before being analyzed for insights, which leads to more efficient decision-making. Smart big data can be defined as big data that has been cleaned, filtered, and prepared for data analysis.

Recently, researchers are gaining interest of the smart big data in precision agricultural applications [50, 125, 177]. For example, Li and Niu proposed a design for smart agriculture using the big data and IoT in [78]. They optimized the data storage, data processing, and data mining procedures generated in the agricultural production process and used the \( k \)-means algorithm to study the data mining. Based on the experimental results, the improved \( k \)-means clustering method had an average reduction of 0.23 second in total time and an average increase of 7.67% in the \( F \) metric value. In [149], Tseng et al. utilized the IoT devices to monitor the environmental factors on a farm. The experimental results demonstrated that farmers could gain a better understanding if a crop was appropriate for their farm by looking into factors such as temperature and soil moisture content. In [68], a big data analytic agricultural framework was developed to identify disease based on symptoms similarity, and a solution was suggested based on the high similarity. Although their framework is crop and location specific, it has great potential to expand to more crops and areas in the future.

Researchers are exploring all kinds of methods to turn the collected big data into smart big data to gain better understanding of our agricultural system. The authors believes that the smart big data will be a core component of big data applications in precision agriculture, which enables the stakeholders and researchers to identify
patterns, make better decisions, and adapt to new environment. Smart big data will also lay the foundation of agricultural data analysis.

1.3.2 Plant Physiology-Informed Machine Learning: A New Frontier for Precision Agriculture

Machine learning (ML) is the science (and art) of programming computers so they can learn from data [45]. A more engineering-oriented definition was given by Tom Mitchell in 1997: “A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E [98].” In 2006, Hinton et al. trained a deep neural network (DNN) to recognize handwritten digits with an accuracy of more than 98% [61]. Since then, researchers are more and more interested in deep learning (DL), and this enthusiasm extends to many areas of ML, such as image processing [181, 183], natural language processing [62], and even precision agriculture [110, 112, 182].

Why do we need ML? In summary, ML algorithms can usually simplify a solution and perform better than traditional methods, which may require much more hand-tuning rules. Furthermore, there may not exist a right solution for the complex phenomena by traditional methods. The ML techniques can help explain that kind of complexity and can adapt to new data better. The ML algorithms can obtain the variability about the complex problems and big data [114]. There are many different types and ways for ML algorithms classification (Fig. 1.1). ML can be classified as supervised, unsupervised, semi-supervised, and reinforcement learning (RL) based on whether human supervision is included. According to whether or not the ML algorithms can learn incrementally on the fly, they can be classified into online and batch learning. Based on whether or not the ML algorithms detect the training data patterns and create a predictive model, the ML can be classified into instance-based and model-based learning [45].

Considering the volume, diversity, and complexity of the agricultural dataset, plant physiology-informed machine learning is proposed in this monograph. The key of this concept is to extract meaningful agricultural information out of the big data to guide stakeholders and researchers to make better decisions for agriculture, in which the big data becomes “smart.” Instead of training the ML models directly, plant physiology knowledge will be added into the training process, which helps explain the complexity and model performance. When complexity is under scrutiny, it is fair that we ask what it means. At what point do investigators begin identifying a system, network, or phenomenon as complex [160, 161]? It seems that a clear and unified definition of complexity is still unknown for us to answer the following questions:

1. How can we characterize complexity?
1.3 Smart Big Data in Precision Agriculture: Acquisition and Advanced.

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**Fig. 1.1** The ML can be classified as supervised, unsupervised, semi-supervised, and reinforcement learning (RL) based on whether or not human supervision is included. According to whether or not the ML algorithms can learn incrementally on the fly, they can be classified into online and batch learning. Based on whether or not the ML algorithms detect the training data patterns and create a predictive model, the ML can be classified into instance-based and model-based learning.

2. What method should be used for the analysis of complexity in order to better understand real-world complex phenomena, such as the evapotranspiration of trees?

There is agreement among a significant fraction of the scientific community that when the distribution of the data associated with the process of interest is inverse power law (IPL), the phenomenon is complex. In the book by West and Grigolini [162], there is a table listing a sample of the empirical power laws and IPLs uncovered in the past two centuries. For example, in scale-free networks, the degree distributions follow an IPL in connectivity [11, 144]; in the processing of signals containing pink noise, the power spectrum is IPL [119]. For other examples, such as the probability distribution function (PDF), the autocorrelation function (ACF) [77], allometry \( Y = aX^b \) [179], anomalous relaxation (evolving over time) [143], anomalous diffusion (mean squared dissipation versus time) [96], and self-similar, they can all be described by an IPL.
1.3.3 Big Data Acquisition and Advanced Analytics

Smart big data involves the use of artificial intelligence and machine learning to make big data acquisition and advanced analytics actionable, to transform big data into insights, and to provide engagement capabilities for researchers and stakeholders. The smart big data acquisition and advanced analytics refer to the use of classification, conversion, extraction, and analysis methods to extract meaningful information from agricultural data. The acquisition and advanced analytics process generally contain the data preparation, the data analysis, and the result evaluation and explanation. Data preparation involves the agricultural data collection and integration using smart big data acquisition platforms, such as UAVs, Edge AI sensors, and UGVs. Data analytics refers to examining the large dataset and extracting the useful information out of the raw dataset by using ML algorithms and tools, such as PyTorch, TensorFlow, OpenCV, etc. Result evaluation and explanation involves the verification of patterns or characteristics produced by data analytics.

1.3.4 Fractional Calculus (FC) and Fractional-Order Thinking (FOT)

Fractional calculus (FC) is the quantitative analysis of functions using non-integer-order integration and differentiation, where the order can be a real number, a complex number, or even the function of a variable. The first recorded query regarding the meaning of a non-integer-order differentiation appeared in a letter written in 1695 by Guillaume de l’Hôpital to Gottfried Wilhelm Leibniz, who at the same time as Isaac Newton, but independently of him, co-invented the infinitesimal calculus [153]. Numerous contributors have provided definitions for fractional derivatives and integrals since then [151], and the theory along with the applications of FC have been expanded greatly over the centuries [1, 121, 130]. In more recent decades, the concept of fractional dynamics has merged and gained followers in the statistical and chemical physics communities [71, 123, 147]. For example, optimal image processing has improved through the use of fractional-order differentiation and fractional-order partial differential equations as summarized in Chen et al. [24, 25, 172]. Anomalous diffusion was described using fractional diffusion equations in [96, 133], and Metzler et al. used fractional Langevin equations to model viscoelastic materials [97].

Recently, big data and machine learning (ML) are two of the hottest topics of applied scientific research, and they are closely related to each other. To better understand them, we also need fractional dynamics, as well as fractional-order thinking (FOT). Section 1.3.7 is devoted to the discussion of the relationships between big data, variability, and fractional dynamics, as well as to fractional-order data analytics (FODA) [136]. The topics touched on in this section include the Hurst parameter [46, 94], fractional Gaussian noise (fGn), fractional Brownian
motion (fBm), the fractional autoregressive integrated moving average (FARIMA) [84], the formalism of continuous-time random walk (CTRW) [101], unmanned aerial vehicles (UAVs), and precision agriculture (PA) [81]. The key to developing an efficient learning process is the method of optimization. Thus, it is important to design an efficient or perhaps optimal optimization method. The derivative-free methods, and the gradient-based methods, such as the Nesterov accelerated gradient descent (NAGD) [105], are both discussed.

FOT is a way of thinking using FC. For example, there are non-integers between the integers; between logic 0 and logic 1, there is the fuzzy logic [173]; compared with integer-order splines, there are fractional-order splines [150]; between the high-order integer moments, there are non-integer-order moments, etc. FOT has been entailed by many research areas, for example, self-similar [29, 132], scale-free or scale-invariant, power-law, long-range dependence (LRD) [19, 119], and $1/f^\alpha$ noise [57, 165]. The terms porous media, particulate, granular, lossy, anomaly, disorder, soil, tissue, electrodes, biology [10], nano, network, transport, diffusion, and soft matters are also intimately related to FOT. However, in this section, the authors mainly discuss complexity and inverse power laws (IPL).

### 1.3.5 Complexity and Inverse Power Laws (IPLs)

When studying complexity, it is fair to ask, what does it mean to be complex? When do investigators begin identifying a system, network, or phenomenon as complex [160, 161]? There is an agreement among a significant fraction of the scientific community that when the distribution of the data associated with the process of interest obeys an IPL, the phenomenon is complex; see Fig. 1.2. On the left side of the figure, the complexity “bow tie” is the phenomenon of interest, thought to be a complex system [30, 35, 36, 178]. On the right side of the figure is the spectrum of system properties associated with IPL probability density functions (PDFs): the system has one or more of the properties of being scale-free, having a heavy tail, having a long-range dependence, and/or having a long memory [51, 137]. In the book by West and Grigolini [162], there is a table listing a sample of the empirical power laws and IPLs uncovered in the past two centuries. For example, in scale-free networks, the degree distributions follow an IPL in connectivity [11, 144]; in the processing of signals containing pink noise, the power spectrum follows an IPL [119]. Other examples, such as the probability density function (PDF), the autocorrelation function (ACF) [77], allometry ($Y = aX^b$) [179], anomalous relaxation (evolving over time) [143], anomalous diffusion (mean squared dissipation versus time) [96], and self-similarity, can all be described by the IPL “bow tie” depicted in Fig. 1.2.

The power law is usually described as:

$$f(x) = ax^k,$$

(1.2)
where $k$ is negative and $f(x)$ is an IPL. One important characteristic of this power law is scale invariance \cite{69} determined by:

$$f(cx) = a(cx)^k = c^k f(x) \propto f(x). \quad (1.3)$$

Note that when $x$ is the time, the scaling depicts a property of the system dynamics. However, when the system is stochastic, the scaling is a property of the PDF (or correlation structure) and is a constraint on the collective properties of the system.

FC is entailed by complexity, since an observable phenomenon represented by a fractal function has integer-order derivatives that diverge. Consequently, for the complexity characterization and regulation, we ought to use the fractional dynamics point of view because the fractional derivative of a fractal function is finite. Thus, complex phenomena, no matter whether they are natural or carefully engineered, ought to be described by fractional dynamics. Phenomena in complex systems in many cases should be analyzed using FC-based models, where mathematically, the IPL is actually the “Mittag-Leffler law” (MLL), which asymptotically becomes an IPL (Fig. 1.3), known as heavy-tail behavior.

When an IPL results from processing data, one should think about how the phenomena can be connected to the FC. In \cite{48}, Gorenflo et al. explained the role of the FC in generating stable PDFs by generalizing the diffusion equation to one of fractional order. For the Cauchy problem, they considered the space fractional diffusion equation:

$$\frac{\partial u}{\partial t} = D(\alpha) \frac{\partial^\alpha u}{\partial |x|^\alpha}, \quad (1.4)$$
where $-\infty < x < \infty$, $t \geq 0$ with $u(x, 0) = \delta(x)$, $0 < \alpha \leq 2$, and $D(\alpha)$ is a suitable diffusion coefficient. The fractional derivative in the diffusion variable is of the Riesz-Feller form, defined by its Fourier transform to be $|k|^{\alpha}$. For the signalling problem, they considered the so-called time-fractional diffusion equation [91]:

$$\frac{\partial^{2\beta} u}{\partial t^{2\beta}} = D(\beta) \frac{\partial^2 u}{\partial x^2},$$  

(1.5)

where $x \geq 0$, $t \geq 0$ with $u(0, t) = \delta(t)$, $0 < \beta < 1$, and $D(\beta)$ is a suitable diffusion coefficient. Equation (1.5) has also been investigated in [87–89]. Here, the Caputo fractional derivative in time is used.

There are rich forms in stochasticity [102], for example, heavy-tailedness, which corresponds to fractional-order master equations [80]. In Sect. 1.3.6, heavy-tailed distributions are discussed.

### 1.3.6 Heavy-Tailed Distributions

In probability theory, heavy-tailed distributions are PDFs whose tails do not decay exponentially [8]. Consequently, they have more weight in their tails than does an exponential distribution. In many applications, it is the right tail of the distribution...
that is of interest, but a distribution may have a heavy left tail, or both tails may be heavy. Heavy-tailed distributions are widely used for modeling in different disciplines, such as finance [14], insurance [2], and medicine [126]. The distribution of a real-valued random variable $X$ is said to have a heavy right tail if the tail probabilities $P(X > x)$ decay more slowly than those of any exponential distribution:

$$\lim_{x \to \infty} \left( \frac{P(X > x)}{e^{-\lambda x}} \right) = \infty,$$

for every $\lambda > 0$ [128]. For the heavy left tail, an analogous definition can be constructed [42]. Typically, there are three important subclasses of heavy-tailed distributions: fat-tailed, long-tailed, and subexponential distributions.

### 1.3.6.1 The Lévy Distribution

A Lévy distribution, named after the French mathematician Paul Lévy, can be generated by a random walk whose steps have a probability of having a length determined by a heavy-tailed distribution [108]. As a fractional-order stochastic process with heavy-tailed distributions, a Lévy distribution has better computational characteristics [55]. A Lévy distribution is stable and has a PDF that can be expressed analytically, although not always in closed form. The PDF of Lévy flight [170] is:

$$p(x, \mu, \gamma) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} e^{\frac{-(x-\mu)^2}{2\gamma}}, & x > \mu, \\ 0, & x \leq \mu, \end{cases}$$

where $\mu$ is the location parameter and $\gamma$ is the scale parameter. In practice, the Lévy distribution is updated by:

$$\text{Lévy}(\beta) = \frac{u}{|v|^{1/\beta}},$$

where $u$ and $v$ are random numbers generated from a normal distribution with a mean of 0 and standard deviation of 1 [171]. The stability index $\beta$ ranges from 0 to 2. Moreover, it is interesting to point out that the well-known Gaussian and Cauchy distributions are special cases of the Lévy PDF when the stability index is set to 2 and 1, respectively.
1.3.6.2 The Mittag-Leffler PDF

The Mittag-Leffler PDF for the time interval between events can be written as a mixture of exponentials with a known PDF for the exponential rates [58]:

\[
E_\theta(-t^\theta) = \int_0^\infty \exp(-\mu t)g(\mu)d\mu,
\]

with a weight for the rates given by:

\[
g(\mu) = \frac{1}{\pi} \frac{\sin(\theta \pi)}{\mu^{1+\theta} + 2 \cos(\theta \pi)\mu + \mu^{1-\theta}}.
\]

The most convenient expression for the random time interval was proposed by Jayakumar [65]:

\[
\tau_\theta = -\gamma_t \left( \ln u \frac{\sin(\theta \pi)}{\tan(\theta \pi v)} - \cos(\theta \pi) \right)^{1/\theta},
\]

where \( u, v \in (0,1) \) are independent uniform random numbers, \( \gamma_t \) is the scale parameter, and \( \tau_\theta \) is the Mittag-Leffler random number. In [157], Wei et al. used the Mittag-Leffler distribution for improving the cuckoo search algorithm, which showed an improved performance.

1.3.6.3 The Weibull Distribution

A random variable is described by a Weibull distribution if it has a PDF function \( F \):

\[
F(x) = e^{-(x/k)^{\lambda_w}},
\]

where \( k > 0 \) is the scale parameter and \( \lambda_w > 0 \) is the shape parameter [127]. If the shape parameter is \( \lambda_w < 1 \), the Weibull distribution is determined to be heavy tailed.

1.3.6.4 The Cauchy Distribution

A random variable is described by a Cauchy PDF if its cumulative distribution is [39, 66]:

\[
F(x) = \frac{1}{\pi} \arctan \left( \frac{2(x - \mu_c)}{\sigma} \right) + \frac{1}{2},
\]

where \( \mu_c \) is the location parameter and \( \sigma \) is the scale parameter. Cauchy distributions are examples of fat-tailed distributions, which have been empirically
encountered in a variety of areas including physics, earth sciences, economics, and political science [83]. Fat-tailed distributions include those whose tails decay like an IPL, which is a common point of reference in their use in the scientific literature [9]:

### 1.3.6.5 The Pareto Distribution

A random variable is said to be described by a Pareto PDF if its cumulative distribution function is:

\[
F(x) = \begin{cases} 
1 - \left(\frac{b}{x}\right)^a, & x \geq b, \\
0, & x < b, 
\end{cases}
\]

(1.14)

where \( b > 0 \) is the scale parameter and \( a > 0 \) is the shape parameter (Pareto’s index of inequality) [44].

### 1.3.6.6 The \( \alpha \)-Stable Distribution

A PDF is said to be stable if a linear combination of two independent random variables, each with the same distribution, has the same distribution for the conjoined variable. This PDF is also called the Lévy \( \alpha \)-stable distribution [76, 92]. Since the normal distribution, Cauchy distribution, and Lévy distribution all have the above property, one can consider them to be special cases of stable distributions. Stable distributions have \( 0 < \alpha \leq 2 \), with the upper bound corresponding to the normal distribution, and \( \alpha = 1 \), to the Cauchy distribution. The PDFs have undefined variances for \( \alpha < 2 \) and undefined means for \( \alpha \leq 1 \). Although their PDFs do not admit a closed-form formula in general, except in special cases, they decay with an IPL tail called the IPL index, which determines the behavior of the PDF. As the IPL index gets smaller, the PDF acquires a heavier tail.

### 1.3.6.7 Mixture Distributions

A mixture distribution is derived from a collection of other random variables. First, a random variable is selected by chance from the collection according to given probabilities of selection. Then, the value of the selected random variable is realized. The mixture PDFs are complicated in terms of simpler PDFs, which provide a good model for certain datasets. The different subsets of the data can exhibit different characteristics. Therefore, the mixed PDFs can effectively characterize the complex PDFs of certain real-world datasets. In [86], a robust stochastic configuration network (SCN) based on a mixture of Gaussian and Laplace PDFs was proposed. Thus, Gaussian and Laplace distributions are mentioned in this section for comparison purposes.
1.3.6.8 The Gaussian Distribution

A random variable $X$ has a Gaussian distribution with the mean $\mu_G$ and variance $\sigma_G^2$ ($-\infty < \mu_G < \infty$ and $\sigma_G > 0$) if $X$ has a continuous distribution for which the PDF is as follows [140]:

$$f(x|\mu_G, \sigma_G^2) = \frac{1}{(2\pi)^{1/2}\sigma_G} e^{-\frac{1}{2} \left( \frac{x-\mu_G}{\sigma_G} \right)^2}, \text{ for } -\infty < x < \infty. \quad (1.15)$$

1.3.6.9 The Laplace Distribution

The PDF of the Laplace distribution can be written as follows [86]:

$$F(x|\mu_l, \eta) = \frac{1}{(2\eta^2)^{1/2}} e^{-\frac{\sqrt{2|x-\mu_l|}}{\eta}}, \quad (1.16)$$

where $\mu_l$ and $\eta$ represent the location and scale parameters, respectively.

1.3.7 Big Data, Variability, and FC

Here the authors discussed the ten characteristics (properties) of big data to prepare for both the challenges and advantages of big data initiatives (Table 1.3). In this section, variability is the most important characteristic being discussed. Variability can refer to multiple research topics (Table 1.4) [41].

| Characteristics | Description |
|-----------------|-------------|
| 1. Volume       | Best known characteristic of big data; more than 90 percent of the whole data were created in the past couple of years |
| 2. Velocity     | The speed at which data are being generated |
| 3. Variety      | Processing structured, unstructured, and semistructured data |
| **4. Variability** | Inconsistent speed of data loading, multitude of data dimensions, and number of inconsistencies |
| 5. Veracity     | Confidence or trust in the data |
| 6. Validity     | Refers to how accurate and correct the data are |
| 7. Vulnerability| Security concerns, data breaches |
| 8. Volatility   | Design policy for data currency, availability, and rapid retrieval of information when required |
| 9. Visualization| Develop new tools considering the complex relationships between the above properties |
| 10. Value       | The most important of the 10 Vs; substantial value must be found |
Table 1.4 Variability in multiple research topics

| Topics                        | Description                                                                 |
|-------------------------------|-----------------------------------------------------------------------------|
| 1. Climate variability        | Changes in the components of the climate system and their interactions       |
| 2. Genetic variability        | Measurements of the tendencies of individual genotypes between regions      |
| 3. Heart rate variability     | Physiological phenomenon where the time interval between heart beats varies  |
| 4. Human variability          | Measurements of the characteristics, physical or mental, of human beings    |
| 5. Spatial variability        | Measurements at different spatial points exhibit different values           |
| 6. Statistical variability    | A measure of dispersion in statistics                                        |

Considering variability, Xunzi (312 BC–230 BC), who was a Confucian philosopher, made a useful observation: “Throughout a thousand acts and ten thousand changes, his way remains one and the same [64].” Therefore, we ask: what is the “one and the same” for big data? This is the variability, which refers to the behavior of the dynamic system. The ancient Greek philosopher Heraclitus (535 BC–475 BC) also realized the importance of variability, prompting him to say: “The only thing that is constant is change”; “It is in changing that we find purpose”; “Nothing endures but change”; “No man ever steps in the same river twice, for it is not the same river and he is not the same man.”

Heraclitus actually recognized the (fractional-order) dynamics of the river without modern scientific knowledge (in nature). After two thousand years, the integer-order calculus was invented by Sir Isaac Newton and Gottfried Wilhelm Leibniz, whose main purpose was to quantify that change [12, 16]. From then, scientists started using integer-order calculus to depict dynamic systems, differential equations, modeling, etc. In the 1950s, Scott Blair, who first introduced the FC into rheology, pointed out that the integer-order dynamic view of change is only for our own “convenience” (a little bit selfish). In other words, denying fractional calculus is equivalent to denying the existence of non-integers between the integers!

Blair said: “We may express our concepts in Newtonian terms if we find this convenient but, if we do so, we must realize that we have made a translation into a language which is foreign to the system which we are studying (1950) [146].”

Therefore, variability exists in big data. However, how do we realize the modeling, analysis, and design (MAD) for the variability in big data within complex systems? We need fractional calculus! In other words, big data are at the nexus of complexity and FC. Metrics based on using the fractional-order signal processing techniques should be used for quantifying the generating dynamics of observed or perceived variability [136].
1.3.7.1 The Hurst Parameter, fGn, and fBm

The Hurst parameter or Hurst exponent ($H$) was proposed for the analysis of the long-term memory of time series. It was originally developed to quantify the long-term storage capacity of reservoirs for the Nile river’s volatile rain and drought conditions more than a half century ago [46, 94]. To date, the Hurst parameter has also been used to measure the intensity of long-range dependence (LRD) in time series [23], which requires accurate modeling and forecasting. The self-similarity and the estimation of the statistical parameters of LRD have commonly been investigated recently [138]. The Hurst parameter has also been used for characterizing the LRD process [23, 142]. A LRD time series is defined as a stationary process that has long-range correlations if its covariance function $C(n)$ decays slowly as:

$$\lim_{n \to \infty} \frac{C(n)}{n^{-\alpha}} = c, \quad (1.17)$$

where $0 < \alpha < 1$, which relates to the Hurst parameter according to $\alpha = 2 - 2H$ [120, 131]. The parameter $c$ is a finite, positive constant. When the value of $n$ is large, $C(n)$ behaves as the IPL $c/n^\alpha$ [53]. Another definition for an LRD process is that the weakly stationary time series $X(t)$ is said to be LRD if its power spectral density (PSD) follows:

$$f(\lambda) \sim C_f |\lambda|^{-\beta}, \quad (1.18)$$

as $\lambda \to 0$, for a given $C_f > 0$ and a given real parameter $\beta \in (0,1)$, which corresponds to $H = (1 + \beta)/2$ [26]. When $0 < H < 0.5$, it indicates that the time intervals constitute a negatively correlated process. When $0.5 < H < 1$, it indicates that time intervals constitute a positively correlated process. When $H = 0.5$, it indicates that the process is uncorrelated.

Two of the most common LRD processes are fBm [31] and fGn [72]. The fBm process with $H(0 < H < 1)$ is defined as:

$$B_H(t) = \frac{1}{\Gamma(H + 1/2)} \left\{ \int_{-\infty}^{0} [(t - s)^{H-1/2} - (-s)^{H-1/2}]dW(s) + \int_{0}^{t} (t - s)^{H-1/2}dW(s) \right\}, \quad (1.19)$$

where $W$ denotes a Wiener process defined on $(-\infty, \infty)$ [93]. The fGn process is the increment sequences of the fBm process, defined as:

$$X_k = Y(k + 1) - Y(k), \quad (1.20)$$

where $Y(k)$ is a fBm process [117].
1.3.7.2 Fractional Lower-Order Moments (FLOMs)

The FLOM is based on $\alpha$-stable PDFs. The PDFs of an $\alpha$-stable distribution decay in the tails more slowly than a Gaussian PDF does. Therefore, for sharp spikes or occasional bursts in signals, an $\alpha$-stable PDF can be used for characterizing signals more frequently than Gaussian-distributed signals [22]. Thus, the FLOM plays an important role in impulsive processes [85], equivalent to the role played by the mean and variance in a Gaussian process. When $0 < \alpha \leq 1$, the $\alpha$-stable processes have no finite first- or higher-order moments; when $1 < \alpha < 2$, the $\alpha$-stable processes have a first-order moment and all the FLOMs with moments of fractional order that is less than 1. The correlation between the FC and FLOM was investigated in [27, 28]. For the Fourier transform pair $p(x)$ and $\phi(\mu)$, the latter is the characteristic function and is the Fourier transform of the PDF; a complex FLOM can have complex fractional lower orders [27, 28]. A FLOM-based fractional power spectrum includes a covariation spectrum and a fractional low-order covariance spectrum [90]. FLOM-based fractional power spectrum techniques have been successfully used in time-delay estimation [90].

1.3.7.3 Fractional Autoregressive Integrated Moving Average (FARIMA) and Gegenbauer Autoregressive Moving Average (GARMA)

A continuous-time linear time-invariant (LTI) system can be characterized using a linear difference equation, which is known as an autoregression and moving average (ARMA) model [129, 134]. The process $X_t$ of ARMA($p, q$) is defined as:

$$\Phi(B)X_t = \Theta(B)\epsilon_t,$$

(1.21)

where $\epsilon_t$ is white Gaussian noise (wGn) and $B$ is the backshift operator. However, the ARMA model can only describe a short-range dependence (SRD) property. Therefore, based on the Hurst parameter analysis, more suitable models, such as FARIMA [56, 135] and fractional integral generalized autoregressive conditional heteroscedasticity (FIGARCH) [79], were designed to more accurately analyze the LRD processes. The most important feature of these models is the long memory characteristic. The FARIMA and FIGARCH can capture both the short- and the long-memory nature of time series. For example, the FARIMA process $X_t$ is usually defined as [18]:

$$\Phi(B)(1 - B)^d X_t = \Theta(B)\epsilon_t,$$

(1.22)

where $d \in (-0.5, 0.5)$ and $(1 - B)^d$ is a fractional-order difference operator. The locally stationary long-memory FARIMA model has the same equation as that of Eq.(1.22), except that $d$ becomes $d_t$, which is a time-varying parameter [15]. The locally stationary long-memory FARIMA model captures the local self-similarity of the system.
The generalized locally stationary long-memory process FARIMA model was investigated in [15]. For example, a generalized FARIMA model, which is called the Gegenbauer autoregressive moving average (GARMA), was introduced in [52]. The GARMA model is defined as:

\[
\Phi(B)(1 - 2uB + B^2)^d X_t = \Theta(B)\epsilon_t,
\]

where \( u \in [-1, 1] \), which is a parameter that can control the frequency at which the long memory occurs. The parameter \( d \) controls the rate of decay of the autocovariance function. The GARMA model can also be extended to the so-called \( k \)-factor GARMA model, which allows for long-memory behaviors to be associated with each of \( k \) frequencies (Gegenbauer frequencies) in the interval [0, 0.5] [166].

