Cloud-based monitoring and analysis of yield efficiency in precision farming *

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Abstract

Yield mapping visualizes yield rate per geological distribution. It is frequently used as a baseline metric to measure yield efficiency in precision farming. A major challenge in mapping yield for specialty crops is how to collect accurate yield data without incurring substantial overhead to a farming operation. We design a yield efficiency analysis system that uses a cloud-based computing platform to acquire and analyze yield data. By reusing labor data collected by a cloud-based labor monitoring system that we developed earlier [1], our system calculates yield data from labor data, and computes yield map in real time and without the overhead for data acquisition. A distinctive feature of our approach is the introduction of a customizable yield distribution function that quantifies the probability of geographic distribution of fruits weighted at a Labor Monitoring Device. Practitioners may define yield distribution functions based on operational characteristics of an orchard, enabling our system adaptive for a variety of orchards with different harvesting operations and canopy architecture. Using a multi-tenancy software architecture, our system can support multiple orchards concurrently with improved scalability and data privacy. Our system has been deployed and tested on Amazon Web Services (AWS).

1 Introduction

Specialty crops, defined by USDA as "fruits and vegetables, tree nuts, dried fruits, horticulture, and nursery crops (including floriculture)" [2], represent a multi-billion dollar industry in the United States alone. Taking Cherry as an example, the United States exports more than $206 million worth of Cherry in 2006-7. With an increasingly larger population worldwide with more purchasing power and health consciousness, the demand for special crops will likely continue to grow in the foreseeable future. A constant theme in special crop industry is *how to improve yield efficiency in an orchard*. An important metric to measure yield efficiency is yield mapping, which maps yield rate with its geological distribution. Yield map provides practitioners an intuitive tool to assess the yield distribution in an orchard. When overlaid with other datasets, such as terrain and sensor data, an augmented yield map visualizes the relation between yield and these datasets.

A major bottleneck to map yield for specialty crop is to acquire accurate yield data at a reasonable cost. Unlike commodity crops such as wheat and corn, for whom yield data may be collected using GPS-equipped machine harvesters, most of specialty crops still reply on manual harvesting. Using existing technology, measuring and geotagging yield in a manual harvesting operation requires additional equipment and extra steps, making it unpractical to collect yield data via manual harvesting. Because of this difficulty, researchers have been experimenting a variety of techniques to estimate yield distribution. These techniques include satellite and airborne imagery [3, 4], machine vision [5], and thermal imaging [6]. Nevertheless, these techniques require expertise and often costly equipment, which them unpractical for field use. Besides the concerns on the cost, these techniques are indirect measurement of yield distribution. What is needed is an accurate and low-cost yield-mapping method for specialty crop.

We develop a novel cloud-based yield-mapping approach that acquires yield data directly from harvesting operations via data reuse. Using a patent-pending technology, we previously developed a labor monitoring system (LMS) that analyzed labor data collected by purposely designed Labor Monitoring Devices (LMDs) [1]. Our yield-mapping approach derives yield data from the labor data collected by LMDs, and uses the yield data for visualizing yield efficiency. By reusing the labor data otherwise already col-

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lected for the purpose of labor monitoring, our approach obtains yield data without additional cost. We implemented our approach on top of a cloud-based labor monitoring system [1]. The yield mapping function reuses labor data at the level of cloud computing. Our approach does not require additional hardware other than enhancing an existing LMD with an off-the-shelf GPS unit, nor it incurs substantial overhead to a harvesting operation.

Figure 1 shows the architecture design of our yield mapping system. The process starts with collecting labor data using the Labor Monitoring system (LMS) developed by our team [1]. Using a patent-pending technology, the LMS collects harvesting data from the field via LMDs. By extending a LMD with a GPS unit, we augment the harvesting labor data with its geological location information. The LMD sends the geo-tagged harvesting labor data to a data acquisition server. The data is pre-processed and stored in the database for use in a variety of data-processing functions, including the real-time labor monitoring [1], and yield mapping described in this paper. The data processing server relates the geo-located harvest data to yield distribution in the orchard. Many factors, such as orchard layout and trees' canopy architecture, may alter the temporal and spatial patterns of a harvesting operation. A distinctive feature of our approach is the introduction of a yield distribution function that quantifies the probability of geographic distribution of fruits weighted at a LMD location. A grower may define his/her own yield distribution function, to reflect the temporal and spatial patterns of his/her harvesting operation. Once the geo-tagged harvesting data is processed and translated to yield distribution, our visualization server overlays it with other data sets, for example, the terrain data from Google earth, to help users visualize the relation between yield and these data sets. Growers may access yield maps through our cloud-based web server, from a web browser. The entire server platform, including a data acquisition server, a data processing server, a databases server, a data visualization server, and a web server, is deployed on a cloud computing platform (Amazon Web Services). Our labor monitoring and yield mapping system deploys a multi-tenancy software architecture, which enables us to serve multiple orchards concurrently with improved data privacy and security.

