DEVELOPMENT OF CORNSOYWATER, A WEB-BASED IRRIGATION APP FOR CORN AND SOYBEAN

by

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Irrigation decision making is critical for crop producers in the Midwestern United States because of the high demand for water during the peak of growing season of corn and soybean fields. Agronomists try to use agricultural-related data to optimize irrigation decision making. The biggest obstacle is the gap of transforming data to usable information which producers can access and take corresponding actions regarding when to irrigate their fields.

We developed CornSoyWater (http://cornsoywater.unl.edu), a web-based app that can be used in a web browser of any desktop computers or mobile devices. The goal is to use state-of-the-art quantitative agronomic sciences and information technologies, and in-season real-time weather data with field-specific crop management information to predict crop development and growth, crop water use and soil water balance to aid producers' irrigation decision making.

For practical use of the app, the corn crop model (Hybrid-Maize model) which runs inside of the app needed to be tested for its accuracy. We used a 5-year field dataset to test the performance of Hybrid-Maize model on estimating soil water balance near Mead, NE. We conducted a 2-year field experiment to test the

performance of Hybrid-Maize model on maize growth and crop water use under a range of irrigation treatments including 100% (recharge top 30 cm soil to field capacity), 75% and 50% of the 100%, and 0% (rainfed) in Lincoln, Nebraska. The results showed that the Hybrid-Maize model simulated soil water balance well for the entire root zone, but underestimated the soil water balance at 0-30 cm and 60 cm to maximum rooting depth, respectively. For the fields at Mead, Hybrid-Maize model can reduce irrigation pumping by 93 mm during the season compared to actual irrigation scheduling by delaying the first irrigation and reducing the overall number of irrigation events. The Hybrid-Maize model performed well in a relatively wet year for biomass and grain yield simulation.

The test results indicated that producers can utilize this app for irrigation decision making. A business plan was proposed on how a startup can commercialize this type of agricultural-related apps or technologies to benefit producers.

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PREFACE

Chapter 2 has been submitted for publication in *Agronomy Journal*. (James Han, Dharmic Payyala, Haishun Yang. CornWater: An Irrigation Decision Support for Corn Fields. (submitted for publication in *Agronomy Journal,* October 2016).)

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Chapter 1

Behind the Development of the Irrigation App CornSoyWater -- What, Why, and How

Introduction

CornSoyWater (http://cornsoywater.unl.edu) was an application development project funded by the Water, Energy and Agriculture Initiative to develop an online irrigation aid for corn and soybean producers. It is a web-based application that can be used in a web browser of any desktop computer or mobile device. The goal was to use state-of-the-art quantitative agronomic sciences and information technologies, and in-season real-time weather data with field-specific crop management information to predict crop development and growth, crop water use and soil water balance to aid producers' irrigation decision making.

Background

The innovation of cener pivot, modern agricultural mechanization, and genetically modified crops have revolutionized the entire North American agricultural production in the last decades. Those innovations have doubled or tripled the crop yields and become the driving force for agroeconomics. However, with the need of raising the yield to the next level to feed the world and improve profitability, the current solution of increasing inputs (e.g. water, nitrogen, and control of abiotic stresses) to the system, or increasing production area does not always favor producers.

The good news is that by leveraging the power of quantitative simulation modeling and data science, the problem may have a better solution. The world is generating data in an unbelievable volume each day. To put it into perspective, the amount of data generated in one day is equivalent to that of 90 years of high-definition videos (Mikal Khoso, 2016). Even with only a fraction of the data related to food and agriculture, it is sufficient to make impacts on the industry by using the data in innovative ways. We have seen data-driven technologies change the way of how businesses operate. Millions of apps provide us various services at the speed of a single click on the screen. With the anticipation of technological revolution, agriculture is eager to ride the wave.

Problems

Although the agricultural-related data are available, the biggest obstacle is the gap of transforming data into usable information which producers can access and take corresponding actions. Years of science and basic research from academic institutions with billions of dollars of investment have tried to help producers improve their productivities and efficiencies. Successes have been made in breaking through some persistent obstacles such as helping producers adopt new farming practices to maintain a sustainable ecosystem while gaining high yields. However, many new practices and technological advancements promoted by academic institutions can take a remarkably long time for producers to adopt, simply because agriculture is not only a market-driven business but also a “culture”. Shooting for higher profits in the short term using familiar methods is always more desirable than trying something different with delayed benefits. Many times, the latest or most promising innovations from research might help farmers in the long run, but they may not show immediate tangible benefits in the short run because of limited research capital. Also, the science or research entities may not make adequate efforts in marketing and public relations, leading to the failure of their innovations to reach producers in a timely manner. Even if a product or service has reached producers, its maintenance can become a significant burden for keeping its function, not mentioning for its improvement, without revenue streams from the market or a further funding support. Countless examples of such products developed by university research have failed or disappeared after a couple of years or only has reached a fraction of its end users regardless of the quality of the product.

Solutions

One of the effective solutions is to bridge the gap between scientific products for agriculture and producers by startup entrepreneurs. A startup, a new business venture, can create disruptive innovation which combines technology and science with viable business models which can generate equity and deliver market values with minimum capital. A model of having startup partners with university research R&D sectors can be used to fill the gap and it will make innovation no longer far to reach. With university research experts developing the concept or prototype of a product while the startup refines the prototype of the product to a market ready level and tests it on the market, producers will be able to get their hands on the product faster. The benefit of this collaboration model is that it can accelerate the development iterations of a product. Usually, a product may experience an early failure by the testing of the market, which a research team from the university may not be able to solve by themselves. With the effort of the startup to pinpoint the defect of the current product or the real need for the product based on market feedbacks, the university side can pivot their research direction to things that matter to the majority of producers and keep improving the next generation of the product. Meanwhile, university research can get funding support from the collaboration startup to keep improving the science and technology of the product. This fast pace of the production-testing circle by collective efforts among university, startup, and producers can benefit all three sides.

So, how does a university research team bring its research product to a potentially commercial level in the first place? The answer is straightforward – to create a product which is close enough to a commercial level by combining science and information technology together. This is the focus of this dissertation. In the agricultural science research, scientists have reached a level that they can use the environmental conditions to predict how a crop is growing and developing or so-called crop modeling. This long known technology can benefit many consumers such as producers, crop consultants, insurance agents, etc., whoever needs to know what the crop yield is going to be at the end of a season. However, due to the complexity of operating a model, not everyone can easily make the model work even with proper training. After years of work, scientists have improved their models by furnishing them with friendly and intuitive user interfaces so that the consumers can use the models easily. Still, the accessibility and visibility of many programs are far from reach for a majority of consumers. In this dissertation, we discuss how we built a web-based irrigation app that can help producers on irrigation decision making. This app is a product which combined crop models, meteorological and environmental data using the latest web technologies. This is one step further to transform a research only product to a consumer friendly product.

However, the remaining question is how to answer the natural question from the users proactively when they receive such a program: “Can this program really predict yield/ water /nitrogen/ pesticide correctly?” The simple answer is that a model needs to be validated. A program may perform well for one region but may fail in another region because of the climate variation and/or management differences. Most times scientists cannot give a straight answer and also may not know whether or not the program will work for a given case. That is why validation and calibration of a model are two necessary steps to identify how well a model can be used to predict a particular case. In this dissertation, we focussed on validation of the model. By validating the model, we can conclude in what conditions the model can perform well, and vice versa.

Significance

Imagine how powerful it would be if a producer can make irrigation decision from his/her fingertips. The routine for irrigation management is time and labor consuming. During the cropping season, a producer gets up every day and needs to check the weather forecast on TV or the internet. Although producers can control a center pivot from a smartphone, he/she often needs to drive to the field to make crop and soil observations before deciding whether to irrigate. After walking into the field for scouting, he/she needs to check plants to determine whether the plant is currently or will soon be under water stress. In addition, he/she needs to check the soil to see if it is dry or wet. Very often, the spot he/she checked does not represent the whole field due to the spatial variation of the soil or crop, which can lead to misjudgment and irrigating either too early or too late. All the issues can be addressed effectively by using an app to support the irrigation decision making. The producer can make a decision in a second by the app recommendation without stepping out of the house.

Objectives

The objective of this study is to develop a user-friendly and reliable irrigation app using crop modeling science and information technology; we strive to make the prototype, an easy-to-use irrigation decision support tool. We also test and validate irrigation recommendations from the app against field observations. We hope the app can aspire and eventually reach its market potential by the AgTech segment, and contribute to irrigated agricultural production. The main focus of this dissertation is the development and testing of the app. In Chapter 2, I discussed how we brought a crop model into a web-based prototype app for corn irrigation guidance and the app performance on soil water balance prediction. In Chapter 3, I further tested the model's capabilities on estimating crop growth and development, which are the major intermediate components of the model outputs. The accuracy of those outputs are critical and also directly related to the soil water balance estimation and final irrigation recommendation. In Chapter 4, I upgraded the app by adding another crop model for simulating soil water balance in soybean fields to the app. The integrated app is called CornSoyWater (http://cornsoywater.unl.edu). I documented the development process of CornSoyWater along with the technical details. In Chapter 5, we summarized the findings from Chapters 2 to 4 and addressed how are we going to tackle remaining issues, which is centered around how a startup can utilize this technology by making it a viable business and benefit the consumers after the prototype is produced.

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Chapter 2

Field Validation of Soil Water Balance in CornWater, An Irrigation Decision Support for Corn Fields

Abstract

Irrigation decision making is critical for farmers in U.S. Mid-West because of the high demand for water during the peak of the growing season for corn and soybean fields. We developed CornWater (http://cornwater.unl.edu), a web-based app to help farmers improve their irrigation scheduling for corn fields. CornWater uses real-time weather data with a 10-d forecast and web-based simulation to predict current and future 10-d crop stage, root-zone soil water balance, and possibility of crop water stress. The trigger for irrigation is the emergence of crop water stress, which in turn is quantified by the larger of the water depletion stress (WDS) and evapotranspiration water stress (ETS). We used 5-yr field data to test the performance of CornWater. Results showed CornWater simulated well the overall root zone soil water balance (RMSE = 25 mm, EF = 0.46), but underestimated the soil water amount at 0-30 cm and 60 cm to rooting depth, respectively. Simulated ET matched measured ET better in irrigated fields than the rainfed field. Using CornWater can save irrigation water by 93 mm during the season compared with actual irrigation scheduling by delaying the first irrigation and reducing the overall number of irrigation events. CornWater can help farmers irrigate their fields at the most needed time with less field scouting.

Abbreviations: ET, evapotranspiration; WDS, water depletion stress; ETS, ET stress; LAI, leaf area index; GDD, growing degree days

Introduction

Irrigation management is one of the important farming practices in western US Corn Belt as it directly affects yield (Payero et al., 2009). Missing irrigation at critical crop growth stages can cause crops to suffer water stress and yield loss. Most farmers use traditional “look” and “feel” approaches to make irrigation scheduling decision during growing season (USDA-NASS, 2012). Typically, they scout their fields, check crop stage, look for signs of crop water stress, assess soil water condition, and determine if irrigate or not (USDA-NASS, 2012). The traditional irrigation scheduling methods are time consuming as they require frequent field scouting. Moreover, traditional hand-feel based assessment of soil water condition is empirical, less quantitative, and can be biased if a field has significant spatial variability in topography or soil properties. Meanwhile, more and more farmers have adopted new technologies for assisting irrigation decision making (USDA-NASS, 2012). For example, 10% of farmers used soil water sensors to monitor soil water status in the fields and 8% farmers used daily crop ET reports for irrigation guideline. Using sensors to monitor soil water leads to objective and quantitative assessment of soil water condition, but the results may only represent the specific spots of the field where the sensors are installed and not the entire field. In addition, malfunction of sensors can cause farmers to make wrong irrigation decisions. Daily crop ET report normally covers a large area and the values are too general, while the crop in a specific field can be significantly different from the norm in terms of crop stage, plant population, and tillage management. Even with ET reports from various weather services from public or private institutions, farmers still need to process and convert the raw data to intuitive information for crop management decision making. At present, this step still lags behind or totally missing. For example, farmers need to manually track cumulative rainfall from daily weather report for individual fields when the crop is sowed at different dates, and they also need to keep separate water balance sheets for different fields because of differences in soil properties and crop management (Kranz et al, 2008). Although farmers make right decisions in most cases, sometimes they make mistakes because of unexpected weather conditions or simply errors in their manual calculations on water balance.

The improvement of internet coverage and speed in the rural areas has made it possible for information technology products such as irrigation scheduling apps to tap into conventional farming practices (Vellidis et al., 2016; González Perea et al., 2016; USDA 2015). For instance, using mobile applications, farmers can remotely control center pivots from their homes. The improvement of the weather forecast in recently years and easier data accessibility have also made it possible to incorporate short-term future weather conditions into irrigation decision making (Migliaccio et al., 2016; Fraisse et al., 2006). Migliaccio et al. (2016) developed the SmartIrrigation apps for providing real-time irrigation schedules for crops including avocado, citrus, cotton, peanut, strawberry, and vegetables for southeastern USA. The apps run simulation models on the server using weather data from online sources and crop and soil data from users to provide decision support for crop management. Andales et al. (2014) developed an online irrigation management system which estimates soil water dynamic of various crops in Colorado. Another integrated research and extension project Useful to Usable (U2U) has grabbed farmer attention by providing various weather graphic summaries supported by climatologists' study (Dai et al., 2016). Meanwhile, private sectors have utilized weather data and remote sensing technology to produce a series of integrated online farming management platforms, such as Farmlogs online product and FieldView from the Climate Corporation (Carbonell, 2016). Such apps and platforms can significantly facilitate farmers to improve their farming efficacy and can potentially reduce farming costs.

The objectives of this study were to 1) introduce CornWater, an irrigation app which simulates soil water balance for a corn field and predicts crop water stress for coming days, 2) test CornWater app for its performance against measured field data, and 3) compare the irrigation amount recommended by the app with the actual irrigation records.

Materials and Methods

What CornWater does

The CornWater app (http://cornwater.unl.edu) uses user specified, field-specific crop and soil data, and real-time weather data with a10-d forecast as input and a tailored corn-specific simulation model as a processor. It predicts crop growth, soil water consumption, and root-zone soil water balance. It estimates the possibility and magnitude of crop water stress to recommend the date for the next irrigation for stress-free crop growth. CornWater also takes into account the time required to complete irrigation for a common field when making a recommendation for irrigation. The availability of real-time weather data determines where the app can be used. The weather data of the app is from the weather stations of Automated Weather Data Network (AWDN) operated by the High Plains Regional Climate Center (HPRCC; http://www.hprcc.unl.edu). The AWDN collects weather data on a daily basis and stores the data in a server after quality control. The AWDN has 225 active weather stations which cover most farming areas of Nebraska, and part of Colorado, Iowa, Kansas, Minnesota, Missouri, Montana, North Dakota, and Wyoming. In addition, we also have access to Michigan Automated Weather Network (MAWN) which covers the Michigan state. Currently, CornWate can be used by the western part of the U.S. Corn Belt.

How CornWater works

CornWater is very simple, intuitive, and straightforward to use, even for a first-time user. First, go to the CornWater homepage at http://cornwater.unl.edu in a web browser. A new user can click “Try” button without the need for account registration. The user will be asked to specify a field on the Google Map in the app and provide crop and soil information of the field as indicated in Fig 1. Graphic results will be shown immediately on this “demo” field (Fig. 1). The user can also register an account for free. After registration for an account and logging into it by the username and password, the user will need to locate each of his/her fields on the Google Map by clicking at the center of a field. In the background, CornWater will use the coordinates of the location to determine the closest weather station in the network and retrieve the weather data as the input of the model. If the nearest weather station is beyond a threshold distance, which is currently set at 32 km, CornWater will pop up a warning message and disqualify the field because the simulation results may not be accurate due to that rainfall is highly variable. After that the user also needs to provide crop information, including 1) hybrid relative maturity (days), 2) date of planting, 3) plant population (*1000/ha), 4) maximum soil rooting depth, 5) soil surface residue coverage (%), 6) representative topsoil texture and bulk density, and subsoil texture, and 7) soil water balance of top 30 cm and below 30 cm at planting. If irrigation has been applied, the user also must provide irrigation dates and amount in an irrigation record table in order to receive up-to-date simulation results.

After clicking the “Proceed” button, CornWater produces a result page which shows in a graph with the date on the X-axis. The graph includes crop stage, past rainfall events and irrigation record, and the dynamics of the amount of soil available water in the root zone along with the threshold line for irrigation. The prediction is up to date with a forecast of the next 10 d. A notification message shows at the top of the web page in either green or red color: recommendation for irrigation in red if crop water stress is predicted for the next 10 d, or no-irrigation recommendation in green if no water stress is predicted in the next 10 d (Fig. 1). The recommendation for irrigation also suggests considering possibilities of rainfall in the near future. Below the graph, a summary table shows the user specified crop and soil data, up-to-date total water input (rain and irrigation) and crop water use.

Model mechanism

The core of CornWater is Hybrid-Maize (http://hybridmaize.unl.edu/; Yang et al, 2004, 2006), a simulation model for corn. Briefly, Hybrid-Maize model combines corn-specific crop development functions of CERES-Maize model (Jones et al., 1986), and generic mechanistic models of plant physiology such as WOFOST (Diepen et al., 1989) and INTERCOM (Kropff and Spitters, 1992; Kropff et al., 1992; Yang et al., 2004). Hybrid-Maize model has been tested and validated primarily in rainfed and irrigated corn system of Nebraska and Iowa (Yang et al., 2004, Grassini et al., 2009).

The critical role of crop simulation in CornWater is to predict 1) crop stage, 2) root depth and length density distribution in the soil profile, 3) potential requirement for crop water uptake as determined by weather, 4) actual crop water uptake as determined by root distribution and soil water condition, and 5) crop water stress. Below is a brief description of Hybrid-Maize functions related to the functions summarized above. Detailed and complete description of the model formulation is in Yang et al. (2013).

1) Root depth and soil water uptake

Root growth starts from germination and stops shortly after silking. Root depth (RD) increases until root growth stops and is simulated as:

$$RD = GDD10 * RGR$$

$$RGR = \frac{\mathrm{RDpotential}}{1.15 * GDD_{\mathrm{silking}}}$$

where GDD10 is GDD from sowing using a base temperature of 10 ^{o}C, and RGR is the root growth rate (cm per GDD10). And RDpotential is the depth corn root potentially can reach (default = 1.5 m), but the increase of root depth will stop at the maximum rooting depth (RD_{max}) set by users for a specific field and RD_{max} is smaller or equal to RDpotential.