### 1.3.7.4 Continuous-Time Random Walk (CTRW)

The CTRW model was proposed by Montroll and Weiss as a generalization of diffusion process to describe the phenomenon of anomalous diffusion [101]. The basic idea is to calculate the PDF for the diffusion process by replacing the discrete steps with continuous time, along with a PDF for step lengths and a waiting-time PDF for the time intervals between steps. Montroll and Weiss applied random intervals between the successive steps in the walking process to account for local structure in the environment, such as traps [159]. The CTRW has been used for modeling multiple complex phenomena, such as chaotic dynamic networks [175]. The correlation between CTRW and diffusion equations with fractional time derivatives has also been established [60]. Meanwhile, time-space fractional diffusion equations can be treated as CTRWs with continuously distributed jumps or continuum approximations of CTRWs on lattices [49].

### 1.3.7.5 Unmanned Aerial Vehicles (UAVs) and Precision Agriculture

As a new remote sensing platform, researchers are gaining interest in the potential of small UAVs for precision agriculture [21, 32, 33, 47, 109–113, 145, 174], especially for heterogeneous crops, such as vineyards and orchards [180, 182]. Mounted on UAVs, lightweight sensors, such as RGB cameras, multispectral cameras, and thermal infrared cameras, can be used to collect high-resolution images. The higher temporal and spatial resolutions of the images, relatively low operational costs, and nearly real-time image acquisition make the UAV an ideal platform for mapping and monitoring the variability of crops and trees. UAVs can create big data and demand the FODA due to the “complexity” and, thus, variability inherent in the life process. For example, Fig. 1.4 shows the normalized difference vegetation index (NDVI) mapping of a pomegranate orchard at the USDA-ARS experimental field. Under different irrigation levels, the individual trees can show strong variability during the analysis of water stress. Life is complex! Thus, it entails variability, which
as discussed above, in turn, entails fractional dynamics. UAVs can then become “Tractor 2.0” for farmers in precision agriculture.

**1.3.8 Optimal Machine Learning and Optimal Randomness**

Most ML algorithms perform training by solving optimization problems that rely on first-order derivatives (*Jacobians*), which decide whether to increase or decrease weights. For huge speed boosts, faster optimizers are being used instead of the regular gradient descent optimizer. For example, the most popular boosters are momentum optimization [122], Nesterov accelerated gradient [105], AdaGrad [37], RMSProp [148], and Adam optimization [70]. The second-order (*Hessian*) optimization methods usually find the solutions with faster rates of convergence but with higher computational costs. Therefore, the answer to the following question is important: (1) What is a more optimal ML algorithm? (2) What if the derivative is fractional order instead of integer order? In this section, we discuss some applications of fractional-order gradients to optimization methods in ML algorithms and investigate the accuracy and convergence rates.

As mentioned in the big data section, there is a huge amount of data in human society and nature. During the learning process of ML, we care not only about the speed but also the accuracy of the data the machine is learning (Fig. 1.5).
The learning algorithm is important; otherwise, the data labeling and other labor costs will exhaust people beyond their abilities. When applying the artificial intelligence (AI) to an algorithm, a strong emphasis is on artificial, only followed weakly by intelligence. Therefore, the key to ML is what optimization methods are being applied. The convergence rate and global searching are two important parts of the optimization method.

**Reflection** The ML is a hot research topic and will probably remain so into the near future. How a machine can learn efficiently (optimally) is always important. The key for the learning process is the optimization method. Thus, in designing an efficient optimization method, it is necessary to answer the following three questions:

- What is the optimal way to optimize?
- What is the *more optimal* way to optimize?
- Can we demand “*more optimal machine learning,*” for example, deep learning with the minimum/smallest labeled data?

**Optimal Randomness** In the section of the Lévy PDF, the Lévy flight is the search strategy for food that the albatross has developed over millions of years of evolution. Admittedly, this is a slow optimization procedure [154]. From this perspective, we should call “Lévy distribution” an optimized or learned randomness used by albatrosses for food search. Therefore, we pose the question: “Can the search strategy be more optimal than Lévy flight?” The answer is yes if one adopts the FC [176]! Optimization is a very complex area of study. However, few studies have investigated using FC to obtain a better optimization strategy.
1.3.8.1 Derivative-Free Methods

For derivative-free methods, there are single agent search and swarm-based search methods (Fig. 1.6). Exploration is often achieved by randomness or random numbers in terms of some predefined PDFs. Exploitation uses local information such as gradients to search local regions more intensively, and such intensification can enhance the rate of convergence. Thus, a question was posed: what is the optimal randomness? Wei et al. investigated the optimal randomness in a swarm-based search [158]. Four heavy-tailed PDFs have been used for sample path analysis (Fig. 1.7). Based on the experimental results, the randomness-enhanced cuckoo search (CS) algorithms [155–157] can identify the unknown specific parameters of a fractional-order system with better effectiveness and robustness. The randomness-enhanced CS algorithms can be considered as a promising tool for solving real-world complex optimization problems. The reason is that optimal randomness is applied with fractional-order noise during the exploration, which is more optimal than the “optimized PSO,” CS. The fractional-order noise refers to the stable PDFs [48]. In other words, when we are discussing optimal randomness, we are discussing fractional calculus!

1.3.8.2 Gradient-Based Methods

The gradient descent (GD) is a very common optimization algorithm, which can find the optimal solutions by iteratively tweaking parameters to minimize the cost function. The stochastic gradient descent (SGD) randomly selects times during the training process. Therefore, the cost function bounces up and down, decreasing on average, which is good for escape from local optima. Sometimes, noise is added into the GD method, and usually, such noise follows a Gaussian PDF in the literature.
Fig. 1.7 Sample path analysis. Wei et al. investigated the optimal randomness in a swarm-based search. Four heavy-tailed PDFs were used for sample path analysis. The long steps, referring to the jump length, frequently happened for all distributions, which showed strong heavy-tailed performance. (a) Mittag-Leffler distribution. (b) Weibull distribution. (c) Pareto distribution. (d) Cauchy distribution

We ask, “Why not heavy-tailed PDFs”? The answer to this question can lead to interesting future research.

1.3.8.3 The Nesterov Accelerated Gradient Descent (NAGD)

There are many variants of GD analysis as suggested in Fig. 1.8. One of the most popular methods is the NAGD [105]:
Fig. 1.8 Gradient descent and its variants

\[
\begin{align*}
    y_{k+1} &= ay_k - \mu \nabla f(x_k), \\
    x_{k+1} &= x_k + y_{k+1} + by_k,
\end{align*}
\]  
(1.24)

where by setting \( b = -a/(1 + a) \), one can derive the NAGD. When \( b = 0 \), one can derive the momentum GD. The NAGD can also be formulated as:

\[
\begin{align*}
    x_k &= y_{k-1} - \mu \nabla f(y_{k-1}), \\
    y_k &= x_k + \frac{k-1}{k+2} (x_k - x_{k-1}).
\end{align*}
\]  
(1.25)

Set \( t = k \sqrt{\mu} \), and one can, in the continuous limit, derive the corresponding differential equation:

\[
\ddot{X} + \frac{3}{t} \dot{X} + \nabla f(X) = 0.
\]  
(1.26)

The main idea of Jordan’s work is to analyze the iteration algorithm in the continuous-time domain [164]. For differential equations, one can use the Laypunov or variational method to analyze the properties; for example, the convergence rate is \( O\left(\frac{1}{t^2}\right) \). One can also use the variational method to derive the master differential equation for an optimization method, such as the least action principle [40], Hamilton’s variational principle [54] and the quantum-mechanical path integral approach [59]. Wilson et al. built a Euler-Lagrange function to derive the following equation [164]:

\[
\ddot{X}_t + 2\gamma \dot{X}_t + \frac{\gamma^2}{\mu} \nabla f(X_t) = 0.
\]  
(1.27)

which is in the same form as the master differential equation of NAGD.
Jordan’s work revealed that one can transform an iterative (optimization) algorithm to its continuous-time limit case, which can simplify the analysis (Laypunov methods). One can directly design a differential equation of motion (EOM) and then discretize it to derive an iterative algorithm (variational method). The key is to find a suitable Laypunov functional to analyze the stability and convergent rate. The new exciting fact established by Jordan is that optimization algorithms can be systematically synthesized using Lagrangian mechanics (Euler-Lagrange) through EOMs.

Thus, is there an optimal way to optimize using optimization algorithms stemming from Eq. (1.27)? Obviously, why not an equation such as Eq. (1.27) of fractional order? Considering the \( \dot{X}_t \) as \( X_t^{(\alpha)} \), it will provide us with more research possibilities, such as the fractional-order calculus of variation (FOCV) and fractional-order Euler-Lagrange (FOEL) equation. For the SGD, optimal randomness using the fractional-order noises can also offer better than the best performance, similarly shown by Wei et al. [158].

1.4 Main Contributions

The major contributions of this monograph include, but are not limited to, the following:

1. Reviewed the most commonly used ET estimation methods with small UAVs. The discussed ET estimation methods with UAVs and their advantages and disadvantages were also summarized.
2. Investigated the approaches of estimating crop coefficient (\( K_c \)) using UAV-based NDVI for an experimental pomegranate orchard. The spatial and temporal variability of \( K_c \) and NDVI were analyzed by using the Deep Stochastic Configuration Networks (DeepSCNs).
3. Established a regression model between the NDVI and \( K_c \). The performance of the new regression model was evaluated by the data collected by the UAVs.
4. Developed a reliable tree-level ET estimation method using UAV high-resolution multispectral images.
5. Provided a framework to establish a linear regression model between the NDVI and \( K_c \) to estimate the actual daily ET.
6. Developed a reliable tree-level water stress detection method using UAV-based high-resolution thermal images.
7. Proposed the concept of CIML and proved its performance on the classification of tree-level irrigation treatments. The CNN model was also evaluated for tree-level water status inference.
1.5 Book Organization

This monograph is structured as follows: The research motivations and contributions are introduced in Chap. 1.

In Chap. 2, small UAVs and remote sensing payloads were introduced and discussed. UAV image acquisition and processing methods were also presented. The challenges and opportunities for UAV ET estimation methods were also discussed in this chapter.

In Chap. 3, the authors reviewed the most commonly used ET estimation methods with small UAVs. The OSEB, HRMET, machine learning (ML), artificial neural networks (ANN), TSEB, DTD, SEBAL, and METRIC were introduced in this chapter. The discussed ET estimation methods with UAVs and their advantages and disadvantages were also summarized in this chapter.

In Chap. 4, the authors investigate the approaches of estimating $K_c$ using UAV-based NDVI for an experimental pomegranate orchard. The spatial and temporal variability of $K_c$ and NDVI were analyzed by using the Deep Stochastic Configuration Networks (DeepSCNs). A regression model was established between the NDVI and $K_c$. The performance of the new regression model was evaluated by the data collected by the UAVs.

In Chap. 5, a reliable tree-level ET estimation method was developed using UAV high-resolution multispectral images. Then, a framework was provided to establish a linear regression model between the NDVI and $K_c$ to estimate the actual daily ET. Results showed that the linear regression model could estimate tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively, which showed a state-of-the-art performance.

In Chap. 6, the authors evaluated the reliability of the UAV thermal camera on individual tree canopy temperature measurements. Then, the authors investigated and validated the approaches of irrigation treatment inference using UAV-based $\Delta T$ at individual tree level and demonstrated the performance of the CIML models on irrigation treatment inference.

In Chap. 7, the authors drew the conclusive remarks in the monograph and discussed the future research directions.

1.6 Results Reproducibility

The dataset for the methods presented in this monograph will be published on https://github.com/niuhaoyu16/ET-Springer-Book/ so that readers can reproduce the results more easily.
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Chapter 2
Small Unmanned Aerial Vehicles (UAVs) and Remote Sensing Payloads

2.1 The UAV Platform

Many kinds of UAVs are used for different research purposes, such as ET estimation. Some popular UAV platforms are shown in Fig. 2.1. Typically, there are two types of UAV platforms, fixed wings and multirotors. Fixed wings can usually fly longer with a larger payload. It can usually fly for about 2 hours, which is suitable for a large field. Multirotors can fly about 30 minutes with payload, which is suitable for short flight missions. Both of them have been used in agricultural research, such as [70, 71], which promises great potential in precision agriculture.

The authors mainly used a quadcopter named “Hover” to collect aerial images, as shown in Fig. 2.1e. The “Hover” was equipped with a Pixhawk flight controller, GPS, and telemetry antennas. It can fly over the field by waypoints mode (designed by using Mission Planner software). The lithium polymer battery of “Hover” has a capacity of 9500 mAh, which can support a 30-minute flight mission with cameras mounted on it. The specifications of the “Hover” are listed in Table 2.1 for reference. The “Hover” is equipped with high efficient power system, including T-Motor MN3508 KV380 motor, 1552 folding propeller, and Foxtech Multi-Pal 40A OPTO ESC, to ensure long flight time.

2.2 Lightweight Sensors

Mounted on UAVs, many lightweight sensors can be used for collecting UAV imagery, such as RGB, multispectral, and thermal images, for agricultural research. In this section, the authors listed the sensors that had been commonly used in most of his research work. The sensors being introduced here will be mentioned in the following chapters frequently. Therefore, the authors introduced the sensors in this section in detail.
Fig. 2.1 (a) The QuestUAV 200 UAV. (b) The MK Okto XL 6S12. (c) The DJI S1000. (d) The eBee Classic. (e) The Hover

Table 2.1 The specifications of “Hover.” The quadcopter is equipped with high efficient power system, including T-Motor MN3508 KV380 motor, 1552 folding propeller, and Foxtech Multi-Pal 40A OPTO ESC, to ensure long flight time

| Specifications                  | Details                                   |
|---------------------------------|-------------------------------------------|
| Wheelbase                       | 610 mm                                    |
| Folding size                    | $285 \times 285 \times 175$ mm            |
| Propeller                       | Foxtech 1552 folding propeller            |
| Motor                           | T-Motor MN3508 KV380                      |
| ESC                             | Foxtech Multi-Pal 40A OPTO ESC(Simonk Firmware) |
| Flight controller               | Pixhawk cube orange standard set with Here 2 GNSS |
| Operating temperature           | $-20^\circ$ to $+50^\circ$ C              |
| Suggested flight altitude       | $<1000$ m                                 |
| Max airspeed                    | 20 m/s                                    |

2.2.1 RGB Camera

The Survey 2 (MAPIR, San Diego, CA, USA)\(^1\) camera has four bands, blue, green, red, and near infrared (NIR), with a spectral resolution of $4608 \times 3456$ pixels and a spatial resolution of $1.01$ cm/pixel (Fig. 2.2). The Survey 2 camera has a fast interval timer, 2 seconds for JPG mode and 3 seconds for RAW + JPG mode. Faster interval

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\(^1\) Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the University of California. The University of California is equal opportunity providers and employers.
2.2 Lightweight Sensors

Fig. 2.2 The Survey 2 sensors and the reflectance calibration ground target package

Fig. 2.3 The RedEdge-M is a commonly used multispectral camera. The RedEdge-M has five bands, which are blue, green, red, near infrared, and red edge. It has a spectral resolution of 1280 × 960 pixel, with a 46° field of view.

timer would benefit the overlap design for UAV flight missions, such as reducing the flight time and enabling higher overlapping.

2.2.2 Multispectral Camera

The RedEdge-M is a commonly used multispectral camera (Fig. 2.3). The RedEdge-M has five bands, which are blue, green, red, near infrared, and red edge. It has a spectral resolution of 1280 × 960 pixel, with a 46° field of view. With a Downwelling Light Sensor (DLS), which is a five-band light sensor that connects to the camera, the RedEdge-M can measure the ambient light during a flight mission for each of the five bands. Then, it can record the light information in the metadata of the images captured by the camera. After the camera calibration, the information detected by the DLS can be used to correct lighting changes during a flight, such as changes in cloud cover during a UAV flight.
2.2.3 Shortwave Infrared Camera

The SWIR 640 P-Series (Infrared Cameras Inc, Beaumont, TX, USA), which is a shortwave infrared camera, has also been commonly used for agricultural research (Fig. 2.4). The spectral band is from 0.9 to 1.7 μm. The accuracy for the SWIR camera is ±1°C. It has a resolution of 640 × 512 pixels.

2.2.4 Thermal Camera

The thermal camera ICI 9640 P (Infrared Cameras Inc, Beaumont, TX, USA) has been used for collecting thermal images as reported in [38, 44, 51, 69]. The thermal camera has a resolution of 640 × 480 pixels. The spectral band is from 7 to 14 μm. The dimension of the thermal camera is 34 mm × 30 mm × 34 mm (Fig. 2.5). The accuracy is designed to be ±2°C. A Raspberry Pi Model B computer (Raspberry Pi Foundation, Cambridge, UK) can be used to trigger the thermal camera during flight missions.

2.3 UAV Image Acquisition and Processing

2.3.1 Flight Mission Design

The authors used the Mission Planner to program all flight missions (Fig. 2.6). The flight height was usually set up as 30, 60, 90, and 120 m based on research purpose. The overlapping of UAV imagery was set up as 80%, so that the UAV imagery of the crops or trees can be stitched together during image processing. A biweekly UAV flight schedule is suggested to collect sufficient data. If there is a UAV crash,
### Fig. 2.5
The thermal camera has a resolution of $640 \times 480$ pixels. The spectral band is from 7 to 14 $\mu$m. The dimension of the thermal camera is $34 \text{ mm} \times 30 \text{ mm} \times 34 \text{ mm}$. The accuracy is designed to be $\pm 2 ^\circ C$.

### Fig. 2.6
The user interface of Mission Planner. The example of flight mission was for nematode data collection using UAV for Project 30 at UC Kearney Center.

Unexpected weather conditions, hardware issues, or unknown reasons, data may not be collected successfully. If data is missed, people may have to wait for another year.

To minimize the shading effect on the images, the UAVs are usually flying at noon with clear sky conditions. Because each pixel in a UAV image is a percentage of the reflected light, pixel values need to be calibrated by using a known reflectance value. Therefore, the image of a calibration board needs to be taken before and after the flight missions, servicing as the reflectance reference. It is important to take pictures of the reference panel immediately before and after the flight missions.
because the solar angle and light intensity can change [61], which causes inaccurate experiment results. UAV images usually have higher radiometric homogeneity than aircraft or satellite images because of the lower flight altitude [28]. However, there are also special UAV image quality problems. For example, the camera position on the UAVs might be different for each flight mission, which can cause different spatial resolution or different viewing angles [28]. The low flight height of UAVs can also result in geometric distortion [28, 59]. Besides, lower flight height results in greater numbers of UAV images to keep effective overlapping, which makes image processing more time-consuming.

2.3.2 UAV Image Processing

After the flight missions, all of the aerial images were stitched together to generate the orthomosaick images (Table 2.2 and Fig. 2.7) in Metashape (Agisoft LLC, Russian). Preselection is recommended because it can speed up the processing of large datasets. Building the dense cloud can reconstruct a more accurate surface, which can improve the quality of the final orthomosaick. Higher quality usually can result in a more accurate surface, which means a greater number of points. However, higher quality is not recommended because of longer data processing time. Medium quality is sufficient for UAV image processing, especially for low variations field. Building digital elevation model (DEM) allows generating an accurate surface, which can be used as a source for the orthomosaick generation. This will shorten the data processing time compared with Build Mesh operation because Build Mesh is usually used for a more complex surface. The source data for building DEM is the dense cloud. For the interpolation method, Extrapolated option is selected because it can generate a surface without gaps being extrapolated to the bound box sides. The default option for Interpolation is Enabled, which is not recommended because it will leave the valid elevation values only for fields that are seen from at least one aligned camera.

| Step 1: Align Photos | Step 2: Build Mesh | Step 3: Build Orthomosaick |
|----------------------|---------------------|-----------------------------|
| Accuracy: medium     | Surface type: height field (2.5D) | Type: planar |
| Generic preselection: yes | Source data: sparse cloud | Projection plane: TOP XY |
| Key point limit: 40,000 | Face count: medium (30,000) | Rotation angle: 0 |
| Tie point limit: 4000 | Interpolation: enabled (default) | Surface: mesh |
| Adaptive camera model fitting: no | Point classes: all | Blending mode: mosaic (default) |
|                       | Calculate vertex colors: yes | Enable hole filling: yes |
|                       | Enable back-face culling: no |
2.4 Challenges and Opportunities

Compared with traditional remote sensing tools, such as satellite, the UAVs’ flight can be more flexible and frequent in the field. UAVs can fly at a lower altitude and can take higher spatial and temporal resolution images of crops [69]. As a low-cost scientific data collection platform, UAVs also make data acquisition relatively less expensive. While there are many advantages by using UAVs for agricultural research, such as ET estimation, there are still challenges for UAVs. These challenges are also commonly shown in different ET research works [6, 9, 11, 12, 20, 31, 32, 34, 35, 40, 41, 58].

2.4.1 UAVs

Although UAVs have shown great potential for precision agriculture, there are still many technical problems for UAVs, such as flight time, flight height control, path planning, stability in winds, and turbulence [17, 26]. For example, most UAVs can only fly around 30 minutes with payload, which is not enough for a large field. The power can also run low faster because of unexpected headwinds or other factors. Increasing the payload of UAVs will make the UAVs more capable. Flight height is another concern; in the USA, the maximum altitude for UAVs is limited to 120 m. The UAVs need to be in the sight of the operator, and a pilot license is also required. Consequently, it is necessary to have a flying team for UAVs. For a detailed

Fig. 2.7 Agisoft Metashape image processing workflow: (a) Align Photos. (b) Build Mesh. (c) Generate orthomosaick
discussion on technical limitations for UAVs, please refer to [18]. Fortunately, it is expected that with the development of UAV technology, new camera designs, lower costs, improved image processing techniques, and a greater number of experimental studies of UAV-based remote sensing for agriculture applications, UAVs will have better performance for agricultural research.

### 2.4.2 UAV Path Planning and Image Processing

Many researchers fly the UAVs in different height, using specialized equipment, controlling environments, and relying on data analysis expertise [49]. Is there any optimal point where the data can be the best representation of crops or trees? In [49], Stark et al. built a conceptual framework for describing the optimality as a function of spatial, spectral, and temporal factors that represent the best solution. As researchers try to understand the potential of the UAVs, efficient workflow, image processing methods, and better software are still under development [19, 29, 53, 54].

### 2.4.3 Preflight Path Planning

Being used as a remote sensing platform, UAVs also create new research problems, such as UAV image processing and flight path planning. Flight missions are usually designed by different kinds of software. The flight height is usually set up as 30 m, 60 m, and 120 m. For all the flight missions in the reviewed papers, the overlap was usually set up between 75 and 85% to enable the images stitched together during image processing. The UAV sensors are designed to take images at nearly 0 nadir angle.

Researchers usually fly UAVs biweekly to collect data. If there is a UAV crash, unexpected weather conditions, hardware issues, or unknown reasons, data may not be collected successfully. If data is missed, people may have to wait for another year. A biweekly UAV flight schedule is suggested to collect sufficient data.

### 2.4.4 Multispectral Image Calibration

To minimize the shading effect on the images, the UAVs are usually flying at noon with clear sky conditions. Because each pixel in a UAV image is a percentage of the reflected light, pixel values need to be calibrated by using a known reflectance value. Therefore, the image of a calibration board needs to be taken before and after the flight missions, servicing as the reflectance reference (Fig. 2.8).
It is important to take pictures of the reference panel immediately before and after the flight missions because the solar angle and light intensity can change [61], which causes inaccurate experiment results. The digital number of the images are converted to reflectance by Smith and Milton [47]

\[
\rho_\lambda = \frac{DN - DN_d}{DN_w - DN_d},
\]

where \(\rho_\lambda\) is the reflectance and \(DN\) is the digital number of the raw image and \(DN_d\) and \(DN_w\) are the dark reflectance point and white reflectance point in the color checker, respectively.

UAV images usually have higher radiometric homogeneity than aircraft or satellite images because of the lower flight altitude [28]. However, there are also special UAV image quality problems. For example, the camera position on the UAVs might be different for each flight mission, which can cause different spatial resolution or different viewing angles [28]. The low flight height of UAVs can also result in geometric distortion [28, 59]. Besides, lower flight height results in greater numbers of UAV images to keep effective overlapping, which makes image processing more time-consuming.

Although multispectral cameras have light sensors to calibrate light conditions, saturation issues can still be found in UAV images. For example, with a Downwelling Light Sensor (DLS), which is a five-band sensor that connects to the multispectral camera, the RedEdge-M can measure the ambient light during a flight and record the light information in the images. After the camera calibration, the information detected by the DLS can be used to correct lighting changes during a flight, which usually happen because the clouds cover the sun during a UAV flight. The clouds are believed to affect the saturation issues, even though sunshine is supposed to correct reflectance for real-time conditions. Saturated values decrease
the quality of the data. The retrieval of required indices, such as NDVI and LAI, is important for the estimation of soil heat flux $G$ and sensible heat flux $H$.

Another critical issue with UAVs is the bidirectional reflectance distribution function (BRDF) effects. For many UAV application, the reflectance model for canopy measurements is simplified to assume a strict nadir (or straight down) viewing angle and a static illumination source [4, 50, 61]. However, this assumption does not consider the BRDF. The BRDF is a function of wavelength, observer azimuth, observer zenith, illumination azimuth, and illumination zenith [50]. In satellite images, the effect of BRDF is relatively uniform because the satellite covers a wide region in a single frame. However, this simplification is not valid for UAV platforms equipped with an imaging system with a wide field of view (FOV).

Further experiment should be based on multispectral measurements, and UAV image acquisition should be conducted to select those spectral bands which are most useful and sensitive for specific research purpose. Cameras should be designed only for those needed bands, which will lower the cost of the sensors. The availability of low-cost UAV platforms and specialized cameras will also make the UAV application on agriculture more competitive.