The rest of the paper is organized as follows: Section 2 discusses the method of deriving yield data from the labor data collected by the labor monitoring system [1]; Section 3 discusses the yield mapping with customizable yield distribution functions; Section 4 discusses the multi-tenancy software architecture of our system, which improves scalability and data privacy on a cloud-computing platform; Section 5 discusses our implementation and cloud deployment; and finally Section 6 concludes the paper.

2 Data Aquisition via Harvest Labor Monitoring

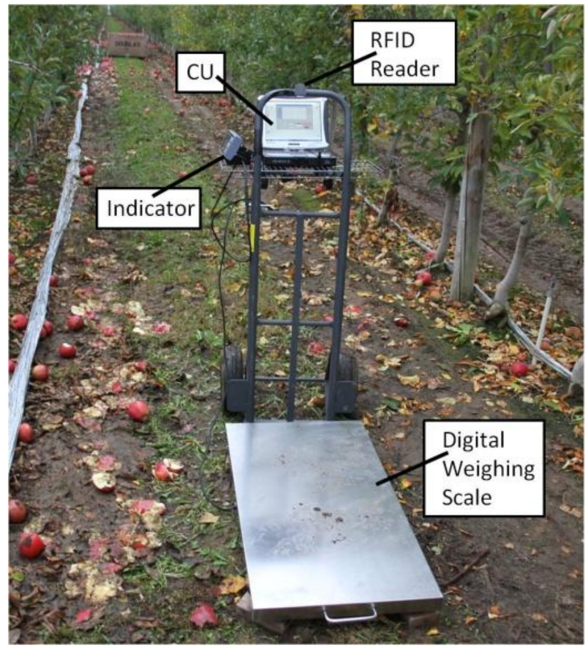


Figure 2. A variant of Labor Monitoring Device on a dolly [1].

Our cloud-based yield efficiency analysis system is built on the top of a novel labor monitoring system (LMS) [1]. It extracts yield data from labor activity data collected by the LMS. The LMS comprises a cloud-based data analaysis platform and purposely designed Labor Monitoring Devices (LMD) in the field. A typical workflow in the LMS is as follows: first, a picker registers with the LMS, and he/she is assigned with a personal identification device (PID). During harvesting, the picker picks fruits and put them in a basket as usual. The picker then comes to a LMD, and put the basket on a digital scale integrated with the LMD. The picker also presents to the LMD his PID. The LMD then sends to the data acquisition server a record bearing the weight of fruits, the identification of PID, and the identification of LMD. Using a patent pending technology [7], the LMS can accurately accrue the labor for the worker, even with complex many-to-many employment relations.

The design of a LMD is often application-specific. Practitioners may choose a LMD design that fits best into their operations. We developed the LMS so that it can work with a variety of LMDs. We defined a communication protocol between a LMD and the LMS. The LMS can work with any LMD, as long as it conforms to our communication protocol. During our field tests in Cherry orchards, we used radio