The rooting depth is divided into layers of 10 cm depth. Water uptake at each layer is determined by the root density and soil water pressure. At early stage of growth when the plant is small and rooting depth is shallow (less than 30 cm), root density distribution was assumed to be a V shape and estimated as:

$$\mathrm{WUweight}_{\mathrm{absolute}} = \exp\left(\frac{-VDC * \mathrm{Depth}_{\mathrm{layer}}}{RD}\right)$$

$$\mathrm{WUweight}_{\mathrm{relative}} = \frac{\mathrm{WUweight}_{\mathrm{absolute}}}{\Sigma \mathrm{WUweight}_{\mathrm{absolute}}}$$

where $\mathrm{Depth}_{\mathrm{layer}}$ is the depth of the layer to its bottom. RD is the current rooting depth. VDC is the vertical distribution coefficient that determines the shape of the exponential function, $WUweight_{absolute}$ and $WUweight_{relative}$ are the absolute and relative layer weight for water uptake, respectively. The greater the VDC value is, the greater the WUweight is for upper layers. As the upper part of roots will cross into neighboring rooting zone when the root system grows deeper, it leads to an effective rectangle shape root zone while the deepest 30 cm root still keeps the V shape.

2) Crop ET

Three terms related to ET are used bellows. They are reference ET (ET_0), potential ET (ET_{pot}), and actual ET (ET_{act}). ET_0 refers to grass-referenced FAO Penman-Monteith evapotranspiration provided in the weather data (Allen et al., 1998), ET_{pot} refers to ET at current canopy size with adequate water supply in soil, ET_{act} is co-determined by ET_{pot} and current soil water condition.

CornWater calculates ET_{act} by separate procedures of soil evaporation and crop transpiration. First, ET_0 is adjusted for corn if its canopy is largely closed (i.e., around LAI of 4 or greater) because corn with a closed canopy has an ET about 1.2 times of the reference grass (Allen et al., 1998). To make the adjustment smooth from 1 to 1.2, the adjustment starts from LAI 3.5 and ends at LAI 4.5 as:

If LAI < 3.5 than $adjET_0 = ET_0$

else $adjET_0 = ET_0 * 1.2 * (LAI – 3.5) / (4.5 – 3.5)$

$adjET_0 <= 1.2 * ET_0$

Where $adjET_0$ is the adjusted ET_0. Second, the potential transpiration at current LAI ($Transp_{pot}$) is estimated from $adjET_0$ as:

$$Transp_{pot}=adjET0*[1-exp(-LAI*k)]$$

where k is the canopy light extinction coefficient. $Transp_{pot}$ indicates the maximum transpiration under the condition.

Third, the potential evaporation ($Evap_{pot}$) is estimated by considering the effect of soil coverage by crop residues (Rosenberg et al., 1983):

$$Evap_{pot} = (adjET_0 - Transp_{pot}) * exp(-soilCoverFrac)$$

in which soilCoverFrac is the fraction of soil surface covered by crop residues. Then, the actual evaporation was estimated using the two-stage approach in FAO report 56 (Allen et al., 1998) with evaporation soil depth set to top 10 cm soil. The maximum evaporable amount of soil water is the amount of field capacity to 50% of the value of permanent wilting point. Actual evaporation rate ($Evap_{act}$) is at $Evap_{pot}$ when soil content is greater than a level equivalent to 70% of total evaporable soil water. When the top 10 cm of soil becomes drier, $Evap_{act}$ is estimated as:

$$Evap_{act} = \frac{Evap_{pot} * (Theta - 0.5*PWPtheta)}{step2threshold * (FCtheta - 0.5*PWPtheta)}$$

where Theta, FCtheta, and PWPtheta are the topsoil volumetric water content in fraction, field capacity, and permanent wilting point, respectively, and step2threshold is the fraction in total evaporable soil water below which evaporation changes from stage 1 to stage 2, and is set at 0.7.

After that, the maximum crop water uptake ($Uptake_{max}$) is estimated from soil water status and root distribution at each soil layer. For each layer with presence of roots, $Uptake_{max}$ is estimated as:

$$Uptake_{max} = \frac{(PSI_{leaf} - PSI)}{(Rplant + Rroot) * WUweight_{relative}}$$

where PSI is soil water potential of the layer, PSI_{leaf} is the leaf water suction (=17000 cm). R_{plant} (d^{-1}) is the resistance of the plant to water flow (=9690 d^{-1}). $WUweight_{relative}$ is the relative weight of that soil layer for water uptake and is calculated from root length density of that layer relative to the total root length density. Then, total maximum water uptake is calculated from the sum of $Uptake_{max}$ of each layer. Finally, actual transpiration ($Transp_{act}$) is obtained from the smaller one between $Transp_{pot}$ and $Uptake_{max}$.

3) Soil water balance

CornWater calculates daily water balance as:

$$W = W_{d-1} - Evap_{act} - Transp_{act} + P + I - RO$$

where W is the soil water amount at the end of a day, W_{d-1} is the soil water balance of the previous day, $Evap_{act}$ is the actual soil evaporation, $Transp_{act}$ is the actual soil transpiration, P is the precipitation for that day, and I is irrigation amount of that day. Runoff (RO) is also estimated using the simplified curve number method as in Soltani and Sinclair (2012).

4) Crop water stress

CornWater estimates two water stresses indices: water depletion stress (WDS) and ET stress (ETS). Soil available water threshold ($AW_{threshold}$, in fraction) for triggering irrigation is set at 0.5 of available water depletion when the crop starts to sense water stress (Grant et al., 1989). WDS is calculated as:

$$WDS = 1 - \frac{\mathrm{AW}}{\mathrm{AW_{threshold}}}$$

where AW (in fraction) is total available water in soil rooting zone. WDS ranges from 0 to 1, with 0 for no stress and 1 for complete stress and stop of photosynthesis for that day. A future version of the app will allow users to modify $AW_{threshold}$. In addition, CornWater also estimates ETS, because under certain circumstances crop can still suffer from water stress even when soil is relative wet, but water supply from soil cannot meet water demand from the weather condition. ETS is estimated as:

$$ETS = 1 - \frac{\mathrm{Transp_{act}}}{\mathrm{Transp_{pot}}}$$

where ETS is ET stress, $Transp_{act}$ is actual transpiration, and $Transp_{pot}$ is potential transpiration. CornWater uses the greater value between WDS and ETS as the final water stress for that day.

5) Irrigation recommendation

Irrigation recommendation was on the basis of avoiding the occurrence of water stress. Whenever water stress is about to occur, the model will trigger a recommendation of irrigation. If the user takes the recommendation and irrigates, the actual date and irrigation amount must be specified in the irrigation log of the app so that the app will update soil water balance.

Field experimental data

We used a 5-yr field dataset (2001 to 2005) collected from University of Nebraska Agricultural Research and Development Center at Mead, NE to test the performance of CornWater. The dataset were collected from three production-scale (from 49 to 65 ha) fields. Site 1 (i.e., the first field, 41°09'54.2" N, 96°28'35.9"W) was irrigated continuous corn. Site 2 (i.e., the second field, 41°09'53.5" N, 96°28'12.3" W) was next to Site 1 and was irrigated corn-soybean annual rotation. Both Sites 1 and 2 were equipped with center pivot irrigation systems. Site 3 (i.e., the third field, 41°10'46.8" N, 96°26'22.7" W) was rainfed corn-soybean annual rotation. In total, there were 11 site-year combinations, including five yr of Site 1, and three yrs for Sites 2 and 3, respectively as Sites 2 and 3 were planted soybean in 2002 and 2004. Before 2001, both Sites 1 and 2 had a 10-yr of corn-soybean rotation under on-till, while Site 3 had various crops with conventional tillage (Hunt et al., 2014). All three sites were uniformly tilled by disking before the initiation of the study (Verma et al., 2005), and had been under no-till since initiation in 2001, except Site 1 was disked again in 2005 (Suyker and Verma, 2009). The predominant soil texture of the three sites was silty clay loam (Verma et al., 2005), with volumetric water content at field capacity of the top 1 m depth at 0.41 for Sites 1 and 2, and 0.39 for Site 3 (Suyker and Verma, 2012). Table 1 summarizes crop and management information on the study sites. The weather data for the three sites were obtained from an automated weather station that was very close to Sites 1 and site 2, and 2.4 km from Site 3. Augustine (2010) suggested the rain gauge should be installed within 2 km of a field to represent the accurately on-site precipitation in Colorado area. So we assume the precipitation records were representative of the three sites.

Soil water measurement

At three locations within each field, the Dynamax Theta probes (Delta-T Devices, Cambridge, UK) were installed at 10, 25, 50, and 100 cm soil depths in the spring of 2001 for monitoring volumetric water content. The soil water sensors were installed at a 45° angle from the surface at the 10 and 25 cm depths and were installed by a drip loop method at 50 and 100 cm (Hunt et al., 2014). Sensors at 10 and 25 cm were temporarily removed during planting and harvest operations and reinstalled at the same locations later. Sensor readings were logged on an hourly basis but averaged daily for final output. Senor data of the same depth at the three locations in each field were averaged to represent that depth of the field. The data of 10 and 25 cm, 25 and 50 cm, and 50 and 100 cm were averaged respectively to represent water content at 0-30, 30-60, and below 60 cm to the maximum rooting depth layers in order to match the output of soil water balance of the CornWater app. Because the deepest sensors were at 100 cm, we compared the total water amount at the 100 cm soil depth for irrigated sites and 120 cm soil depth for the rainfed site with our model simulation, respectively.

ET measurement

Eddy covariance flux method was used to measure ET (Baldocchi et al., 1988). An open-path infrared CO2/ H2O gas analyzing system (Model LI7500: Li-Cor Inc., Lincoln, NE) and an omnidirectional 3D sonic anemometer (Model R3: Gill Instruments Ltd., Lymington, UK) were installed to measure vertical transfer of water vapor for each site (Suyker and Verma, 2009).

Calibration of input settings to model

Input settings for model simulation should be independent of a model and representative of the actual situation. In reality, however, some input settings are either difficult to measure, or measured values do not completely represent the real situation due to either temporal changes through the simulation period or spatial variation across the simulated space. In this study, we calibrated the values of several input settings, including bulk density, rooting depth, and soil water content at planting.

We first used measured bulk densities at soil depth of 5, 15, 30, 60, and 90 cm as model inputs setting for simulation. For the first year (i.e., 2001), however, we increased the topsoil (0-30 cm) bulk density by 5%, because the samples for topsoil bulk density was collected soon after the initial disk tillage before planting of 2001, and as a result; the topsoil likely experienced compaction during the 2001 growing season (Häring et al., 2013). The bulk density below 30 cm was used to calculate porosity as a model input parameter. Measured soil water data showed water content did not change significantly at 100 cm depth during growing season for the irrigated sites across years, while the rainfed site showed water depletion at this depth. As a result, we set 100 cm as the maximum rooting depth for the irrigated sites and 120 cm for the rainfed site, respectively. As soil water sensors were temporarily removed during planting operations and no directly measured soil water data available as input soil water content at planting time, we used the best value that would match simulated water balance with measured value after planting date.

Statistical measures

We compared the simulated soil water balance with the measurement throughout each of the growing seasons. We also compared the irrigation recommendation from the model and actual management record.

The performance of model was evaluated by root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), and modeling efficiency (EF):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - M_i)^2}$$

$$MAE = \frac{\sum_{i=1}^{n}|S_i - M_i|}{n}$$

$$MBE = \frac{\sum_{i=1}^{n}(S_i - M_i)}{n}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}(M_i - \overline{M})^2}$$

Where S_i is the simulated value, M_i is the measured value, n is the number of data pairs, $\overline{M}$ is the average of measured value. RMSE measured the deviation of overall mean between simulated and measured values with values close to zero indicating good model performance. RMSE has the same unit as S_i and M_i thus it is easy to interpret, however, large errors can be weighted heavily (Willmott, 1982). MAE is the absolute value of simulated minus measured results which is more objective compared with RMSE to examine overall model error although RMSE is more widely used. MBE directly indicates if the model underestimates (negative value) or overestimates (positive value) the measured values and meanwhile offers uniformity of error distribution. EF ranges from -∞ to 1. An EF value close to 1 indicates better model performance. In crop modeling, EF = 0 is considered as the lower limit of model quality (Wallach et al., 2006).

Results and Discussion

Soil water balance

Overall, CornWater simulated reasonably well the daily soil water balance to the maximum rooting depth for all the growing seasons with the EF of 0.46 (Fig. 2, Table 2). On average across all 11 site-year combinations, the simulated daily soil water balance to the maximum rooting depth was 25 mm from the measurements (based on the RMSE). The linear regression of the simulated daily water balance with the measured values was y= 19.5 + 0.925x, R^2 = 0.62 (Fig. 2). Although the slope of the regression showed a slight deviation from 1:1 line, most points are around the 1:1 line. In site 3, CornWater did not simulate as well as Sites 1 and 2. In general, the measured and simulated values had a tendency to agree with each other when soil water balance was close to 300 mm.

For seasonal dynamics of daily soil water balance during the growing seasons, CornWater simulations demonstrated acceptable agreement with the measured values (Fig. 3). Nevertheless, several site-year combinations showed poor agreement between simulations and measurements. For Site 1 in 2002, the model underestimated soil water balance during June and July (DOY 152 - 212) with EF of -3.28, MAB of -25 mm, and MAE of 36 mm (Table 2). A negative EF value indicates the model cannot even use the average of observed values to predict every situation for this site (Garnier et al., 2001). The greatest differences between simulated and measured daily soil water balance occurred at Site 3 in the late season of both 2001 and 2005, where the model underestimated daily soil water balance by 100 and 50 mm, respectively (Fig. 3). Meanwhile, measured soil water balance showed a smoother trend compared to the simulated results for the two irrigated sites, and was less responsive to irrigation as well (for example, Sites 1 and 2 in 2003 before August 1st on DOY 213.

Figures 4-6 showed daily soil water balance of 0-30, 30-60, and 60 cm to the maximum rooting depth, respectively. For the 0-30 cm soil depth, simulated values showed an overall overestimation compared with measured ones by an average of 50 mm after June (DOY 160) at the two irrigated sites (Fig. 4). At Site 3 in 2001 and 2003, however, the simulated daily soil water balance underestimated measured values.

For the 30-60 cm soil depth, the model simulated more intense water withdrawal during the middle of the season than measured results (Fig, 5). Moreover, the simulated soil water balance showed stronger response to water input from precipitation and irrigation than measured results. Overall, the model tended to underestimate soil water balance from the beginning of July (DOY 182) even with significant rainfall or irrigation events, e.g., Site 1 in 2002 and 2005 showed such a trend. Site 3 in 2001 and 2005 showed much less water recharge in the simulation compared with the measured ones after August (DOY 213).

For the soil layer of 60 cm to the maximum rooting depth, the model simulated significant water withdrawal in most site-year combinations while measurements showed little water withdrawal from this depth in most cases (Fig. 6). In many cases, the model underestimated daily soil water balance at the deepest soil depth. Taking Site 1 in 2002 for instance, the measured soil water was 100 mm higher than simulated at the end of the season.

ET

The simulated cumulative ET was consistently greater than measured ET except in Site 3 in 2001 and 2003, especially during early season (Fig. 7, Table 3). Simulated ET underestimated measured ET by 107 mm at Site 3 in 2003 at the end of the season which was the greatest difference among all site-year combinations. Meanwhile, average daily simulated ET was 0.9 mm lower than measured at the same site and year.

Irrigation recommendation

The main purpose of CornWater app was to estimate soil water balance and optimize irrigation timing and probable water saving. CornWater recommended less irrigation water than the actual management by 93 mm (Table 3). The difference in the irrigation amount recommended by the model and actual management can be large. For instance, at Site 1 in 2005, the recommended irrigation amount was 160 mm or 56% of the 280 mm of the actually applied. Also, the app suggested first irrigation after July 1st (DOY 182), which was later than the first actual irrigation date.

Discussion

Soil water balance

The model can simulate daily soil water balance reasonably well. However, the simulation performance for the rainfed site was less satisfactory than irrigated sites. The model predicted the rainfed sites experienced water stress at the late of the season (data not shown) which can change the behavior of crop growth and development. Moreover, the changes will also affect crop water uptake. The model may not accurately capture all the interactions between water stress and crop growth and development. So it created a greater deviation on simulated soil water balance from the measurement for the rainfed site compared with the irrigated sites.

On the seasonal dynamics of soil water balance, the model performed well. However, some mismatch between measured and simulated inevitably showed on daily soil water balance of total or each soil layer. The main reason for the mismatch is the model assumed soil would reach equilibrium at the end of the day regardless rainfall amount, intensity and the time. The assumption can be valid for sandy soil, while less likely for other types of soils with a significant amount of clay. In reality, the soil may reach equilibrium after a few days after rainfall. Thus, a direct comparison of day-by-day measured and simulated soil water balance can be tricky. The measured soil water balance could lag for two days compared with today's simulated soil water balance under a silty clay loam condition. Moreover, because the ET consumption by the crop is considered on a daily basis, it could guarantee even with a perfect simulation, the measured soil water balance at two days later would not be the same but less than today's simulated soil water balance.

Site 3 (rainfed) had a great difference between measured and simulated soil water balance in 2001 and 2005, respectively. This difference might be caused by unrepresentative rainfall inputs to the model. Because the weather station is 2.4 km away from Site 3 and summer rainfall may vary significantly within a short distance.

Differences in rainfall amount between weather station report and onsite received can cause significant simulation deviations. In addition, if the actual rainfall occurred across 24:00 (i.e., midnight) when the weather stations upload data to the server, the amount of rainfall after the midnight will be recorded as an input for the next day's calculation, which can disturb the daily comparison of measured and simulated soil water balance. For Site 3 in 2001, the rapid increase in measured water balance during the late season was likely caused by formations of cracks after an extended dry period, leading to quick infiltration of rainfall to deeper depths.

Meanwhile, the smoother trends of measured soil water balance compared with simulation can be due to the fact that the measured daily results were the averages of three sensor measurements of the same depth but at different locations in each site. Water input from a center pivot forms a line across the field and revolves gradually with a cycle time of three to four d to cover an entire field, resulting in a gradual change of soil water balance over the duration of pivot operation.