### 2.4.5 Thermal Camera Calibration and Image Processing

The thermal image from UAVs is becoming a useful source for agricultural research because of the higher temporal and spatial resolution compared with those obtained from the satellite. The thermal camera has a spectral response from 7 to 14 μm. The accuracy can be as high as $\pm 1 ^\circ$C. Thermal remote sensing images were first used in 1973 to estimate ET [7]. Temperature information is usually converted into land surface characteristics such as albedo, LAI, and surface emissivity. The TIR band is considered as the most critical variable for estimating the sensible heat flux and ground heat flux [12]. The cooled thermal cameras are usually more sensitive and accurate than uncooled thermal cameras [46]. However, cooled thermal cameras are very big, expensive, and energy-consuming [44]. Therefore, cooled thermal cameras can hardly be used on UAV platforms. In contrast, the uncooled thermal cameras are usually lighter [4], which are usually less than 200 grams, have low power consumption [15], and are less expensive than cooled thermal cameras.

The thermal camera has many advantages, though its microbolometer is not always sensitive and accurate [44]. Most thermal cameras are not always calibrated, which can only measure the relative temperature instead of the absolute values. In precision agriculture, it is necessary to measure the absolute temperature in many applications [4], such as crop monitoring [24], pest detection [16], and disease detection [30]. Unstable outdoor environmental factors can also cause serious measurement drift during flight missions. Post-processing like mosaicking might further lead to measurement errors. To solve these two fundamental problems,
in [69], the authors conducted three experiments to research the best practice of thermal image collection using UAVs. To calibrate TIR images, in [41], Park et al. used the water body and rubber plates as cold and hot features. IR Flash Version 2 is usually used to process thermal UAV images for image format transformation.

The correlation between the measured IR temperature from calibration boards and the estimates by thermal cameras were found to be unacceptable sometimes. Without warming up the uncooled thermal camera, the temperature difference between the thermal camera and calibration board can be as high as ±10°C. For instance, the land surface temperature is the most important data for SEBAL and the estimation of surface energy fluxes; thus, its accuracy is the key for a reliable ET estimation.

Many researchers also focus on thermal camera calibration issues. For example, Ribeiro et al. proposed a new calibration algorithm based on neural networks [44]. The calibration algorithms considered the thermal camera temperature and the digital response of the microbolometer as input data. Based on the calibration result, the accuracy increased from 3.55 to 1.37°C. In [51], Torres-Rua et al. presented a vicarious calibration methodology (UAV-specific, time-specific, flight-specific, and sensor-specific) for thermal camera images traceable back to NIST standards (National Institute of Standards and Technology) and current atmospheric correction methods.

For future research, uncooled thermal cameras can be used to evaluate with other temperature sensor information to acquire reliable thermal information, such as atmospherically corrected satellite images and temperature canopy sensors.

### 2.4.6 Image Stitching and Orthomosaick Image Generation

After UAV images are collected, all of the aerial images need to be stitched together to generate the orthomosaick images. Some problems are identified when creating mosaics, such as fault lines, blurriness, and replicated features, especially with the thermal data. To overcome the thermal camera’s effect, a higher overlap for the thermal camera can be a good choice. With an increase in the image overlap by 5%, most of the fuzziness and replicated problems were eliminated [31].

There are many types of software that can be used for image stitching, such as Pix4D (Pix4D, Prilly, Switzerland), Agisoft Metashape, RealityCapture, and DroneDeploy (DroneDeploy, San Francisco, CA, USA). For example, during the image stitching workflow using the Agisoft Metashape, there are several steps for image processing, which include aligning photos, optimizing cameras, building mesh, building dense cloud, building digital elevation model (DEM), and generating orthomosaick.
2.5 Case Study I: A UAV Resolution and Waveband Aware Path Planning for Irrigation

2.5.1 Introduction

Over the past a few years, unmanned aerial vehicles have been widely used as a remote sensing platform in agricultural applications, such as crop yield estimation [67], soil moisture monitoring, water stress estimation [63], and pest management [33]. Compared with traditional remote sensing tools, such as satellites, UAV flight time can be more flexible and more frequent in the field. UAVs also fly at lower altitude and can take higher-resolution multispectral images or thermal images of crops [69]. As a low-cost scientific data collection platform, UAVs also make data acquisition relatively less expensive. While there are many advantages by using UAVs for agricultural applications [67], there is still a lot of work for UAVs. Many researchers fly the UAVs in different standard, using specialized equipment, controlling environments, and relying on data analysis expertise [49]. Is there any optimal point where the data can be the best representation of crops? In [49], Brandon built a conceptual framework for describing the optimality as a function of spatial, spectral, and temporal factors which represent the best solution.

How to collect remote sensing data effectively can still be a big challenge. Many UAV tunable parameters can have significant impact on data quality and the data analysis, such as flight height, flight time, overlapping, and airspeed. In this section, flight height’s effect on data analysis was discussed. It assumed that there must be an optimal point where the data analysis results from multispectral images or thermal images can greatly represent for, for example, the crops’ water stress status [63] or other crop characteristics. In this section, a resolution and waveband aware path planning was conducted in order to optimally collect remote sensing aerial images with drones. Then, the flight mission design was tested in an onion field at USDA during the growing season in 2017.

Onion is one of the most widely produced vegetables all over the world. Onion also plays an important role in human diet and medical properties [45]. Therefore, onion is consumed among all nationalities and cultures [10]. Based on the data from Food and Agriculture Organization, onion production has been increasing continuously by 65 million tonnes (1999–2009 period), in an area of 2.1 million hectares in 2009 [10]. California is the biggest onion producer in the USA, which is also the only state that can produce spring- and summer-harvested onions in the USA. Thirty-one percent of the total onion in the USA was produced in California in 2015 [27].

In the semiarid and arid areas of California, onion production is highly dependent on irrigation. Water stress could happen in any onion growing stage and cause onion yield loss. Therefore, to optimize irrigation management, it’s important to have an optimal onion water stress monitoring method. Many research results have been published on using drones to detect water stress [61, 62, 64–66], which prove UAVs can be a reliable and effective remote sensing platform. In onion study area,
multispectral cameras are mounted on the unmanned aerial vehicles for onion yield estimation, biomass monitoring [2], and disease detection [56]. However, to our best knowledge, nobody has studied the effect of UAV flight height on onion’s multispectral image data analysis and irrigation treatment inference.

Therefore, in this section, the authors mainly designed a UAV flight mission in order to optimally collect onion remote sensing aerial images with UAVs. By using multispectral and thermal images collected by UAVs, the authors was able to apply supervised learning methods to find the relationship between image features and onions’ irrigation treatments. The authors also figured out how UAV flight height or resolution settings affected the accuracy of estimating onion irrigation treatment. Different spectral bands combination also had effect on onion irrigation treatment prediction.

### 2.5.2 Material and Methods

#### 2.5.2.1 Onion Study Area

As shown in Fig. 2.9, the field study was conducted at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Palier, California, 93648, USA. Since 2016, an onion test field has been set up for research of biomass soil amendments and deficit irrigation. There were three irrigation treatment levels and four soil amendments. Three irrigation levels were low, medium, and high.

![](image)

**Fig. 2.9** Onion test site. The field study was conducted at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Palier, California, 93648, USA. Since 2016, an onion test field has been set up for research of biomass soil amendments and deficit irrigation.
The four soil amendments were biochar, check, biochar + compost, and biochar + compost + one bag of sulfur. There were also three replicate plots for each treatment combination.

### 2.5.2.2 A UAV Platform and Sensors

In this study, the authors used a “Hover” (brand of the UAV) quadcopter as the UAV platform. The “Hover” was equipped with a Pixhawk flight controller, GPS, and telemetry antennas. It was able to fly over the onion field by waypoints mode (designed by using Mission Planner software). The lithium polymer battery had a capacity of 9500 mAh, which could support a 30-minute flight mission with cameras mounted on the UAV.

Multispectral images were collected by Survey 2 (MAPIR, USA) cameras with four bands, blue, green, red (RGB), and near infrared (NIR). The MAPIR camera has a resolution of 4608 × 3456 pixels, with a space resolution at 1.01 cm/pix. The Survey 2 cameras have a faster interval timer, 2 seconds for JPG mode and 3 seconds for RAW + JPG mode. Faster interval timer would benefit the overlap design for UAV flight missions, such as reducing the flight time, enabling higher overlapping.

The thermal camera ICI 9640 P-Series (ICI, USA) was applied for collecting thermal images of onions. The thermal camera has a resolution of 640 × 480 pixels. The spectral band is from 7 to 14 μm. The dimensions of the thermal camera is 34 mm × 30 mm × 34 mm. The accuracy is supposed to be ±1 °C. A Raspberry Pi Model B computer was used to trigger the thermal cameras during the flight missions.

### 2.5.2.3 UAV Image Collection and Preprocessing

Flight missions were programmed by using Mission Planner software. The flight height was set up as 10 m, 15 m, 30 m, and 60 m in order to compare the resolution’s effect on onion irrigation treatment inference. For all the flight missions, the overlap was set up as 75% to make sure the onions’ images can be stitched together during image preprocessing.

The authors flew the UAV biweekly over the onion field at noon during the growing season in 2017. The images of a color panel were taken right before and after the flight missions, servicing as the reflectance reference. After the flight missions, all of the aerial images were stitched together to generate the orthomosaick images in PhotoScan (Agisoft LLC, Russian). An RGB image was shown in Fig. 2.10, and an NIR image was shown in Fig. 2.11. The process included aligning photos and building orthomosaick. The Agisoft PhotoScan settings and workflow for RGB and NIR images were shown as below:
2.5 Case Study I: A UAV Resolution and Waveband Aware Path Planning for...

Fig. 2.10 RGB image for onion field

Fig. 2.11 NIR image for onion field
Step 1: Align Photos
General
- Accuracy: medium
- Generic preselection: yes
Advanced
- Key point limit: 40,000
- Tie point limit: 4000
- Adaptive camera model fitting: no

Step 2: Build Mesh
General
- Surface type: height field (2.5D)
- Source data: sparse cloud
- Face count: medium (30,000)
Advanced
- Interpolation: enabled (default)
- Point classes: all
- Calculate vertex colors: yes

Step 3: Build Orthomosaick
Projection
- Type: planar
- Projection plane: TOP XY
- Rotation angle: 0
Parameters
- Surface: mesh
- Blending mode: mosaic (default)
- Enable hole filling: yes
- Enable back-face culling: no

All of the thermal images were preprocessed by IR Flash (ICI, USA) in order to get .TIF thermal images. Then, thermal images were stitched together to generate the orthomosaick images in PhotoScan (Agisoft LLC, Russian). The process also included aligning photos and building orthomosaick. The Agisoft PhotoScan settings and workflow for thermal images were shown as below:

Step 1: Align Photos
General
- Accuracy: high
- Pair preselection: disabled
- Generic preselection: yes
Advanced
- Key point limit: 40,000
- Tie point limit: 4000
- Adaptive camera model fitting: yes

Step 2: Build Mesh
General
- Surface type: height field
2.5.2.4 Principal Component Analysis

For image processing, the authors used two different machine learning methods, the Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA). Both of them could reduce the dataset dimensionality and increased the classification accuracy.

Principle Component Analysis (PCA) is a fast and flexible unsupervised method for data dimensionality reduction \[23\]. It can achieve linear projection to a lower-dimensional subspace by using singular value decomposition. PCA can also maximize the variance of the projected data. Therefore, PCA is widely used in exploratory data analysis and making predictive models.

2.5.2.5 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a classifier with a linear decision boundary. It is generated by using Bayes’ rule to fit class conditional densities to the data. It assumes that all classes share the same covariance matrix. After that, LDA model can be used to reduce the dimensionality of the input data by projecting it to the most discriminative directions. Then, the output dimensionality is usually less than the number of classes, so that LDA is a very strong dimensionality reduction \[14\].

2.5.3 Results and Discussion

To prepare the multispectral and thermal image datasets, the authors firstly segmented 36 plots from the whole onion field in order to focus only on the area of interest, as shown in Fig. 2.12. Every image was converted into 2048 dimensions vector for data processing by Python packages. The data was distributed as
Fig. 2.12 Thirty-six plots of onion. Every image was converted into 2048 dimensions vector for data processing by Python packages. The data was distributed as 67% for training and 33% for testing.

67% for training and 33% for testing. Several classifiers in scikit-learn machine learning algorithms were used for onion irrigation treatment inference, such as “nearest neighbors,” “linear SVM,” “RBF SVM,” “Gaussian process,” “decision tree,” “random forest,” “neural net,” “AdaBoost,” “naive Bayes,” and “quadratic discriminant analysis (QDA).”

The accuracy was evaluated by scikit-learn accuracy classification score function. This function computed the subset accuracy, in which the labels predicted for a sampling must exactly match the corresponding true labels. Estimators used this score method as the evaluation criterion for the classification problems. All scorer objects followed the convention that higher return values were better than lower return values.

The authors mainly discussed two topics in this section, flight height or different resolution’s effect on onion irrigation treatment estimation and different wavebands combination on onion irrigation treatment prediction.

2.5.3.1 UAV Flight Height or Resolution’s Effect

In this section, near-infrared images were used to analyze the flight height or image resolution’s effect on data analysis. At 30 m height, the MAPIR had a resolution as 1.01 cm/pix. By image processing, the authors set up four different resolutions, A,
Table 2.3 Different resolutions accuracy for onion treatment inference. The best accuracy was 0.726, which showed up when the resolution was at 2.02 cm/pixel by using “neural net” classifier. Compared with the other classifiers, the “neural net” classifier performed the best in all resolution levels.

| Classifiers         | A 0.55 cm/pix | B 1.01 cm/pix | C 2.02 cm/pix | D 4.04 cm/pix |
|---------------------|---------------|---------------|---------------|---------------|
| “Nearest neighbors” | 0.625         | 0.608         | 0.593         | 0.608         |
| “Linear SVM”        | 0.684         | 0.660         | 0.691         | 0.691         |
| “RBF SVM”           | 0.375         | 0.365         | 0.347         | 0.323         |
| “Gaussian process”  | 0.653         | 0.674         | 0.708         | 0.642         |
| “Decision tree”     | 0.663         | 0.587         | 0.618         | 0.601         |
| “Random forest”     | 0.663         | 0.608         | 0.649         | 0.601         |
| “Neural net”        | 0.719         | 0.708         | 0.726         | 0.684         |
| “AdaBoost”          | 0.649         | 0.590         | 0.653         | 0.639         |
| “Naive Bayes”       | 0.600         | 0.604         | 0.618         | 0.538         |
| “QDA”               | 0.708         | 0.694         | 0.694         | 0.642         |
| “LDA”               | 0.691         | 0.684         | 0.691         | 0.677         |

B, C, and D for onion images. Resolution A meant 0.55 cm/pix, resolution B meant 1.01 cm/pix, resolution C meant 2.02 cm/pix, and resolution D meant 4.04 cm/pix, as shown in Table 2.3.

From Table 2.3, the authors could figure out that the best accuracy was 0.726, which showed up when the resolution was at 2.02 cm/pixel by using “neural net” classifier. Compared with the other classifiers, the “neural net” classifier performed the best in all resolution levels. Based on most classifiers resolution analysis results in Table 2.3, it turned out that when the authors flew a UAV in the field, higher resolution did not mean better analysis results. The best resolution did not promise the best estimation. Based on the accuracy trend of “neural net” classifier, for example, it existed an optimal point near 2.02 cm/pixel resolution when “neural net” was applied for onion irrigation estimation.

2.5.3.2 Wavebands Configuration’s Effect

In this section, remote sensing images were generated by using different wavebands configurations. There were red, green, blue (RGB), near-infrared (NIR), thermal (TIR), and NDVI (normalized difference vegetation index) wavebands being used in this section. As shown in Table 2.4, there were four combinations being used, RGB-NIR, all bands, RGB-NIR-TIR, and TIR. Because RGB and NIR had a higher resolution (1.01 cm/pixel) than thermal image resolution (9 cm/pixel), the multispectral images were preprocessed in order to match the thermal image resolution.

From the Table 2.4, the authors could figure out that the best accuracy was 0.840, which appeared when the RGB-NIR-TIR waveband images were used by “Gaussian process” classifier. Compared with the other classifiers, the “Gaussian
Table 2.4 Bands configuration accuracy for onion treatment inference. The best accuracy was 0.840, which appeared when the RGB-NIR-TIR waveband images were used by “Gaussian process” classifier. Compared with the other classifiers, the “Gaussian process” classifier performed the best in all wavebands configuration.

| Classifiers        | RGB-NIR | All   | RGB-NIR-TIR | TIR   |
|-------------------|---------|-------|-------------|-------|
| “Nearest neighbors” | 0.583   | 0.538 | 0.691       | 0.723 |
| “Linear SVM”      | 0.569   | 0.590 | 0.774       | 0.743 |
| “RBF SVM”         | 0.622   | 0.552 | 0.316       | 0.764 |
| “Gaussian process” | 0.729   | 0.646 | 0.840       | 0.792 |
| “Decision tree”   | 0.615   | 0.569 | 0.715       | 0.719 |
| “Random forest”   | 0.590   | 0.615 | 0.646       | 0.750 |
| “Neural net”      | 0.625   | 0.618 | 0.826       | 0.785 |
| “AdaBoost”        | 0.576   | 0.549 | 0.767       | 0.681 |
| “Naive Bayes”     | 0.521   | 0.514 | 0.566       | 0.622 |
| “QDA”             | 0.611   | 0.597 | 0.788       | 0.753 |
| “LDA”             | 0.677   | 0.628 | 0.809       | 0.781 |

process” classifier performed the best in all wavebands configuration. Based on most classifiers resolution analysis results in the Table 2.4, it turned out that when we flew a UAV in the field, more wavebands information did not mean better analysis results. Knowing all the remote sensing data did not mean the best estimation. Based on the accuracy of “Gaussian process” classifier, it was meaningful to point out that TIR images itself could already get pretty good estimation results, as high as 0.792, which meant that we did not always need multispectral wavebands information for some coarse estimation research work. On the other side, adding RGB-NIR information did increase accuracy from 0.792 to 0.840, which was meaningful for precision agriculture applications.

2.5.4 Conclusions

In this study, a UAV resolution and waveband aware path planning was conducted in order to optimally collect remote sensing aerial images with UAVs. Using multispectral and thermal images collected by UAVs, we were able to apply supervised learning methods to find the relationship between image features and onion irrigation treatments.

First, the authors found out that the best accuracy for onion irrigation treatments was 0.726, which showed up when the resolution was at 2.02 cm/pixel by using “neural net” classifier. The best resolution did not promise the best estimation. According to the accuracy trend of “neural net” classifier, it did exist an optimal point near 2.02 cm/pixel resolution when “neural net” was applied for onion irrigation estimation.
Second, this study also found out that different spectral bands combination also had effect on onion irrigation treatment prediction. Applying all the remote sensing data did not mean the best estimation. Based on the accuracy of “Gaussian process” classifier, we figured out that TIR images itself could already get relatively good estimation results for onion irrigation estimation, as high as 0.792, which meant we do not always need multispectral bands information for it. On the other side, adding RGB-NIR information did increase accuracy from 0.792 to 0.840, which was important for precision agriculture applications.

2.6 Case Study II: A Detailed Study on Accuracy of Uncooled Thermal Cameras

2.6.1 Introduction

Because the uncooled thermal camera is light [4], it has low power consumption [15], and it is less expensive than cooled thermal cameras, it has been widely used in many agricultural applications, such as plant disease detection [30], crop water stress estimation [61, 62], and soil moisture detection [48]. Mounted on the UAVs, the uncooled thermal camera makes it possible for UAVs to collect high-resolution thermal images in precision agriculture (PA) [65]. Compared with traditional remote sensing method, such as satellites, the thermal camera and UAVs make the data collection more flexible and lower cost. The cooled thermal cameras are usually more sensitive and accurate than uncooled thermal cameras [46]. However, cooled thermal cameras are very big, expensive, and energy-consuming [44]. Thus, they can hardly be used on UAV platform. In contrast, the uncooled thermal camera plays a more and more important role in remote sensing by UAV platforms.

The thermal camera has so many advantages, though its microbolometer is not always sensitive and accurate [44]. Also, most thermal cameras are not always calibrated, which means it can only measure the relative temperature instead of the accurate value. In precision agriculture, however, most time it is necessary to measure the accurate temperature in many applications [4] such as crop monitoring [24], pest detection [16], and disease detection [30]. We are using thermal camera more and more frequently without understanding its truth. Therefore, there is a highly strong demand to find a calibration method for the thermal camera in UAV applications.

Researchers have published many thermal camera calibration methods when the thermal camera was used in UAV platforms [22]. In [44], Ribeiro-Gomes et al. proposed a new calibration algorithm based on neural network [5]. It also improved the photogrammetry process by using Wallis filter [55]. They increased the measurement accuracy from 3.55 to 1.37 °C. In [4], Berni et al. implemented an internal calibration for a thermal camera controlled by PC/104 embedded computer [8], which built a grid with resistive wires. When the wires were heated up,
the thermal camera could detect the grid and calibrate the camera. In [3], they designed a lab calibration by using a calibration blackbody source (RAYBB400, Raytek, CA, USA). As mentioned above, researchers tried to solve the thermal camera calibration issues, though the methods used in these papers were not quite appropriate in UAV platforms [65]. For example, the thermal camera can have internal and external disturbance during the UAV flight. Internal disturbance can be caused by microbolometer [57]. For external disturbance, the wind can cool down the thermal cameras. The unstable outdoor environment can also cause serious measurement drift during flight missions. Not all of these factors were considered into the previous papers.

Therefore, in this section, the authors mainly focused on the thermal camera calibration in UAV applications. The authors tried to focus on the thermal camera itself. In agriculture applications, the thermal cameras were not always calibrated; researchers might use a thermal camera for several years without calibration. Therefore, it is very important to figure out how the calibration will affect the thermal camera’s data collection. Also, when the UAVs are flying in the field, the thermal camera will capture images in different view of angles. In this section, the authors also studied the effects of the thermal camera’s view of angles on the temperature data. For the photogrammetry process, the software Agisoft PhotoScan is frequently used. Thermal images are stitched together into an orthomosaick picture. In this section, the authors also figured out if the stitching had any effect on the data process. To our best knowledge, there were no study talking about these thermal camera calibration issues before.

2.6.2 Material and Methods

2.6.2.1 Study Site

This research was conducted in a field near MESA Lab in Atwater, California, USA (37°22′30.6″N, 120°34′40.9″W). There were five different materials being used, water, dry soil, wet soil, leaves, and white panels. All materials were put in cups, as shown in Fig. 2.13.

2.6.2.2 Image Collection

The thermal camera ICI 9640 P-Series (ICI, USA) was used to collect thermal images. The thermal camera has a resolution of 640 × 480 pixels. The spectral band is from 7 to 14 μm. The dimensions of the thermal camera is 34 mm × 30 mm × 34 mm. The accuracy is supposed to be ±1°C. In these research experiments, the .TIF images were taken for further image processing by Agisoft PhotoScan. The camera was attached under the experiment platform, as shown in Fig. 2.14a. The
2.6 Case Study II: A Detailed Study on Accuracy of Uncooled Thermal Cameras

Fig. 2.13 This research was conducted in a field near MESA Lab in Atwater, California, USA (37°22′30.6″N, 120°34′40.9″W). There were five different materials being used, water, dry soil, wet soil, leaves, and white panels. The camera was triggered ten times per second by the ICI Software’s function Capture Series Images in ground station computer (Fig. 2.14b).

2.6.2.3 Groundtruth Data Collection

The infrared radiometer Apogee MI-220 was used in the research experiments to collect thermal data as groundtruth value. The MI-220 has an 18° half-angle field of view (FOV). The response time for the MI-220 is only 0.6 seconds. It can be used in many areas, such as tree canopy temperature measurement, water stress estimation, soil temperature measurement, and so on.

2.6.3 Results and Discussion

2.6.3.1 Experiment Setup

There were three different experiments in this section. In the first experiment, the authors analyzed the calibration’s effect on thermal cameras. Second, the authors studied the thermal camera’s angle effect on the temperature data. Third, the authors analyzed stitching’s effect on the orthomosaic pictures. The authors prepared five different materials for all experiments to stimulate the situations we might meet in the field. As shown in Fig. 2.14, there were water, wet soil, fresh leaves, dry soil, and
Fig. 2.14 Calibration’s effect experiment. (a) Experiment field. (b) Thermal picture by IR Flash
2.6.3.2 Thermal Camera Warm-Up Time

A thermal camera needs to be at (or close to) thermal equilibrium in order to produce accurate data. When the camera is turned on, the electronics inside produce heat, and it takes a while for the camera body to heat up enough for the rate of heat loss at the surface to match the rate of heat being produced on the inside.

This poses a challenge to flying a thermal camera on a UAV: even if the camera has been given sufficient time to reach equilibrium on the ground, the airflow increases heat transport away from the camera, upsetting the equilibrium again and requiring additional time to adjust. However, due to the limited flight time of UAVs, especially multirotors, this time may be longer than the available flight time itself. The recommended equalization time for the camera used in our experiments (an ICI 9640) was about half an hour.

2.6.3.3 Calibration Experiment

In this section, the authors compared two thermal cameras’ temperature data. One was a new thermal camera, which meant calibrated thermal camera. The other one was a used camera, which was not calibrated. To minimize the thermal camera’s itself effects on the experiments results. The authors used exactly the same model ICI 9640 P for the calibrated and non-calibrated thermal cameras. As shown in Fig. 2.14a, the authors put the two thermal cameras at the same height 69.5325 cm to our materials. Both of them captured the same materials at the same time. Apogee MI-220 was used to collect data as ground truth. As seen in Fig. 2.14b, all materials were labeled by IR Flash, so it could test exactly the same temperature at the selected areas.