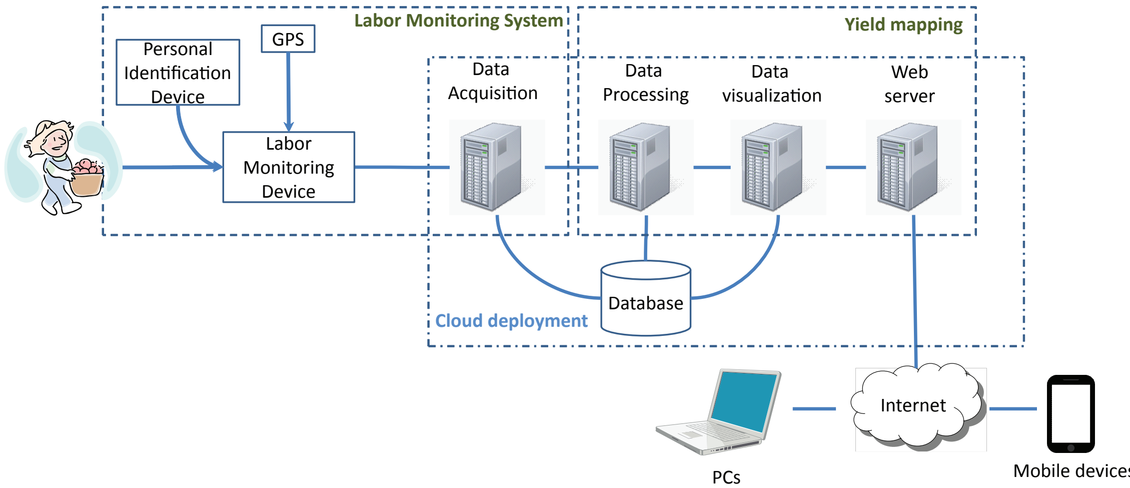


Figure 1. Architecture design of a Labor Monitoring-Based Yield Mapping system

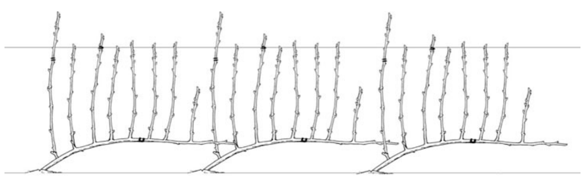


Figure 3. Upright Fruiting Offshoot (UFO) canopy architecture [8]

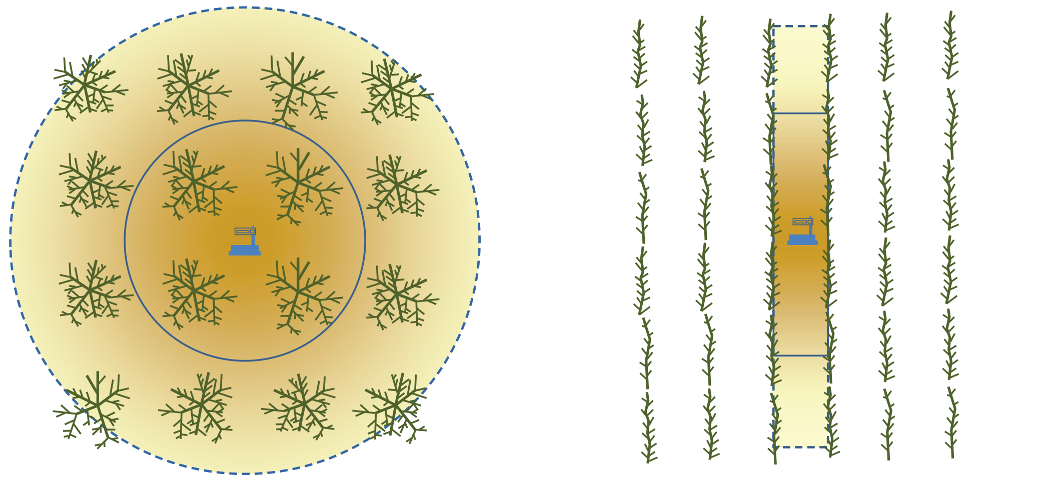
frequency identification devices (RFID) as Personal Identification Devices. RFID may be in a variety of forms such as a wristband or a tag. A LMD designed for cherry harvesting typically consists of: (i) a digital scale; (ii) a radio frequency identification (RFID) reader; and (iii) a computational unit (CU) with a wireless transceiver. A personal identification device in this case is a RFID. Figure 2 shows a LMD used in our field test, which has the components installed on a dolly for portability. To reuse the labor data for analyzing yield efficiency, we need to know the geological location where the labor data is registered at a LMD. To obtain the geo-tagged labor data, we enhance a LMD with an off-the-shelf GPS.

3 Mapping yield using Labor Monitoring Data

An important measurement of efficiency of an orchard is the yield of its end product, that is, fruits, nuts, and/or other specialty crops produced in the orchard. Growers concern not only the total amount of yield, but also how it is distributed within the orchard. An important tool to measure and illustrate yield distribution is yield mapping. A yield map associates geographical data with the weight of the fruit being harvested, and visualizes the association in a visual format. One common format is a geographical map with colors representing the distribution of yield. When overlaid with other datasets (e.g. soil nitrogen content, irrigation, weather data, fertilizer usage, etc), a yield map provides imporant visual clue that may help uncover the relations between the yield and these datasets. In addition to show the spatial distribution of yield, a yield map may also be overlaid with historical data to show the temporal variation of yield.