CornWater simulates the field as a whole and assumes that an irrigation event happens on one day. To address this complexity, a producer could use CornWater to simulate the stop position in his field (the last position to receive water during a center pivot revolution), and could initiate irrigation early enough so that the revolution is completed and the stop position is irrigated before water stress occurs. In this way, the producer would be managing for the driest point in the field.

In the model, simulated root depth and root density distribution directly determines where and the amount of the water uptake. However, the root architecture and water uptake depend much on the availability of water and nutrients, as well as soil structure. In our case, the frequent irrigation and no tillage in previous years may have resulted in thick lateral roots in the upper layers of soil. It has been reported that corn growth under no-tillage conditions can produce more roots at top 10 cm soil layers compared with corn in tilled fields (Krishna 2012). This report may explain the more aggressive water withdrawal at 0-30 cm depth from the model simulation (Fig. 4). Fig. 4-5 suggest that most of the roots concentrate on the top 60 cm which presumably is responsible for water update (Peng et al., 2012). Meanwhile, many studies have shown that corn roots can reach 1.5 m soil depth when growing with no constraints (Dardanelli et al., 1997; Djaman and Irmak, 2012). When upper soil layers are dry, however, roots tend to be more active in deep layers (Sharp and Davies, 1985). Besides, the model parameters for root growth are not specifically for Pioneer hybrid (Table 1), which may lead to differences in root density in the simulation and reality (York et al., 2015). Ning et al.(2014) reported that roots of modern corn hybrids are larger and deeper post-silking than old hybrids. Nevertheless, accurate simulation of the top 30 cm root density distribution is important because it directly affects soil water update and the irrigation requirement. Leitner et al. (2014) recommended a 3D root architecture for a better understanding of root functions.

Simulated soil water balance responded instantaneously to rainfall or irrigation, especially for the top 30 cm layer (Fig 4), whereas the responses of soil water sensors were more slow and gradual. The differences in the response were most drastic in the deepest layer. The reason was that the model used a cascading method (the so-called "tipping bucket" method) which satisfies the top soil layer recharge to field capacity first before allocating water to layers underneath. This method was simple and straightforward at a daily time scale (Jones et al., 1986). However, when it came to the soil water simulation at deeper depths, the equilibrium arrives without delay, which is not very realistic, especially for soils of moderate to heavy textures. The Richards method (Richards, 1931) may work better (Buttler and Riha, 1992). Richards method allows water to move to the underneath layers while the upper layer is still being recharged. This can be shown in Site 3 in 2005. When an irrigation event occurred before August 1 (DOY 213), the rise of measured soil water of the top 30 cm was less compared with the simulation, whereas at 30-60 cm depth the measurement increased more than simulation (Fig. 4-5). In addition, soil cracks or difference between actual precipitation in the field and recorded weather data may have also contributed to the increase of measured soil water at 30-60 cm and the below.

ET

The reason for simulated cumulative ET greater than measurements could be the no-till system with a significant amount of residues left in the field, which reduced the early season ET in those sites as reported by Suyker and Verma (2009). At Site 3 in 2001 and 2003, the water stress predicted by the model at the late season (data not shown) was directly related to the simulated lower actual ET compared with measured ones.

Irrigation recommendation

For Sites 1 and 2, irrigation recommendations of the app would reduce irrigation pumping by 93 mm per season on average, which was about three rounds of center pivot operations. This is significant not only for reduced water withdrawals but also operational costs, assuming $800 to $1000 per round of center pivot operation (Dumler et al., 2007).

A further question would be whether irrigation pumping reduction may affect corn yield. To answer this question, we need to compare the measured daily cumulative ET with the model estimations. Site 3, the rainfed site, was more likely to experience actual ET lower than the ET demand. For instance, model simulation suggested that Site 3 in 2003 had 107 mm lower ET than the ET demand due to drought in soil. On average, the difference between simulated and measured total ET was 49 mm, which was about 10% of total measured ET. Such a difference is not considered significant for field studies at such a large scale. However, with a lower simulated total ET, the yield can be affected since crop yield usually has a linear response to cumulative ET (Tolk et al., 1998). Still, it is hard to conclude the effect of the lower simulated total ET on yields. A side-by-side experiment is needed for direct comparison of grain yield under conventional irrigation schedule and CornWater irrigation scheduling. Predicting water stress accurately is the key to protecting yield when it comes to pumping reduction. For the 16 major corn models, the Hybrid-maize model 2014 version, which runs on the backend of CornWater, was one of a few models which used water depletion stress and evapotranspiration water stress mechanisms together to determine the water stress (Jin et al., 2016). CornWater had this feature because there could be cases where one of the mechanisms does not capture crop water stress but another does. By using this double mechanism, CornWater became more reliable to estimate the water stress.

In summary, the CornWater app can perform satisfactorily at the irrigated sites, but less so in the rainfed site. The performance of the model was good for daily soil water balance at the total rooting depth but less satisfactory at 0-30, 30-60, and below 60 cm depths. Future improvements in the model include input accuracy, model functions on water flow at certain soil types, and ET simulation.

Conclusion

With the fast improvement of internet coverage and speed worldwide, model-based apps like CornWater can remotely estimate soil water balance in the field and predict water stress using real-time weather data and increasingly reliable weather forecasts.

This study showed that with user specified crop management data and major soil properties, the CornWater app can estimate overall daily soil water balance of the entire rooting depth and predict future crop water stress reasonably well for the purpose of irrigation scheduling. However, the model still showed relatively significant differences in water balance for individual soil depths. The overestimation of ET can be one of the reasons for poor simulation of the 0-30 cm soil water. Another reason could be the cascading method in the model for simulating soil water balance, which could be improved by using the Richards method, especially if hourly water input data becomes available. When rainfall data come from an instrument not installed on-site, representation of rainfall to the field can be a potential issue for simulation accuracy. On-site rain gauges, or spatially interpolated rainfall data may lead to better simulation results. We are deploying an upgraded product, which combines CornWater with SoyWater (http://soywater.unl.edu), a soybean irrigation app developed by University of Nebraska - Lincoln Soybean team. The new app is called CornSoyWater (http://cornsoywater.unl.edu). CornSoyWater app is available for downloading from Apple Store or Google Play.

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Table 1. Corn crop information of three experimental sites near Mead, NE.

Year& Site	Hybrid	Maturity, GDD	Planting date	Population, 1000/ha	Simulated date of R6	Observed date of R6
2001&1	Pioneer 33P67	1511	10-May	82	9-Sep	19-Sep
2001&2	Pioneer 33P67	1511	11-May	81	9-Sep	18-Sep
2001&3	Pioneer 33B51	1472	14-May	53	8-Sep	12-Sep
2002&1	Pioneer 33P67	1511	09-May	81	5-Sep	17-Sep
2003&1	Pioneer 33B51	1472	15-May	77	17-Sep	23-Sep
2003&2	Pioneer 33B51	1472	14-May	78	17-Sep	17-Sep
2003&3	Pioneer 33B51	1472	13-May	58	5-Sep	05-Sep
2004&1	Pioneer 33B51	1472	04-May	80	20-Sep	30-Sep
2005&1	Pioneer 33B51	1472	04-May	69	31-Aug	22-Sep
2005&2	Pioneer 33B51	1472	03-May	76	31-Aug	16-Sep
2005&3	Pioneer 33B51	1472	27-Apr	54	31-Aug	20-Sep

Table 2. Statistical summary of CornWater performance on simulation of daily soil water balance to the maximum rooting depth (100 cm for the irrigated sites and 120 cm for the rainfed site) during the growing seasons. N is the sample size, RMSE is the root mean square, MAE is the mean absolute error, MBE is the mean bias error, and EF is the modeling efficiency. Year 2001 had fewer data points because the soil moisture sensors were installed later than other years.

Year&Site	N	MBE, mm	MAE, mm	RMSE, mm	EF
2001&1	82	17	20	27	-0.24
2001&2	82	13	19	23	-1.77
2001&3	81	-22	25	37	0.58
2002&1	120	-25	36	40	-3.28
2003&1	126	3	15	18	0.45
2003&2	124	-3	9	12	0.68
2003&3	116	2	8	10	0.98
2004&1	140	0	11	14	-1.4
2005&1	120	-5	14	20	-1.8
2005&2	121	-14	15	18	0.3
2005&3	127	1	34	38	-0.06
Pooled data	1239	-3	18	25	0.46

Table 3. Growing season total water inputs and outputs, and model recommended and actual irrigation amount. The unit for all variables is mm. Total water loss (total of leaf interception, runoff, and percolation), Total ET demand, and Total simulated ET were simulated from the Hybrid-Maize model by weather data and soil type.

Year& Site	Type	Actual irrigation	Model recommended irrigation	Total rainfall	Total water loss	Total simulated ET	Total measured ET	Simulated minus measured ET
2001&1	Irrigated	300	185	242	71	498	505	-7
2001&2	Irrigated	292	183	242	74	501	466	35
2001&3	Rainfed			242	67	347	428	-81
2002&1	Irrigated	271	223	339	48	552	474	78
2003&1	Irrigated	313	213	196	23	507	494	13
2003&2	Irrigated	297	212	197	18	508	531	-23
2003&3	Rainfed			149	11	297	404	-107
2004&1	Irrigated	191	128	352	90	526	472	54
2005&1	Irrigated	283	160	271	65	524	450	74
2005&2	Irrigated	270	160	271	66	536	471	65
2005&3	Rainfed			271	15	414	421	-7
Average		276	183	256	42	474	465	49

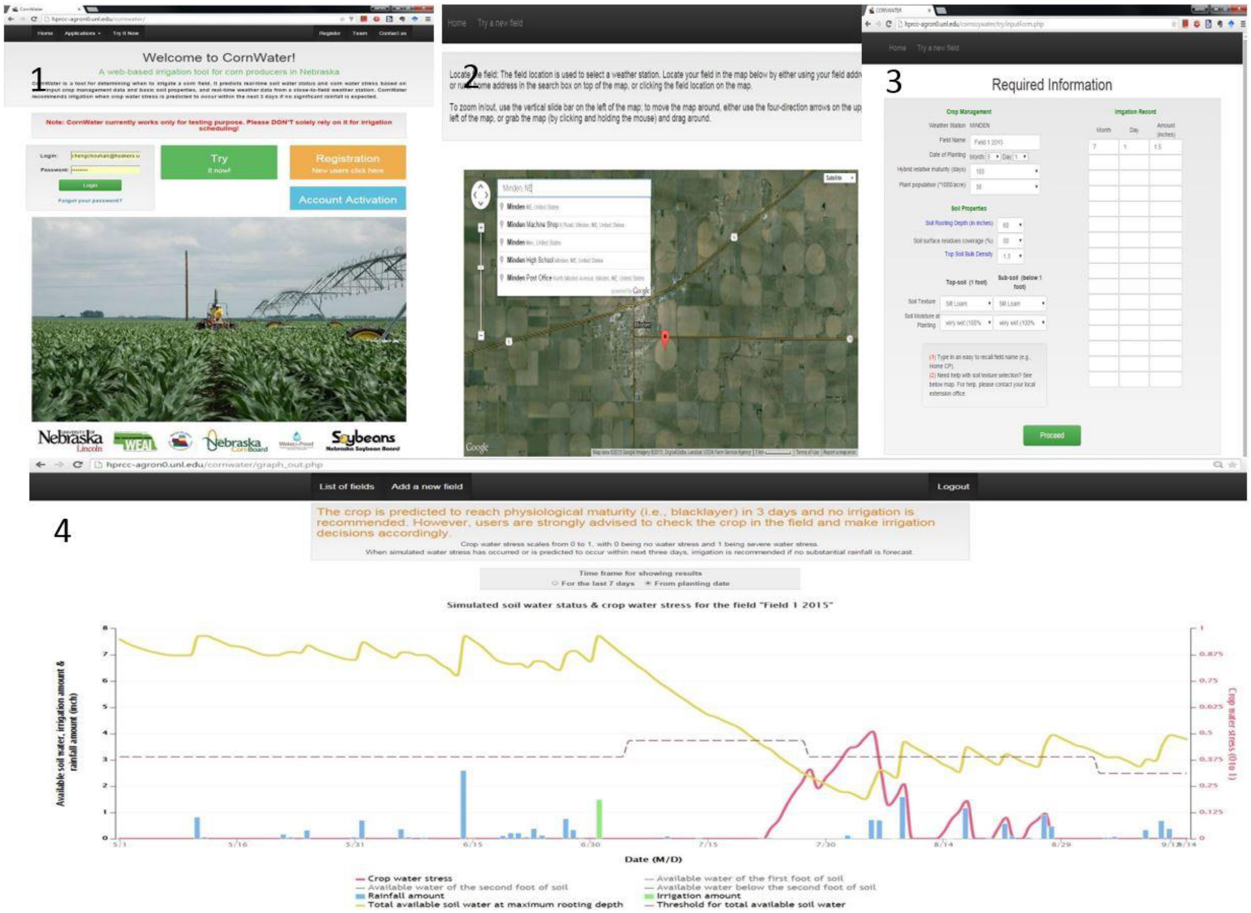

Fig. 1. The CornWater web application (http://cornwater.unl.edu). A user can choose to register an account for free or try it first. 1. Homepage for registration and login. 2. Google map for locating a field. 3. Page for user specified crop management information. 4. Output page with a notification message for irrigation recommendation and a graph showing rainfall and irrigation events and model predicted soil water balance and crop water stress.

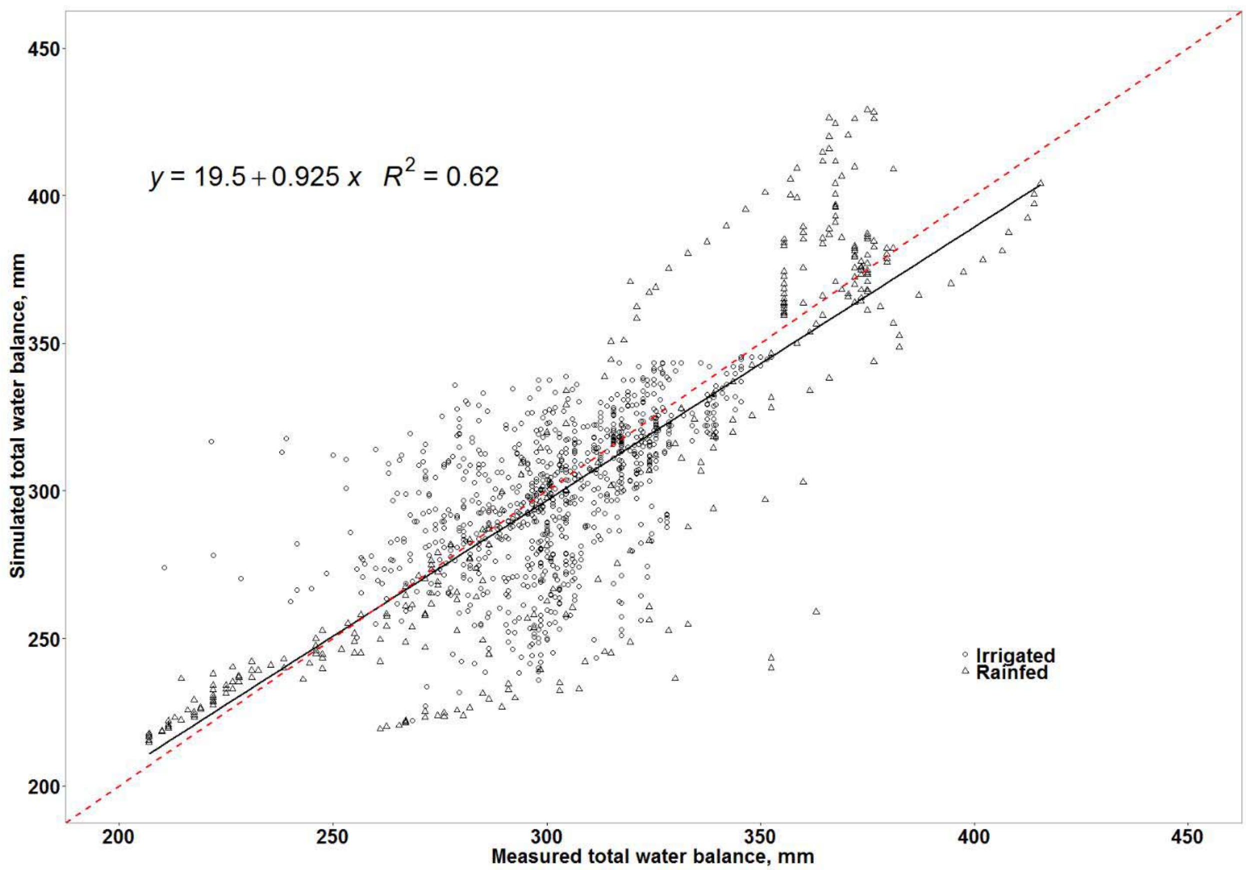

Fig. 2. Simulated vs. measured daily soil water balance to the maximum rooting depth during the growing seasons for the 11 site-year combinations at Mead, NE. The sample size is 1239. The dashed line is 1:1 line; the solid line is the regression line of all points.

Fig. 3. Simulated vs. measured daily soil water balance to the maximum rooting depth during the growing season at the three sites at Mead, NE. The empty panels indicate the field was planted soybean, not maize that year. The thin black line is measured soil water balance, and the thick red line is simulated soil water balance. S1, S2, and S3 indicate Site 1, Site 2, and Site 3, respectively.