According to Tables 2.5, 2.6, 2.7, and 2.8, the calibrated camera had better root mean square error than the non-calibrated camera. For the calibrated camera, the root mean square errors for water, wet soil, dry soil, and leaf were 1.61 °C, 1.92 °C, 2.89 °C, and 1.47 °C. For the non-calibrated camera, the root mean square errors were 3.07 °C, 3.00 °C, 4.09 °C, and 2.83 °C. The result was obviously as expected that calibrated camera had better results than non-calibrated thermal camera. In this experiment, however, we tried to figure out if the data collected by thermal cameras was always consistent. If the thermal camera was not accurate, was the temperature value always above or below the groundtruth value? Unfortunately, the answer was no. It made thermal calibration more difficult to estimate and to deal with.
Table 2.5  Ground truth

| Time  | Water (°C) | Wet soil (°C) | Dry soil (°C) | Leaf (°C) |
|-------|------------|---------------|---------------|-----------|
| 2:53  | 34.2       | 36.9          | 51.2          | 44.1      |
| 3:02  | 34.1       | 34.7          | 52.3          | 42.9      |
| 3:06  | 35.2       | 36.3          | 51.7          | 41.2      |
| 3:10  | 35.0       | 36.4          | 52.5          | 43.0      |
| 3:14  | 32.1       | 35.1          | 50.3          | 41.0      |
| 3:17  | 36.5       | 37.0          | 49.8          | 41.3      |
| 3:21  | 35.0       | 37.5          | 50.2          | 41.2      |
| 3:25  | 34.1       | 37.4          | 51.5          | 40.8      |
| 3:29  | 34.1       | 34.6          | 50.5          | 39.7      |
| 3:32  | 34.2       | 36.9          | 49.6          | 39.6      |
| 3:36  | 34.5       | 33.6          | 50.5          | 41.6      |
| 3:40  | 34.1       | 34.3          | 50.3          | 41.6      |
| 3:44  | 33.9       | 34.0          | 49.5          | 42.9      |
| 3:48  | 33.8       | 35.2          | 50.3          | 41.3      |
| 3:51  | 33.0       | 33.1          | 49.0          | 38.3      |

Table 2.6  Non-calibrated camera

| Time  | Water (°C) | Wet soil (°C) | Dry soil (°C) | Leaf (°C) |
|-------|------------|---------------|---------------|-----------|
| 2:53  | 41.27      | 42.53         | 59.22         | 48.45     |
| 3:02  | 37.32      | 38.30         | 54.96         | 44.91     |
| 3:06  | 36.42      | 37.46         | 54.86         | 43.91     |
| 3:10  | 35.44      | 36.10         | 53.63         | 45.04     |
| 3:14  | 36.67      | 37.13         | 54.55         | 46.13     |
| 3:17  | 36.59      | 36.71         | 53.96         | 43.11     |
| 3:21  | 37.38      | 38.63         | 55.86         | 42.91     |
| 3:25  | 36.03      | 42.32         | 53.85         | 41.95     |
| 3:29  | 33.82      | 34.39         | 51.66         | 39.71     |
| 3:32  | 36.64      | 37.09         | 53.69         | 40.26     |
| 3:36  | 37.53      | 38.33         | 54.97         | 46.21     |
| 3:40  | 35.50      | 35.89         | 52.78         | 41.93     |
| 3:44  | 35.87      | 36.66         | 52.94         | 42.93     |
| 3:48  | 38.29      | 39.30         | 55.37         | 45.38     |
| 3:51  | 35.83      | 36.34         | 52.69         | 42.01     |

2.6.3.4  The View Angle of Thermal Camera

In this experiment, the authors tested the thermal cameras’ view angle effect on temperature. In an unmanned aerial vehicle system, the thermal cameras are usually mounted on the UAVs and capturing images when the UAVs are flying over the field. For example, in an almond tree orchard, the tree canopies can show up in different positions in thermal images. This may cause the canopy to have different
Table 2.7 Calibrated camera

| Time  | Water (°C) | Wet soil (°C) | Dry soil (°C) | Leaf (°C) |
|-------|------------|---------------|---------------|-----------|
| 2:53  | 34.38      | 35.99         | 53.21         | 41.95     |
| 3:02  | 36.03      | 37.38         | 54.28         | 43.50     |
| 3:06  | 34.42      | 35.88         | 52.85         | 40.23     |
| 3:10  | 35.22      | 36.21         | 53.31         | 42.24     |
| 3:14  | 35.83      | 37.01         | 54.00         | 44.33     |
| 3:17  | 35.73      | 36.53         | 53.47         | 41.03     |
| 3:21  | 34.96      | 36.03         | 53.45         | 40.20     |
| 3:25  | 36.12      | 37.41         | 54.60         | 41.38     |
| 3:29  | 35.39      | 36.49         | 53.44         | 37.89     |
| 3:32  | 35.53      | 36.63         | 53.11         | 40.07     |
| 3:36  | 35.39      | 36.72         | 53.46         | 42.63     |
| 3:40  | 35.46      | 36.74         | 53.26         | 43.60     |
| 3:44  | 36.22      | 37.47         | 53.52         | 44.36     |
| 3:48  | 34.60      | 36.03         | 51.91         | 39.75     |
| 3:51  | 35.00      | 36.06         | 52.28         | 39.06     |

Table 2.8 Root mean square error

| Materials | Calibrated camera (°C) | Non-calibrated camera (°CA) |
|-----------|------------------------|----------------------------|
| Water     | 1.61                   | 3.07                       |
| Wet soil  | 1.92                   | 3.00                       |
| Dry soil  | 2.89                   | 4.09                       |
| Leaf      | 1.47                   | 2.83                       |

temperature in different view of angles. In this section, the authors figured out if the view angles had any effect on the thermal images. The thermal picture has a pixel value of 640 × 480. The central point pixel value is 320 × 240. After we found the test point temperature, we also found the pixel value of the test point (Fig. 2.15). In the thermal picture, one pixel value represented 0.09525 cm. Then, we could calculate the horizontal distance between the camera center and the test point. As mentioned in the previous section, the camera’s vertical distance to the test point was 69.5325 cm. Then, the accurate half view angle could be calculated in this experiment.

According to Table 2.9, there were eight different half view angles, 4.2°, 4.6°, 6.0°, 8.3°, 11.6°, 12.7°, 14.3°, and 16.7°. The errors between the ground truth and the collection data were less than 0.5 °C. The root mean square error was much less than 0.01 °C. The results showed that the thermal camera’s view angles had little effect on collecting data.
Fig. 2.15  View angle experiment. (a) Thermal picture by IR Flash, horizontal measurement. (b) Thermal picture by IR Flash, vertical measurement
Table 2.9 View angle experiment table

| Half view angle (°) | Location in the picture | Point temperature (°C) | Ground truth (°C) |
|--------------------|-------------------------|------------------------|-----------------|
| 4.2                | 363 × 275               | 12.41                  | 12.40           |
| 4.6                | 372 × 269               | 12.52                  | 12.40           |
| 6                  | 354 × 311               | 11.79                  | 12.40           |
| 8.3                | 352 × 344               | 12.28                  | 12.40           |
| 11.6               | 342 × 391               | 12.38                  | 12.40           |
| 12.7               | 337 × 406               | 12.11                  | 12.40           |
| 14.3               | 336 × 428               | 11.90                  | 12.40           |
| 16.7               | 329 × 462               | 12.26                  | 12.40           |

2.6.3.5 The Effect of Stitching

After the thermal images were collected from thermal cameras, many researchers liked to process the data by Agisoft PhotoScan software. In this software, we could stitch all the pictures into one orthomosaick picture which represented the whole field, as shown in Fig. 2.16b. In this experiment, it figured out if this Align Photos function had any effect on temperature data. As shown in Table 2.10, there were 28 samples in this experiment. They were divided into four groups, which were water, dry soil, wet soil, and white paper panels. There were labels in each picture, so we could accurately find the same temperature point in the single image and the orthomosaick picture. To calculate the temperature, the authors used the MATLAB 2017b to get the average temperature for a selected area.

Based on the data in Table 2.10, the temperature errors between the single image and the orthomosaick were less than 1 °C. According to Table 2.11, for different materials, the root mean square errors were different. For example, the water in a single image had a root mean square error as 0.646 °C. In the orthomosaick picture, the value was 0.834 °C. The result showed that the Agisoft PhotoScan’s stitching process had little effect on the thermal data.

2.6.4 Conclusions and Future Work

In this section, the authors discussed three factors’ effect on thermal camera calibration. They were fundamental and useful. First, calibrated thermal camera did have better results compared with the non-calibrated thermal camera. However, even the calibrated thermal camera’s data was not consistent. The thermal camera itself could be a reason. The uncooled thermal camera’s microbolometer was not accurate and sensitive. Second, the thermal camera’s view angles had little effect on the temperature data. The thermal camera’s accuracy was ±1 °C. The data errors in this section was less than 1 °C and the root mean square error was less than 0.01 °C. Third, after the photogrammetry process, the stitching did have a little effect on the
Fig. 2.16 The effect of stitching experiment. (a) Single images taken by ICI thermal camera. (b) The thermal orthomosaick picture which represented the whole field orthomosaick picture we got. The temperature in the orthomosaick was greater than the temperature in single image. This could be caused by the stitching process.

In the future, the authors will keep working on the thermal camera calibration problem. A more accurate, real-time, and state-of-the-art thermal camera calibration method will be proposed in the future.
Table 2.10  Stitching’s effect data

| Sample number | Materials | Ground truth (°C) | Single image (°C) | Orthomosaick (°C) |
|---------------|-----------|------------------|------------------|------------------|
| 1             | Water     | 17.4             | 17.74            | 18.2648          |
| 2             | Water     | 17.5             | 17.53            | 17.9962          |
| 3             | Water     | 17.4             | 17.75            | 18.1876          |
| 4             | Water     | 17.2             | 18.23            | 18.4245          |
| 5             | Water     | 17.2             | 16.35            | 16.5322          |
| 6             | Water     | 17.4             | 16.73            | 17.2438          |
| 7             | Water     | 16.8             | 17.47            | 17.9345          |
| 8             | Dry soil  | 15.8             | 15.72            | 16.6309          |
| 9             | Dry soil  | 14.4             | 13.93            | 14.5372          |
| 10            | Dry soil  | 14.2             | 13.53            | 13.3192          |
| 11            | Dry soil  | 14.7             | 14.61            | 14.8676          |
| 12            | Dry soil  | 15.4             | 15.45            | 15.6241          |
| 13            | Dry soil  | 14.8             | 15.51            | 15.6242          |
| 14            | Dry soil  | 14.5             | 15.26            | 15.3906          |
| 15            | Wet soil  | 14.8             | 14.84            | 15.8454          |
| 16            | Wet soil  | 13.9             | 14.38            | 15.7918          |
| 17            | Wet soil  | 14.8             | 14.06            | 14.9511          |
| 18            | Wet soil  | 14.1             | 15.37            | 14.3389          |
| 19            | Wet soil  | 14.9             | 14.89            | 15.7558          |
| 20            | Wet soil  | 14.6             | 14.24            | 14.8981          |
| 21            | Wet soil  | 14.3             | 14.77            | 15.2562          |
| 22            | Paper     | 13.6             | 12.67            | 13.9083          |
| 23            | Paper     | 13.8             | 12.42            | 12.9427          |
| 24            | Paper     | 14.5             | 14.02            | 15.2562          |
| 25            | Paper     | 12.8             | 11.55            | 13.9083          |
| 26            | Paper     | 12.4             | 11.75            | 12.9427          |
| 27            | Paper     | 13.9             | 11.13            | 12.1386          |
| 28            | Paper     | 12.4             | 11.36            | 11.8678          |

Table 2.11  Root mean square error

| Materials          | Single images (°C) | Orthomosaick (°C) |
|--------------------|--------------------|-------------------|
| Water              | 0.646              | 0.834             |
| Dry soil           | 0.503              | 0.658             |
| Wet soil           | 0.626              | 0.963             |
| White panel        | 0.912              | 0.949             |
2.7 Case Study III: High Spatial Resolution Has Little Impact on NDVI Mean Value

2.7.1 Introduction

The normalized difference vegetation index (NDVI) has been used for many agriculture-related research topics, such as water stress detection \cite{61,64}, crop yield assessment \cite{67}, and ET estimation \cite{37,39}. The NDVI is usually calculated by:

\[
NDVI = \frac{\rho_{nir} - \rho_r}{\rho_{nir} + \rho_r},
\]

where \(\rho_{nir}\) and \(\rho_r\) are the reflectances of the near-infrared and red wavebands, respectively. NDVI is a standardized method to measure healthy vegetation. When the NDVI is high, it indicates the vegetation has a higher level of photosynthesis.

To date, satellite-derived NDVI has been commonly used for crop coefficient values estimation \cite{21,25,43}. For example, Trout et al. \cite{52} and Zhang et al. \cite{60} applied a remote sensing method using the NDVI to estimate canopy ground cover as a basis for generating crop coefficient \(K_c\). Kamble et al. \cite{25} used a simple linear regression model to establish a relationship between the NDVI and \(K_c\). Although satellite imagery can obtain spatially distributed measurements, they cannot acquire high spatiotemporal resolution images for precision agriculture applications \cite{13}. The timing of satellite overpass is not always synchronous with research requirements, either.

With the development of new remote sensing technology, the unmanned aerial vehicles (UAVs) have been commonly used in agricultural applications, such as crop yield estimation \cite{67}, irrigation managements \cite{38,68}, water stress estimation \cite{63}, and pest management \cite{33,36}. Compared with the satellite, the flight of UAVs can be more flexible and frequent in the field. The UAVs fly at a lower altitude and take higher-resolution imagery of crops \cite{69}. The UAVs also make data acquisition relatively less expensive. However, one may fly the UAV at different flight heights. What is the optimal UAV flight height for research can be an interesting topic. In previous paper \cite{1}, Awais et al. investigated the optimal timing and altitude for thermal imagery collection using UAV in an Anji tea plant experimental field. The results reported that the thermal imagery could provide the best correlation and accurate canopy temperature when the UAV flights were at 11 am and 60 m altitude. In previous article \cite{38}, the authors applied supervised learning methods to study the correlation between imagery features and onion irrigation treatments. Then, it figured out how UAV flight height or resolution settings affect the accuracy of onion irrigation treatment inference.

Studies of \cite{1,38} showed the importance of UAV flight height or spatial resolution’s effect on data analysis. To date, few studies have investigated the association between NDVI and UAV flight height or spatial resolution at individual tree level. The objectives of this study are as follows: (1) Investigate how the UAV
flight height or spatial resolution affects the mean NDVI for individual tree-level canopy. (2) Check the reliability of the multispectral sensor for different heights of UAV flight missions. The major contributions of this section are the following: (1) Publish a dataset on Dryad for a high spatial resolution UAV imagery research study. All the datasets will be available at Dryad\(^2\) for research purpose. (2) Point out the importance of variability analysis of individual tree-level research.

### 2.7.2 Material and Methods

#### 2.7.2.1 The Study Site

The flight missions were conducted in a pomegranate field (Fig. 2.17) at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Parlier, California, 93648, USA.

#### 2.7.2.2 The UAV and the Multispectral Sensor

In this article, the UAV platform, named “Hover,” was adopted to conduct this exploratory study. The authors chose the RedEdge-M camera (MicaSense, Seattle,

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\(^2\) All the datasets will be available at https://doi.org/10.6071/M3JH4Q for research purpose. Citation: Niu, Haoyu; Chen, YangQuan (2021), RedEdge-M pomegranate field 60 m, 90 m, 120 m, Dryad Dataset, https://doi.org/10.6071/M3JH4Q.
Table 2.12  The UAV flight schedule. The UAV flight height was 60 m, 90 m, and 120 m to acquire different high-resolution multispectral imagery. Data was collected successfully for three different days, May 8, 2019, September 19, 2019, and October 3, 2019.

| Dates               | Flight time | Flight height          |
|---------------------|-------------|------------------------|
| May 8, 2019         | 12–1 pm     | 60 m, 90 m, and 120 m  |
| September 19, 2019  | 12–1 pm     | 60 m, 90 m, and 120 m  |
| October 3, 2019     | 12–1 pm     | 60 m, 90 m, and 120 m  |

WA, USA) to obtain multispectral imagery. The multispectral sensor has five different bands, which are blue (475 nm), green (560 nm), red (668 nm), near infrared (840 nm), and red edge (717 nm). The RedEdge-M has a spectral resolution of 8.2 cm/pixel (per band) at 120 m (400 ft.) above ground level (AGL), with a 46° field of view.

2.7.2.3 Details of the UAV Imagery Dataset

The UAV flight height was 60 m, 90 m, and 120 m to acquire different high-resolution multispectral imagery. Data was collected successfully (Table 2.12) for three different days, May 8, 2019, September 19, 2019, and October 3, 2019. All of the multispectral images were then processed to generate the orthomosaic images in Metashape (Agisoft LLC, Russian).

The source data for building DEM was the dense cloud. For the interpolation method, Extrapolated option was selected because it could generate a surface without gaps being extrapolated to the bound box sides. The default option for Interpolation was Enabled, which was not recommended because it would leave the valid elevation values only for fields seen from at least one aligned camera.

2.7.3 Results and Discussion

2.7.3.1 The Relationship Between NDVI and UAV Flight Height

The mean NDVI values of each sampling tree were shown in Figs. 2.18, 2.19, and 2.20. Theoretically, for each sampling tree, the mean NDVI value of the tree canopy should have the same value at 60 m, 90 m, and 120 m. However, the values of NDVI could be very different from each other considering the weather conditions (Fig. 2.19), such as the cloud.

Key Observation  In Fig. 2.19, the NDVI values were significantly different for trees from 1 to 20, and from 31 to 50. The reason was that for image segmentation, more shades were included in the tree canopy. In Figs. 2.18 and 2.20, the data was more consistent for different UAV flight height. For example, in Fig. 2.21, the
2.7 Case Study III: High Spatial Resolution Has Little Impact on NDVI Mean.

Fig. 2.18 The mean NDVI values of each sampling tree at 60 m, 90 m, and 120 m on May 8, 2019. The x-axis was the identification number (ID) for sampling trees, 82 in total. The y-axis was the mean NDVI value for each tree canopy.

Fig. 2.19 The mean NDVI values of each sampling tree at 60 m, 90 m, and 120 m on September 19, 2019. The x-axis was the identification number (ID) for sampling trees, 82 in total. The y-axis was the mean NDVI value for each tree canopy.

Fig. 2.20 The mean NDVI values of each sampling tree at 60 m, 90 m, and 120 m on October 3, 2019. The x-axis was the identification number (ID) for sampling trees, 82 in total. The y-axis was the mean NDVI value for each tree canopy.

The authors compared the correlation of NDVI values between 90 and 120 m. The result showed there was a strong correlation between them, with $R^2 = 0.7$. 
Fig. 2.21 The individual tree-level mean NDVI correlation between 120 and 90 m on October 3, 2019. The x-axis was the mean NDVI values for sampling trees at 120 m flight height. The y-axis was the mean NDVI values for sampling trees at 90 m flight height.

2.7.3.2 Individual Tree Canopy Segmentation Using Support Vector Machine (SVM)

To obtain the individual tree-level NDVI values of the 82 sampling trees, the authors used the SVM for classifying the tree canopy. Using the SVM classifier could map the input data vectors into a higher-dimensional feature space. Then, the SVM optimally separated the data into different classes. Since the multispectral UAV imagery was large, the SVM classifier was adopted, which was less susceptible to noise, correlated bands, and unbalanced number or size of training sites within each class. All the sampling trees were successfully segmented using the SVM classifier.

Key Observation For simplicity, the authors only created the NDVI distribution for the two trees in lysimeter (Figs. 2.22, 2.23, and 2.24). For example, in Fig. 2.22, the NDVI distributions for the two trees in the lysimeter were generated. The NDVI was for May 8, and the UAV flight height was at 60 m, 90 m, and 120 m. The color bar meant the range of the NDVI values (from $-1$ to 1). Based on the above section, “The Relationship Between NDVI and UAV Flight Height,” there was no significant difference for mean NDVI value at individual tree level. However, as shown in Fig. 2.22, lower flight height (60 m) gave a higher spatial resolution image. The NDVI distribution inside the canopy was more precise than that in higher flight height. Therefore, what the average told us could be wrong. How to use this high-
Fig. 2.22 The NDVI distribution of two individual lysimeter trees at 60 m, 90 m, and 120 m on May 8, 2019. (a) The NDVI distribution of individual lysimeter trees at 60 m flight height. (b) The NDVI distribution of individual lysimeter trees at 90 m flight height. (c) The NDVI distribution of individual lysimeter trees at 120 m flight height.

resolution benefit from UAV imagery can be discussed in the near future. Variability analysis may play an important role in individual tree-level research.
2.7.3.3 Entropy of Individual Tree-Level NDVI Image

To characterize the texture of the individual tree-level NDVI image of the lysimeter trees, the authors adopted the entropy method, which was a statistical measurement of the randomness in the image. Entropy was defined as 

$$-\sum(p_i \cdot \log_2(p_i))$$

where $p_i$ is the probability of occurrence of pixel $i$. This method helped in quantifying the variability within the NDVI distribution, offering insights into the density and distribution of vegetation within the lysimeter trees at different flight heights.
Fig. 2.24 The NDVI distribution of two individual lysimeter trees at 60 m, 90 m, and 120 m on October 3, 2019. (a) The NDVI distribution of individual lysimeter trees at 60 m flight height. (b) The NDVI distribution of individual lysimeter trees at 90 m flight height. (c) The NDVI distribution of individual lysimeter trees at 120 m flight height.

The normalized histogram counts returned from the MATLAB command “imhist” [42]. It was used in the quantitative analysis and evaluation of image details. Higher value of entropy meant more detailed information in the image.

**Key Observation** As shown in Table 2.13, the higher entropy value for lysimeter trees was obtained at 90 m in May 8. However, the higher entropy value was at 60 and 120 m in September 19 and October 3, respectively. Therefore, high spatial resolution had low impact on the UAV-based individual tree-level NDVI images.
Table 2.13  Entropy was used in the quantitative analysis and evaluation of image information, because it provided better comparison of the image details. Higher value of entropy meant more detailed information in the image

| Dates              | 60 m     | 90 m     | 120 m    |
|--------------------|----------|----------|----------|
| May 8, 2019        | 2.0176   | 2.0789   | 1.7984   |
| September 19, 2019 | 4.5861   | 3.7598   | 3.1027   |
| October 3, 2019    | 3.2812   | 3.6725   | 4.0022   |

There was no significant difference for image information in range of 60–120 m of UAV flight height.

2.7.4 Conclusions and Future Work

In this study, UAV flight missions were conducted to collect multispectral imagery at different flight height (60 m, 90 m, and 120 m). After image processing, the authors contributed a dataset on Dryad for a high spatial resolution UAV imagery research study.

Using the NDVI derived from UAV images, the authors analyzed how spatial resolution could affect the NDVI values at the individual tree level. According to the results, there was no significant difference for mean NDVI value at individual tree level for different flight heights when the data was processed appropriately. The $R^2$ of mean NDVI values between 90 and 120 m was around 0.7, which proved the multispectral sensor was reliable for data collection. However, the shade around the tree canopy could be a key factor for tree canopy segmentation (Fig. 2.19), which could reduce the mean NDVI significantly.

Lower flight height (60 m) did give a higher spatial resolution image. The NDVI distribution inside the canopy was more precise than that in higher flight height. Therefore, what the average tells us can be wrong. How to use this high-resolution benefit from UAV imagery can be discussed in the near future. Variability analysis may play an important role in individual tree-level research. In the future, the authors will apply the conclusion to NDVI-related research topics, such as evapotranspiration estimation, stem water potential, and yield estimation.

2.8 Chapter Summary

In this chapter, small UAVs and remote sensing payloads were introduced and discussed. UAV image acquisition and processing methods were also presented. The challenges and opportunities for UAV ET estimation methods were also discussed
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Chapter 3
ET Estimation Methods with Small UAVs: A Literature Review

3.1 Introduction

Most ET estimation using UAVs is based on satellite remote sensing methods. One-source energy balance (OSEB), High-Resolution Mapping of Evapotranspiration (HRMET) [90], machine learning [1, 37, 41, 43, 56, 66], artificial neural networks (ANN) [69], two-source energy balance (TSEB), Dual Temperature Difference (DTD) [63], Surface Energy Balance Algorithm for Land (SEBAL) [6, 9], and Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) [4] are introduced in this chapter. The discussed ET estimation methods with UAVs and their advantages and disadvantages are summarized in Table 3.1. As mentioned earlier, this chapter is not intended to provide an exhausting review of all direct or indirect methods that have been developed for ET estimation, but rather to provide an overview on ET estimation with UAV applications. Therefore, only those methods (Table 1.1) which have already been used with the UAV platform are discussed.

3.2 Related Work

3.2.1 One-Source Energy Balance (OSEB)

One-source energy balance (OSEB) model assumes the whole surface as a uniform layer. OSEB model does not differentiate potential sources, such as the soil and canopy [9, 78]. The OSEB model uses empirical parameters to explain differences in the aerodynamic and radiometric components [13, 18, 40, 51, 86]. The OSEB model uses the following equation to calculate the latent heat flux,

\[ LE = R_n - G - H, \]  

(3.1)
| Methods | Advantages | Applications with UAVs | Disadvantages |
|---------|------------|-----------------------|---------------|
| OSEB    | (1) Treats the surface as big leaf and therefore as a simple uniform layer; (2) Uses empirical parameters to explain differences in the aerodynamic and radiometric components; (2) Assumes the whole surface as a uniform layer, which does not take advantage of UAV high-resolution imagery; (3) Less sensitive to land surface temperature variations than the TSEB model. | Vineyard [68], grassland [14], and corn | (1) Needs more validation for clumped canopy structure, such as trees and vines. |
| HRMET   | (1) Only requires basic meteorological data, spatial surface temperature, and canopy structure data; (2) Does not depend on wet and dry reference features to calculate turbulent fluxes. | Peach, nectarine [65], and corn | (1) Needs more validation for clumped canopy structure, such as trees and vines. |
| ML/ANN  | (1) Captures nonlinear crop characteristics | Vineyard [69], peach, nectarine, grape, sorghum, and corn [16], grassland | (1) Requires large amount of data for training models and validation; |
| TSEB    | (1) The calculation of sensible heat flux and latent heat flux for canopy and soil is separate; (2) Parameterization of resistances is easier compared with a single-layer model. | Barley [36], vineyard [57, 59, 60, 88], olive [64], sorghum and corn [16], grassland | (1) Requires flights at two times during the morning hours, thus complicating flight missions; |
| DTD     | (1) One more input dataset, the land surface temperature retrieved 1 hour after sunrise; (2) Minimizes the bias in the temperature estimation; (3) Separates the land surface temperature into vegetation and soil temperatures. | Barley [36], corn, and soybean | (1) Requires flights at two times during the morning hours, thus complicating flight missions; |
| SEBAM   | (1) Selecting hot or cold pixels is subjective, which can cause variations in ET estimation. | Corn and soybean [58] | (1) Selecting hot or cold pixels is subjective, which can cause variations in ET estimation. |
| METRIC  | (1) Eliminates the need for absolute surface temperature calibration; (2) Requires minimum ground-based data; (3) Automatic internal correction | Vineyard [2, 25] | (1) Eliminates the need for absolute surface temperature calibration; (2) Requires minimum ground-based data; (3) Automatic internal correction. |
where $LE$ is the latent heat flux (W m$^{-2}$), $R_n$ is the net radiation (W m$^{-2}$), $G$ is the soil heat flux (W m$^{-2}$), and $H$ is the sensible heat flux (W m$^{-2}$). The sensible heat flux $H$ is calculated by

$$H = \rho C_p \frac{T_{aero} - T_{ac}}{R_{ah}},$$  \hspace{5cm} (3.2)$$

where $\rho$ is the air density (kg m$^{-3}$), $C_p$ is the specific heat of air (J kg$^{-1}$ K$^{-1}$), $T_{aero}$ is the aerodynamic temperature (K) [61], and $T_{ac}$ is the air temperature (K) in the vegetation [19, 45, 82]. $R_{ah}$ is the aerodynamic resistance to heat flux (s m$^{-1}$), which is calculated by

$$R_{ah} = \frac{\ln(z_u - d/\bar{z}_{om}) - \Psi_m}{\ln(z_t - d/\bar{z}_{om}) + \ln(\bar{z}_{om} - \bar{z}_{oh}) - \Psi_h}k^2u,$$  \hspace{5cm} (3.3)$$

where $z_u$ and $z_t$ are the wind and air temperature measurement heights, respectively. The parameter $d$ is the zero displacement height, $\bar{z}_{om}$ is the momentum transfer [52, 85], $\Psi_m$ and $\Psi_h$ are the diabatic correction factors for momentum and heat [15], $\bar{z}_{oh}$ is the resistance to heat, $k$ is the Karman constant, and $u$ is the wind speed.