Because of the practical importance of yield mapping, various methods for producing yield maps have been studied (cf. [9]). Nevertheless, yield mapping for specialty crops remains to be challenging. In the United States, harvesting commodity crops such as corn and wheat is automated, and the yield of these crops may be measured directly by GPS-equipped mechanical harvesters. In comparison, specialty crops such as Cherry still rely on manual harvesting. Existing yield-mapping approaches for specialty crops often use indirect measurement such as remote sensoring, which incurs additional cost to growers [10]. Compared with these existing approaches, our LMS-based approach reuses labor data otherwise already collected for labor monitoring purpose, and computes yield maps from the labor data without incurring additional cost. Unlike existing methods that use sensoring and imagery technology to estimate yield, our approach uses the labor data which is a direct measurement of yield being harvested. This also improves the accuracy of yield mapping.

Our approach starts with collecting yield data and its distribution in an orchard. Section 2 describes how the harvest data is collected and augmented with a GPS-equipped



(a) A cherry orchard with a traditional architecture (b) A cherry orchard with the UFO architecture

Figure 4. Yield distribution functions (YDF) for orchards with (a) a traditional canopy architecture; and (b) the UFO architecture.

LMD. As shown in Figure 1, the geo-tagged harvest data is sent to a data acquisition server, which pre-processes the data and store it to databases. Labor data is stored as picking records $\langle w, m_{lat}, m_{long}, ts\rangle$, where w is the weight of fruits being picked, $\langle m_{lat}, m_{long}\rangle$ are the latitude and longitude of the LMD m when the fruits are being weighted, and ts is the time stamp. Each picking record is the result of a weighting event, that is, a picker weights his basket at a LMD. The pre-processing performed by the data acquisition server removes the erroneous inputs and noises in the data, for instance, data records with 0 weight, which may be caused by a picker presenting his/her RFID to LMD without weighting a basket of picked fruit.

Picking records stored in the databases are used as the baseline data points for yield mapping. In our system, a user can specify a *time range* I and a *field* F for which a yield map is drawn. The data processing server (Figure 1) retrieves the set of picking records D whose time stamp and the geological locations fall into the time range and the field selected by the user as below,

$$D = \{\langle w, m_{lat}, m_{long}, ts\rangle \mid ts \in I \wedge \langle m_{lat}, m_{long}\rangle \in F\} \tag{1}$$

3.1 Yield Distribution Functions

Picking records store the quantity of fruits weighted at LMDs, and they are tagged with the locations of the LMDs when fruits are weighted. To compute a yield map, we need to relate the fruits weighted at a LMD to the places where they are picked. Normally it would require additional instruments and extra steps to precisely trace fruits back to the exact place where they are picked. The cost of these instruments and the overhead of the extra steps would make it intractable to track fruits precisely to where they are picked. To solve this problem, we use a statistic method to estimate the geological distribution of fruits weighted at a LMD. We introduce a yield distribution function that quantifies the probability of geological distribution of fruits weighted at a LMD. A yield distribution function is essentially a 2-dimension probability density function $f(p_{lat}, p_{long}, m_{lat}, m_{long})$. Intuitively, the yield distribution function f describes how likely a fruit measured at a LMD of location $\langle m_{lat}, m_{long}\rangle$ may be picked from the location $\langle p_{lat}, p_{long}\rangle$. Given a set of picking records D, the yield rate at the location $\langle p_{lat}, p_{long}\rangle$ is as follows:

$$y(p_{lat}, p_{long}) = \sum_{\langle w, m_{lat}, m_{long}, ts\rangle \in D} w \cdot f(p_{lat}, p_{long}, m_{lat}, m_{long}) \tag{2}$$

Let $\mathcal{B}$ be all the picking records stored at the databases, the yield rate in a field F during a time range I may be computed as follows:

$$y(p_{lat}, p_{long}) = \sum_{\langle w, m_{lat}, m_{long}, ts\rangle \in \mathcal{B} \wedge \langle m_{lat}, m_{long}\rangle \in F \wedge ts \in I} w \cdot f(p_{lat}, p_{long}, m_{lat}, m_{long}) \tag{3}$$

3.2 Defining yield distribution functions

For a professional fruit harvesting operation, the pattern of harvesting activities are usually well planned to maximize the harvesting productivity. To improve the precision of yield mapping, our system enables practitioners to customize yield distribution functions based on the temporal and spatial patterns of their harvesting operations.