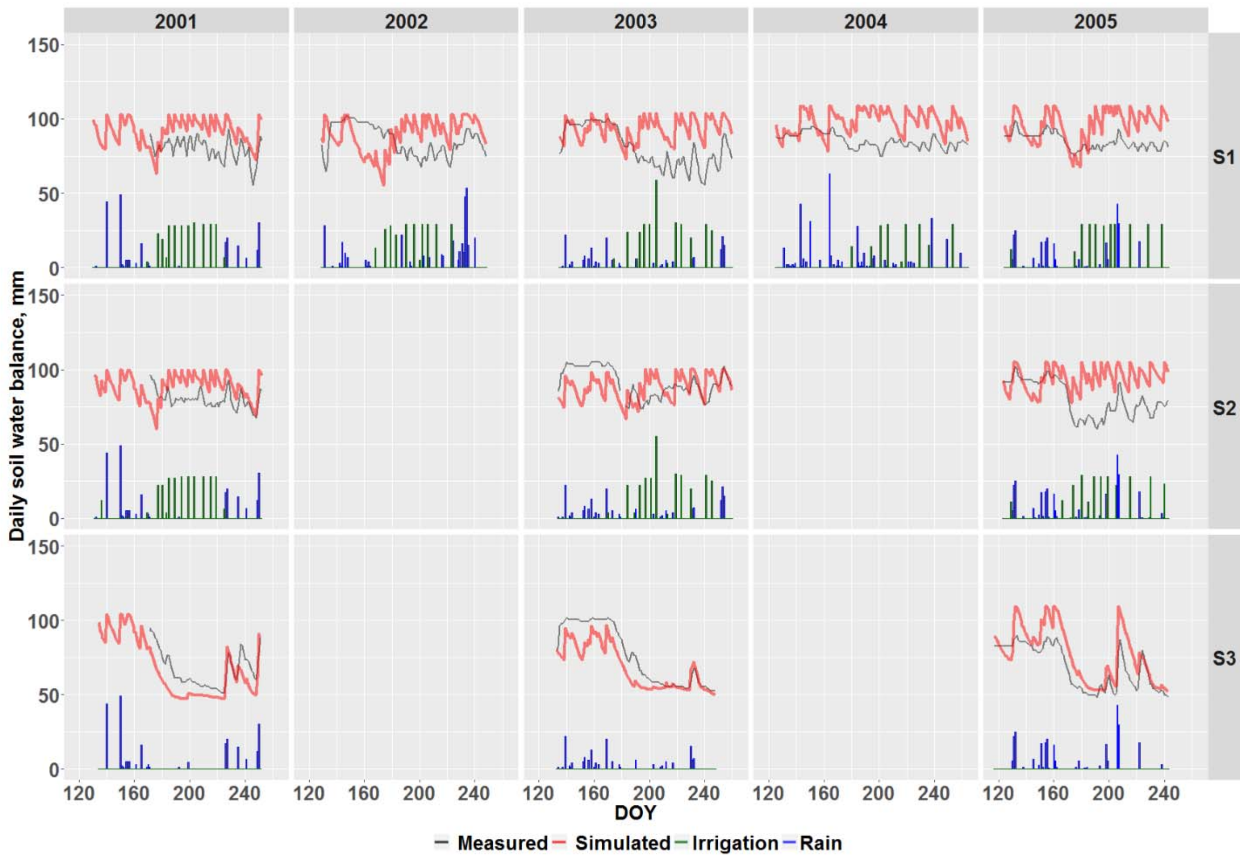

Fig. 4. Simulated vs. measured soil water balance of 0-30 cm depth during the growing season at three sites at Mead, NE. The empty panels indicate no maize crop planted that year. The thin black line is measured soil water balance, and the thick red line is simulated soil water balance. S1, S2, and S3 indicate Site 1, Site 2, and Site 3, respectively.

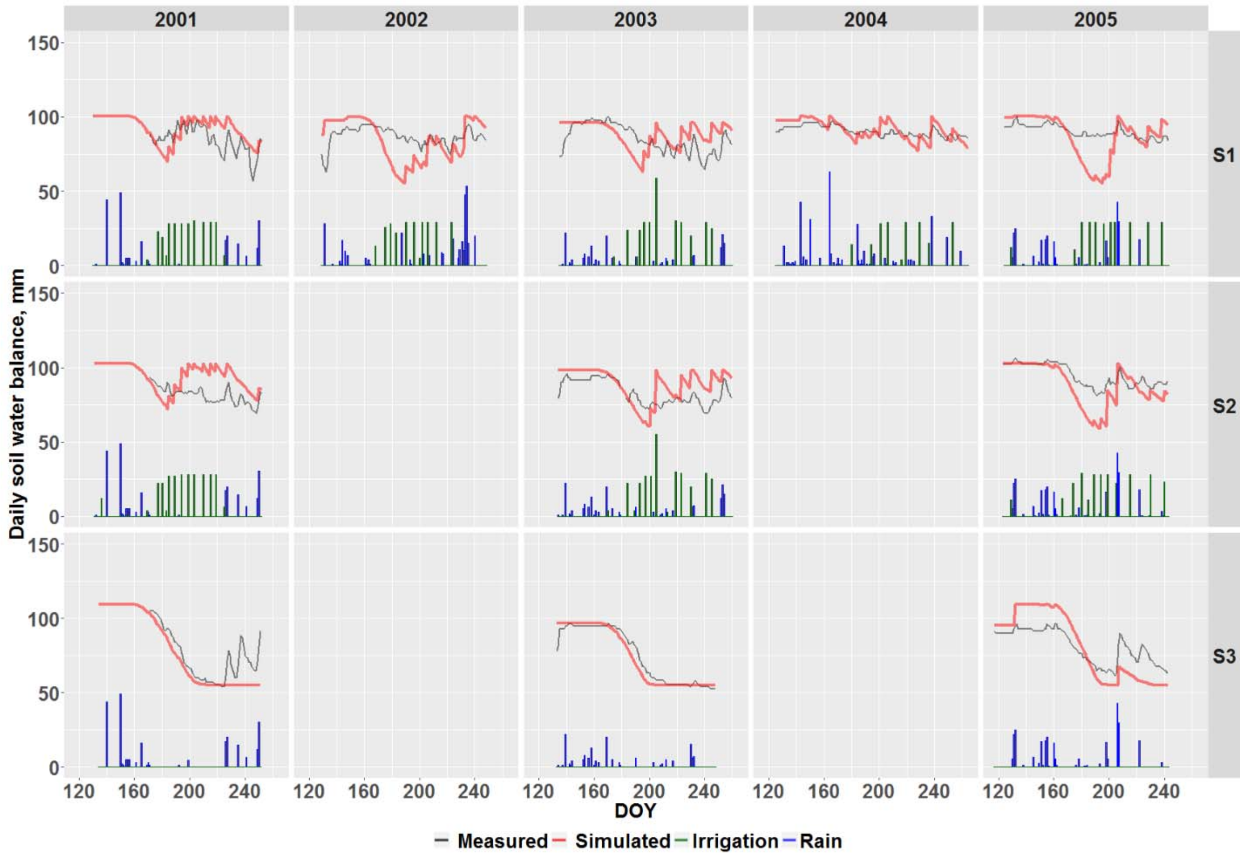

Fig. 5. Simulated vs. measured soil water balance of 30-60 cm depth during the growing season at three sites at Mead, NE. The empty panels indicate no maize crop planted that year. The thin black line is measured soil water balance, and the thick red line is simulated soil water balance. S1, S2, and S3 indicate Site 1, Site 2, and Site 3, respectively.

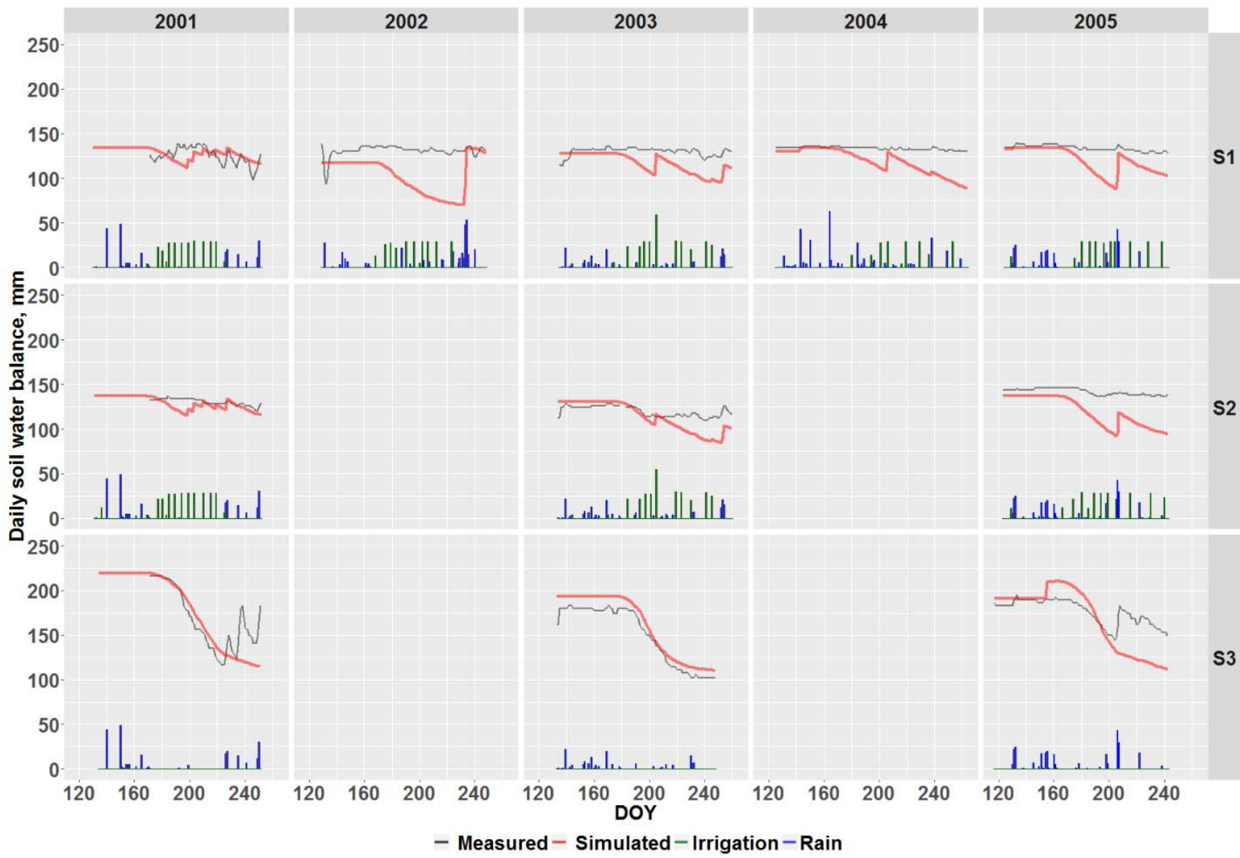

Fig. 6. Simulated vs. measured soil water balance of 60 cm to rooting depth during the growing season at three sites at Mead, NE. The empty panels indicate no maize crop planted that year. The thin black line is measured soil water balance, and the thick red line is simulated soil water balance. S1, S2, and S3 indicate Site 1, Site 2, and Site 3, respectively.

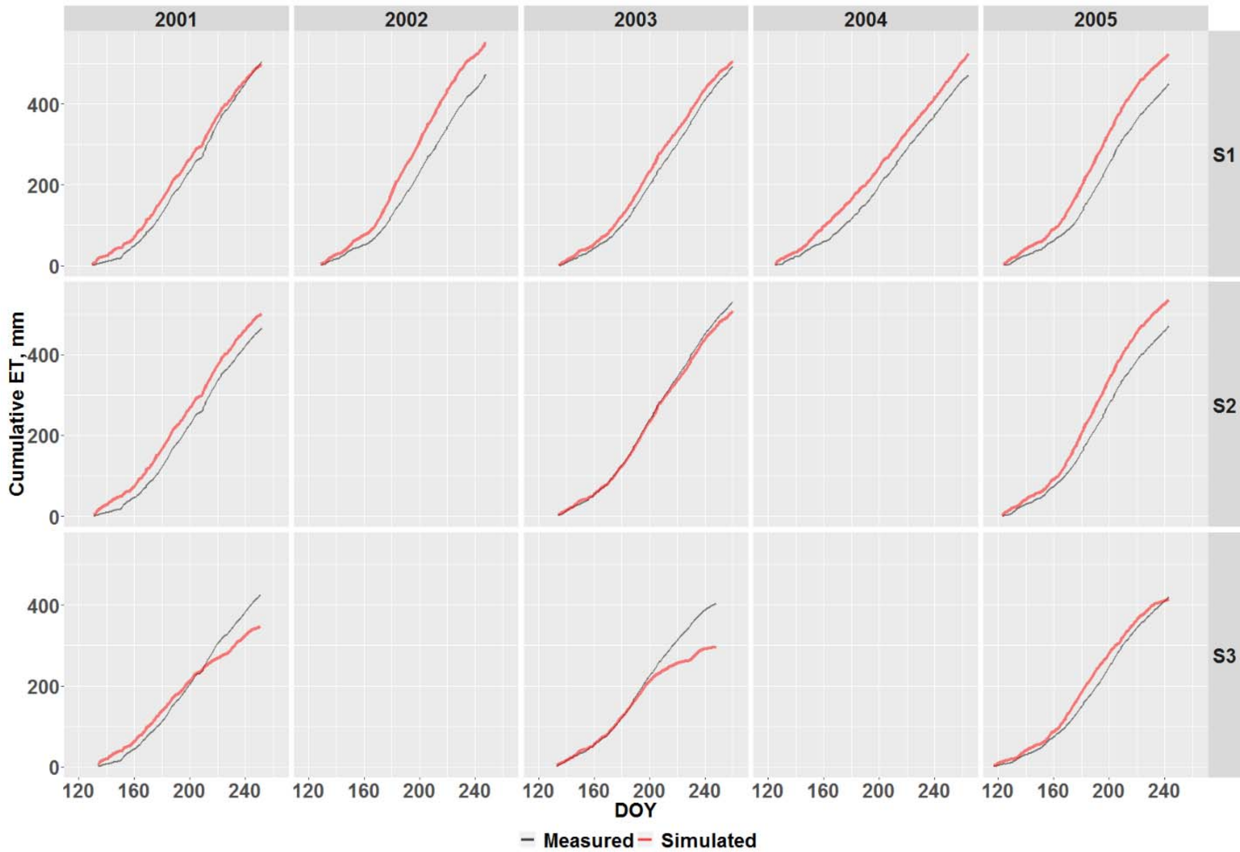

Fig. 7. Simulated vs. measured cumulative ET depth during the growing season at three sites at Mead, NE. The empty panels indicate no maize crop planted that year. The thin black line is measured cumulative ET, and the thick red line is simulated cumulative ET. S1, S2, and S3 indicate Site 1, Site 2, and Site 3, respectively.

Chapter 3

Validating Hybrid-Maize Model on Crop Growth and Water Use under Variable Irrigation in Nebraska

Abstract

Crop simulation models have the potential of guiding irrigation and saving water. A 2-yr field experiment was conducted to test the performance of the Hybrid-Maize (HM) model on maize growth and crop water use under variable irrigation treatments included 100% (recharge top 30 cm soil to field capacity), 75% and 50% of the 100%, and 0% (rainfed) in Lincoln, Nebraska. The HM model simulated crop stages well in 2014 but in 2013 predicted silking and maturity 5 and 15 d earlier, respectively, than observations. The model simulated LAI reasonably well in 2014 but overestimated LAI by 1.0 at maximum LAI for all treatments in 2013. HM model predicted in-season aboveground biomass dynamics well but underestimated it at maturity by 1.58 Mg ha^{-1} with RMSE = 2.05 Mg ha^{-1}. HM model underestimated grain yield for all treatments in both years by 1.69 Mg ha^{-1} with RMSE = 2.17 Mg ha^{-1}, indicating that the model needs to be improved for a dry year such as 2013. Simulated daily soil moisture balance agreed well with observations for the whole root zone (1.5 m), but less well for soil depths at 0-30 cm, 30-60, and 60-150 cm, respectively. The results indicated that the performance of HM model is no solely affected by total water input in the season, but also the climate such as average mean temperature and the planting date. HM model can perform well in a relatively wet year for biomass and grain yield simulation, while it performed well on estimating total soil water balance at the root zone for a silty clay loam soil type.

Abbreviations: HM model, Hybrid-Maize Model; LAI, leaf area index

Introduction

The state of Nebraska has the largest irrigated crop area in USA with 8.3 Mha mostly for maize and soybean production (USDA-NSSA, 2014). Average irrigated maize yield was 12.1 Mg ha^{-1} while the rainfed maize yield was 7.9 Mg ha^{-1} (USDA-NASS, 2012). On the other hand, irrigation has led to a decrease of groundwater table despite regular recharging of the Ogallala Aquifer (Singh et al., 2016; Xue et al., 2014).

Drought has happened more frequently in the last 20 yr (Woodhouse et al., 2015). As a result, demand for irrigation water has been high and increasing. Sometimes, producers don't pay close attention to water use efficiency simply because the yield of irrigated maize can be 30% higher than rainfed maize (USDA-NASS, 2012) and, producers tend to apply an excessive amount of irrigation water to reduce the risk of yield losses due to drought stress (Fereres and Gonzalez-Dugo, 2009; Grassini et al., 2011). This farming practice can lead to lower economic returns because of unnecessary irrigation water while increasing the risk of nitrogen leaching (Irmak, 2008; Hu et al., 2010). Improving water productivity should be considered as one of the targets of farming practice (Djaman and Irmak, 2012).

Deficit irrigation is a practical and promising irrigation strategy for saving water in a semiarid environment such as Nebraska (Payero et al., 2005; 2006). It saves irrigation water while producing high yield although not the maximum yield compared to full irrigation. Although deficit irrigation can affect the crop growth (Payero et al., 2006), it will likely become a trend of the future with freshwater becoming a more limited resource (Elliott et al., 2014).

Using crop models to study yield response to irrigation has become common. Studies have been conducted to test the accuracy of model simulation on crop growth and development, and water uptake simulation under various irrigation conditions (Khoshravesh et al., 2013; Attia et al., 2016a; Attia et al., 2016b; Heng et al., 2009). However, cautions must be taken because of model limitations and deficiencies (Di Paola et al., 2016). Under conditions of full irrigation, models can capture well crop growth, development, and yield. For example, Yang et al. (2004) reported the Hybrid-Maize model accurately simulated maize yield in Nebraska and Iowa of the USA under good crop management without drought stresses. Under conditions of deficit irrigation, however, crop growth can be affected, especially if the crop water requirement cannot be met during pollination and grain filling stages, whereas crop models may not be able to capture all the effects adequately (Ahmadi et al., 2015). It has been reported that crop biomass accumulation responds linearly to ET water use, and the decrease of water supply can affect grain yield (Payero et al., 2006). Meanwhile, water stress occurs when water supply from soil does not meet crop water demand as determined by weather conditions (Denmead and Shaw, 1960; Traore et al., 2000). For maize, water stress during pollination and grain filling reduces the ear size, number of kernels per ear, as well as kernel weight (Hall et al., 1982). As a result, deficit irrigation makes it more difficult for models to accurately predict crop yield (Lovelli et al. 2007) compared with full irrigation condition. Jin et al. (2016) reported that sixteen major maize models which used different mechanisms such as water supply/water demand, ET supply/ET demand, soil water content, etc., to determine the water stress. However, the performance of those models under extreme weather conditions needs to be tested. The objective of this study was to test the performance of the Hybrid-Maize model on the prediction of maize growth stage, LAI, aboveground biomass, grain yield, and soil water balance under variable irrigation in eastern Nebraska.