The parameter $kB^{-1}$ is also used in OSEB model to adjust the radiometric to the aerodynamic temperature. The measured radiometric temperature can be used in Eq. (3.2) instead of $T_{aero}$. The parameter $kB^{-1}$ is calculated by

$$kB^{-1} = \ln\left(\frac{\bar{z}_{om}}{\bar{z}_{oh}}\right).$$  \hspace{5cm} (3.4)$$

There are also some other types of OSEB models. For example, deriving atmosphere turbulent transport useful to dummies using temperature (DATTUTDUT) [83] is an energy balance model which only needs the land surface temperature as the input for ET estimation. The DATTUTDUT estimates ET by scaling the energy fluxes between the hot and cold pixels. The DATTUTDUT model is similar to the simplified surface energy balance index (S-SEBI) proposed by Roerink [72]. However, the DATTUTDUT model is more simplified to acquire the radiometric temperature. More details can be found in [83].

### 3.2.2 High-Resolution Mapping of ET (HRMET)

For most current ET models such as METRIC and SEBAL, they are highly relied on selecting hot and cold pixels to separate energy fluxes between latent and sensible heat in the images. Therefore, their ability is limited to map ET throughout the growing season at extremely high spatial resolutions. Thus, Zipper et al. [90] developed a field-validated surface energy balance model, which is called High-Resolution Mapping of Evapotranspiration (HRMET). The HRMET only requires
basic meteorological data, spatial surface temperature, and canopy structure data. For more detailed calculation steps about the HRMET, please refer to [90].

### 3.2.3 Machine Learning (ML) and Artificial Neural Networks (ANN)

Machine learning techniques and ANN models have already been used for estimating hydrological parameters [1, 37, 41, 43, 56, 66] and ecological variables [21]. Because of the ML’s ability to capture nonlinear characteristics, many research results suggest that machine learning methods can provide better ET estimates than empirical equations based on different meteorological parameters [7, 29, 42, 54, 55, 68, 80, 89]. Traditional multispectral indices have limitations to assess water status. Therefore, artificial neural networks (ANN) were used in [69] to improve the estimation of spatial variability of vine water status. In [23], Dou et al. used four different machine learning approaches in different terrestrial ecosystems for ET estimation. ANN, support vector machine (SVM), extreme learning machine (ELM) [30], and adaptive neuro-fuzzy inference system (ANFIS) [2, 35, 67, 70, 75, 80] were compared with each other on estimating ET. In [84], Torres-Rua et al. built a narrowband and broadband emissivities model for UAV thermal imagery using a deep learning (DL) model. The resulting emissivities were incorporated into the TSEB model to analyze their effect on the estimation of instantaneous energy balance components against ground measurements.

### 3.2.4 Two-Source Energy Balance (TSEB) Models

The TSEB model is developed to improve the accuracy of LE estimation [44–46, 62], using the assumptions of canopy transpiration in Priestley and Taylor potential evapotranspiration [71] calculations. Therefore, this TSEB model is also called TSEB-PT to differentiate it from other TSEB methods. The calculation of sensible heat flux and latent heat flux for canopy and soil is separate, which makes the parameterization of resistances easier compared with a single-layer model. Based on [17, 27], the TSEB is effective over homogeneous land and environmental conditions. The TSEB model reproduces fluxes with similar results to tower-based observations.

The TSEB model separates the land surface temperature into soil surface temperature $T_s$ and vegetation surface temperature $T_c$. Subscripts “s” and “c” mean soil and canopy. It considers sensible and latent heat fluxes are transferred to the atmosphere from both surface temperature components, as shown in the following equations [88]:
3.2 Related Work

\[ R_n = R_{ns} + R_{nc}, \]  
\[ (3.5) \]

\[ R_{ns} = H_s + LE_s + G, \]  
\[ (3.6) \]

\[ R_{nc} = H_c + LE_c. \]  
\[ (3.7) \]

The net radiation \( R_n \) is divided into two parts, the soil net radiation \( R_{ns} \) and the canopy net radiation \( R_{nc} \) \[20, 77\],

\[ R_{ns} = \tau_l L_d + (1 - \tau_l)\varepsilon_c \sigma T^4_c - \varepsilon_s \sigma T^4_s + \tau_s (1 - \alpha_s) S_d, \]  
\[ (3.8) \]

\[ R_{nc} = (1 - \tau_l)(L_d + \varepsilon_s \sigma T^4_s - 2\varepsilon_c \sigma T^4_c) + (1 - \tau_s)(1 - \alpha_c) S_d, \]  
\[ (3.9) \]

where \( \tau_l \) and \( \tau_s \) are the longwave and shortwave radiation transmittances through the canopy, respectively. \( L_d \) and \( S_d \) are the incoming longwave and shortwave radiation (W m\(^{-2}\)), which are usually measured from a nearby weather station. The Stefan-Boltzmann constant is given by \( \sigma \), which is approximately \( 5.67 \times 10^{-8} \) (W m\(^{-2}\) K\(^{-4}\)). The surface emissivity is denoted by \( \varepsilon \), \( \alpha \) is the surface albedo, and \( T \) is the surface temperature (K).

For the soil sensible heat flux \( H_s \) and canopy sensible heat flux \( H_c \), they can be calculated based on the following equations:

\[ H_s = \rho C_p \frac{T_s - T_{ac}}{R_s}, \]  
\[ (3.10) \]

\[ H_c = \rho C_p \frac{T_c - T_{ac}}{R_x}, \]  
\[ (3.11) \]

where \( \rho \) is the air density (kg m\(^{-3}\)), \( C_p \) is the specific heat of air (J kg\(^{-1}\) K\(^{-1}\)), \( T_{ac} \) is the air temperature in the vegetation \[19, 45, 82\], \( R_s \) is the resistance to heat flux above the soil surface (s m\(^{-1}\)), and \( R_x \) is the boundary layer resistance of the canopy leaves (s m\(^{-1}\)).

3.2.5 Dual-Temperature-Difference (DTD) Model

The DTD model separates the land surface temperature into vegetation and soil temperatures \[63\]. Then, it calculates the surface energy balance components by using the same procedures as the TSEB. The TSEB model is very sensitive to the temperature difference between the land surface and air, which makes the
absolute land surface temperature inaccurate. To solve this problem, the DTD model added one more input dataset, the land surface temperature retrieved 1 hour after sunrise. The energy fluxes are minimal at sunrise, which minimizes the bias in the temperature estimation. For the soil sensible heat flux $H_s$ and canopy sensible heat flux $H_c$, Eqs. (3.10) and (3.11) become

$$H_s = \rho C_p \frac{(T_{s_i} - T_{s_o}) - (T_{ac_i} - T_{ac_o})}{R_s},$$  \hspace{1cm} (3.12)$$

$$H_c = \rho C_p \frac{(T_{c_i} - T_{c_o}) - (T_{ac_i} - T_{ac_o})}{R_x},$$  \hspace{1cm} (3.13)$$

where subscript $i$ means the measurements are at midday and subscript $o$ refers to observations 1 hour after the sunrise.

In [32], Guzinski et al. produced surface energy flux successfully by using the DTD model with satellite images, who used night observations to substitute for the early morning observation. However, the temporal resolution of the satellite observations is limited, especially when the weather conditions are limiting. For example, satellite thermal infrared observations cannot penetrate clouds when there is a cloud cover. The incapacity to collect data in overcast situations applies to all satellite sensors except for those operating in the microwaves region [32].

The calculation of soil heat flux $G$ is different between midday and sunrise observations. This difference can be used to estimate the soil surface temperature variations. Soil heat flux is calculated based on the model of [74]. The soil heat flux equation is

$$G = R_{ns}Acos\left(\frac{2\pi (t + 10800)}{B}\right),$$  \hspace{1cm} (3.14)$$

$$A = 0.0074\Delta T_R + 0.088,$$  \hspace{1cm} (3.15)$$

$$B = 1729\Delta T_R + 65013,$$  \hspace{1cm} (3.16)$$

where $\Delta T_R$ is the diurnal variation in the soil surface temperature and $t$ is the time between the data collection time and the solar noon. For more details about the TSEB and DTD equations, see [33, 34].

### 3.2.6 Surface Energy Balance Algorithm for Land (SEBAL)

The Surface Energy Balance Algorithm for Land (SEBAL) model uses surface temperature $T_s$; visible, near-infrared, thermal infrared radiation; albedo maps; and
NDVI to estimate surface fluxes with many different land cover types [8, 9]. SEBAL is currently one of the most reliable algorithms to estimate actual ET ($ET_a$), and it is one of the most promising approaches currently for local and regional estimation with minimum ground data [49]. SEBAL has been validated in many different climatic conditions around the world [10, 11, 73, 76, 79]. Typically, the SEBAL’s accuracy is around 85 and 95% at daily and seasonal scales, respectively [10, 12]. To calculate ET as a residual of the energy balance model, the sensible heat flux $H$ needs to be estimated first.

In the SEBAL model, two reference air temperatures are measured to compute the air temperature difference ($dT$). One air temperature is measured at the height $h_1$ close to the surface. The other is measured at an upper height of $h_2$. To calculate $dT$ for each pixel, SEBAL assumes that there is a linear relationship between $dT$ and the surface temperature $T_s$ as

$$dT = a + bT_s,$$

where $a$ and $b$ are derived parameters empirically based on two extreme hot and cold pixels, also called “anchor” pixels [8]. These hot and cold pixels defined the boundary of the sensible heat flux. The cold pixel is usually selected from a well-watered area with no water stress. The $H$ is assumed to be minimum, and ET should be maximum. The hot pixel is taken from a dry and bare field where $H$ is maximum and ET is almost zero. Hot and cold pixels are usually selected by an empirical method.

Most SEBAL applications for estimating energy fluxes and ET have used spaceborne platforms with a relatively low spatial resolution. There is not much-published work related to the use of the SEBAL model to estimate ET using UAVs. Selecting hot or cold pixels is subjective, which can cause variations in ET estimation. Estimated sensible heat flux $H$ is easily affected by the surface-air temperature differences or surface temperature measurements. The radiometer’s viewing angle can also cause variations in $T_s$ by several degrees for some images.

Although SEBAL has limitations, there are also several advantages of SEBAL for estimating land surface fluxes from thermal remote sensing data. First, SEBAL does not need a lot of ground-based data. Second, SEBAL has an automatic internal correction. Third, every image has an internal calibration in SEBAL.

### 3.2.7 Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC)

METRIC is originally a satellite image processing model for estimating ET as a residual of the energy balance [4], which is based on SEBAL. The METRIC can generate ET maps with a 30-m spatial resolution by using Landsat images. METRIC has a self-calibration process which contains ground-based hourly reference ET and
the selection of hot and cold pixels [31]. It eliminates the need for absolute surface temperature calibration [6].

SEBAL uses $T_s$, $\rho$, NDVI, and their relationships to calculate the surface fluxes [9], which have been evaluated all over the world [10, 11, 73, 76, 79]. The METRIC model uses the same method with the SEBAL to estimate $dT$. Thus, there is no need to get an accurate aerodynamic surface temperature. In [49], Liou et al. summarized three differences between the SEBAL and METRIC. First, for the cold pixel, the METRIC does not consider sensible heat flux as zero. Instead, a surface soil water balance is applied to set ET as 1.05 times reference ET at cold pixels. Reference ET is calculated by using the standardized American Society of Civil Engineers (ASCE) Penman-Monteith equation. Second, in METRIC, cold pixels are selected in agricultural settings instead of biophysical characteristics. Third, the extrapolation of instantaneous ET is based on reference ET instead of the actual evaporative fraction.

METRIC estimates ET using the energy balance Eq. (3.1). For the net radiation $R_n$ (W m$^{-2}$), it can be calculated by adding all the incoming radiation and subtracting all the outgoing radiation based on the following equation [4]:

$$R_n = (1 - \alpha)R_{s\downarrow} + R_{L\downarrow} - R_{L\uparrow} - (1 - \varepsilon_o)R_{L\downarrow}, \quad (3.18)$$

where $R_{s\downarrow}$ is the incoming shortwave radiation (W m$^{-2}$), $\alpha$ is the surface albedo, and $R_{L\downarrow}$ and $R_{L\uparrow}$ are the incoming longwave radiation (W m$^{-2}$) and outgoing longwave radiation (W m$^{-2}$), respectively. $\varepsilon_o$ is the thermal emissivity, which is also dimensionless. These parameters can be calculated in METRIC with several submodels that use other parameters derived from the ground-based weather data, digital elevation model (DEM), and satellite images [4].

Sensible heat flux $H$ (W m$^{-2}$) is computed from surface roughness, wind speed, and surface temperature ranges:

$$H = \rho_{air} C_p \frac{dT}{r_{ah}}, \quad (3.19)$$

where $r_{ah}$ is the aerodynamic resistance (s m$^{-1}$) between two surface height. In METRIC, $r_{ah}$ is usually calculated by using the wind speed, LAI or NDVI, and an iterative stability correction, as shown in the following equation:

$$r_{ah} = \frac{\ln(z_2/z_1)}{u^*_k}, \quad (3.20)$$

where $z_1$ and $z_2$ are heights above the zero-plane displacement of the vegetation. $k$ is the von Karman constant (0.41). $u^*$ is the friction velocity (m s$^{-1}$), which is calculated by using

$$u^* = \frac{ku_{200}}{\ln(200/z_{om})}, \quad (3.21)$$
where $u_{200}$ is the wind speed at a blending height 200 m and $z_{om}$ is the momentum roughness length (m).

The temperature difference between the air and the surface is represented by $dT$. A strong linear relationship between the $dT$ and the surface temperature was found in [4, 9, 12, 39], as shown in Eq. (3.17). The sensible heat fluxes for the cold and hot pixels are calculated by Eq. (3.1). According to [81], for the cold pixel, the ratio $LE$ and $ET_r$ is assumed to be 1.05. However, this assumption is not always true at the beginning or outside of the growing season when the vegetation is much less than the alfalfa [53]. Therefore, the ratio of the $LE$ and $ET_r$ for the cold and hot pixels is calculated by NDVI [4]. Then, the $dT$ and land surface temperature $T_s$ for the cold and hot pixels are applied for calculating the $a$ and $b$ in Eq. (3.17) as

$$a = \frac{dT_{hot} - dT_{cold}}{T_{hot} - T_{cold}},$$  \hspace{1cm} (3.22)

$$b = \frac{dT_{hot} - a}{T_{hot}},$$  \hspace{1cm} (3.23)

where $T_{hot}$ and $T_{cold}$ are the land surface temperature (K) at the hot and cold pixels, respectively.

### 3.3 Existing ET Estimation Methods with UAVs: Results and Discussion

Compared with traditional satellite remote sensing approaches, the UAV platform and the lightweight cameras can estimate the surface energy fluxes with similar accuracy. Therefore, the UAVs can be used for modeling ET estimation with high confidence. In this section, different crop ET estimations with UAV platforms (Table 3.2) are compared with each other. The reasons behind the errors of ET estimation are also discussed in related sections.

#### 3.3.1 OSEB and TSEB Models

In [14], Brenner et al. compared the OSEB model with the TSEB model by using an octocopter MikroKopter OktoXL (HiSystems GmbH, Moormerland, Germany). This UAV platform could carry a payload of 4 kg for each flight mission. An ES80 camera (Samsung, Seoul, South Korea) and an Optris Pi 400 thermal camera were mounted on the UAV to collect images. According to the specification, Pi 400 had an accuracy of $\pm 2$ °C. The thermal image resolution was 382 $\times$ 288 pixels with a field of view 38° $\times$ 29°. Approximately 700–1000 thermal images were collected.
### Table 3.2 Comparisons of the different ET estimation methods with UAVs

| Methods | Applications with UAVs | Accuracy of $R_n$ | Accuracy of $G$ | Accuracy of $LE$ | Accuracy of $H$ |
|---------|------------------------|-------------------|----------------|-----------------|----------------|
| OSEB    | Grassland [14]         | $R^2$ of 0.98     | $R^2$ of 0.73  | $R^2$ of 0.92   | $R^2$ of 0.79  |
| TSEB    |                        | $R^2$ of 0.99     | $R^2$ of 0.83  | $R^2$ of 0.93   | $R^2$ of 0.84  |
| TSEB    | Barley [36]            | RMSE of 44 W m$^{-2}$ | RSME of 38 W m$^{-2}$ | RMSE of 94 W m$^{-2}$ | RMSE of 85 W m$^{-2}$ |
| DTD     |                        | RMSE of 44 W m$^{-2}$ | RSME of 48 W m$^{-2}$ | RSME of 67 W m$^{-2}$ | RSME of 59 W m$^{-2}$ |
| TSEB    | Vineyard [88]          | RMSE of 33 W m$^{-2}$ | RSME of 33 W m$^{-2}$ | RMSE of 87 W m$^{-2}$ | RMSE of 42 W m$^{-2}$ |
| DATTUTDUT |                    | RMSE of 66 W m$^{-2}$ | RSME of 40 W m$^{-2}$ | RSME of 150 W m$^{-2}$ | RSME of 68 W m$^{-2}$ |
| TSEB    | Olive [64]             | RMSE of 38 W m$^{-2}$ | RSME of 19 W m$^{-2}$ | RMSE of 50 W m$^{-2}$ | RMSE of 56 W m$^{-2}$ |
| SEBAL   | Corn, soybean [58]     | $R^2$ of 0.71     | $R^2$ of 0.17 and 0.22 | $R^2$ of 0.82 | $R^2$ of 0.5  |
for every flight mission. The eddy covariance system was used to evaluate the UAV ET estimation.

Based on the comparison between UAV fluxes and eddy covariance (EC) fluxes, the net radiation $R_n$ for TSEB was in good agreement with $R_n$ measured from EC with an R-squared value ($R^2$) of 0.99. The $R^2$ value for OSEB was 0.98. The sensible heat flux ($H$) for TSEB had an $R^2$ value of 0.84, and the OSEB had an $R^2$ value of 0.79. For the soil heat flux $G$, the $R^2$ value for OSEB was 0.73. The TSEB had an $R^2$ value of 0.83. Both models underestimated the ground heat flux compared with the eddy covariance system. For the latent heat flux $LE$, OSEB had an $R^2$ value of 0.92. The TSEB had an $R^2$ value of 0.93.

**Remark** The results showed that the OSEB model significantly underestimated measured values for flux conditions. The poor performance of the OSEB model mainly resulted from an underestimation of high fluxes. Different from the TSEB model, the OSEB model needs an empirical adjustment parameter $kB_{-1}$ to explain the difference between the radiometric and aerodynamic surface temperature. The parameter $kB_{-1}$ is usually overestimated in case of strong temperature gradients between the surface and the atmosphere [14].

### 3.3.2 HARMET Model

In [65], Park et al. used the HARMET model when flying a DJI S1000 UAV. A thermal infrared camera A65 and a multispectral camera RedEdge-M were mounted on the UAV to collect thermal and multispectral images. The thermal camera image resolution was $640 \times 512$ pixels with a field of view of $25^\circ \times 20^\circ$. The Rededge had a spatial resolution of $1280 \times 960$ pixels. The UAV was flown at solar noon for capturing the period of high ET and for minimizing tree canopy shadows.

The energy fluxes were estimated in the HARMET model. For the reference trees, the estimated ET was around 0.62 mm h$^{-1}$. The study site was small and the UAV flight time was less than 15 minutes; thus, the meteorological data, such as incoming shortwave radiation, wind speed, and vapor pressure, were considered to be consistent during the UAV flight mission. The different ET rates along the trees were mainly decided by the differences in tree canopy temperature and LAI. The estimated ET had a strong linear relationship with leaf transpiration ($R^2 = 0.9$).

**Remark** Although it was challenging to evaluate the results because of the absence of sufficient data such as the directly measured ET or multi-seasonal UAV data, the HARMET model still showed a great potential to estimate tree-by-tree ET and capturing intra-field variability.
3.3.3 Machine Learning and Neural Networks

In [69], Poblete et al. used ANN and multispectral images from a UAV platform to predict vine water status. A multispectral camera MCA-6 (Tetracam Inc, Chatsworth, CA, USA) was mounted on an octocopter MikroKopter OktoXL for data collection. The data were grouped into training and validation, where 80% was used for the ANN model calibration and 20% was used to validate the model. Although this research was not exactly for ET estimation, it proved that neural networks, such as ANN, had a great potential for ET estimation when combing with high-resolution multispectral UAV images.

In [23], four machine learning methods, ANN, SVM, ELM, and ANFIS, were used to estimate ET. Results showed that all four models could detect the variations of ET. The reason is that ML algorithms can identify complex nonlinear relationships between ET and environmental variables. As a new model, ELM exhibits strong modeling accuracy for daily ET estimation. ANFIS can estimate ET more efficiently than ANN and SVM. More importantly, these new machine learning approaches show a novel perspective for ET estimation with remote sensing data. Therefore, UAV platforms should be used with ML algorithms together, which will have great potential for ET estimation in the future.

3.3.4 TSEB and DTD Models

The UAVs can help generate more accurate maps of NDVI, LAI, $f_r(\theta)$, and $T_R(\theta)$, which are the critical input data for the TSEB and DTD models [38]. In [36], Hoffmann et al. used the TSEB model and the DTD model when flying a Q300, which has a 2.2-m wingspan and can carry a payload of 2 kg for a 25-minute flight. An Optris PI 450 camera was mounted on the UAV to collect thermal images. Hoffmann et al. concatenated the LST thermal images into the orthomosaic, which were applied as the input for TSEB model [36]. According to the specifications, the thermal camera has an accuracy of $\pm2$ °C or $\pm2\%$ at an ambient temperature of 23 $\pm$ 5 °C. The thermal image resolution is 382 × 288 pixels at 90 m flying height. Around 700–1000 thermal images were collected for every flight mission. The eddy covariance system was used to compare with the UAV results.

Based on the comparison between UAV fluxes and eddy covariance (EC) fluxes, the net radiation $R_n$ for TSEB was in good agreement with $R_n$ measured from EC with a root mean square error (RMSE) of 44 W m$^{-2}$ (11%); the correlation coefficient was 0.98. The sensible heat flux ($H$) for DTD has RMSE of 59 W m$^{-2}$ (64%), and the mean absolute error (MAE) value was 49 W m$^{-2}$ (52%). Compared with DTD, the TSEB model had a RMSE of 85 W m$^{-2}$ (91%) and the MAE was 75 W m$^{-2}$ (81%). The TSEB had a better linear relationship between measured sensible heat flux $H$ and modeled $H$. The soil heat fluxes ($G$) were underestimated, which had RMSE and MAE of 48 W m$^{-2}$ (91%) and 45 W m$^{-2}$ (86%) for DTD,
respectively. The RSME and MAE for TSEB were 38 W m$^{-2}$ (72%) and 35 W m$^{-2}$ (66%), respectively. The correlation between the modeled $G$ and measured $G$ was very poor. Soil heat flux $G$ was measured with the heat flux plates, which could lead to uncertainties in measured $G$ [28]. For the latent heat flux $LE$, DTD had RMSE and MAE of 67 W m$^{-2}$ (26%) and 57 W m$^{-2}$ (22%), respectively. The TSEB had RMSE and MAE values of 94 W m$^{-2}$ (37%) and 84 W m$^{-2}$ (33%), respectively.

Remark The results showed that the DTD model predicted the energy fluxes better than TSEB, which demonstrated that adding another input, the land surface temperature retrieved 1 hour after sunrise, made the DTD model more robust. It concluded that the thermal camera placed on a UAV platform could provide high spatial and temporal resolution data for estimating energy balance fluxes of ET. Calibration of the thermal camera was also likely to improve TSEB heat flux computations. This study showed similar results with Guzinski’s work [33], who applied the TSEB at the same site but using satellite images instead of UAV images. In [33], the RMSE is 46 W m$^{-2}$ for $R_n$, 56 W m$^{-2}$ for $H$, and 66 W m$^{-2}$ for $LE$. The DTD model in [36] achieved RMSE of 44 W m$^{-2}$ for $R_n$, 59 W m$^{-2}$ for $H$, and 67 W m$^{-2}$ for $LE$.

3.3.5 TSEB and DATTUTDUT Models

Xia et al. [88] used the TSEB model and DATTUTDUT model for a subfield and plant canopy scale ET monitoring over vineyards. Based on the results, the TSEB model estimated sensible heat flux and latent heat flux with the RMSE ranging from 20 to 60 W m$^{-2}$. DATTUTDUT estimated heat fluxes with a larger error; the RMSE for latent heat flux $LE$ was 105 W m$^{-2}$. The net radiation $R_n$ had an RMSE of 65 W m$^{-2}$. It concluded that the TSEB model could simulate the energy balance components in two vineyards with MAE ranging from 15 to 90 W m$^{-2}$. They found that the TSEB model was fairly robust and was able to calculate LE and ET values under varying environmental conditions. By using the TSEB, the $T_s$ and $T_c$ had a bias of 0.5 $^\circ$C and RMSE on the order of 2.5 $^\circ$C. The accuracy was similar with [19, 45–47], in which the RMSE values were between 2.4–5.0 $^\circ$C for $T_s$ and 0.83–6.4 $^\circ$C for $T_c$.

Remark In general, the TSEB has a better performance than the DATTUTDUT model. The reason might be that the TSEB has a better physical representation of the energy exchange. DATTUTDUT, as a single-source model, is more sensitive when the surface temperature pixels are selected [26, 50]. The actual extremes may not even exist in the thermal images. Besides, the effect of aerodynamic resistance (surface roughness) is also not considered in the DATTUTDUT model.