Many factors may impact the pattern of harvesting activities. One of such key factors is the canopy architecture of trees. Since yield is a result of plant photosynthesis process and the plant's canopy architecture impacts how the leaves receive sunlight, plants of speciality crops may be trained to achieve certain canopy architectures for improving yield. Canopy architecture also impacts how trees are planted and fruits are harvested. For trees with a traditional cone-shaped canopy architecture, pickers generally use ladders to retrieve fruits at the top branches of trees. It takes times for pickers to climbing up/down ladders and to move them from tree to tree. If not handled carefully, ladders may also pose safety risk. Recently Whiting *et al.* developed the Upright Fruiting Offshoot (UFO) architecture, a novel canopy architecture for Cherry. Figure 3 shows the UFO canopy architecture for Cherry. Briefly speaking, Cherry trees with the UFO architecture are trained to grow as 2-dimension wall, instead of a traditional cone-shaped canopy. The UFO architecture has been shown to improve the yield as well as harvest labor efficiency [11]. A cherry tree with the UFO architecture is pruned to have a maximal height within arm's reach. Pickers move along the "picking aisle" between two "walls" of the Cherry trees, picking fruits without ladders.

Figure 4 illustrates the yield distribution functions we used for mapping yield in orchards with a traditional and the UFO architecture, respectively. In an orchard using a traditional cone-shaped canopy architecture, workers pick up fruits from the trees adjacent to a LMD. The further a tree is away from a LMD location, The less likely a fruit weighted at the LMD would come from that tree. In an orchard using the UFO architecture, the probability of a fruit coming from a tree is decided by the distance on the aisle between the tree and the LMD that weights the fruit. Note that the yield distribution function is bounded to the walls enclosing the "picking aisle", as these walls represent physical barriers for pickers to walk through.

In our experiment, we use 2-dimension Gauss distribution function as the yield distribution function for an orchard with a traditional canopy architecture. The function is defined as follows:

$$f(p_{lat}, p_{long}, m_{lat}, m_{long}) = \frac{e^{-\left(\frac{\gamma(p_{lat}, p_{long}, m_{lat}, m_{long})^2}{2\cdot\sigma^2}\right)}}{(2\cdot\pi\cdot\sigma^2)} \quad (4)$$

where $\gamma(p_{lat}, p_{long}, m_{lat}, m_{long})$ is the distance be-

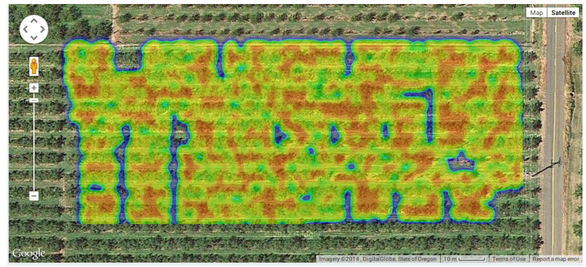


Figure 5. Yield map for a traditional orchard using the YDF in equation (4)

tween p and m, and σ^2 is the variance. Figure 5 shows a yield map for an orchard with traditional canopy architecture, using the yield distribution function in (4).

For an orchard with the UFO canopy architecture, we use a distribution function which uses a Gauss distribution along "picking aisle", and is bounded between walls enclosing the aisle. Without loss of generality, let us consider an orchard with the trees being planted (and thus picking aisle) along the longitude, that is, on the north/south line. The yield distribution function is defined as follows:

$$f(p_{lat}, p_{long}, m_{lat}, m_{long}) = \begin{cases} \frac{e^{-\left(\frac{\alpha(p_{lat}, m_{lat}, m_{long})^2}{2\cdot\sigma^2}\right)}}{(b\cdot\sigma\cdot\sqrt{2\cdot\pi})} & \text{if } \beta(p_{long}, m_{long}, m_{lat}) \leq \frac{b}{2} \\ 0 & \text{Otherwise} \end{cases} \quad (5)$$