Materials and Methods

Field experiment

The field experiment was conducted in two years in 2013 and 2014 at Lincoln, Nebraska (43°38'19.39"N, 116°14'28.86"W). Lincoln is in a temperate continental climate with an average seasonal (May-Sep) precipitation of 435 mm (Torrion et al., 2014). The soil at the study site is a fine, smectitic, mesic Cumulic Vertic Endoaquoll silty clay loam (Soil Survey Staff, 2016). The field was under an annual maize-soybean rotation. Prior to the start of the trial, the field was disked to a 15-cm depth after soybean harvest, and leveled by a field cultivator in the spring. After that, urea fertilizer was broadcast at a rate of 202 kg ha^{-1}. Pre-pesticide Dual II Magnum (1.3 pt) and Atrazine (1.13 kg ha^{-1}) were mixed and sprayed before another round of field cultivator operation. Other field management practices followed University of Nebraska guidelines for high yield maize production.

There were four irrigation treatments: 100% (recharge top 30 cm soil to field capacity), 75% and 50% of the 100%, and 0% (rainfed). Due to the annual rotation with soybean, the experiment area was in two different parts of the field each year. For both years, a drought tolerant hybrid Syngenta Agrisure Artesian X43297WP with a relative maturity 102 d was planted to an area of 0.3 ha (73 m long x 37 m wide). The experiment was a randomized complete block design with four replicates. Each plot was 8 rows wide and 6 m long with 0.76 m spacing between rows. The timing of 100% irrigation treatment was guided by soil water sensor readings (see next paragraph). Irrigation started whenever the reading in the 100% irrigation plots suggested depletion of around 50% of available soil water in the rooting depth. For the 100% irrigation treatment, 38 mm of water was applied each time, which is the common amount a center pivot delivers in Nebraska (Klocke et al., 1989). For the 75% and 50% irrigation treatments, their amount was 75% and 50% of the 100% irrigation treatment, respectively. All three irrigated treatments started at the same time, but their water supply was shut off at different times depending on their designed irrigation amount.

We used surface drip tapes of 16 mm in diameter for irrigation. Water pressure was regulated and water flow rate was monitored. We checked readings of soil water sensors of the 100% irrigation plots each day and started irrigation when the water potential got close to the 150 centibars, which was considered as the 50% depletion of available water for a silty clay loam soil in Nebraska (Irmak et al., 2006).

We used Watermark Granular Matrix sensors (WGMS, Irrometer, Co., Riverside, Cal.) to monitor soil water pressure. The sensors were glued to PVC pipe and installed at V3 stage to 30, 60, 90, and 120 cm soil depths close to a crop row. In addition, another two sensors were installed to 90 and 120 cm depth in the middle of two rows. All sensors were installed vertically and removed before harvest. The sensors were connected to a Watermark Monitor datalogger (Irrometer Co., Riverside, Cal.) to record data each hour. Soil water sensors were installed in two replicates. The sensor readings were converted to volumetric water content by the method developed for soils in Nebraska (Irmak et al., 2006).

For crop data, we recorded crop stages twice a week, and measured LAI every ten days using LAI-2200C (LI-COR Biosciences Inc., Lincoln, NE, USA (Pearse et al., 2016), total aboveground biomass 3 times before maturity, and final grain yield and total biomass at maturity. For biomass measurement, we randomly sampled 6 plants per plot for 2013 growing season and 10 plants per plot in 2014. Two weeks after maturity, we harvested a section of 6 m long of the two middle rows for total biomass and grain yield. We used a hand held moisture meter

(Dickey-john Harvest hand, Dickey-john Corp., Auburn, IL) to measure the kernel moisture and converted grain yield to 15.5% standard moisture content.

For each season, we used Hybrid-Maize model to simulate the crop growth and development, and daily soil water balance based on actual the crop management information and weather data collected from an automated weather station of 1.3 km away from the study field. The crop management information is given in Table 1.

Statistical analysis

A two-tailed paired Student's t-test was used to test significant differences of the mean differences between measurements and simulations ($\alpha = 0.05$) for LAI, aboveground biomass, and grain yield respectively. ANOVA was used to test the treatment effects on LAI, aboveground biomass, and grain yield, respectively, and Tukey's HSD test was conducted to find the differences between treatments. The performance of the model was evaluated by mean bias error (MBE), root mean squared error (RMSE), and modeling efficiency (EF) for LAI, aboveground biomass, grain yield, and total soil water balance:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - M_i)^2}$$

$$MBE = \frac{\sum_{i=1}^{n}(S_i - M_i)}{n}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}(M_i - \overline{M})^2}$$

Where S_i is the simulated value, M_i is the measured value, n is the number of data pairs, $\overline{M}$ is the average of measured values. RMSE measures the deviation of overall mean between simulated and measured values. A RMSE value close to zero indicates good model performance. RMSE has the same unit as S_i and M_i thus it is easy to interpret, however, large errors can be weighted heavily (Willmott, 1982). MBE directly indicates if the model underestimates (negative value) or overestimates (positive value) the measured values and offers uniformity of error distribution. EF ranges from $-\infty$ to 1. An EF value close to 1 indicates the model is better, while an EF value smaller than zero indicates $\overline{M}$ predicts better than the model. In crop modeling, EF = 0 is considered as the lower limit of model quality (Wallach et al., 2006).

Results

Weather conditions from emergence to maturity

The temperature in 2013 and 2014 growing season was similar, but the mean minimum temperature after silking was 1 °C lower in 2014 than in 2013. 2013 was drier than 2014 with 60 mm less in-season rainfall (Table 2). 2013 was particularly dry after silking, with only 53 mm rainfall, which was 190 mm less than 2014. In comparison, the long-term average rainfall for the same period was 155 mm. Moreover, the after-silking water input (rainfall after silking + irrigation) indicated the 100% irrigated and rainfed treatments received 69 and 190 mm more water in 2014 than 2013, respectively (Table 1). The planting date of 2014 was May 18th (DOY 138), which was 10 d later than 2013, but both years had almost the same date of silking (Table 1). In addition, the shorter growing period in 2014 than 2013 can be translated into 301 MJ m^{-2} less total solar radiation than in 2014.

Crop stages

The performance of simulation was better in 2014 than in 2013 for reproductive stages simulation, while was similar for vegetative stages. HM model predicted vegetative and reproductive stages in a reasonable range for 2014 but not for 2013 (Fig. 1). The greatest difference between simulations and observations was the maturity date in 2013. The simulated maturity date was August 25th (DOY 237), which was 12 and 15 d earlier than the observations in rainfed and irrigated treatments, respectively. The rainfed treatment matured on September 6th (DOY 252) in 2013 because of the occurrences of water stress. In 2014, the simulated maturity was only 2 d earlier than the observation. For the silking date simulation in 2013, irrigated treatments predicted 4 d earlier than the actual date, but only 1 d earlier for the rainfed treatment. Most other simulated reproductive stages of 2013 differed from the measurements by 6 to 11 d. In 2014, HM model predicted silking dates by 2 d late for all treatments. For vegetative stage simulation in both years, the differences were less than 3 d. The less variations between simulated and observed reproductive stages in 2013 can be attributed to the adequate rainfed amount (243 mm) after silking stage in 2014 (Table 2).

LAI

HM model overestimated the maximum LAI in the mid-season across all treatments in the 2 yr (Fig. 2), and the difference between simulated and measured LAI was greater in 2013 than in 2014. The treatments caused LAI differences between rainfed to 100% irrigation (p = 0.03) and rainfed to 75% irrigation (p = 0.003) respectively in 2014, but the differences between simulated and measured were similar regardless of treatments. The rainfed treatment in both years showed accelerating effects of drought on leaf senescence shortly after the silking, while the three irrigated treatments showed no difference. The EF showed HM model can barely simulate LAI well (EF = 0.01) with a RMSE = 0.94 (Table 3). Such a value of RMSE is 20% of the measured mean LAI, which is considered to be large. However, the t-test showed there was no statistical difference between measured and simulated values (p = 0.27). The negative MAB values in 2014 were caused by underestimated LAI after August 8th (DOY 220) when intensive measurements were taken. Different irrigation treatments did not affect the maximum LAI simulation and the relative low LAI in 50% irrigation in 2013 was caused by a lower plant population. When the measured LAI reached a peak of 4.0, simulated LAI was 5.0 in 2013. The measured and simulated LAI reached their peak at the same date which indicated HM model simulate the maximum LAI well at the silking stage in DOY 194 and DOY 193 when the plant started to flowering in 2013 and 2014, respectively. The simulated LAI showed a similar trend of declining compared with measured LAI after silking. However, the decline of measured LAI slowed down in mid-August (DOY 220) compared with simulated LAI, which showed a quicker decline. This indicated a slower leaf senescence than in the fields than HM model prediction.

Aboveground biomass

HM model estimated well in-season aboveground biomass accumulation but underestimated the end-season value in both years, especially in 2014 (Fig. 3). The treatment effects were not significant in both years (p = 0.47). The differences between simulated and measured values among treatments varied but were obvious at the final measurements. The underestimation of final aboveground biomass was largely affected by grain yield estimation (Fig. 5). Because when we compared simulated stover biomass with measured ones at harvest, we found the simulated one was greater than averaged measurements by 1.3 Mg ha^{-1} in 2013 and less than the measurements by 0.4 Mg ha^{-1} in 2014, respectively. Still, the performance of HM model on aboveground biomass simulation was acceptable with EF = 0.85. The RMSE was 3.25

Mg ha^{-1} which is 15% of measured aboveground biomass with an overestimation of 0.27 Mg ha^{-1}. The simulated value decreased after mid-August (DOY 220), possibly caused by the use of carbohydrate reserve for grain filling at times when daily net dry matter production grain cannot be meet the demand for grain filling (Yang et al., 2004).

Yield

HM model underestimated grain yield (at 15.5% moisture) by 1.8 and 1.3 Mg ha^{-1} in 2013 and 2014 respectively with a RMSE = 2.17 Mg ha^{-1}, which accounted for about 18% of the average yield of 12.36 Mg ha^{-1} for the field (Fig. 4; Table 3). The treatments did not affect the performance of simulations except in rainfed treatment in 2013. For the rainfed treatment in 2013, the model underestimated the yield the most by 3.35 Mg ha^{-1} among all treatments and years combined. The actual yield was not affected by the end season water stress in 2013. In fact, the rainfed treatment caused slight reduction of the yield compared with 75% and 50% irrigation treatment in 2013, which indicated either the total water supply from rainfall was close to being sufficient, or we did not apply enough irrigation for irrigated treatments. In 2014, the rainfed treatment showed differences compared with 100% irrigation (p = 0.006) and 75% irrigation (p = 0.009), respectively. In contrast, simulated yields showed almost no differences for the three irrigated treatments in 2013 and in 2014, except the 50% irrigation with low plant population in 2013.

Soil water balance

Simulated soil water balance to 1.5 m depth agreed well with the measured water balance (Fig. 5). The EF was 0.67 which indicated the model can simulate water balance well for a silty clay loam soil (Table 3). An underestimation by the model in irrigated treatments appeared during the mid-season of 2013 while the measured water balance did not show such trend (Fig. 5). In 2014, there was a rapid increase of simulated water balance showed after July 19th (DOY 200). Surprisingly, HM model estimated water balance well for rainfed treatment in both years. The sensors did not be installed until June which resulted the measured results started late compared with simulated one, while the simulated maturity date was earlier than the measurement so as the end date of water balance simulation.

The 0 to 30 cm soil depth saw a large variation between simulated water balance and the measurement (Fig. 6). The rapid decrease of simulated water balance in the mid-season in 2013 corresponded to the low water input from rainfall and irrigation for all irrigation treatments. This pattern was clear especially under 50% irrigation when early season rainfall was adequate but in-season water input was low (Fig. 6). In contrast, the simulation showed less water withdrawal and fast soil profile recharge in 2014 when water input was higher than 2013 during the same period for the irrigation treatments. Clearly, the measured results were less affected by water input compared with simulated ones, which reflected HM model was more sensitive to water input at this soil depth than the measurement. The best simulations occurred in 50% irrigated and rainfed treatments in 2014 when they matched the measurement well, while other simulations showed less than 30% difference on various dates across treatments.

For the 30 to 60 cm soil depth, the greatest difference was about 20 mm between measured and simulated water balance (Fig. 7). The trend difference between simulated and measured soil water balance appeared in the mid-season. The model simulated a deep drop in water balance for all treatments in the two years. For the irrigated treatments, this decline caused a mismatch between measurement and simulation but led to a good match for the rainfed treatment in 2014. The measured water balance showed a delay of decrease compared with simulated results, which looks similar at 0 to 30 cm soil depth (Fig. 6). The drop of water balance by simulation indicated HM model might estimate water depletion faster than what actually happened in the field. Also, the less water input under 50% irrigation and rainfed condition could increase the possibility of predicting water stress too early with corresponding early maturity.

From 60 to 150 cm soil depth, the measurement and simulation were surprisingly close except in 100% irrigation treatment in 2014 where HM model overestimated water balance by 25 mm (Fig. 8). In the rainfed treatment, the measured water balance showed a continuous decrease even when the simulated one slowed down the pace of decrease, which indicated an intense water withdrawal happened which was not captured by HM model. It was possible the root of maize could have reached more than 1.5 m in the treatment for both years which caused the continuous decrease. The simulation overestimated measured values by only 50 mm by August 28th (DOY 240) at rainfed treatments in both years.

Discussion

Crop growth stage

For cereal crops like maize, the accuracy of model simulation of grain yield depends greatly on whether the flowing and maturity dates are be predicted reliably. Because a right partition of vegetative and reproductive stages corresponds with a reasonable partition of LAI, aboveground biomass, and grain yield, respectively. The HM model evaluation study showed relatively less satisfactory model performance under high plant density conditions with high temperature (Yang et al., 2004). In our study, since there was only plant density across all treatments, HM model performance was attributed to not only the differences in water input but climate variations in the two years, especially mean maximum and minimum temperature. Our results suggest HM model simulated crop stages well in 2014 when irrigation was sufficient. The low water input (rainfall + irrigation) after silking in 2013 may have caused the crop to behave differently compared with a regular hybrid. And since HM was previously developed and parameterized for non-drought-tolerant hybrids, the model may not be able to capture all characteristics of the new hybrid. And a relative higher whole season mean maximum temperature and a relative low night temperature in reproductive stages in 2014 compared with in 2013 may result in a better crop stage simulation. In addition, the relative maturity of the hybrid we used was 102 d, which was considered a shorter maturity in this area. The length of crop growth cycle in 2013 was 125 d, which was 19 d longer than 2014. The reason of the relatively long maturity in 2013 could be the cause by that we missed the actual maturity date at the end of August.

The observed silking and maturity dates were 5 d and 15 d later than the simulation, respectively. It demonstrated the inaccuracy of stage simulation in 2013. However, it was not caused by observation error on the silking date because the silking event was hard to miss with our high observation frequency. With such a difference in silking date simulation, the poor following estimation on maturity date was expected. However, it did not fully explain why the maize matured so late in 2013 in the field than simulation. The cumulative GDD from planting to the observed date of black layer in 2013 was 263 higher than the total GDD of RM 102, but only 33 higher than 2014. Again, it can only be explained by that we measured the black layer later than its actual appearance since the formation of black layer was subjective to some extent.

LAI

Because the plant population and crop management were similar in both years, the lower measured LAI in 2013 could be due to lack of calibration of the Plant Canopy Analyzer used for measured for measure LAI. In 2014, we upgraded the LAI instrument to LAI-2200C and found a new feature of diffusion correction changed measured LAI by about 5% in 2014. The lack of diffusion correction could introduce deviation on measurement in 2013. However, it would not be a major factor. Also, the sky condition will influence the measurement accuracy. We took measurements in the afternoon under a clear sky condition for 90% of the times which meet a standard requirement. In order to improve the measurement representation, we increased the measurement frequency in the late season of 2014. The overestimation of LAI by HM model lead to over simulation of dry matter production and carbohydrate reserve that be used for grain filling (Yang et al., 2004). And the reason of overestimation of LAI can be due to the hybrid parameter setting which is not specific to this drought tolerant hybrid since we did not have the information. The rainfed treatment only slightly affected LAI values compared to irrigated treatments in both years. This indicated irrigation and rainfed treatment did neither greatly influence the performance of HM model nor actual crop growth itself.

Aboveground Biomass

The model underestimated final aboveground biomass across all treatments although the in-season simulation was acceptable (Fig. 4). The reason of this underestimation of aboveground biomass was HM model underestimated the grain yield while it simulated the final stover biomass well. Note that the final biomass sampling was taken 10 d and 15 d after the observed maturity dates, respectively, in 2013 and 2014. A higher final yield could be the result from the hybrid which may actually had a longer maturity than the suggested 102 d. If so, before sampling the hybrid would be still growing, and naturally the simulated final aboveground biomass would be greater. Nevertheless, the irrigated treatment resulted in greater underestimation of final aboveground biomass than the rainfed treatment in 2014. It could demonstrate the baseline of HM model performance on biomass simulation under an adequate irrigation and rainfall environment. Moreover, the performance of aboveground biomass simulation did not closely relate to adequate total water input.

Grain yield

It was unusual for a crop model such as HM model to underestimate grain yield because most of the crop models estimate potential yield at optimal farming conditions and usually show overestimation. The essence of this phenomenon could be that HM model was not optimized for a drought tolerant hybrid rather than just used parameters as for regular hybrids. With a short relative maturity of 102 d, HM model would predict maize reached R6 at the end of August. The longer duration of growing cycle along with a longer grain filling period would result in higher yield. When a late season drought occurred in 2013, the yield of rainfed treatment predicted by HM model was much lower than in 2014 because the model terminated the grain filling due to severe water stress. In reality, the hybrid may have grown normally because of the drought tolerance. Although water stress played an important role on the grain filling, we suspect HM model overweighed the impact of the level of water stress on yield. The average yield in the two years was similar while the model predicted 2014's yields reasonably well but not for 2013's which also was an indication that climate effect was critical for simulation accuracy. The model used water and ET supply/demand relationship to determine crop water stress. It may be over sensitive to stress conditions for the new drought-tolerant hybrids. On the other hand, the distribution of water input throughout the season might be more important than the total amount. Grain yield will be affected if water supply does not meet crop ET demand on a daily basis during grain filling although total water input may meet the total demand on a seasonal basis.