Ortega et al. [64] used the TSEB model to estimate the energy balance fluxes over a drip-irrigated olive orchard by using a helicopter-based UAV platform. The UAV flight height was at 60 m, which enabled the thermal camera’s image at 6 cm spatial
resolution. For the multispectral camera Mini MCA-6, the resolution was 3.3 cm. The remote sensing energy balance (RSEB) algorithm was well implemented, and only the climatic parameters, such as air temperature $T_a$ and wind speed $u$, were measured as the input data. The UAV images were used for calculating the NDVI and soil temperature $T_s$. Ortega et al. used the Bowen ratio approach to balance $(R_n - G)$ and $(H + LE)$ to close the energy balance.

For the net radiation $R_n$, the RMSE and MAE were 38 W m$^{-2}$ and 33 W m$^{-2}$, respectively. For the estimated soil heat flux $G$ by TSEB, the RMSE and MAE were 19 W m$^{-2}$ and 16 W m$^{-2}$, respectively. Results showed that the algorithm estimated $LE$ and $H$ with errors of 7% and 5%, respectively. The RMSE and MAE for the sensible heat flux $H$ were 56 W m$^{-2}$ and 46 W m$^{-2}$, respectively. The RMSE and MAE for latent heat flux $LE$ were 50 W m$^{-2}$ and 43 W m$^{-2}$, respectively. It showed that the largest differences for $H$ and $LE$ were found when the wind speed was greater than 2.7 m s$^{-1}$.

**Remark** The results indicated that the UAV could be an excellent tool to evaluate the effects of spatial variability for ET estimation. The high spatial resolution images were able to show significant differences between the energy balance fluxes above the tree canopy and the soil surface. It concluded that the TSEB model was fairly robust and could estimate ET at a subfield scale level under different environmental conditions. UAV can also help the satellite platforms for estimating intra-field spatial variability of the energy fluxes to improve the estimation of water requirements of sparse canopies, for example, orchards and vineyards, which have different plant densities and fractional covers.

### 3.3.6 SEBAL Model

In [58], Montibeller et al. used the SEBAL model to estimate energy fluxes and ET of corn and soybean in Ames, Iowa. The UAV being used was the eBee Ag (SenseFly, Cheseaux-sur-Lausanne, Switzerland), which weighed about 700 g and could cover a 12 km$^2$ area in one flight. A modified S110 camera (Canon Inc, Ota City, Tokyo, Japan), the Sequoia multispectral sensor (MicaSense, Seattle, WA, USA), and the thermoMAP camera (SenseFly, Cheseaux-sur-Lausanne, Switzerland) were equipped with the UAV to collect data for running the SEBAL model. The thermal and multispectral images are the most important data for this project. UAV images were collected from different growing stages of the crops, such as flowering, yield formation, and the ripening. The seasonal variability of ET and energy fluxes were also considered. Surface albedo and surface reflectance were measured by a spectroradiometer.

To evaluate the accuracy of estimated energy fluxes, [58] used linear regression models and residual plots methods. All pixels in the energy flux images were averaged to compare with the observed values measured from the flux towers. The $R^2$ for the net radiation $R_n$ predicted by SEBAL was 0.71, which was
underestimated by about 17% compared with the flux towers. Underestimation was most likely caused by clouds at the time when UAV was flying. The net radiation $R_n$ ranged from 427.24 W m$^{-2}$ to 688.76 W m$^{-2}$ during the UAV flight missions, with a RMSE of 6.09 W m$^{-2}$.

Estimating soil heat flux $G$ is the most challenging part. The estimated soil heat flux was compared with two soil heat plates in the test field. For the soil heat flux $G$, the $R^2$ for the plate 1 is 0.17, with the RMSE of 11.23 W m$^{-2}$. The $R^2$ for the plate 2 is 0.22, with the RMSE of 31.02 W m$^{-2}$. Both show a poor correlation. There are mainly two reasons behind it. First, the accuracy of the soil heat flux plates is very low. The grown canopy can cover the soil surface, which gives errors for soil heat flux estimations. The soil heat flux plates can detect the heat rate flow difference when the canopy is developing during the growing season. Second, the flux plates’ depth and the soil types also affect the heat flux estimation [28]. The soil heat flux $G$ ranged from 14.57 W m$^{-2}$ to 119.76 W m$^{-2}$ for the whole growing season, which was not a good estimation. Several factors could affect the soil heat flux values, such as the quality of the UAV images and the spatial distribution of surface albedo. The SEBAL model estimates $G$ as the function of surface albedo, vegetation index, and surface temperature, which depends on the empirical equation developed by Bastiaanssen [8]. This equation was originally developed for Mediterranean regions; thus, different climatic conditions may have different results.

For the sensible heat flux, it requires an internal calibration method. The challenge is how to select hot and cold pixels appropriately. To solve this challenge, Montibeller et al. [58] created a water body for the cold pixel selection by placing an evaporative pan. The evaporative pan, however, differs from a natural water body, which affects the calculation of net radiation $R_n$ and soil heat flux $G$. Therefore, the anchor pixels are usually selected from the coldest pixels in the UAV images. The $R^2$ for the sensible heat flux $H$ is 0.5, with the RMSE of 8.84 W m$^{-2}$. The estimated value by SEBAL overestimated the sensible heat flux by 5%. The sensible heat flux within the field was around 91.84 W m$^{-2}$ during the growing season.

The $R^2$ of the latent heat flux $LE$ is 0.82, with an RMSE of 2.67 W m$^{-2}$. The research result shows that the $LE$ varies as the crop grows. The ET rate is also relevant to the crop growth stage. Corn, for example, has higher ET rates up until the tassel appears. The maximum mean for $LE$ is 564.90 W m$^{-2}$, and the minimum mean is 256.22 W m$^{-2}$.

The relationship between NDVI and ET was also evaluated by the authors while using SEBAL. It assumes that there is a linear relationship between NDVI and ET. However, the correlation between the NDVI and ET is very poor; the $R^2$ is around 0.01. One of the reasons is that soil wetting may affect NDVI prediction [3]. Further study needs to be explored.

Remark Overall, the research proves that the SEBAL model can be used for estimating ET with UAVs. The MAE and RMSE values show that SEBAL can estimate ET with the UAV images very well. UAV platform also has great potential to help farmers in making decisions with real-time crop conditions in the near future, which can monitor the water consumption of each crop in the field. The SEBAL
algorithms being used by Montibeller [58] were automated by reprogramming the model with Python, which improved the data processing for ET estimation.

### 3.3.7 METRIC and METRIC-HR Models

METRIC is discussed here because of its potential in UAV applications. For satellite images, monthly images can be effective for estimating seasonal ET [4] by the METRIC model. However, during times of rapid vegetative growth, multiple dates of satellite images may be needed, which are usually not available because of limitations on the satellite revisit cycles. UAVs have a more flexible flight schedule. Since METRIC is designed to use satellite images as inputs, several adjustments are usually needed for the high-resolution UAVs’ input data [58].

In [25], a modified METRIC model called METRIC high resolution (METRIC-HR) was proposed to use the UAVs’ high-resolution images. There are several differences between the METRIC and METRIC-HR. First, the digital elevation model (DEM) has a higher image resolution in METRIC-HR. Manal replaced the original DEM with a 15 cm resolution DEM, which was generated by using the PhotoScan (Agisoft, St. Petersburg, Russia). Second, the National Land Cover Database (NLCD) is also replaced by a 15 cm NLCD in METRIC-HR, which can be used to develop NLCD high-resolution maps. Third, METRIC uses shortwave infrared (SWIR) bands generated by Landsat 8. SWIR is usually used for calculating the normalized difference water index. SWIR value is usually less than zero for water, which can help identify water more accurately than NDVI. In METRIC-HR, SWIR was neglected because there was no water in the study site. The thermal band (TIR) resampling of METRIC-HR is also different from the METRIC model. The thermal band resolution being used in METRIC-HR is acquired by AggieAir, which has a 60 cm resolution. Since METRIC requires all bands to have identical resolutions, TIR resampling is necessary. Nearest neighbor resampling was performed in ArcGIS software, which did not change the original pixel values [24, 48]. The shortwave radiance images (BGR) also have higher reflectance than Landsat 8 images. Therefore, upscaling BGR with Landsat 8 PSF and developing correction equations are necessary for the METRIC-HR model.

As mentioned earlier in the METRIC model section, selecting hot and cold pixels as anchor pixels can be subjective and requires experience. Different hot and cold pixels can lead to significant deviations in the final ET estimation [87]. METRIC recommends selecting cold pixels in a homogenous, well-watered place where the range of NDVI is from 0.76 to 0.84. The surface albedo range is from 0.18 to 0.24. Hot pixels are selected in a homogeneous bare, dry soil location with NDVI less than 0.2. The surface albedo for hot pixels is recommended to be from 0.17 to 0.23. More information about anchor pixel selection can be found in [4, 5]. After METRIC and METRIC-HR models were run, the final output was the instantaneous $ET_r F$ (fraction of the alfalfa-based reference ET). For the METRIC-HR results, the $ET_r F$ values ranged from 0 to 1.15. Lower values represented hotter areas, such
as bare soil. Higher values meant wet areas. Compared with METRIC, METRIC-HR had a higher $ETr_F$ estimated; this could be caused by the presence of pixels of multiple vegetation growth with significant differences in some covers. The maximum difference was around 20%.

**Remark** The results showed the values estimated between METRIC and METRIC-HR had a 0.9 coefficient of correlation. This proves that METRIC-HR has a similar performance with METRIC. Higher-resolution images in the METRIC-HR model has a better performance in mixed areas. This work demonstrates that UAVs equipped with lightweight cameras can estimate ET quantitatively. However, cameras need further calibration to relate spectral response to METRIC-HR models.

### 3.4 Chapter Summary

In this chapter, the authors reviewed the most commonly used ET estimation methods with small UAVs. One-source energy balance (OSEB), High-Resolution Mapping of Evapotranspiration (HRMET), machine learning (ML), artificial neural networks (ANN), two-source energy balance (TSEB), Dual Temperature Difference (DTD), Surface Energy Balance Algorithm for Land (SEBAL), and Mapping Evapotranspiration at high Resolution with Internalized Calibration (METRIC) are introduced in this chapter. The discussed ET estimation methods with UAVs and their advantages and disadvantages are also summarized in this chapter.

In the next chapter, the authors will propose a new framework for estimating the actual ET in a pomegranate experimental field.

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Chapter 4
Estimating ET Using Stochastic Configuration Network and UAV-Based Crop Coefficients

4.1 Introduction

Estimating evapotranspiration (ET) by crop coefficient (Kc) is one of the most commonly used methods for water irrigation management. The crop evapotranspiration (ETc) is determined by the Kc approach whereby the effect of the various weather conditions is incorporated into reference ET (ETo) and the crop characteristics into the Kc [1]:

\[ ETc = Kc \times ETo \]  \hspace{1cm} (4.1)

The Kc curve is the crop coefficient distribution during a growing season. At the beginning of the growing season, the value of Kc increases from a minimum value. When the canopy cover is full, the Kc reaches a maximum around the mid-season. Then, the Kc starts decreasing before the end of the growing season.

The normalized difference vegetation index (NDVI) has been commonly used for vegetation monitoring, such as water stress detection [31, 33], crop yield assessment [34], and ET estimation [15, 17]. The NDVI is calculated by

\[ NDVI = \frac{\rho_{NIR} - \rho_{R}}{\rho_{NIR} + \rho_{R}} \]  \hspace{1cm} (4.2)

where \( \rho_{NIR} \) and \( \rho_{R} \) are the reflectance of near-infrared and red wavebands, respectively. NDVI is a standardized method to measure healthy vegetation. When the NDVI is high, it indicates the vegetation has a higher level of photosynthesis.

Many studies have used satellite-derived NDVI to estimate crop coefficient values [6, 7, 20]. For example, Trout et al. [23] and Zhang et al. [30] applied a remote sensing method using NDVI to estimate canopy ground cover as a basis for generating Kc. Kamble et al. [7] used a simple linear regression model to establish a relationship between NDVI and Kc. Satellite imagery can provide spatially dis-
tributed measurements, though they cannot acquire useful spatiotemporal resolution images for precision agriculture applications [4]. The timing of satellite overpass is not always synchronous with research requirements, either.

As a new remote sensing platform, the unmanned aerial vehicles (UAVs) have been commonly used in agricultural applications, such as crop yield estimation [34], irrigation management [16, 35], water stress estimation [32], and pest management [13, 14]. Compared with the satellite, the flight of UAVs can be more flexible and frequent in the field. The UAVs fly at a lower altitude and take higher-resolution imagery of crops [36]. The UAVs also make data acquisition relatively less expensive.

The objective of this chapter was to investigate the approaches of estimating $K_c$ using UAV-based NDVI for an experimental pomegranate orchard. The pomegranate is widely grown all over the world, which has drought resistance and high economic value. There are approximately 11,000 ha of pomegranate in the semi-arid and arid areas of California [30]. The spatial and temporal variability of $K_c$ and NDVI are analyzed by using the Deep Stochastic Configuration Networks (DeepSCNs). A regression model is established between the NDVI and $K_c$. The performance of the new regression model was evaluated by the data collected by the UAVs.

### 4.2 Material and Methods

#### 4.2.1 Pomegranate Study Area

As shown in Fig. 4.1, this study was conducted in an experimental pomegranate orchard at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Parlier, California, 93648, USA. The pomegranate was planted in 2010 with a 5 m spacing between rows and 2.75 m within-row tree spacing in a 1.3 ha field. There were two large weighing lysimeters [30], which were 2 m × 4 m by 3 m deep. The lysimeters had a resolution of 0.1 mm of water loss, which were located in the center of the field, marked in red boxes in Fig. 4.1.

#### 4.2.2 The UAV Platform and Multispectral Camera

In this study, the authors used a quadcopter, called “Hover,” as the unmanned aerial vehicle (UAV) platform. The “Hover” was controlled by a Pixhawk flight controller, which can fly over the pomegranate field by waypoints mode (designed by using Mission Planner software) for 30 minutes. Multispectral imagery was collected by the RedEdge-M camera (MicaSense, Seattle, WA, USA). The RedEdge-M has five bands, which are blue, green, red, near infrared, and red edge. It has a spectral
4.2 Material and Methods

Fig. 4.1 Pomegranate test site. The pomegranate was planted in 2010 with a 5 m spacing between rows and 2.75 m within-row tree spacing in a 1.3 ha field. There were two large weighing lysimeters, which were 2 m × 4 m by 3 m deep. The lysimeters had a resolution of 0.1 mm of water loss, which were located in the center of the field, marked in red boxes.

resolution of 1280 × 960 pixel, with a 46° field of view. With a Downwelling Light Sensor (DLS), which is a five-band light sensor that connects to the camera, the RedEdge-M can measure the ambient light during a flight mission for each of the five bands. Then, it can record the light information in the metadata of the images captured by the camera. After the camera calibration, the information detected by the DLS can be used to correct lighting changes during a flight, such as changes in cloud cover during a UAV flight.

4.2.3 UAV Image Collection and Preprocessing

Flight missions were programmed by using the Mission Planner. The flight height was set up as 60 m. The overlapping of UAV images was set up as 80%, so that the UAV imagery of the pomegranate could be stitched together during image processing. The image of a calibrated reflectance panel (CRP) was taken before and after the flight missions, servicing as the reflectance reference.

The authors flew the UAV biweekly over the pomegranate field at noon during the growing season in 2019. The successful data collections were shown in Table 4.1. After the flight missions, all of the aerial images were stitched together to generate the orthomosaic images in PhotoScan (Agisoft LLC, Russian).
Table 4.1 The UAV flight schedule. The flight height was set up as 60 m. The overlapping of UAV images was set up as 80%, so that the UAV imagery of the pomegranate could be stitched together during image processing. The authors flew the UAV biweekly over the pomegranate field at noon during the growing season in 2019.

| Dates             | Flight time | Flight height |
|-------------------|-------------|---------------|
| May 8, 2019       | 12–1 pm     | 60 m          |
| June 5, 2019      | 12–1 pm     | 60 m          |
| July 25, 2019     | 12–1 pm     | 60 m          |
| August 7, 2019    | 12–1 pm     | 60 m          |
| August 29, 2019   | 12–1 pm     | 60 m          |
| September 19, 2019| 12–1 pm     | 60 m          |
| October 3, 2019   | 12–1 pm     | 60 m          |
| October 29, 2019  | 12–1 pm     | 60 m          |

4.2.4 Deep Stochastic Configuration Networks (DeepSCNs)

Deep Stochastic Configuration Networks (DeepSCNs) were first proposed by Wang et al. in 2017 [25]. Compared with the known randomized learning algorithms for single hidden layer feed-forward neural networks, the DeepSCNs randomly assign the input weights and biases of the hidden nodes in the light of a supervisory mechanism. The output weights are analytically evaluated in a constructive or selective method. DeepSCNs have better performance than other randomized neural networks in terms of the fast learning, scope of the random parameters, and the required human intervention. Therefore, it has already been used in many data processing projects, such as [5, 9].

The most commonly used simple linear regression could only plot the best fit line which shows that the model was not a good fit for the data because the data had a nonlinear pattern. Therefore, in this study, the DeepSCNs were used to derive a better regression model than the simple linear regression model.

4.3 Results and Discussion

4.3.1 Seasonal $K_c$ and NDVI

The values of $K_c$ and NDVI were shown in Fig. 4.2. The values of $K_c$ were derived using Eq. (4.1). The $ET_c$ was recorded by the weighing lysimeter in the center of the pomegranate field. The $ET_o$ was calculated by the California Irrigation Management Information System (CIMIS) near the pomegranate field. The NDVI was derived by image processing tools in MATLAB.

A strong correlation was shown between the $K_c$ and NDVI during the growing season in 2019. The maximum values of $K_c$ and NDVI were 1.0069 and 0.8429 in...
4.3 Results and Discussion

Fig. 4.2 Seasonal $K_c$ and NDVI at the pomegranate field in 2019. The values of $K_c$ were derived using Eq. (4.1). The $ET_c$ was recorded by the weighing lysimeter in the center of the pomegranate field. The $ETo$ was calculated by the CIMIS near the pomegranate field. The NDVI was derived by image processing tools in MATLAB.

July 25 (DOY 206), respectively. The high values of $K_c$ and NDVI showed that the trees in the lysimeter were in a well-irrigated condition. The $K_c$ increased fast at the beginning of the growing season. After the peak of the mid-season, $K_c$ started decreasing. Both $K_c$ and NDVI had very low values in October 29 (DOY 302). The reason was that most leaves fell off the pomegranate trees after the harvest. Therefore, the data of DOY 302 was not used for the data analysis.

4.3.2 Regression Models for $K_c$ and NDVI

As shown in Fig. 4.3, there was a strong correlation between the $K_c$ and NDVI. A simple linear regression model was built using the NDVI values derived from the UAV imagery and the $K_c$ from field measurement,

$$K_c(NDVI) = 4.6666NDVI - 2.9277,$$

where $4.6666$ and $-2.9277$ were the slope and intercept coefficients, respectively. The correlation coefficient ($R^2$) was 0.975. The root mean square error (RMSE) was 0.05.

With the development of machine learning technology, many neural networks have been applied for agricultural applications [37, 38]. Since the dataset of $K_c$ and NDVI was not large, in this study, DeepSCNs were used for building the regression model between $K_c$ and NDVI. Four out of 7 days of data were used for training...
Fig. 4.3 Linear regression model for $K_c$ and NDVI. A strong correlation was shown between the $K_c$ and NDVI during the growing season in 2019.

Fig. 4.4 DeepSCNs training model. Since the dataset of $K_c$ and NDVI was not large, in this study, DeepSCNs was used for building the regression model between $K_c$ and NDVI. Four out of seven days of data were used for training the DeepSCNs regression model. All the data points were fitted very well in the trained model, as shown in Fig. 4.4. The weights and bias were shown in Table 4.2. The parameter L meant that there were four hidden nodes of the trained DeepSCNs model. For the other parameters in the DeepSCNs model, please refer to [25].
4.3 Results and Discussion

Table 4.2 DeepSCNs with properties. For example, the maximum times of random configuration $T_{max}$ were set as 100. The scale factor Lambdas in the activation function, which directly determined the range for the random parameters, was examined by performing different settings (0.5–200). The tolerance was set as 0.001.

| Properties   | Values                                      |
|--------------|---------------------------------------------|
| Name:        | “Stochastic Configuration Networks”         |
| Version:     | “1.0 beta”                                  |
| L:           | 4                                           |
| W:           | $[-0.4924 \ldots -0.4987 -4.3543 \ldots 9.2007]$ |
| b:           | $[-0.4650 \ldots -0.4197 -4.7048 \ldots -9.2846]$ |
| Beta:        | $[4 \times 1 \text{ double}]$               |
| r:           | $[0.9000 0.9900 0.9990 0.9999 1.0000 1.0000]$ |
| tol:         | $1.0000e-03$                                |
| Lambdas:     | $[0.5000 1 5 10 30 50 100 150 200 250]$      |
| $L_{max}$:   | 250                                         |
| $T_{max}$:   | 100                                         |
| nB:          | 1                                           |
| verbose:     | 50                                          |
| COST:        | $5.5250e-13$                                |

Fig. 4.5 The SCNs model evaluation performance. Three days of data were used to evaluate the trained model. The value of $R^2$ was 0.995. The value of RMSE was 0.046. Both of them showed good performance for estimating $K_c$ by using NDVI. The variations of $K_c$ were well explained by using the NDVI from UAV images.

Three days of data were used to evaluate the trained model, as shown in Fig. 4.5. The value of $R^2$ was 0.995. The value of RMSE was 0.046. Both showed good performance for estimating $K_c$ by using NDVI. The variations of $K_c$ were well explained by using the NDVI from UAV images. The trained model was used to generate the $K_c$. For example, the spatial mapping of NDVI and $K_c$ in September 19 were shown in Fig. 4.6. The spatial mapping of ET in September 19 was shown in Fig. 4.7.
Fig. 4.6 NDVI (top) and $K_c$ (bottom) maps of the pomegranate using UAVs (September 19, 2019)

Fig. 4.7 Spatial and tree-by-tree view of ET distribution
4.4 Conclusions

In this study, UAV flight missions were conducted to collect remote sensing multispectral images in a pomegranate orchard at USDA. Using the NDVI derived from the multispectral imagery, the authors could apply DeepSCNs for a regression model between NDVI and $K_c$. The parameters of the DeepSCNs model was shown in Table 4.2. The $K_c$ represents the actual growth conditions in the field. Therefore, $K_c$ can be used for estimating the $ET$ temporally and spatially in the pomegranate field.

The simple linear regression model was $K_c(NDVI) = 4.6666NDVI - 2.9277$. Compared with the simple linear regression model, the DeepSCNs model could better fit the data points in the training dataset. The simple linear regression model had $R^2$ and RMSE of 0.975 and 0.05, respectively. The DeepSCNs regression model had $R^2$ and RMSE of 0.995 and 0.046. The DeepSCNs showed a better performance than the linear regression model.

Although only the data of 2019 was used for analysis, the study had provided evidence that variations of NDVI from UAV imagery could be used to explain the variations of $K_c$. In the future, the data of 2017 and 2018 will be added to train a more robust DeepSCNs model.

To help readers better understand the benefits using the SCN, a case study was given by the authors in the following section.

4.5 Case Study: Optimal Randomness for SCN with Heavy-Tailed Distributions

4.5.1 Introduction

The Stochastic Configuration Network (SCN) model is generated incrementally by using stochastic configuration (SC) algorithms [25]. Compared with the existing randomized learning algorithms for single-layer feed-forward neural networks (SLFNNs), the SCN can randomly assign the input weights ($w$) and biases ($b$) of the hidden nodes in a supervisory mechanism, which is selecting the random parameters with an inequality constraint and assigning the scope of the random parameters adaptively. It can ensure that the built randomized learner models have universal approximation property. Then, the output weights are analytically evaluated in either a constructive or selective manner [25]. In contrast with the known randomized learning algorithms, such as the Randomized Radial Basis Function (RBF) Networks [2] and the Random Vector Functional Link (RVFL) [18], SCN can provide good generalization performance at a faster speed. Concretely, there are three types of SCN algorithms, which are SC-I, SC-II, and SC-III. SC-I algorithm uses a constructive scheme to evaluate the output weights only for the newly added hidden node [26]. All of the previously obtained output weights are
kept the same. The SC-II algorithm recalculates part of the current output weights by analyzing a local least squares problem with user-defined shifting window size. The SC-III algorithm finds all the output weights together by solving a global least squares problem.

SCN algorithms have been commonly studied and used in many areas, such as image data analytics [9, 17], prediction of component concentrations in sodium aluminate liquor [27], etc. [5, 11]. For example, in [9], Li et al. developed two-dimensional SCNs (2DSCNs) for image data modeling tasks. Experimental results on handwritten digit classification and face recognition showed that the 2DSCNs have great potential for image data analytics. In [27], Wang et al. proposed a SCN-based model for measuring component concentrations in sodium aluminate liquor, which were usually acquired by titration analysis and suffered from larger time delays. From the results, the mechanism model showed the internal relationship. The improved performance can be achieved by using the SCN-based compensation model. In [10], Lu et al. proposed a novel robust SCN model based on a mixture of the Gaussian and Laplace distributions (MoGL-SCN) in the Bayesian framework. To improve the robustness of the SCN model, the random noise of the SCN model is assumed to follow a mixture of Gaussian distribution and Laplace distributions. Based on the research results, the proposed MoGL-SCN could construct prediction intervals with higher reliability and prediction accuracy.

Neural networks (NNs) can learn from data to train feature-based predictive models. However, the learning process can be time-consuming and infeasible for applications with data streams. An optimal method is to randomly assign the weights of the NNs so that the task can become a linear least squares problem. In [22], Wang et al. classified the NN models into three types: first, the feed-forward networks with random weights (RW-FNN) [19], second, recurrent NNs with random weights [12], and, third, randomized kernel approximations [8]. According to [22], there are three benefits of the randomness: (1) simplicity of implementation, (2) faster learning and less human intervention, and (3) possibility of leveraging linear regression and classification algorithms. Randomness is used to define a feature map, which converts the data input into a high-dimensional space where learning is simpler. The resulting optimization problem becomes a standard linear least squares, which is a simpler and scalable learning procedure.