Where σ^2 is the variance, b is the distance between two adjacent walls of trees (i.e. the width of the picking aisle), $\beta(p_{long}, m_{long}, m_{lat}) = \gamma(m_{lat}, p_{long}, m_{lat}, m_{long})$, and $\alpha(p_{lat}, m_{lat}, m_{long}) = \gamma(p_{lat}, m_{long}, m_{lat}, m_{long})$. Intuitively, $\beta(p_{long}, m_{long}, m_{lat})$ and $\alpha(p_{lat}, m_{lat}, m_{long})$ specify the latitudinal (east/west) and longitudinal (north/-south) distances between a location and a LMD, respectively. Figure 6 shows a yield map for an orchard with traditional canopy architecture, using the yield distribution function in Equation 5.

4 Multi-Tenancy Software Architecture

A major challenge in developing a cloud-based agriculture information system is how to serve multiple customers (orchards) simultaneously, each of which generates a large volume of data on-the-fly from an array of sensors and other sources. In addition, a major concern among early adopters of cloud-based agriculture information systems is data privacy. The data collected from a farming operation often contain sensitive and proprietary information that a grower

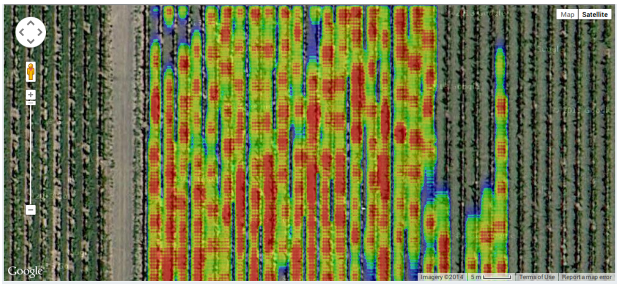


Figure 6. Yield map for a UFO orchard using the YDF in equation (5)

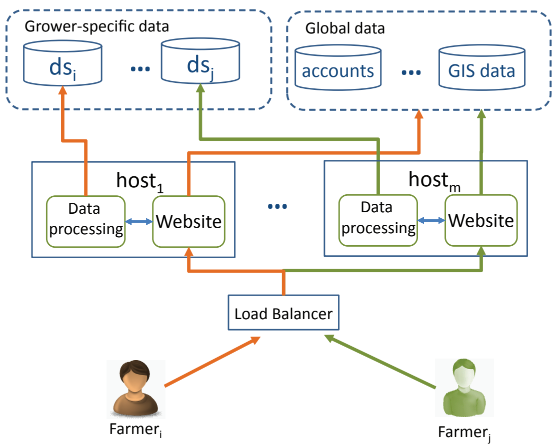


Figure 7. Multi-Tenancy Software Architecture

may not want to share. To address these issues, we developed a multi-tenancy software architecture for our system. The multi-tenancy technology (cf. [12]) has been studied and used to increase the scalability and maintainability of a web application. At the core of the multi-tenancy technology is a set of techniques that enable a single software application to serve multiple customers simultaneously, using datasets specific to each customer.

Figure 4 shows the multi-tenancy software architecture of our system. The data tables in our database are organized into one of the following two sets: (a) global data comprising data tables accessible to all the users with an appropriate accessible right. Examples of such global data include GIS data such as the terrain and field data, and the account data used to verify a user's identity; and, (b) grower-specific data comprising data tables that are only accessible to a grower. In the cloud deployment of our system, the same software application is running on all the hosts. When a grower accesses our website, his/her request will be directed by a load balancer to a host. The website module of our application running on the host authenticates the user, using the account data in the global dataset. When a grower accesses a yield map of his orchard, the data-processing module retrieves the yield data from the grower-specific dataset. Our role-based access management ensures that only the grower can access his grower-specific data set. Note that all the data tables in the grower-specific data set use the same set of schema, regardless of whom the data tables belong to. Thus, the data-processing module can switch between different growers on the grower-specific data set.

Our multi-tenancy software architecture brings several benefits to our cloud-based system: first, the multi-tenancy architecture leverages cloud computing for better scalability. The number of hosts can be changed on demand, based on the traffic from users; second, it improves the maintainability of our system. Since all the hosts are running the exactly same application, we only need to maintain a single code base for the application; and, finally the architecture improves the data privacy, as the yield and other operations data are part of the grower-specific data only accessible to a specific grower.