Soil water balance

HM model performed well to match the measured soil water balance for the entire 1.5 m rooting zone. The difference between measured and simulated water balance happened more frequently when there were intensive water input events or a shortage of water input in a continuous period. For the upper 30 cm soil depth, however, the fluctuation of simulated water balance was more obvious, which is directly related to the frequency and amount of water input during the growing season. The reason that simulated water balance was sensitive to water input was HM model used a "tipping bucket" method to calculate soil water balance of a given layer. Water does not move from the upper layer to the lower layer until that layer has reached field capacity. In reality, however, water starts to infiltrate to the next soil layer before the current layer reaches field capacity as Richards equation describes (Van Dam and Feddes, 2000). So when an input from rainfall or irrigation causes an increase of the simulated water balance only at the upper soil layer before the soil reaches field capacity, the measured water balance was rising in top soil layer but also the layer beneath. That was the reason we did not see the measured water balance increase to a similar degree as simulated. For the 30 to 60 cm soil depth, the measured water balance naturally had a greater water content than the simulation simply because of more water infiltration from the 0 to 30 cm soil layer. In contrast, HM model estimated more water retention in the top 30 cm soil layer and relative less water infiltration in the 30 to 60 cm. We assumed that, if the model simulated the root density distribution at each soil layers correctly, we would have more intense water withdrawal at 30 to 60 soil depth compared with the measurement since less input water would reach this layer after rainfall or irrigation in the model. It turned out that when roots have reached most of the soil volume and plant canopy has closed in the mid-season, an increase of water withdrawal would be shown by a rapid decrease of water content at 30 to 60 cm soil depth as a significant amount of roots were present in this depth. For the 60 to 150 cm soil layer, the simulation behaved very well under the irrigated treatments, which was similar to the rainfed treatment. This good match was because there was little water input into this depth, and daily water uptake across all treatment was similar while the water amount was sufficient at this depth. We can see a similar pattern at 30 to 60 cm soil depth whenever there was little or no water input to the system, such as the rainfed treatment; the simulation tended to perform well until HM model predicted water stress. However, we have not found a good explanation about the delay of measurement under rainfed treatment at top 30 cm soil depth in 2013. In general, HM model performed well on simulating water balance at the total rooting depth, which was critical to irrigation management in the field when using such a model as irrigation decision support tool.

The simulation of soil water balance was almost independent to the biomass and grain yield simulation unless there was water stress. This made the water stress extremely important in the model. In the model, crop water stress will occur if water supply from the soil cannot meet crop ET demand as determined by weather conditions. Another aspect related to drought was how sensitive the HM model would respond to heat stress, as heat stress would likely occur with drought. Although several physical processes in the model, including photosynthesis, maintenance respiration, and kernel growth, respond to temperature, there are no specific functions to account for possible heat stress or damage to crop functions. More quantitative research and model improvement are needed to account better for effects of drought and resulting heat stress.

Conclusion

Overall, HM model simulated maize phenology, LAI, and yield reasonably well under different irrigation conditions of Nebraska. The model also simulated well water balance of the total rooting depth. However, the model has the tendency of predict crop stage earlier, underestimated maize grain yield for the two years' experiment. Deficit irrigation and rainfed have less effect on simulation accuracy for soil water balance, but more effect on biomass and yield simulations, respectively. The climate from different years had more effect on simulation quality than water input.

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Table 1. Maize crop information of the experiment in Lincoln, NE. The hybrid was Syngenta Agrisure Artesian X43297WP with a relative maturity 102 d.

Year	Treatment	Plant population, 1000/ha	Date, DOY[1]				Total irrigation, mm	irrigation + after-silking rainfall, mm	Total water supply, mm[2]
			Planting	Emergence	Silking	Maturity			
2013	100%	82	128	135	194	252	387	440	1012
	75%	82	128	135	194	252	295	348	920
	50%	72	128	135	194	252	194	247	819
	Rainfed	82	128	135	194	249	0	53	625
2014	100%	80	138	143	193	243	266	509	951
	75%	79	138	143	193	243	203	446	888
	50%	80	138	143	193	243	133	376	818
	Rainfed	80	138	143	193	243	0	243	685

[1]DOY: date of the year.

[2]The total water supply in the field included available soil water in the maximum rooting depth (1.5 m) at planting, total rainfall from planting to maturity, and total irrigation.

Table 2. Summary of weather conditions during planting to maturity of 2013 and 2014 at Lincoln, NE.

Year	Planting to maturity				Planting to silking				Silking to maturity			
	Days	Tmax, ºC	Tmin ºC	Rainfall mm	Days	Tmax ºC	Tmin ºC	Rainfall mm	Days	Tmax ºC	Tmin ºC	Rainfall mm
2013	125	28.8	17.3	294	66	27.5	15.9	240	59	30.3	19.0	53
2014	106	29.3	17.2	354	55	28.8	16.5	179	51	29.9	18.0	243

Table 3. HM model performance on simulation of LAI, aboveground biomass (AGB, Mg ha^{-1}), grain yield (Mg ha^{-1}, and daily soil water balance (WB, mm) to the maximum rooting depth (1.5 m) during the growing seasons of 2013 and 2014. RMSE is the root mean square error, MBE is the mean bias error, and EF is the modeling efficiency.

		LAI			AGB			Yield			WB		
Year	Treatment	MBE	RMSE	EF	MBE	RMSE	EF	MBE	RMSE	EF	MBE	RMSE	EF
2013	100%	0.5	1	0.33	-0.23	2.85	0.87	-2.31*	2.34	-35.29	-11	29	-1.51
	75%	0.69	1.15	0.06	0.52	2.31	0.89	-1.13	1.56	-1.1	-18	33	-0.46
	50%	0.49	0.98	0.29	0.92	2.2	0.9	-1.23	1.8	-0.86	-24	33	0.18
	Rainfed	0.42	1.16	-0.05	0.66	2.27	0.84	-3.35*	3.47	-12.66	-16	33	0.83
2014	100%	-0.19	0.8	-0.17	-1.59	4.32	0.81	-1.85	2.23	-2.2	38	48	-2.28
	75%	-0.26	0.83	-0.39	-1.24	4.44	0.81	-1.81	2.08	-3.1	23	35	-0.35
	50%	-0.23	0.79	-0.14	-0.88	3.74	0.84	-0.93	1.48	-0.65	-5	21	0.65
	Rainfed	-0.45	1.06	-1.1	-0.29	2.95	0.86	-0.91	1.74	-0.38	21	33	0.87
Pooled data		-0.04	0.94	0.01	-0.27	3.25	0.85	-1.69*	2.17	-0.91	2	34	0.67

* indicates significant at p=0.05 in the paired two-tailed t-test.

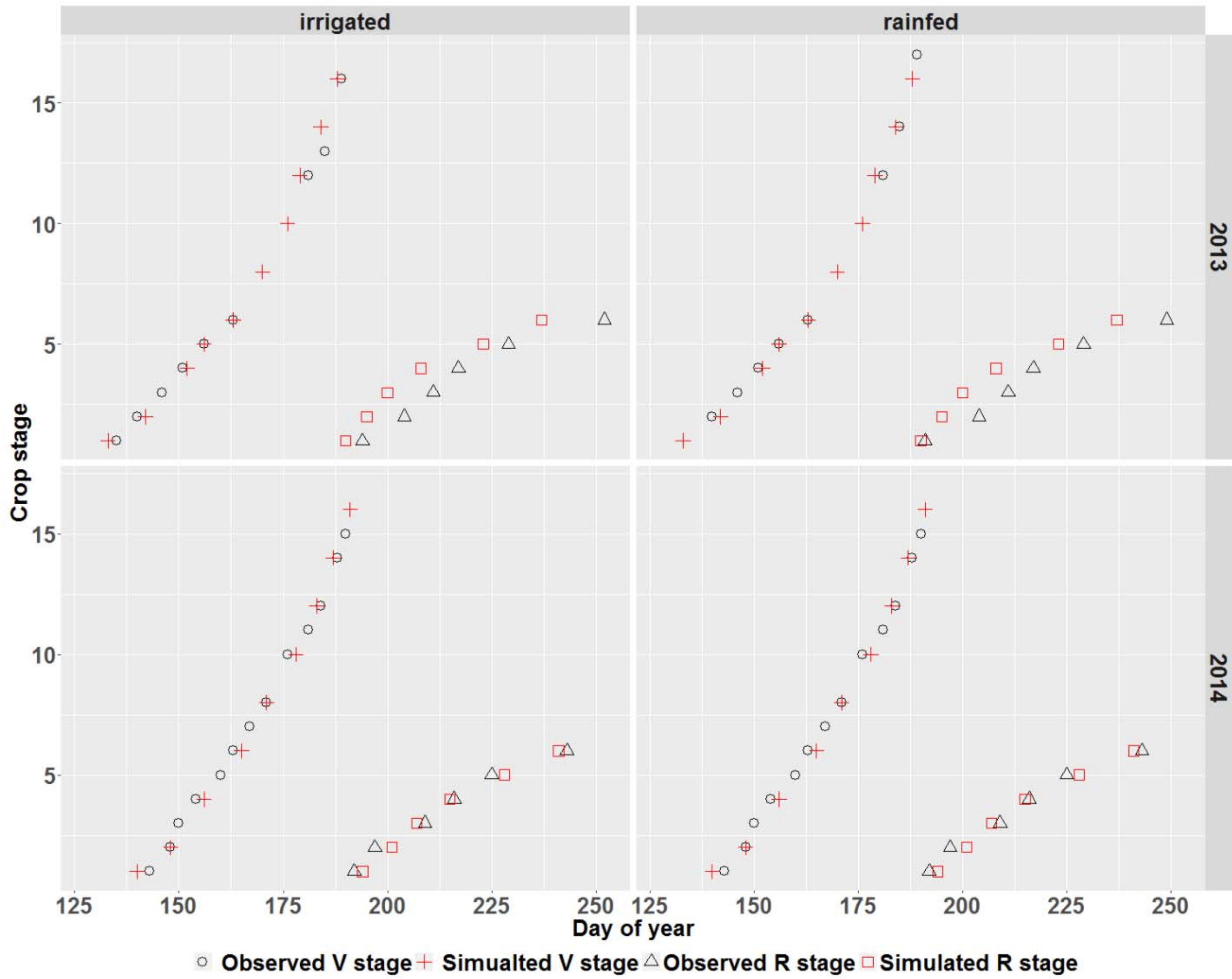

Fig. 1. Observed vs simulated maize growth stage. The y axis represents both vegetative stage and reproductive stage. The black circle is observed vegetative stage, and the red cross is simulated vegetative stage, the black triangle is observed reproductive stage, and the red square is simulated reproductive stage.

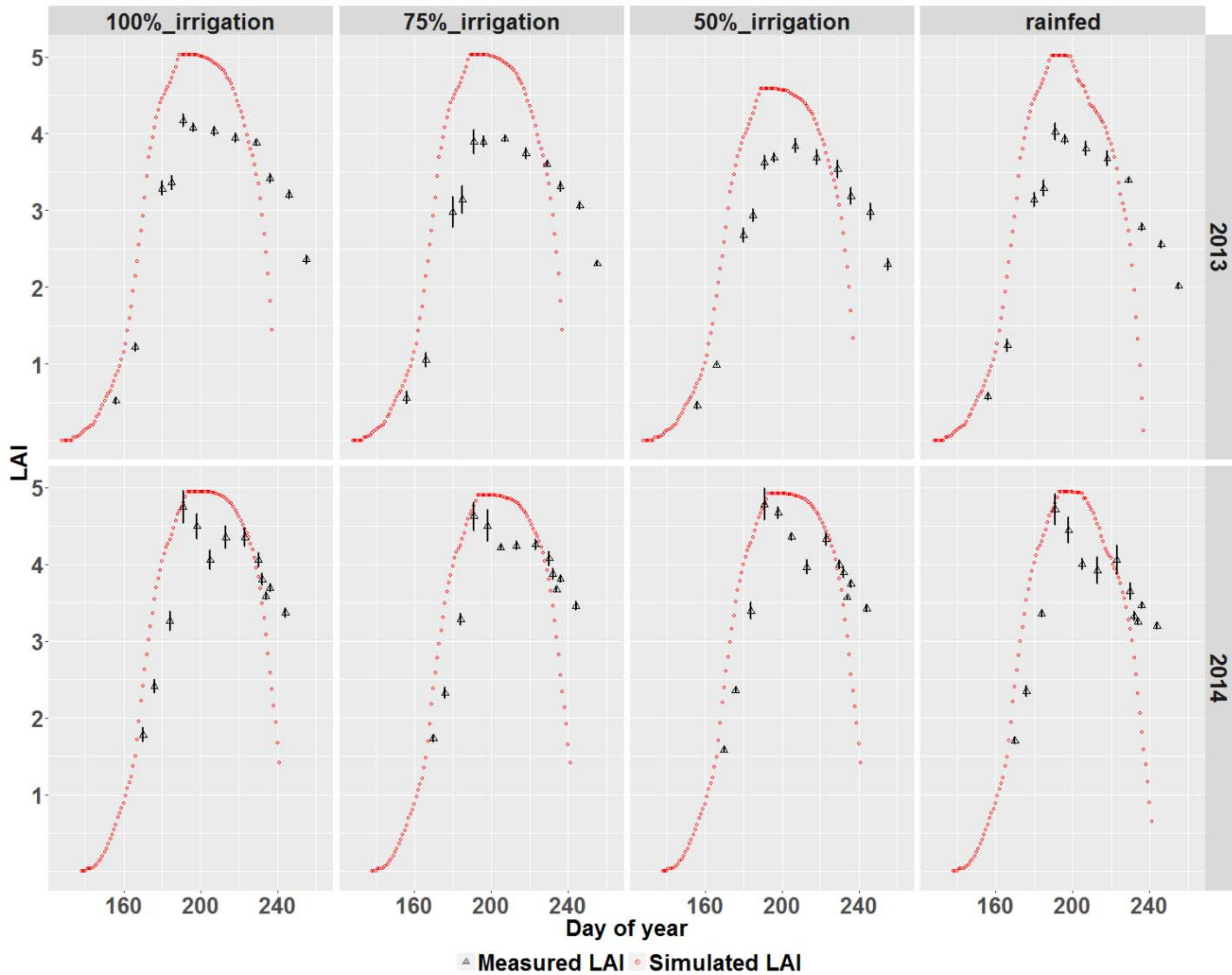

Fig. 2. Measured vs simulated LAI. The red circle is simulated LAI, and the black triangle is the measured LAI. The black bar is S.E. of the measurements.

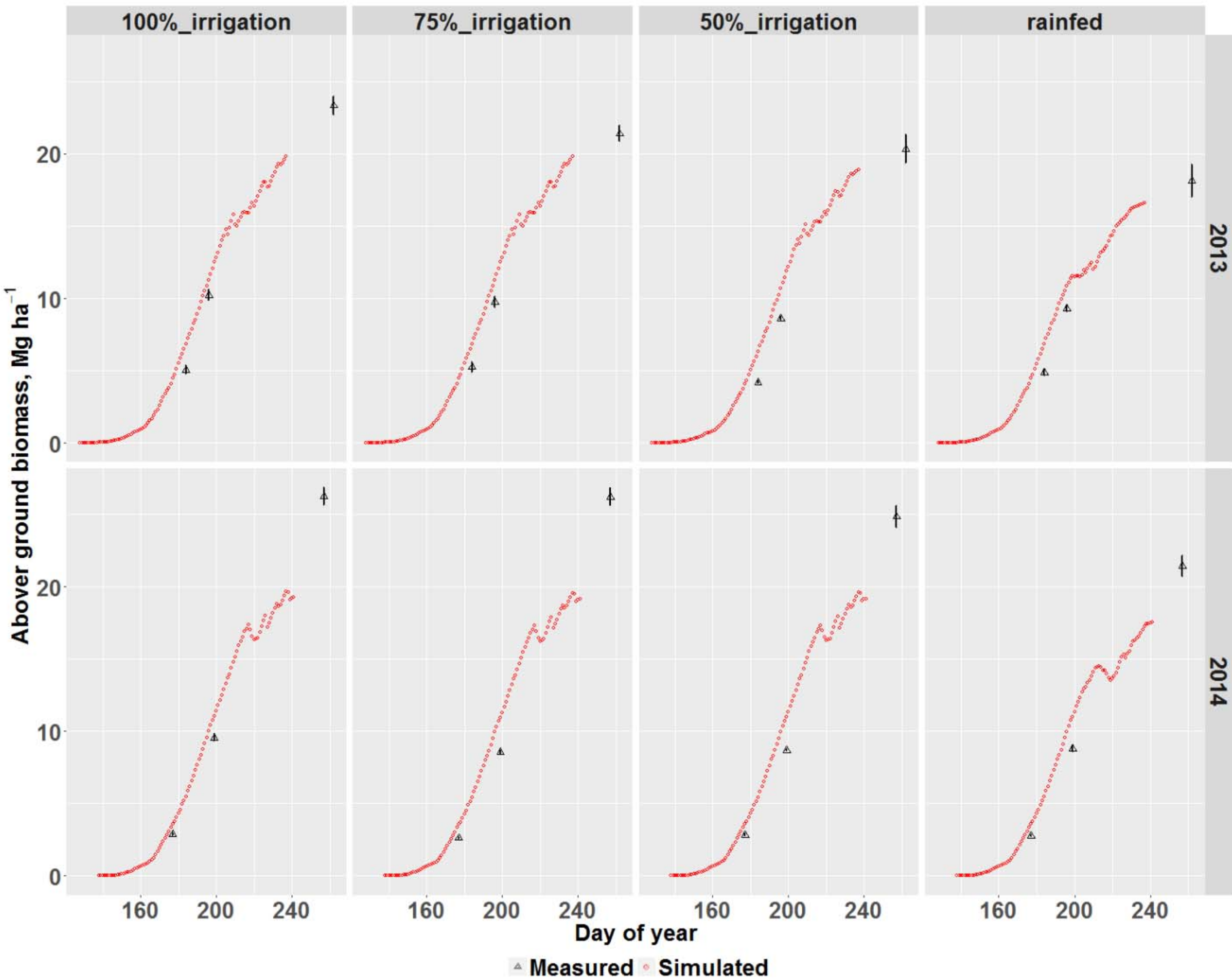

Fig. 3. Measured vs simulated in-season dynamics of aboveground biomass. The red circles are simulated values, and the black triangles are measured value. The black bar is S.E. of the measurements.