For the original SCN algorithms, weights and biases are randomly generated in uniform distribution. Randomness plays a significant role in both exploration and exploitation. A good NNs architecture with randomly assigned weights can easily outperform a more deficient architecture with finely tuned weights [22]. Therefore, it is critical to discuss the optimal randomness for the weights and biases in SCN algorithms. In this study, the authors mainly discussed the impact of three different heavy-tailed distributions on the performance of the SCN algorithms, Lévy distribution, Cauchy distribution, and Weibull distribution [21]. Heavy-tailed distribution has shown optimal randomness for finding targets [28], which plays a significant role in exploration and exploitation [29]. It is important to point out that the proposed SCN models are very different from Lu et al. [10]. As mentioned earlier, Lu et al. assumed that the random noise of the SCN model
4.5 Case Study: Optimal Randomness for SCN with Heavy-Tailed Distributions

followed a mixture of Gaussian distribution and Laplace distributions. In this research study, the authors randomly initialized the weights and biases with heavy-tailed distributions instead of uniform distribution. To compare with the mixture distributions, the authors also used the mixture distributions for weight and bias generation. A more detailed comparison of the two heavy-tailed methods is shown in the following Results and Discussion section.

There are two objectives for this research: to (1) compare the performance of SCN algorithms with heavy-tailed distributions on a linear regression model \[24\] and (2) evaluate the SCN algorithms performance on MNIST handwritten digit classification problem with heavy-tailed distributions.

### 4.5.2 SCN with Heavy-Tailed PDFs

For the original SCN algorithms, weights and biases are randomly generated using a uniform PDF. Randomness plays a significant role in both exploration and exploitation. A good neural network architecture with randomly assigned weights can easily outperform a more deficient architecture with finely tuned weights \[22\]. Therefore, it is critical to discuss the optimal randomness for the weights and biases in SCN algorithms. Heavy-tailed PDFs have shown optimal randomness for finding targets \[3, 28\], which plays a significant role in exploration and exploitation \[29\]. Therefore, herein, heavy-tailed PDFs were used to randomly update the weights and biases in the hidden layers to determine if the SCN models display improved performance. Some of the key parameters of the SCN models are listed in Table 4.3. For example, the maximum times of random configuration \(T_{\text{max}}\) were set as 200. The scale factor \(\text{Lambdas}\) in the activation function, which directly determined the range for the random parameters, was examined by using different settings (0.5–200). The tolerance was set as 0.05. Most of the parameters for the SCN

| Properties               | Values                                      |
|--------------------------|---------------------------------------------|
| Name:                    | “Stochastic Configuration Networks”         |
| Version:                 | “1.0 beta”                                  |
| L:                       | Hidden node number                          |
| W:                       | Input weight matrix                         |
| b:                       | Hidden layer bias vector                    |
| Beta:                    | Output weight vector                        |
| r:                       | Regularization parameter                    |
| tol:                     | Tolerance                                   |
| Lambdas:                 | Random weights range                        |
| \(L_{\text{max}}\):     | Maximum number of hidden neurons            |
| \(T_{\text{max}}\):     | Maximum times of random configurations      |
| nB:                      | Number of node being added in one loop      |
with heavy-tailed PDFs were kept the same with the original SCN algorithms for comparison purposes. For more details, please refer to [25].

4.5.3 A Regression Model and Parameter Tuning

The dataset of the regression model was generated by a real-valued function [24]:

\[
f(x) = 0.2e^{-(10x-4)^2} + 0.5e^{-(80x-40)^2} + 0.3e^{-(80x-20)^2},
\]

where \( x \in [0, 1] \). There were 1000 points randomly generated from the uniform distribution on the unit interval \([0, 1]\) in the training dataset. The test set had 300 points generated from a regularly spaced grid on \([0, 1]\). The input and output attributes were normalized into \([0, 1]\), and all the results reported in this research represented averages over 1000 independent trials. The settings of the parameters were similar to the SCN in [25].

Heavy-tailed PDF algorithms have user-defined parameters, for example, the power-law index for SCN-Lévy, and location and scale parameters for SCN-Cauchy and SCN-Weibull, respectively. Thus, to illustrate the effect of parameters on the optimization results and to offer reference values for the proposed SCN algorithms, parameter analysis was conducted, and corresponding experiments were performed. Based on the experimental results, for the SCN-Lévy algorithm, the most optimal power-law index is 1.1 for achieving the minimum number of hidden nodes. For the SCN-Weibull algorithm, the optimal location parameter \( \alpha \) and scale parameter \( \beta \) for the minimum number of hidden nodes are 1.9 and 0.2, respectively. For the SCN-Cauchy algorithm, the optimal location parameter \( \alpha \) and scale parameter \( \beta \) for the minimum number of hidden nodes are 0.9 and 0.1, respectively.

4.5.3.1 Performance Comparison Among SCNs with Heavy-Tailed PDFs

In Table 4.4, the performance of SCN, SCN-Lévy, SCN-Cauchy, SCN-Weibull, and SCN-Mixture are shown, in which mean values are reported based on 1000 independent trials. Wang et al. used time cost to evaluate the SCN algorithms’ performance [25]. In the present study, the authors used the mean hidden node

| Models         | Mean hidden node number | RMSE   |
|----------------|-------------------------|--------|
| SCN            | 75 ± 5                  | 0.0025 |
| SCN-Lévy       | 70 ± 6                  | 0.0010 |
| SCN-Cauchy     | 59 ± 3                  | 0.0057 |
| SCN-Weibull    | 63 ± 4                  | 0.0037 |
| SCN-Mixture    | 70 ± 5                  | 0.0020 |
numbers to evaluate the performance. The number of hidden nodes was associated with modeling accuracy. Therefore, the analysis determined if an SCN with heavy-tailed PDFs used fewer hidden nodes to generate high performance, which would make the NNs less complex. According to the numerical results, the SCN-Cauchy used the lowest number of mean hidden nodes, 59, with a root mean square error (RMSE) of 0.0057. The SCN-Weibull had a mean number of 63 hidden nodes, with an RMSE of 0.0037. The SCN-Mixture had a mean number of 70 hidden nodes, with an RMSE of 0.0020. The mean number of hidden nodes for SCN-Lévy was also 70. The original SCN model had a mean number of 75 hidden nodes. A more detailed training process is shown in Fig. 4.8. With fewer hidden node numbers, the SCN models with heavy-tailed PDFs can be faster than the original SCN model. The neural network structure is also less complicated than the SCN. Our numerical results for the regression task demonstrate remarkable improvements in modeling performance compared with the current SCN model results.

4.5.4 MNIST Handwritten Digit Classification

The handwritten digit dataset contains 4000 training examples and 1000 testing examples, a subset of the MNIST handwritten digit dataset. Each image is a 20 × 20 pixel grayscale image of the digit (Fig. 4.9). Each pixel is represented by a number indicating the grayscale intensity at that location. The 20 × 20 grid of pixels
is “unrolled” into a 400-dimensional vector. Similar to the parameter tuning for the regression model, parameter analysis was conducted to illustrate the impact of parameters on the optimization results and to offer reference values for the MNIST handwritten digit classification SCN algorithms. Corresponding experiments were performed. According to the experimental results, for the SCN-Lévy algorithm, the most optimal power law index is 1.6 for achieving the best RMSE performance. For the SCN-Cauchy algorithm, the optimal location parameter $\alpha$ and scale parameter $\beta$ for the lowest RMSE are 0.2 and 0.3, respectively.

### 4.5.4.1 Performance Comparison Among SCNs on MNIST

The performance of the SCN, SCN-Lévy, SCN-Cauchy, and SCN-Mixture is shown in Table 4.5. Based on the experimental results, the SCN-Cauchy, SCN-Lévy, and SCN-Mixture have better performance in training and test accuracy, compared with the original SCN model. A detailed training process is shown in Fig. 4.10. Within around 100 hidden nodes, the SCN models with heavy-tailed PDFs perform similarly to the original SCN model. When the number of the hidden nodes is greater than 100, the SCN models with heavy-tailed PDFs have lower RMSEs. Since more parameters for weights and biases are initialized in heavy-tailed PDFs, this may cause an SCN with heavy-tailed PDFs to converge to the optimal values at a faster speed. The experimental results for the MNIST handwritten classification
problem demonstrate improvements in modeling performance. They also show that SCN models with heavy-tailed PDFs have a better search ability for achieving lower RMSEs.

4.6 Chapter Summary

Crop coefficient ($K_c$) methods have been commonly used for evapotranspiration estimation. Researchers estimate $K_c$ as a function of the vegetation index because of similarities between the $K_c$ curve and the vegetation index curve. A linear regression model is usually developed between the $K_c$ and the normalized difference vegetation index (NDVI) derived from satellite imagery. However, the spatial resolution of satellite imagery is in the range of meters or greater, which is often not enough for crops with clumped canopy structures, such as trees, and vines. In this chapter, the unmanned aerial vehicles (UAVs) were used to collect high-resolution images in an experimental pomegranate orchard located at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center, Parlier, CA. The NDVI values were derived from UAV images. The $K_c$ values were measured from a weighing lysimeter in the pomegranate field. The relationship between the NDVI and $K_c$ was established by using both a linear regression model and a Deep Stochastic Configuration Networks (DeepSCNs) model. Results show that the linear regression model has an $R^2$ and RMSE value of 0.975 and 0.05, respectively. The DeepSCNs regression model has an $R^2$ and RMSE value of 0.995 and 0.046, respectively. The DeepSCNs model
showed improved performance than the linear regression model in predicting $K_C$ from NDVI.

In the next chapter, the authors will propose a reliable tree-level ET estimation method with small UAVs.

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Chapter 5
Reliable Tree-Level ET Estimation Using Lysimeter and UAV Multispectral Imagery

5.1 Introduction

Because of the recurring water shortages in California, many growers started growing crops that have drought resistance and high economic value to a certain degree [20], such as pomegranate. There is around 11,000 ha of pomegranate in California [19]. Evidence suggests that evapotranspiration (ET) estimation is among the most important factors to manage limited water effectively in agriculture [1]. Mapping the ET temporally and spatially can identify variations in the field, which is useful for evaluating soil moisture [16, 18] and assessing crop water status [5].

Using crop coefficient ($K_c$) to estimate ET is a common method for water irrigation management. The actual crop evapotranspiration ($ET_c$) is determined by the $K_c$ approach whereby the effect of the various weather conditions is incorporated into reference ET ($ETo$) and the crop characteristics into the $K_c$ [1]. At the beginning of the growing season, $K_c$ increases from a minimum value. When the canopy cover is full, the $K_c$ reaches a maximum around the mid-season. Then, the $K_c$ starts decreasing before the end of the growing season. The normalized difference vegetation index (NDVI) has been commonly used for vegetation monitoring, such as water stress detection [21, 23], crop yield assessment [24], and ET estimation [8–12]. The value of NDVI is a standardized method to measure healthy vegetation. When the NDVI is high, it indicates the vegetation has a higher level of photosynthesis. Many studies have used satellite-derived NDVI to estimate crop coefficient values [3, 4, 14]. For example, Trout et al. [15] and Zhang et al. [19] applied a remote sensing method using NDVI to estimate canopy ground cover as a basis for generating $K_c$. Kamble et al. [4] used a simple linear regression model to establish a relationship between NDVI and $K_c$. Although satellite imagery can provide spatially distributed measurements, it cannot acquire useful spatiotemporal resolution images for precision agriculture applications [2]. The timing of satellite overpass is not always synchronous with
research requirements, either. To date, few studies have investigated the association between the $K_c$ and NDVI at the individual tree level.

Recently, unmanned aerial vehicles (UAVs) have been emerging as powerful platforms in agricultural applications, such as crop yield estimation [24], irrigation management [9, 25], water stress estimation [22], and pest management [6, 7]. With lightweight sensors being mounted on UAVs, high-resolution imagery has been taken in massive amounts [26]. The spatial resolution of the UAV imagery can be at the centimeter level and help identify, standardize, and validate methods to calculate the spatial variability for clumped canopy structures, such as trees and vines.

The objectives of this chapter are (1) to investigate and validate the approaches of estimating $K_c$ using UAV-based NDVI for an experimental pomegranate orchard, (2) to establish a linear regression model between the NDVI and $K_c$ in the individual tree level, and (3) to evaluate the performance of the new regression model on estimating 100% ET irrigation sampling trees. The major contributions of this chapter are as follows: (1) developed a reliable tree-level ET estimation method using UAV high-resolution multispectral images and (2) provided a framework to establish a linear regression model between the NDVI and $K_c$ to estimate the actual daily ET. Results showed that the linear regression model could estimate tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively, which showed a state-of-the-art performance.

5.2 Material and Methods

5.2.1 Study Site Description

Field studies were conducted in an experimental pomegranate ($Punica granatum L.$, cv. ‘Wonderful’) field (Fig. 5.1) at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Parlier, California, 93648, USA. The San Joaquin Valley has a Mediterranean climate with hot and dry summers. Rainfall is insignificant, and irrigation is the only source of water for pomegranate growth [17]. There are two large weighing lysimeters installed at the center of the experimental field [13]. According to [20], the lysimeters have a resolution of approximately 0.1 mm of water loss. The soil types are a Hanford fine sandy loam (coarse-loamy, mixed, thermic Typic Xerorthents). The meteorological data was generated by CIMIS (California Irrigation Management Information System) weather station 39, which is about 700 m far from the experimental field.

The pomegranate field was randomly designed into 16 equal blocks, with 4 replications, to test 4 irrigation levels. The irrigation volumes are 35%, 50%, 75%, and 100% of $ET_c$, which were measured by the weighing lysimeter in the field. There were 5 sampling trees in each block, 80 sampling trees in total, marked with red labels in Fig. 5.1.
Fig. 5.1 The pomegranate study site. Field studies were conducted in an experimental pomegranate (*Punica granatum* L., cv. ‘Wonderful’) field at the USDA-ARS, San Joaquin Valley Agricultural Sciences Center (36.594°N, 119.512°W), Parlier, California, 93648, USA. The pomegranate field was randomly designed into 16 equal blocks, with 4 replications, to test 4 irrigation levels. The irrigation volumes are 35%, 50%, 75%, and 100% of $ET_c$, which were measured by the weighing lysimeter in the field. There were 5 sampling trees in each block, 80 sampling trees in total, marked with red labels

5.2.2 UAV Image Collection and Processing

A UAV platform, called the Hover, was deployed for imagery data acquisition. The RedEdge-M (MicaSense, Seattle, WA, USA) was used for collecting multispectral images. The RedEdge-M has five different bands, which are blue (B, 475 nm), green (G, 560 nm), red (R, 668 nm), red edge (RE, 717 nm), and near infrared (NIR, 840 nm). With a Downwelling Light Sensor (DLS), a five-band light sensor that connects to the camera, the RedEdge-M can measure the ambient light during a flight mission for each of the five bands. Then, it can record the light information in the metadata of the images captured by the camera. After the camera calibration, the information detected by the DLS can be used to correct lighting changes during a flight, such as changes in cloud cover during a UAV flight.

The UAV flight missions were configured by using the Mission Planner (ArduPilot, USA). The flight altitude was set up as 60 m. The overlapping of UAV images was set up as 80% forward and 70% by the side. Then, the UAV imagery of the pomegranate can be stitched together during image processing with high confidence. The image of a calibrated reflectance panel (CRP) was taken before and after the flight missions, servicing as the reflectance reference. The authors flew the UAV biweekly over the pomegranate field at noon during the growing season in 2019. The successful data collections were shown in Table 5.1. After the flight missions, all aerial images were stitched together to generate the orthomosaick images in PhotoScan (Agisoft LLC, Russian).
Table 5.1 Flight missions at the USDA in 2019. The UAV flight missions were configured by using the Mission Planner (ArduPilot, USA). The flight altitude was set up as 60 m. The overlapping of UAV images was set up as 80% forward and 70% by the side.

| Dates              | Flight time | Flight altitude |
|--------------------|-------------|-----------------|
| May 8, 2019        | 12–1 pm     | 60 m            |
| July 25, 2019      | 12–1 pm     | 60 m            |
| August 7, 2019     | 12–1 pm     | 60 m            |
| August 29, 2019    | 12–1 pm     | 60 m            |
| September 19, 2019 | 12–1 pm     | 60 m            |
| October 3, 2019    | 12–1 pm     | 60 m            |
| October 29, 2019   | 12–1 pm     | 60 m            |

5.3 Results and Discussion

5.3.1 Determination of Individual Tree $K_c$ from NDVI

The correlation between the $K_c$ and NDVI of an individual tree was analyzed. Daily $K_c$ for the individual tree was calculated as [1]:

$$K_c = \frac{ET_c}{ETo}, \quad (5.1)$$

where the actual ET ($ET_c$) was measured by the weighing lysimeter and the reference ET ($ETo$) was obtained from the CIMIS weather station near the field. The mean NDVI values for the lysimeter tree were calculated by $\rho_{NIR}$ and $\rho_R$, where $\rho_{NIR}$ and $\rho_R$ were the reflectance of near-infrared and red wavebands, respectively. NDVI is a standardized method to measure healthy vegetation. When the NDVI is high, it indicates the vegetation has a higher level of photosynthesis (one of our demos is an NDVI mapping for May 8, 2019). According to the demo, most NDVI values of the tree canopies range from 0.468 to 1. It is interesting to point out that the shade of the trees had a mean NDVI value around 0.5:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R}. \quad (5.2)$$

Key Observation Figure 5.2 showed the relationship between the daily $K_c$ and the derived mean NDVI for the tree in the lysimeter with 100% irrigation treatment. The sampling data started in May 8 and ended in October 29. The linear relationship had an intercept of 0.6114 and a slope of 1.6493. It also had a high correlation coefficient of 0.8865, indicating a significant correlation between the $K_c$ and NDVI at the individual tree level during the growing season in 2019.

5.3.2 The Spatial Variability Mapping of $K_c$ and $ET_c$

Key Observation Inspired by the strong linear correlation between the $K_c$ and NDVI for the individual lysimeter tree, the authors calculated the $K_c$ for all the
results and discussion

Fig. 5.2 Seasonal $K_c$ and NDVI for the tree in lysimeter. The sampling data started in May 8 and ended in October 29. The linear relationship had an intercept of 0.6114 and a slope of 1.6493. It also had a high correlation coefficient of 0.8865, indicating a significant correlation between the $K_c$ and NDVI at the individual tree level during the growing season in 2019.

trees in the experimental field using the linear regression model. The mapping of $K_c$ and $ET_c$ was generated, respectively (Fig. 5.3 is one example for $K_c$ and $ET_c$ spatial variability mapping in May 8). The values of $K_c$ were mostly between 0.578 and 1.039 in May 8. For the $ET_c$, it ranged from 3.2 to 6.0 mm/day.

5.3.3 Performance of the Individual Tree-Level ET Estimation

As mentioned earlier, there were 80 sampling trees in the pomegranate field. Twenty of them were irrigated with 100% of $ET_c$, same with the lysimeter tree.

Key Observation To validate the linear regression model on individual tree-level ET estimation, the authors compared the 20 sampling trees with the lysimeter daily $ET_c$ for the UAV flight dates (almost the whole growing season). The trends of the daily $ET_c$ for the 20 sampling trees (100% irrigation) and the lysimeter tree were shown in Fig. 5.4. Each “Series” meant an individual tree in the field. Then, the boxplot of Fig. 5.5 was generated for analysis. Compared with the lysimeter tree, the linear regression model estimated tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively.
5.3.4 Conclusion

In this study, UAV flight missions were conducted to collect high-resolution multispectral imagery in a pomegranate orchard at USDA. Using the NDVI derived from the multispectral imagery, the authors applied a regression model between NDVI and $K_c$ to estimate the individual tree-level ET estimation. The linear regression model was $K_c(NDVI) = 1.6493NDVI - 0.6114$, which had an $R^2$ of
5.3 Results and Discussion

Fig. 5.4 100% ET irrigation sampling trees vs lysimeter tree. To validate the linear regression model on individual tree-level ET estimation, the authors compared the 20 sampling trees with the lysimeter daily ET for the UAV flight dates (almost the whole growing season). The trends of the daily ET for the 20 sampling trees (100% irrigation) and the lysimeter tree were shown. Each “Series” meant an individual tree in the field.

Fig. 5.5 The boxplot of 100% ET sampling trees vs lysimeter tree. Compared with the lysimeter tree, the linear regression model estimated tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively.

0.8865. Then, $ET_c$ for all the 100% ET irrigation trees were generated individually. Experimental results showed that the estimated daily $ET_c$ has an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day for 100% irrigated sampling trees, which showed a state-of-the-art performance.
Only the data of 2019 was used for analysis; the study had provided evidence that variations of NDVI from UAV imagery could be used to explain the variations of $K_c$ and $ET_c$ at the individual tree level. In the future, the data of 2017 and 2018 will be added for analysis.

5.4 Chapter Summary

The accurate estimation and mapping of evapotranspiration (ET) are essential for crop water management. As one of the traditional ET estimation methods, crop coefficient ($K_c$) has been commonly used. Many studies indicated a linear regression relationship between the $K_c$ curve and the vegetation index curve. The linear regression model is usually developed between the $K_c$ and the normalized difference vegetation index (NDVI) derived from satellite imagery. The satellite images can provide temporally and spatially distributed measurements. However, multispectral satellite imagery’s spatial resolution is in the range of meters, which is often not enough for crops with clumped canopy structures, such as trees and vines. Little ET estimation has been studied based on the single-tree level. Thus, the purpose of this chapter was to develop a reliable tree-level ET estimation method using UAV high-resolution multispectral images. Compared with satellite imagery, the spatial resolution of UAV images can be as high as centimeter level. A field study was conducted to investigate pomegranate trees at the USDA-ARS (US Department of Agriculture, Agricultural Research Service) San Joaquin Valley Agricultural Sciences Center in Parlier, California, USA. The NDVI map was derived from UAV imagery. The $K_c$ values were calculated based on the actual ET from a weighing lysimeter and reference ET from the weather station. The authors then established a linear regression model between the NDVI and $K_c$ to estimate the actual daily ET. Results showed that the linear regression model could estimate tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively.

In the next chapter, the authors will develop a reliable tree-level water stress detection method using UAV-based high-resolution thermal images. The concept of CIML will be proposed. The authors will also propose a CNN model and prove its performance on the classification of tree-level water status.

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Chapter 6
Tree-Level Water Status Inference Using UAV Thermal Imagery and Machine Learning

6.1 Introduction

There is around 11,000 ha of pomegranate in California because of its drought resistance and high economic value [34]. Considering the recurring water shortage in California, it is essential to find effective methods to optimize irrigation water use. Research results suggested that the evapotranspiration (ET) estimation is one of the most critical factors to help manage water use efficiency in agriculture [1]. Mapping the ET temporally and spatially can identify variations in the field, which helps evaluate crop water status [15].

The tree canopy temperature from infrared thermometer (IRT) sensors is an effective tool for detecting plant water stress. Research has been conducted on crops and trees to relate the $\Delta T$ to irrigation management. The main reason is that a significant increase in the midday infrared canopy to air temperature difference ($\Delta T$) will indicate stomata closure and water stress conditions [12–14]. For example, Zhang et al. evaluated the performance of using $\Delta T$ to manage postharvest deficit irrigation of nectarine trees [33]. The results demonstrated that the measured $\Delta T$ values above the tree canopy showed consistent differences among irrigation treatment levels. Clawson et al. used canopy temperature variability and average canopy temperature to schedule irrigation in corn (Zea mays L.). They remarked that canopy temperature variability could show the plant water stress and the need to schedule an irrigation event [7]. Furthermore, Wang et al. investigated the infrared canopy temperature of early ripening peach trees under postharvest deficit irrigation and monitored the stem water potential. The strong correlation between stem water potential and $\Delta T$ ($R^2 \approx 0.7$) indicated that canopy temperature could be used for water stress estimation.

However, little research could be found in the literature on using midday $\Delta T$ derived from UAV thermal infrared (TIR) image as a primary input for mapping irrigation treatment levels of a pomegranate field at individual tree levels. This article evaluated the feasibility and performance of using midday $\Delta T$ (UAV-TIR) and...
machine learning algorithms for spatial mapping of irrigation treatments. Recently, UAVs have been emerging as powerful platforms in agricultural applications, such as irrigation management \[23, 36\] and water stress estimation \[35\]. With lightweight sensors being mounted on UAVs, high spatial and temporal resolution imagery has been taken in massive amounts with low cost \[17, 37\]. Because of the lightweight and low power consumption, the thermal camera has been commonly used in agriculture research \[11, 28\]. The spatial resolution of the UAV-based thermal imagery can be at the centimeter level and help identify, standardize, and validate methods to calculate the spatial variability for clumped canopy structures, such as trees and vines \[26\].

Machine learning (ML) models have been widely used in real-world applications, for example, image processing \[38\], natural language processing \[10\], and precision agriculture \[24\]. ML algorithms can simplify a solution and perform better than traditional statistical approaches, which may require more hand-tuning rules. However, training ML models may require a large amount of data, which may not always be available for scientific problems \[27\]. Then, the smaller dataset may cause ML models to lack robustness and cannot guarantee convergence. Therefore, in this article, the authors proposed the concept of complexity-informed machine learning (CIML) and the principle of tail matching (POTM). The original dataset can exhibit a heavy-tailed distribution phenomenon, and tail-index analysis can be used for ML algorithms \[25, 31\]. Specifically, tail information in the training dataset variability and diversity should indicate the data representativeness. In this sense, we can expect a “smaller dataset” rather than “big data” for ML under the same performance requirement. In summary, we pursue “tail matching” between the dataset and the ML algorithms.

Convolutional neural network (CNN) is one of the most common architectures, which includes the input layer, the convolution layer, the pooling layer, and the fully connected layer \[19\]. Because of its powerful ability for complex data analysis, CNN models have been commonly used in agricultural applications, such as yield estimation \[16\], water stress analysis \[5\], and pest management \[20\]. For example, Yang et al. proposed to estimate corn yield by using the hyperspectral imagery and a CNN model in \[32\]. Research results showed that the spectral and color image-based integrated CNN model had a classification accuracy of 75.5%. In \[20\], Li et al. proposed an effective data augmentation strategy for CNN-based method for pest detection. In the training phase, they adopted data augmentation by rotating images with several degrees followed by cropping into different grids. Then, a large number of extra multi-scale examples were obtained and could be used to train a multi-scale pest detection model. Experimental results showed that their data augmentation strategy with CNN model achieved the pest detection accuracy of 81.4%. Advances in CNN models have been leading to significantly promising progress for agricultural research.

The objectives of this chapter were to (1) evaluate the reliability of the UAV thermal camera on individual tree canopy temperature measurements, (2) investigate and validate the approaches of irrigation treatment inference using UAV-based $\Delta T$ at individual tree level, (3) demonstrate the performance of the CIML models on
irrigation treatment inference, and (4) demonstrate the performance of the CNN model on irrigation treatment inference. The major contributions of this chapter were as follows: (1) developed a reliable tree-level water stress detection method using UAV-based high-resolution thermal images, (2) proposed the concept of CIML and proved its performance on the classification of tree-level irrigation treatments, and (3) proposed a CNN model and proved its performance on the classification of tree-level water status. The rest of the chapter is organized as follows: Sect. 6.2 introduces the materials and methods being used for UAV-based irrigation treatment inference. Results and discussion are presented in Sect. 6.3. In Sect. 6.4, the authors draw conclusive remarks.