5 Implementation and Cloud-Based Deployment

Our cloud-based yield efficiency analysis system is developed with the Ruby-on-Rails application framework. Ruby is a dynamic object-oriented programming language, and Rails is open-source web application framework for Ruby. Ruby-on-Rails refers to the web programming practice of developing a web application in Ruby using Rails framework. Rails framework follows the Model-View-Controller design pattern [13]. In our application, *models* are used to create the underlying database schema. The web interfaces of our applications are implemented as *views*, and the access to the databases from views are defined by *controllers*. Our application uses several off-the-shelf Ruby libraries commonly known as Ruby *gems*, to simplify the implementation of many components and to interface with external applications such as Google Earth [14].

5.1 Cloud-Based Deployment

To improve scalability and accessibility of our system, we designed and implemented our system specifically for a cloud-based computing platform. We deployed our system on Amazon Web Services (AWS), and it currently runs in the Amazon EC2 cloud [15]. Through its management console, AWS provides a set of management tools that enable us to scale up and down the number of instances on demand. The cloud-based deployment also allows growers to access and visualize the yield data anywhere using a web browser. More importantly, the scalability and accessibility of cloud-based deployment also enables our system to support multiple orchard operations concurrently.

As discussed in Section 4, we developed a multi-tenancy software architecture for improved scalability and data privacy in cloud deployment. We implemented the multi-tenancy architecture with the assistance of Apartment gem [16]. The gem compartmentalizes the grower-specific data, and automatically handles the loading of grower-specific data tables based on growers.

5.2 Customizing Yield Distribution Function

As we discussed in Section 3.2, a yield distribution function reflects the characteristics of an orchard operation. We implemented a module that allowed a practitioner to easily define a yield distribution function (YDF). The YDF module allows a practitioner to write a yield distribution function in Ruby. The YDF module provides several pre-defined parameters that define the distance and other metrics between a location and a LMD. A practitioner simply writes the yield distribution function using these parameters as the input variables. Our built-in YDF interpreter then replaces these parameters with real measurements, as it goes through each point on a field and decides the value associated with each point using the custom-defined YDF.

For example, suppose that one wants to define a yield distribution function for equation 4. The YFD module provides three pre-defined parameters: $dlon$, the longitudinal distance between a point p and a LMD m ; $dlat$, the latitudinal distance between the two; and, $dt2t$, the distance between the two. Hence, we have $dt2t = \rho(p_{lat}, p_{long}, m_{lat}, m_{long})$. Let $\sigma = 1$, the custom-defined yield distribution function is written as,

```
Math.exp(-((dt2t**2/2)))/(2*Math::PI)
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As another example, consider the YFD in equation 5. Note that $dlat = \alpha(p_{lat}, m_{lat}, m_{long})$ and $dlon = \beta p_{long}, m_{long}, m_{lat}$. Let $b = 5$ and $\sigma = 1$, the YFD may be written as,

```
dlon <= 5/2? Math::E**(-(dlat**2/2))
/(5*(2*Math::PI)**1/2) : 0
```

6 Conclusion

Yield mapping is an important tool for visualizing and analyzing yield efficiency in precision farming. Because most of specialty crops are still harvested manually, a major challenge of mapping yield for specialty crop is to collect yield data without incurring significant overhead to a manual harvesting process. We proposed and developed a cloud-based yield efficiency monitoring and analysis system for specialty crops. The system is built on the top of a novel Labor Monitoring System we developed in [1]. By reusing labor data otherwise already collected for the purpose of labor monitoring, our cloud-based system computes yield mapping without additional cost of collecting yield data. We developed a method of deriving yield data from labor data using customizable yield distribution functions. A yield distribution function quantifies the geological distribution of fruits weighted at a LMD. Our system enables a practitioner to define a yield distribution function based on the characteristics of his/her harvesting operations. We discussed how different factors of an orchard operation, such as canopy architecture, may impact the harvesting operations and hence change the yield distribution function. As an example, we proposed two yield distribution functions for orchards with traditional canopy architecture and the UFO architecture [8], and used them in our experiments.

Our system has been deployed on Amazon Web Services EC2, a cloud-based computing platform. It provides a real-time and low-cost way for growers to monitor and analyze yield efficiency in orchards, from a web browser. For the future research, we plan to further study the benefits of the cloud-based data reuse and integration, by integrating yield mapping with other sensor data collected from fields. This will provide an intuitive tool for growers to assess the relation between yield and other factors measured by these sensor data.

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