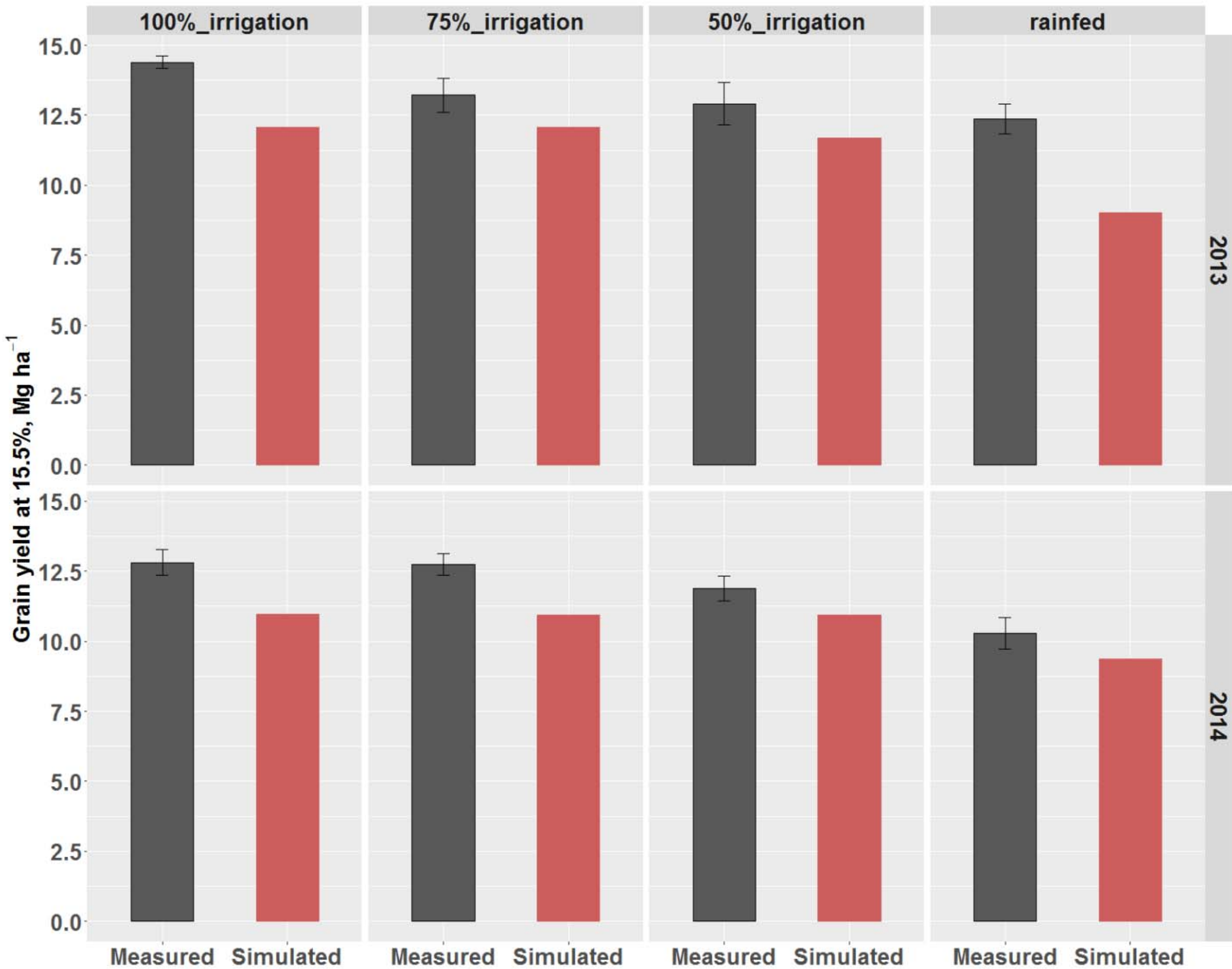

Fig. 4. Measured vs simulated grain yield at 15.5% moisture level. The black bar is S.E. of the measured mean of grain yield.

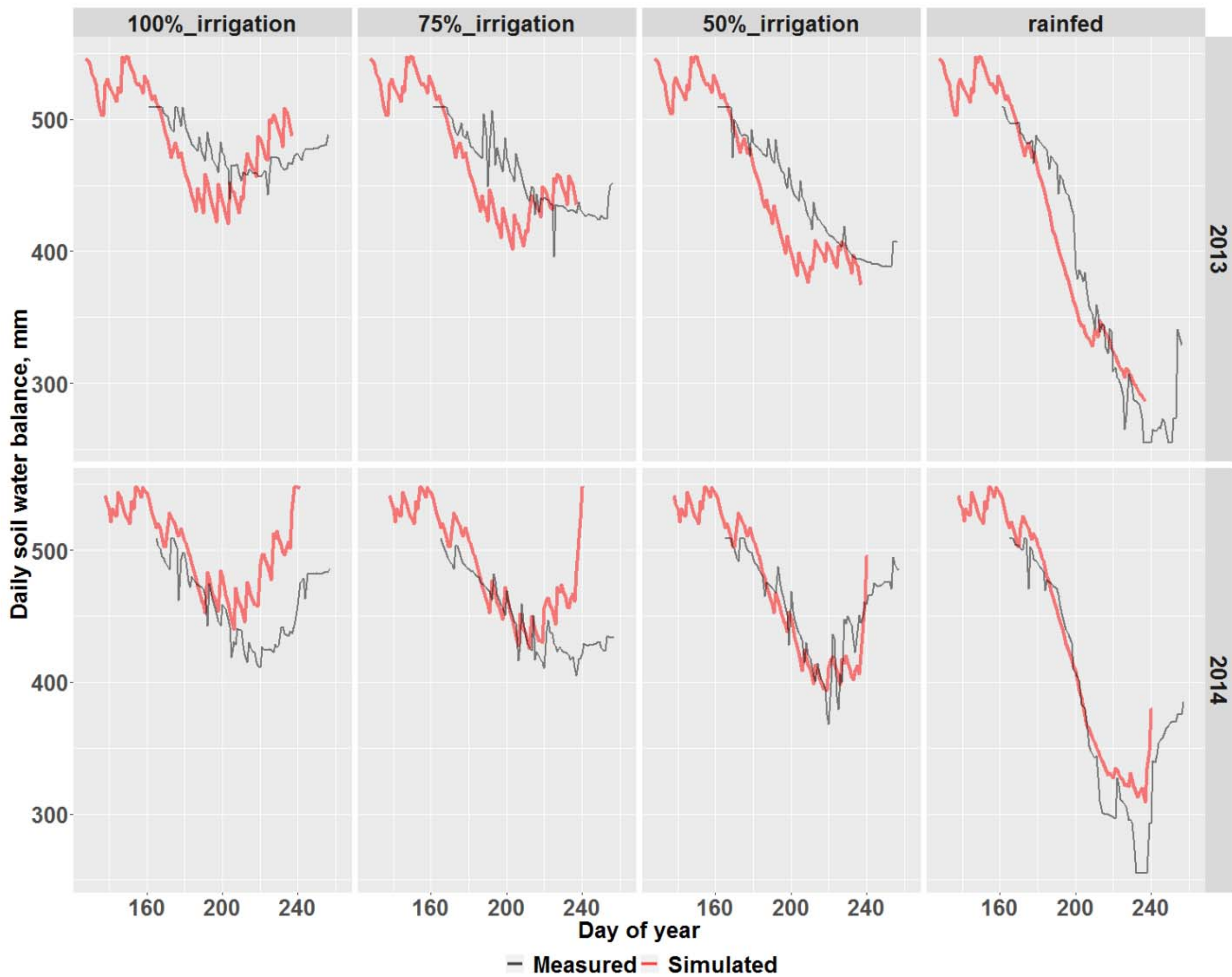

Fig. 5. Simulated vs. measured daily soil water balance to the maximum rooting depth of 1.5 m during the growing seasons of 2013 and 2014 for four irrigation treatments at Lincoln, NE. The thin black line is measured soil water balance, and the thick red line is simulated values.

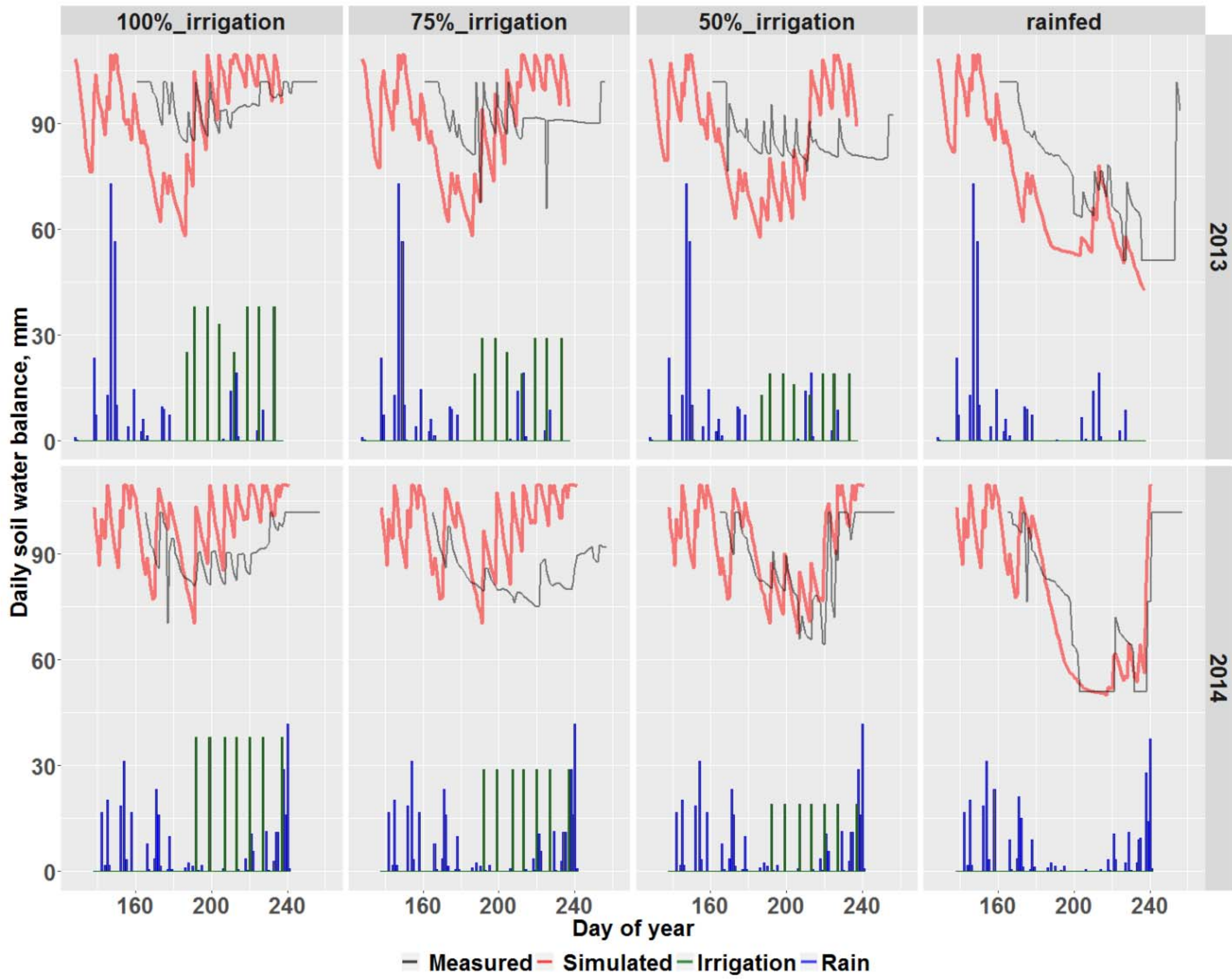

Fig. 6. Simulated vs. measured daily soil water balance for 0 to 30 cm soil depth during the growing seasons of 2013 and 2014 for the four irrigation treatment at Lincoln, NE. The thin black line is measured soil water balance the thick red line is simulated values, the green bar is irrigation, and the blue bar is rainfall.

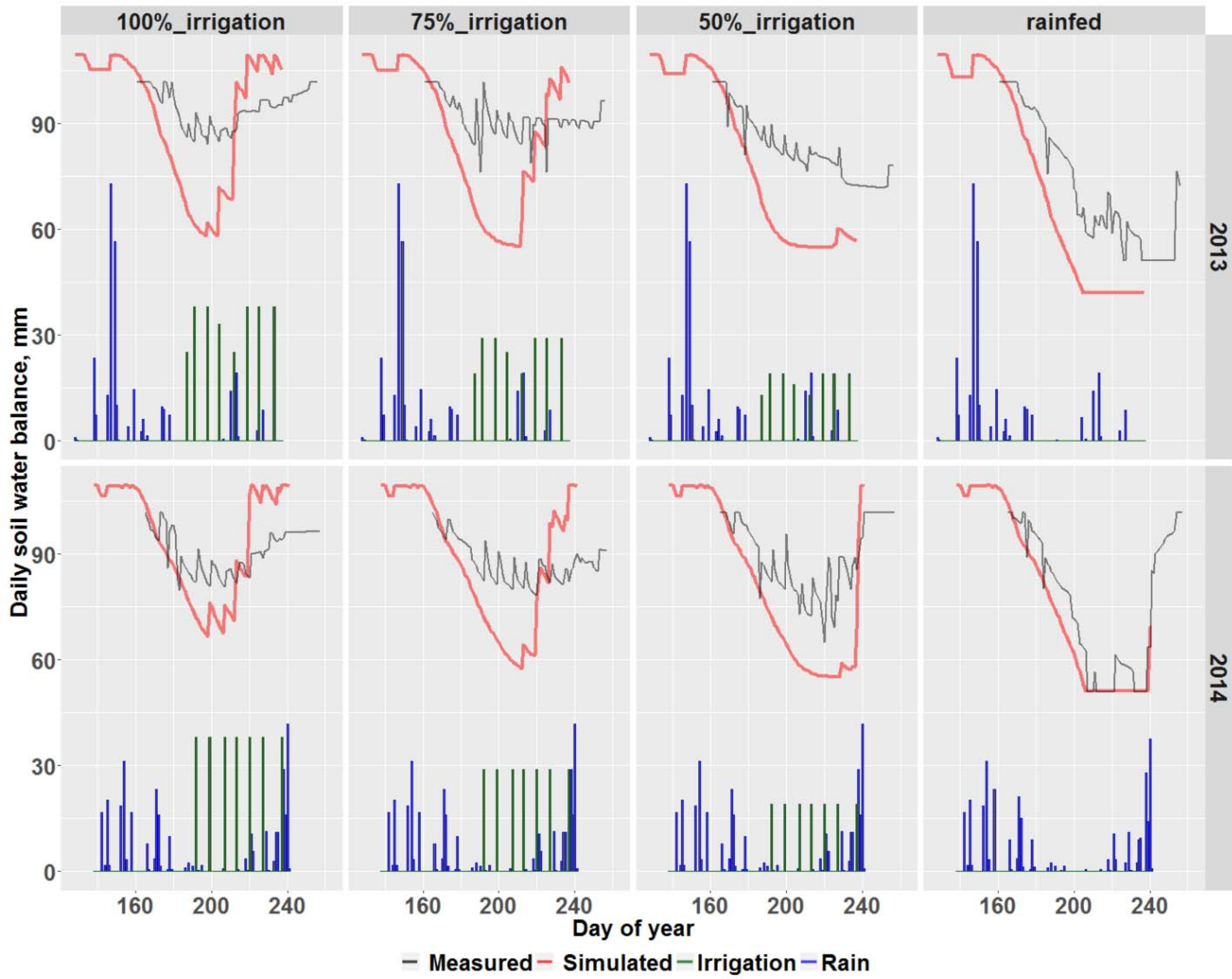

Fig. 7. Simulated vs. measured daily soil water balance for 30 to 60 cm soil depth during the growing seasons for the four irrigation treatments at Lincoln, NE. The thin black line is measured soil water balance, the thick red line is simulated values, the green bar is irrigation, and the blue bar is rainfall.