6.2 Material and Methods

6.2.1 Experimental Site and Irrigation Management

The study was conducted in a 1.3 ha pomegranate field in 2019 at the USDA-ARS San Joaquin Valley Agricultural Sciences Center in Parlier, CA (36.594°N, 119.512°W). The pomegranate (Punica granatum L., cv. ‘Wonderful’) was planted in 2010 with a 5 m spacing between rows and a 2.75 m within-row tree spacing [34]. The soil type was a Hanford fine sandy loam (coarse-loamy, mixed, thermic Typic Xerorthents). There are also two large weighing lysimeters, which are 2 m × 4 m by 3 m in depth and have a resolution of 0.1 mm of water loss. As shown in Fig. 6.1, the weighing lysimeters are located in the center of the pomegranate field. The experimental site was randomly designed into 16 blocks, with 4 replications, to test 4 irrigation rates on the pomegranate growth. As measured by the lysimeter, the irrigation volumes were set up as 35%, 50%, 75%, and 100% of ETc. The trees in the lysimeter were irrigated at the 100% treatment level. For each irrigation treatment

![Fig. 6.1](image.png)

Fig. 6.1 The pomegranate field at the USDA-ARS (36.594°N, 119.512°W). The weighing lysimeter is located in the center of the pomegranate field, marked as a red box. The blue marks are where the 14 IRT sensors were installed
block, there were 3 rows with around 15 trees per row. Only the central row of each block was used as the experimental row. The height of trees was pruned and maintained at approximately 3 m.

6.2.2 Ground Truth: Infrared Canopy and Air Temperature

The tree canopy temperature was measured with 14 IRT sensors (Model SI-100 series, Apogee Instruments, Inc., Logan, UT), which were installed 4.5 m above the soil surface. The field of view (FOV) of the IRT sensor was 20° (Fig. 6.2). The air temperature and relative humidity were also measured with a sensor in the experimental site. Then, the authors could evaluate the performance of using midday infrared canopy to air temperature difference ($\Delta T$) to detect or classify deficit irrigation of pomegranate trees.

6.2.3 Thermal Infrared Remote Sensing Data

A quadcopter named “Foxtech Hover” was used as the low-cost UAV platform (less than $1000) to collect high-resolution thermal images at the height of 60 m. The UAV was equipped with a highly efficient power system, including T-Motor MN3508 KV380 motor, 1552 folding propeller, and Foxtech Multi-Pal 40A OPTO
ESC, to ensure long flight time. The UAV included a Pixhawk flight controller, GPS, and telemetry antennas, enabling it to fly over the pomegranate field by waypoints mode (designed using Mission Planner software). The lithium polymer battery of Hover had a capacity of 9500 mAh, which could support our 30-minute flight mission with the thermal camera mounted on the UAV. The thermal camera ICI 9640 P (Infrared Cameras Inc, Beaumont, TX, USA)\(^1\) was equipped with a UAV for collecting thermal images for the experimental field. The sensor has a resolution of \(640 \times 480\) pixels. The spectral band is from 7 to 14 \(\mu\)m. The dimension of the thermal camera is \(34\) mm \(\times\) \(30\) mm \(\times\) \(34\) mm. The accuracy is designed to be \(\pm 2^\circ\) C.

A Raspberry Pi Model B computer (Raspberry Pi Foundation, Cambridge, UK) was used to trigger the thermal camera during UAV flight missions.

### 6.2.3.1 UAV Thermal Image Collection and Processing

The authors used the Mission Planner to program all flight missions. The flight height was set up as 60 m. The overlapping of UAV imagery was set up as 80% so that the UAV imagery of the pomegranate could be stitched together more successfully during image processing. The UAV was flying at noon with clear sky conditions to minimize the shading effect on the thermal images. Since the thermal camera type is uncooled, it usually takes around 20 minutes to warm up the thermal camera before flight missions. To calibrate the thermal camera, the authors took thermal images of ice water immediately before and after the flight missions as the reference temperature. After the flight missions, all UAV thermal images were stitched together to generate the orthomosaick images in Metashape (Agisoft LLC, Russian). Preselection is recommended because it can speed up the processing of large datasets. Building the dense cloud can reconstruct a more accurate surface, improving the quality of the final orthomosaick. Higher quality usually can result in a more accurate surface, which means a more significant number of points. Building a digital elevation model (DEM) allows generating an accurate surface, which can be used as a source for orthomosaick generation. The above steps will shorten the data processing time compared with the Build Mesh operation because Build Mesh is usually used for a more complex surface.

### 6.2.3.2 Tree Canopy Segmentation Using Support Vector Machine (SVM)

There were 746 trees in total for the pomegranate field. As mentioned earlier, there were 3 rows with around 15 trees per row for each irrigation treatment block. Only

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\(^1\) Mention of trade names or commercial products in this publication is solely to provide specific information and does not imply recommendation or endorsement by the University of California or the US Department of Agriculture. The University of California and the USDA are equal opportunity providers and employers.
Fig. 6.3 (a) All of the UAV thermal images were stitched together to generate the orthomosaic images in Metashape (Agisoft LLC, Russian). (b) To obtain the individual tree canopy images of the 250 sampling trees, the authors used the SVM for classifying the tree canopy. (c) Histogram was generated for each tree canopy to check the variability of each tree canopy temperature.

the central row of each block was used as the experimental row. To obtain the individual tree canopy images of the 250 sampling trees (Fig. 6.3b), the authors used the SVM for classifying the tree canopy with ArcGIS Pro. Using the SVM classifier could map the input data vectors into a higher-dimensional feature space. Then, the SVM optimally separated the data into different classes. Since the file size of UAV-based thermal imagery was large, the SVM classifier was adopted, which was less susceptible to noise, unbalanced number, or size of training sites within each class. All the sampling trees were successfully segmented using the SVM classifier. Then, the mean, variance, and histogram information (Fig. 6.3c) were calculated using MATLAB 2021b as input features for CIML models.

### 6.2.4 Complexity-Informed Machine Learning (CIML)

When the authors discuss complexity-informed machine learning, he focuses on variability analysis using the histogram information of individual tree canopy. Variability refers to several properties of the ML dataset. First, it refers to the number of inconsistencies in the data, which needs to be understood by using anomaly- and outlier-detection methods for any meaningful analytics to be performed. Second, variability can also refer to diversity. For example, when the authors studied the
individual tree-level ET estimation [26], it turned out that the evapotranspiration for each tree is very close to each other. The reason was that the mean pixel values were used for data analysis, making the ET classification challenging to implement. Considering the complexity of each tree canopy, embedding the complex information into the ML training process may have great potential to detect or classify deficit irrigation for pomegranate trees. To analyze the complex information in each tree, we need to use tail-index analysis methods.

6.2.5 Principle of Tail Matching

In probability theory, heavy-tailed distributions are PDFs whose tails do not decay exponentially [2]. The distribution of a real-valued random variable $X$ is said to have a heavy right tail if the tail probabilities $P$ decay more slowly than those of any exponential distribution. Consequently, they have more weight in their tails than does an exponential distribution,

$$
\lim_{x \to \infty} \left( \frac{P(X > x)}{e^{-\lambda x}} \right) = \infty,
$$

for every $\lambda > 0$ [29]. The tail information in the training dataset variability and diversity should be used to indicate the data representativeness. In this article, the generalized Pareto distribution (GP) was developed to model tail index for individual tree canopy thermal imagery.

6.2.5.1 Pareto Distribution

A random variable is said to be described by a Pareto probability density distribution (PDF) if its cumulative distribution function (CDF) is

$$
F(x) = \begin{cases} 
1 - \left( \frac{b}{x} \right)^a, & x \geq b, \\
0, & x < b,
\end{cases}
$$

where $b > 0$ is the scale parameter and $a > 0$ is the shape parameter which is Pareto’s index of inequality [8]. The tail data of the tree canopy temperature were fitted using the generalized Pareto distribution by maximum likelihood estimation. Many fitting models may agree well with the data in high-density regions but poorly in low-density areas. However, in many applications, fitting the data in the tail may also contribute to model performance. The GP was developed as a distribution that can model tails of a wide variety of distributions based on theoretical arguments.
6.2.6 Machine Learning Classification Algorithms

Several classification algorithms were adopted to evaluate the detection performance for irrigation treatment levels. “Neural net,” “support vector machines (SVM),” “random forest,” “AdaBoost,” “nearest neighbors,” “Gaussian process,” “naive Bayes,” “quadratic discriminant analysis,” and “decision tree” were chosen as the classification algorithms. Some of them were briefly introduced for reference.

In the “neural net” library, a multilayer perceptron (MLP) classifier was used. This model optimized the log-loss function using stochastic gradient descent. MLP trained iteratively because the partial derivatives of the loss function concerning the model parameters were computed to update the parameters at every step [30]. The SVM are a set of supervised learning methods used for classification, regression, and outlier detection. The SVM are effective in high-dimensional spaces and effective in cases where the number of dimensions is greater than the number of samples [6]. For the “random forest” classifier, it is a meta-estimator that fits several decision tree classifiers on various subsamples of the dataset and adopts averaging to improve the predictive accuracy and control overfitting [4].

An “AdaBoost classifier” is also a meta-estimator that begins by fitting a classifier on the original dataset. Then, the model fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on complex cases [18]. The “nearest neighbors” method is to figure out a predefined number of training samples closest in the distance to the new point and predict the label from those [9]. The samples can be a constant ($k$-nearest neighbor learning) or vary based on the local density of points (radius-based neighbor learning). Despite its simplicity, the nearest neighbors method has been successfully applied for many research problems, such as the handwritten digit classification. As a nonparametric method, it is often successful in classification situations where the decision boundary is very irregular.

The “decision trees” method is also a nonparametric supervised learning method commonly adopted for classification problems. The objective is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data features [22]. A tree can be seen as a piecewise constant approximation. “Decision trees” usually use a white box model, which means the explanation for the condition is easily explained by Boolean logic if a given situation is observable in a model. In contrast, results may be more challenging to interpret for a black box model, such as an artificial neural network.

6.2.7 Image Preprocessing for the CNN Model

The individual tree canopy images were extracted from the UAV thermal imagery, 250 in total. Then, the dataset was distributed as 67% for training and 33% for testing using the $\text{train\_test\_split}$ method. To verify that the dataset looks correct,
the authors plotted the first 25 images from the training set and displayed the class name below each image (Fig. 6.4). All the images were resized into $32 \times 32 \times 3$ in order to input into our CNN model using TensorFlow 2.0. The summary of the CNN model is shown in Table 6.1. The output of every Conv2D and MaxPooling2D layer is a 3D tensor of shape (height, width, channels). The width and height dimensions tend to shrink as we go deeper in the network. The number of output channels for each Conv2D layer is controlled by the first argument. The authors fed the last output tensor from the convolutional base into the Dense layers to perform classification. Dense layers take vectors as input (which are 1D), while the current output is a 3D tensor. Considering the dataset has two classes, the authors used a final Dense layer with two outputs.

![Images from the training set](chart)

**Fig. 6.4** Twenty-five images were randomly selected from the training set and the class name for each image was displayed below. All the images were resized into $32 \times 32 \times 3$ in order to input into the CNN model.
6.3 Results and Discussion

6.3.1 Comparison of Canopy Temperature Per Tree Based on Ground Truth and UAV Thermal Imagery

To evaluate the reliability of UAV thermal remote sensing, the authors first compared the canopy temperature per tree acquired by IRT sensors and the UAV thermal camera. The correlation between the canopy temperature per tree measured by the IRT sensors and UAV thermal camera was shown by their scatter-related plot and the established regression equation (Fig. 6.5). The coefficient of determination ($R^2$) was 0.8668, which indicated that the difference between the ground truth and UAV thermal camera was acceptable. The method was reliable for monitoring tree-level canopy temperature.

6.3.2 The Relationship Between $\Delta T$ and Irrigation Treatment

The effect of irrigation treatment on canopy to air temperature ($\Delta T$) was plotted in this section (July 25, 2019 and August 7, 2019). As shown in Fig. 6.6, the $\Delta T$ was significantly higher in the 35% irrigation treatment than the 100% irrigation treatment on different days. The values of $\Delta T$ decreased as the irrigation increased. This finding emphasized the importance of irrigation on the tree canopy temperature response. Several researchers reported similar results [3, 33, 34]. At the USDA-ARS, all the pomegranate trees were fully irrigated before 2012, which did not show any significant difference for $\Delta T$ [34]. After the deficit irrigation started in early 2012, the difference of $\Delta T$ was more significant.
6.3 Results and Discussion

**Fig. 6.5** The correlation between the canopy temperature per tree measured by the IRT sensors and UAV thermal camera. The coefficient of determination ($R^2$) was 0.8668, which indicated that the difference between the ground truth and UAV thermal camera was acceptable. The method was reliable for monitoring tree-level canopy temperature.

**Fig. 6.6** The $\Delta T$ was significantly higher in the 35% irrigation treatment than the 100% irrigation treatment on different days. The values of $\Delta T$ decreased as the irrigation increased. This finding emphasized the importance of irrigation on the tree canopy temperature response.
Fig. 6.7 The summary of prediction results using histogram information on the tree-level irrigation treatment inference. “True label” meant the ground truth of ET$_c$-based irrigation treatment levels. “Predicted label” identified the irrigation treatment levels predicted by the trained model. To simplify the visualization, 30 and 50% ET irrigation were labeled as “0,” denoting low-level irrigation; 75 and 100% ET irrigation were labeled as “1,” which meant high-level irrigation.

6.3.3 The Classification Performance of CIML on Irrigation Treatment Levels

For the CIML algorithms, the authors focused on the variability analysis. Variability refers to the individual tree canopy temperature spatial diversity. Different types of tree canopy temperature data were used as the primary input for training, including (1) mean and variance; (2) tail index, mean, and variance; and (3) histogram of tree canopy temperature. The tree canopy temperature of 250 sampling trees was distributed as 75% for training and 25% for testing using the train_test_split method. For evaluating the trained CIML models, a confusion matrix was used.
Table 6.2 The classification performance of CIML algorithms on irrigation treatment levels at individual tree level. All the methods showed a state-of-the-art performance, with an overall accuracy of 87%. The “naive Bayes” had the highest accuracy of 0.90.

| Classification methods       | Prediction accuracy (histogram) | Prediction accuracy (mean, variance, and tail index) | Prediction accuracy (mean + variance) |
|------------------------------|---------------------------------|-----------------------------------------------------|-------------------------------------|
| “KNeighborsClassifier”       | 0.87                            | 0.86                                                | 0.84                                |
| “Linear SVM”                 | 0.89                            | 0.86                                                | 0.84                                |
| “RBF SVM”                    | 0.89                            | 0.84                                                | 0.84                                |
| “Gaussian process”           | 0.89                            | 0.86                                                | 0.86                                |
| “Decision tree”              | 0.84                            | 0.89                                                | 0.87                                |
| “Random forest”              | 0.89                            | 0.87                                                | 0.89                                |
| “Neural net”                 | 0.87                            | 0.89                                                | 0.44                                |
| “AdaBoost”                   | 0.84                            | 0.87                                                | 0.89                                |
| “Naive Bayes”                | 0.90                            | 0.81                                                | 0.68                                |
| “QDA”                        | 0.86                            | 0.83                                                | 0.73                                |

to compare the performances of different classifiers. A confusion matrix was a summary of prediction results on a classification problem. The number of correct and incorrect predictions was tallied with count values and divided into classes. The confusion matrix provided insight not only into the errors being made by a classifier but, more importantly, the types of errors that were being made. “True label” meant the ground truth of ETc-based irrigation treatment levels. “Predicted label” identified the irrigation treatment levels predicted by the trained model. To simplify the visualization, 30 and 50% ET irrigation were labeled as “0,” denoting low-level irrigation; 75 and 100% ET irrigation were labeled as “1,” which meant high-level irrigation.

The trained models had distinct test performance for irrigation treatment prediction at tree level (Fig. 6.7, Table 6.2, and Fig. 6.8). First of all, the most important finding was that using the UAV-based tree canopy to air temperature (ΔT) and machine learning algorithms could successfully classify the irrigation treatment or water stress at the individual tree level. The research results demonstrated that ΔT was highly related to irrigation management. As mentioned earlier, the main reason was that a significant increase in ΔT would indicate stomata closure and water stress conditions [12–14]. Thus, UAV-based thermal remote sensing is a reliable tool for tree irrigation management. The results were highly consistent for different methods, for example, when histogram information was used for training and testing. All the methods showed a state-of-the-art performance, with an overall accuracy of 87%. The “naive Bayes” had the highest accuracy of 0.90.

Another finding was that tail-index information had great potential to benefit training and testing performance. The mean and variance were a simplification of complex information. By adding the tail information into the training dataset, the prediction accuracy of some methods was increased, as shown in Table 6.2. It
Fig. 6.8 The test performance for the histogram dataset. The t-distributed stochastic neighbor embedding (TSNE) method was used for data visualization [21], which learned the most critical axes between the classes. The axes were then used to define the hyperplane to project the high-dimensional training data into two dimensions, which gained important insight by visually detecting patterns. The $x$-axis and $y$-axis had no scale because of hyperplane projection. The irrigation treatment levels were successfully clustered into low level (blue) and high level (green)

inspired us that the tail information in the training dataset variability and diversity should be used to indicate the data representativeness. Then, with more complex information, the histogram information of tree canopy temperature had the best prediction accuracy, without a doubt. In summary, all three situations had overall accuracy above 80%, mainly because the $\Delta T$ was very sensitive to irrigation treatments.

### 6.3.4 The Performance of the CNN Model

As mentioned earlier, there were 250 tree canopy images in total, which were distributed as 67% for training and 33% for testing using the `train_test_split` method. To train the CNN model, the “Adam” optimizer and the cross entropy loss function were adopted during the training process. The epoch was set up as 100. For evaluating the trained CNN models, the authors plotted the training and validation accuracy curves with the epochs increasing (Fig. 6.9). The test accuracy was 87%. To visualize the trained CNN model performance, the authors made predictions
6.3 Results and Discussion

Fig. 6.9 The performance of the CNN model, training and validation accuracy curves

Fig. 6.10 The summary of prediction results on the irrigation treatment classification problem. “True label” meant the ground truth of ET_c-based irrigation treatment levels. “Predicted label” identified the irrigation treatment levels predicted by the trained CNN model. To simplify the visualization, low irrigation (30 and 50% ET) was labeled as “0”; high irrigation (75 and 100% ET) was labeled as “1” about some images in the test dataset (Fig. 6.11). Correct prediction labels are blue and incorrect prediction labels are red. The number gives the percentage (out of 100) for the predicted label. A confusion matrix was also used, which was a summary of prediction results on a classification problem. The number of correct and incorrect predictions was tallied with count values and divided into classes. The confusion matrix provided insight not only into the errors being made by a classifier but, more importantly, the types of errors that were being made. “True label” meant the ground truth of ET_c-based irrigation treatment levels. “Predicted label” identified the irrigation treatment levels predicted by the trained CNN model. To simplify the visualization, low irrigation (30 and 50% ET) was labeled as “0”; high irrigation (75 and 100% ET) was labeled as “1” (Fig. 6.10). The detailed information of precision and recall was shown in Table 6.3 (Fig. 6.11).
| Irrigation level | Precision | Recall | F1-score |
|-----------------|-----------|--------|----------|
| Low irrigation  | 0.92      | 0.81   | 0.86     |
| High irrigation | 0.83      | 0.93   | 0.87     |
| Accuracy        | NA        | NA     | 0.87     |
| Macro avg       | 0.87      | 0.87   | 0.87     |
| Weighted avg    | 0.87      | 0.87   | 0.87     |

Fig. 6.11 To visualize the trained CNN model performance, the authors made predictions about some images in the test dataset. Correct prediction labels are blue and incorrect prediction labels are red. The number gives the percentage (out of 100) for the predicted label.

6.4 Conclusion and Future Research

The aim of this chapter was for irrigation treatment levels inference in the pomegranate field at the individual tree level by using UAV-based thermal images and machine learning algorithms. The authors collected the $\Delta T$ by using a UAV-based high-resolution thermal camera. Then, CIML algorithms were adopted for
the tree-level irrigation treatment classification problem. The authors developed a reliable tree-level irrigation treatment inference method using UAV-based high-resolution thermal images. The research results showed that the best classification accuracy of irrigation treatment levels was 90% when the “naive Bayes” method was adopted. The results of this research supported the idea that a significant increase in the midday infrared canopy to air temperature difference (ΔT) will indicate stomata closure and water stress conditions. The authors also proposed the concept of CIML and proved its performance on the classification of tree-level irrigation treatments. CIML models have great potential for future agriculture research. With more complex information, it will benefit the training and testing process of machine learning algorithms.

6.5 Chapter Summary

Research in irrigation management is accelerating to achieve sustainability and marketability in agriculture, which is estimated to account for over 70% of global water use. The optimal use of water through irrigation has always been critical for the evolution of agriculture and successful farming. Smart irrigation management will also enable growers to irrigate more efficiently, thus making agriculture production more sustainable. Many progressive growers make irrigation decisions using crop evapotranspiration (ETc). Therefore, accurate determination or spatial mapping of crop water status is essential for efficient water management. With the advent of unmanned aerial vehicles (UAVs), lightweight sensors, such as multispectral and thermal cameras, can be mounted on the UAVs to take high-resolution images. Compared with satellite imagery, the spatial resolution of the UAV images can be at the centimeter level. UAVs can also fly on demand, which provides higher temporal imagery. Thus, in this chapter, the authors proposed a reliable individual tree-level plant water status inference system using a small UAV platform and complexity-informed machine learning (CIML) algorithms. A field study was conducted at the USDA-ARS Research Center in Parlier, California, to test and validate the CIML algorithms using pomegranate trees. The pomegranate trees were randomly designed into 16 equal blocks, with 4 replications, to test 4 irrigation levels. The irrigation volumes were 35%, 50%, 75%, and 100% of ETc, measured by a weighing lysimeter in the field. Irrigation treatment inference at the individual tree level was realized by using UAV-based thermal images and CNN model in a pomegranate field. The research results showed that the best classification accuracy of irrigation treatment levels was 87% when the CNN model was adopted. Results showed that the CIML algorithms could successfully classify the individual trees using the thermal UAV imagery into the targeted irrigation levels. The overall prediction accuracy was around 90%, which showed a state-of-the-art performance and indicated that UAV thermal imagery had great potential for irrigation mapping at individual tree levels.
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Chapter 7
Conclusion and Future Research

7.1 Conclusions

In this monograph, the authors mainly investigated the small UAV applications for tree-level evapotranspiration estimation. Several UAVs and remote sensing payloads were introduced and discussed. Then, the authors proposed new methods for reliable tree-level ET estimation and water status inference with machine learning for an experimental pomegranate orchard at USDA.

In Chap. 2, small UAVs and remote sensing payloads were introduced and discussed. UAV image acquisition and processing methods were also presented. The challenges and opportunities for UAV ET estimation methods were also discussed in this chapter.

In Chap. 3, the authors reviewed the most commonly used ET estimation methods with small UAVs. The OSEB, HRMET, machine learning (ML), artificial neural networks (ANN), TSEB, DTD, SEBAL, and METRIC were introduced in this chapter. The discussed ET estimation methods with UAVs and their advantages and disadvantages were also summarized in this chapter.

In Chap. 4, the authors investigate the approaches of estimating $K_c$ using UAV-based NDVI for an experimental pomegranate orchard. The spatial and temporal variability of $K_c$ and NDVI were analyzed by using the Deep Stochastic Configuration Networks (DeepSCNs). A regression model was established between the NDVI and $K_c$. The performance of the new regression model was evaluated by the data collected by the UAVs.

In Chap. 5, a reliable tree-level ET estimation method was developed using UAV high-resolution multispectral images. Then, a framework was provided to establish a linear regression model between the NDVI and $K_c$ to estimate the actual daily ET. Results showed that the linear regression model could estimate tree-level ET with an $R^2$ and mean absolute error (MAE) of 0.9143 and 0.39 mm/day, respectively, which showed a state-of-the-art performance.
In Chap. 6, the authors evaluated the reliability of the UAV thermal camera on individual tree canopy temperature measurements. Then, the authors investigated and validated the approaches of irrigation treatment inference using UAV-based ΔT at individual tree level and demonstrated the performance of the CIML models on irrigation treatment inference.

### 7.2 Future Research

As a new remote sensing platform, researchers are gaining interest in the potential of UAVs in precision agriculture. Compared with traditional remote sensing platforms, the UAVs can be more flexible in the field. For example, UAVs can be operated at any time if the weather is within the operating limitations. The satellite has a fixed flight path; UAVs are mobile and flexible for site selection. Mounted on the UAVs, lightweight sensors, such as RGB cameras, multispectral cameras, and thermal infrared cameras, can be used to collect high-resolution images. While there are many advantages with using UAVs, there are still challenges for UAVs when used for estimating ET. Many researchers fly the UAVs at different height, using specialized equipment and relying on data analysis expertise. As researchers try to understand and realize the potential of the UAVs for ET estimation, efficient workflow, image processing, and better software are still under development.

No existing methods can fully satisfy the spatial, temporal, spectral, and accuracy requirements for ET-based science and applications. Therefore, innovative methods or models for ET estimation are required by using UAVs. There are five requirements to map ET with high fidelity in the future [1], which are high frequency, high spatial resolution, high temporal resolution, large spatial coverage, and long-term monitoring. High frequency will improve the differentiation of water stress between crops, which enables more efficient water management. High spatial resolution can help detect spatially heterogeneous responses to water stress. Because ET is highly variable within and among days, high temporal resolution can help detect crop ET in real time. Large spatial coverage can help detect large-scale drought. Long-term monitoring will be important to record ET variability over time.

Compared with other satellite-based remote sensing methods, the UAV platform and lightweight sensors can provide better quality, higher spatial, and temporal resolution images. The UAVs can be used to estimate ET on an excellent spatial scale and with flexible flight schedules. In the future,

1. The two-source energy balance (TSEB) and Dual-Temperature-Difference (DTD) models have great potential for ET estimation since they can separate the soil and canopy with high-resolution UAV imagery;
2. Taking advantage of the UAV high-resolution imagery, research related to individual tree-level ET estimation will be possible and useful for analyzing the temporal and spatial variability of the crops in the field;
3. Deep learning algorithms can be used for processing high-resolution UAV imagery, such as individual tree-level canopy or soil segmentation;  
4. The author's research results [2] showed that there was strong correlation between the NDVI and crop coefficient at individual tree-level ET estimation. Further study can be conducted to create new generation of vegetation index using machine learning and deep learning algorithms.

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