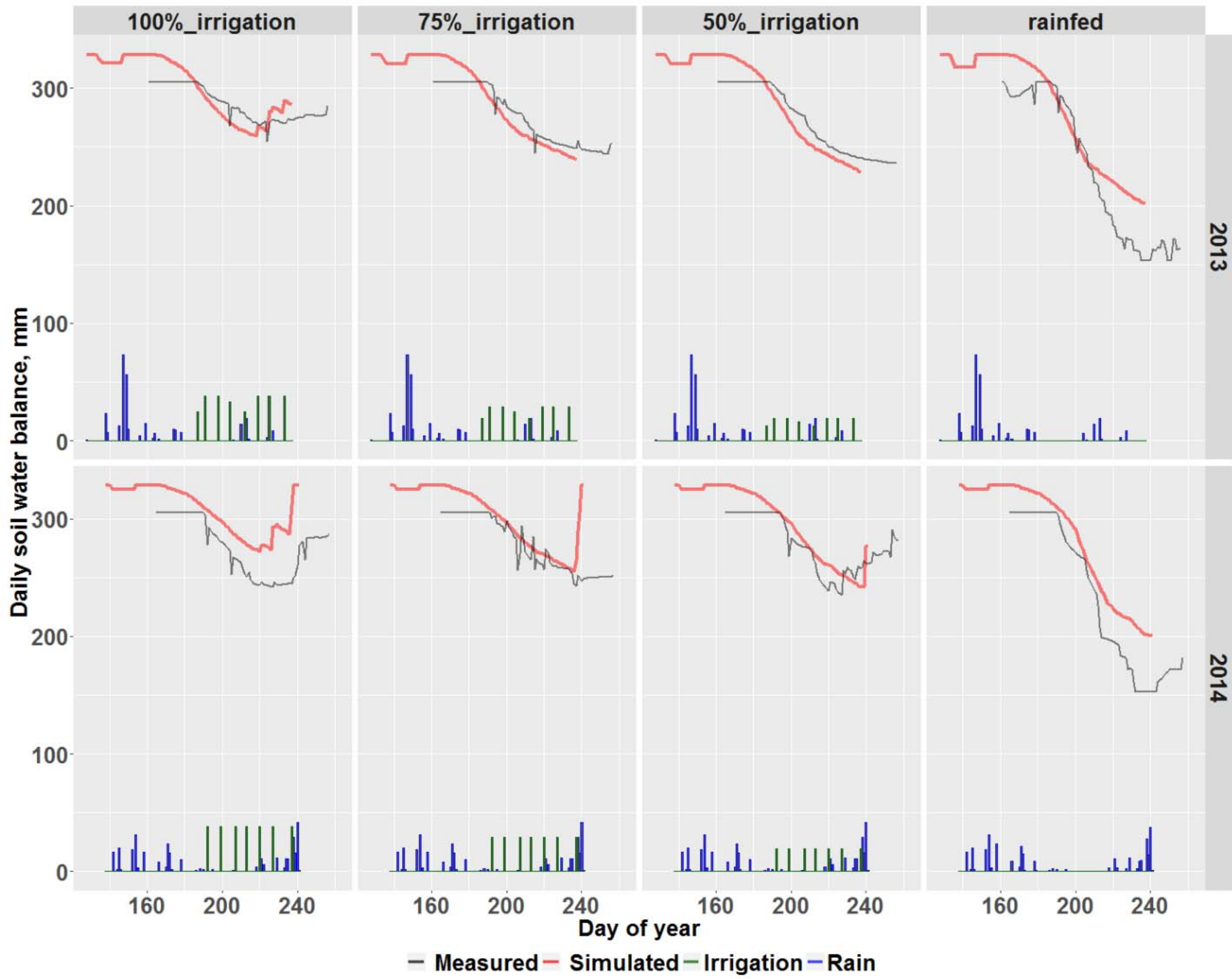

Fig. 8. Simulated vs. measured daily soil water balance for 60 to 150 cm soil depth during the growing seasons of 2013 and 2014 for the four irrigation treatments at Lincoln, NE. The thin black line is measured soil water balance, the thick red line is simulated values, the green bar is irrigation, and the blue bar is rainfall.

Chapter 4

CornSoyWater: A web and mobile app for irrigation decision making for corn and soybean

Abstract

As data related to agriculture become more readily available, researchers and software engineers can work together to deploy science-based applications to aid agricultural decision making. We built an irrigation app called CornSoyWater (http://cornsoywater.unl.edu) for irrigation decision making for corn and soybean fields. This documentation described the use of the app and its component, structure and workflow. The concept was to run multiple crop simulation models on a server while using web services to acquire real-time weather data and forecast; user specified soil data and crop management information were acquired through a user interface (UI). The outputs were rendered to the users' computers or mobile devices (e.g., smartphones). The outputs include the current and 10-day predictions of crop stages, available soil water balance, and recommendation for irrigation. For using the app, a user needs to register a free account of the app that maintains the information of all his/her fields in a secured database. After login, the app first shows all the fields the user has registered in the Google Map using icons of two colors: the red icons are fields that need irrigation now or soon, while the green icons are fields that have adequate water now and in the near future. The user can select any specific fields for detailed outputs and recommendations. Currently, the app covers ten states in the High Plains region in the western U.S. Corn Belt and has been tested by field data. It is being promoted by agricultural extension educators in Nebraska and so far has 1200 registered users.

Keywords: Web mobile app, irrigation, crop modeling

Introduction

Irrigation has been a critical part in crop management, farm profitability, and natural resource conservation in the Midwest USA. Corn and soybean production are the main economic return for agriculture in Nebraska. Better irrigation management, e.g., reducing water withdrawls at crop stages that are less important for yield formation, and synchronizing crop water supply with demand, can lead to reducing water withdrawls, saving energy, increasing crop water use efficiency, and higher profitability (Irmak et al., 2000 and 2012). To achieve this, producers need timely and comprehensive information such as what stage the crop is currently at, how much water is in the soil rooting zone, whether the crop is under water stress, and how much irrigation water is required to meet irrigation targets. With increasing demand for irrigation water and more extreme weather occurring in recent years, irrigation "smarter", data-driven technologies would eventually become the mainstream in agricultural production in the future. For example, instead of manually turning on the irrigation system and letting it run for long hours, nowadays producers can use mobile apps to turn it on only when in-field moisture sensors detect the water stress. With high accessibility of internet and increasingly cheaper data than before, various the web and mobile applications have been developed in the last few years for helping farming practice and decision making, especially on irrigation (Mauget et al., 2013; Caicong et al., 2016; Jordan et al., 2016; Mbabazi et al., 2016; Andales et al., 2014; Bartlett et al., 2015; Vellidis et al., 2016). Those apps operate by a similar principle which is to run a meteorological or a generic/specific crop model(s) on the back end of a server, and use various weather data sources as model input along with crop and soil inputs to create insightful outputs for users such as producers. In order to improve irrigation management and save irrigation water and energy, we developed an irrigation app CornSoyWater (http://cornsoywater.unl.edu) to aid producers in irrigation decision making for corn and soybean fields. This app is HTML 5 based, running on web browsers and can be used on most operating systems including Window, Mac OS, and Linux.

Brief description of CornSoyWater

Prior to the development of CornSoyWater, SoyWater (http//soywater.unl.edu), an irrigation app was developed to aid soybean irrigation. SoyWater was based on the SoySim model (Setiyono et al. 2010). A separate irrigation app for corn, CornWater (http://hprcc-agron0.unl.edu/cornwater/), was developed based on the Hybrid-Maize model (Yang et al., 2004, 2006; http://hybridmaize.unl.edu). CornSoyWater revised and integrated SoyWater and CornWater, with a redesigned user interface. CornSoyWater provides irrigation recommendation to producers in most parts of the High Plains region. CornSoyWater simulates, on daily time steps, up-to-date with 10-day predictions, crop stage and growth, and estimates soil water balance based on water inputs from precipitation and irrigation and simulated crop water use. CornSoyWater will call for irrigation in either of the two situations: available water in the soil rooting zone drops below the pre-defined threshold, or soil water supply to the crop cannot meet water demand based on weather condition and crop canopy size. With the ability to give irrigation recommendations for both corn and soybean fields, CornSoyWater can help producers improve their irrigation management.

In principle, the geographic coverage of CornSoyWater depends on the availability of daily weather data sources. The weather data for CornSoyWater currently are from the Automated Weather Data Network (AWDN) operated by the High Plains Regional Climate

Center at University of Nebraska - Lincoln (HPRCC; http://www.hprcc.unl.edu). AWDN collects weather data each day and uses quality control procedures to ensure the quality of the data before storing the data in the database. Currently, AWDN has 225 active weather stations which cover most farming areas of Nebraska, and part of Colorado, Iowa, Kansas, Minnesota, Missouri, Montana, North Dakota, and Wyoming. We also have access to Michigan Automated Weather Network (MAWN) which covers the Michigan state. At present, the program uses apixu (http://www.apixu.com/), a weather API service for 10-day weather forecast data.

To use CornSoyWater, go to the CornSoyWater home page at http://cornwater.unl.edu in a web browser (Fig. 1). A new user will need to register an account for free. After account registration and activation through the link sent to his/her email, the user can log into the program. To help users know more about the program and its operations, we also prepared YouTube tutorials on the home page. After login, a new user will need to add one or more corn or soybean fields of his/her interest. To do so, the user needs to locate the field on the Google Map by either street name, zip code, or geographic coordinate of the field (Fig. 2). In the background, CornSoyWater uses the field coordinate to determine the closest weather station in AWDN system and retrieves the weather data as the input to the program. The retrieved weather data include maximum and minimum temperature, solar radiation, relative humanity, precipitation, and alfalfa referenced ET. If the closest weather station is beyond a threshold distance (default 20 miles or 32 km), CornSoyWater will pop up a warning message because simulation results may be prone to errors due to poorly represented weather data. Once the nearest weather station is found within 32 km, CornSoyWater will display the next page and ask the user to provide crop management information (Fig. 3). The required crop management information includes 1) crop maturity, 2) date of planting, 3) plant population (*1000/ha), 4) maximum soil rooting depth, 5) soil surface residues coverage (%), and 6) soil water balance of top 30 cm and below at planting, respectively. In addition, the user needs to verify or overwrite if necessary, the default selection for the soil texture class of the field, which is determined by using the field coordinate and corresponding information from the SoilWeb (http://casoilresource.lawr.ucdavis.edu/gmap/) powered by USDA SSURGO data (http://sdmdataaccess.nrcs.usda. gov/) (Beaudette and O'Geen, 2009). The soil texture determination algorithm automatically determines the dominant soil type of the field and aggregates soil texture properties of each description layer to the top 30 cm and below depth (Fig. 3). Each time after irrigation event, the user must register the irrigation date and amount in the program in order to receive updated simulation results.

After clicking "Proceed", the app will show outputs instantly, including the graph on the right side of the page (Fig. 4). On the X-axis of the graph is the date with marks for crop stages, and the left Y-axis is total soil available water, rainfall and irrigation record, while the right Y-axis is crop water stress index (from 0 to 1). The current date is marked, followed by 10 days of predictions. The user can choose past one-week or since planting for the date on the X-axis. On top of the screen is a message either in green or red: A recommendation for irrigation in red if crop water stress is predicted for the next 10 days (Fig. 4, right), or non-irrigation recommendation in green if no water stress is predicted for the next 10 days (Fig. 4, left). The recommendation for irrigation also suggests considering possibilities of rainfall in the near future. Below the graph, a summary table shows the currently available soil water balance, cumulative water input (rain and irrigation) and crop water use (Fig. 5). Note that the irrigation record table below the summary table is for users to register each irrigation date and amount. After the user updates the irrigation records, the app will update all outputs instantly.

If the user clicks crop type on the left side bar of the page, the Google Map will show all fields the user has created in either of red or green color (Fig. 6). Icons in green are for fields that have no water stress, while icons in red are for fields that are or will be under water stress soon. This helps draw user' attention to those fields that are already under or likely to develop water stress and require irrigation. Field data entered in the previous years can be re-used for the current year by simply clicking the "Corn fields" or "Soybean fields" under the Last years' fields tab on the field list at the home page. Select the field to update its information.

We used two datasets (2001 – 2005 in Mead and 2013 – 2014 in Lincoln, Nebraska) to test the performance of CornSoyWater under a common soil type Sharpsburg. The results from chapter 2 showed in Mead, CornSoyWater reduced irrigation pumping on average 93 mm irrigation water during the season compared with conventional irrigation scheduling. Moreover, the average root mean square error between simulated and measured total soil water amount across the two locations was 29 mm, which was acceptable because it could be covered by one round of irrigation of a center pivot. We promoted this app to producers since 2015 through a series of field extension exhibits or educational events. Meanwhile, we keep promoting it to previous SoyWater users who have had experiences with such kind of app. The registration of the app has increased from previously 800 users from SoyWater to 1200 users up to now.

The user can access CornSoyWater account from any desktop, mobile devices with internet access, although we still need to optimize the graphic visualization on mobile devices. The back end of the app was written in PHP; the client side was written by HTML, JavaScript, and CSS. A bootstrap theme was used as the template for CornSoyWater development (https://wrapbootstrap.com/theme/material-admin-responsive-angularjs-WB011H985). Highcharts, a JavaScript library for charting, was used for plotting graphs. In addition, we used a collection of open source libraries including as Apache Web Server, MySQL, and Google Map

API as a framework to support map composition, storage of data, querying, and data visualization.

Discussion

The irrigation app can facilitate the irrigation management for producers as it is able to anticipate the potential occurrence of water stress in the field, thus recommending actions accordingly. Meanwhile, during an irrigation season, which normally starts around silking in Nebraska, producers are very busy on all farming activities and in multiple fields. It can happen that producers miss certain fields which need an immediate irrigation when they are busy dealing with other issues. CornSoyWater can help them better manage irrigation scheduling by estimating what stage the crop is currently at for a given field, how much available water is in the soil rooting zone, if the crop is likely to develop water stress soon, and if irrigation is needed now. It will also dramatically save the time of producer on field scouting for water stress and help them focus on fields that need their attention. Lastly, using CornSoyWater can reduce irrigation pumping by optimizing the irrigation timing, which will also save pumping cost.

It is still challenging to use such app broadly because the adoption in agriculture area is usually slow when it comes to new technologies. In addition, the use of smartphones in the field can be a drag for first time users or users who are less technology savvy. Also, the cellular coverage and quality in a rural area can be an issue sometimes. On the other hand, the onsite rainfall record is critical for accurate irrigation scheduling and management. If a weather station has less accurate rainfall record, the outputs from the app would deviate from the reality, which can mislead irrigation management. Also, the management and maintenance of the app are also challenging regarding funding and personnel. To solve this problem, we are currently working on moving the app to a commercial cloud along with other web services related to the app.

Conclusion

Better decision support is required to improve corn and soybean irrigation management in Nebraska. We developed CornSoyWater, a web app for integrated corn and soybean irrigation decision support. It provides a real-time estimation of soil water balance, crop stage, and water stress with 10-day predictions. We believe it can make a difference in optimizing irrigation timing, reducing irrigation pumping and cost, and reduce producers' travel costs and field scouting time. With CornSoyWater as an aid, producers would be more confident in making smarter irrigation decisions for their corn and soybean fields.

Supplementary materials

CornSoyWater technical documentation – how to build an irrigation app from zero to hero

The app

CornSoyWater runs on a web browser of desktops and mobile devices with internet access. The back end of the app was written in PHP, while the client side was written by HTML, JavaScript, and CSS. We used a collection of open source libraries including Apache Web Server, MySQL, bootstrap theme, Highcharts, and Google Map API as a framework to support map composition, storage of data, querying, and data visualization.

Server setup

The server was installed with CentOS Linux 6.8 (https://wiki.centos.org/Download) and managed by HPRCC. There are several references on how to set up a Linux server (http://www.computernetworkingnotes.com/network-administrations/web-server.html). Basically, you need to install Apache Web Server (https://www.youtube.com/watch?v=-q8Jj4aAWYw ; http://www.wpbeginner.com/glossary/apache/), PHP (http://youtu.be/7Zm9vLh70wI), MySQL (https://www.youtube.com/watch?v=uqaoGTnxqNw) on your service which depends on your needs. Also, you many need SSL (Secure Sockets Layer) for securing your server (http://info.ssl.com/article.aspx?id=10241). Note that different Linux operating systems might vary depending on web server configuration. After configuration, your server would be able to connect to the Internet.

Program structure

The basic idea is this app needs to (1) store user's inputs including field geolocation and crop management information and soil data, and (2) retrieve and store weather data from designated sources. The app then uses the data to conduct the model simulation and present the results to the user in a meaningful way. The structure of the app in Fig. 7 summarizes this logic. The app uses different services including weather service, soil service, map service, and static and dynamic files to provide inputs to the two crop models (corn and soybean). Using the crop management data on users' fields stored in the database, the two models take the inputs and produce visualized outputs by a graph on the client side. The user interacts with the app by updating the irrigation records or revising other field or crop information. Once updated, the app will update the data in the database and re-run the models to produce updated outputs. In Fig. 7, the REST means the user on the client side can interact with the app by four actions, “get”, “put”, “post”, and “delete”. For example, a user can click a field in the field list to select that field, and when clicking another field, the previous one will be “put” down. The user can also choose to “post” a new field, or “delete” a previous one (https://www.infoq.com/articles/rest-introduction). In the next a couple of bullet points, the document will take apart each component of the app and explains how the app uses these components. See components in Fig. 7.

Workflow

Fig. 8 shows the workflow of the app. Readers can navigate the page toward the direction of the arrow pointed to a next page. Readers also can hit the back button to go back to the previous web page of the app. The latest version of the app workflow may vary from Fig. 8 depending on the update of the app design. The workflow turned the abstraction of the app structure to a concrete layout. Here is an example of walking through the Fig. 8 step by step, and we are going to discuss in each step how CornSoyWater would involve the components in Fig. 7.

First, the start point at the Login Page (Fig. 8). After registering and activating a free CornSoyWater account by clicking the activation link sent to his/her email, the user is ready to log in. On the server side, the database also has been updated after registration. There are two databases; one for user-specified data, and the other for weather data showed in Fig. 9. In the user database, there are five tables: fields, login, crop input, irrigation record, and rainfall record. The status column in the login table is also updated from “Not activated” to “activated” in the database. Meanwhile, the user’s information is saved in the user table of the database, and his/her field information is stored in the Field table in the same database.

Second, on the Home Page, the user can click Add a new field, or click an existing field on the Field List (Fig. 2, Fig 7). The default view is the Google Map with existing fields shown. When the user clicks Add a new field, the app will jump to the Add a new field page which contains a new Google Map with a search box and a red marker (Fig. 2). The user will choose to create either a corn or soybean field. After that, the user will need to find his/her field on the Google Map by searching either street number, zip code, or coordinate. The Google Map provides a geographic coordinate of a field which is stored in the database. The app will use the coordinate as the starting point to calculate the distances from the field to each weather station in the database to find the closest one. Note that the app uses a threshold of 32 km (20 miles) beyond which a warning message will pop up to inform the user that the weather data source may not be reliable for the field due to poor representation. In addition, the map shows a red marker on the selected field. We suggest the user place the marker in the center of the field. We use a soil type aggregation algorithm to retrieve the main soil type of the field area. We used SoilWeb developed by UC Davis to support our soil aggregation algorithm (Beaudette and O'Geen, 2009) (Fig. 7). SoilWeb is powered by USDA SSURGO data, one of the widely used soil database in the United States (http://sdmdataaccess.nrcs.usda.gov/). After a user marks the center of the field and proceeds to the next page, the app will generate a square with a side length of 0.5 mile (0.8 km) and uses the marker as the center of the square. The purpose of this invisible square is to capture the field area and calculate the dominant soil type of this field for model simulation. Here is how the algorithm works: 1) the coordinate of the angles of the square is passed to a web service of SoilWeb, and SoilWeb returns the soil types and the corresponding areas of that soil type inside the square, respectively. The algorithm will take the dominant soil type on the basis of its area size and ignore the other soil type; 2) for the dominant soil type, the algorithm retrieves the silt and sand, the percentage for each soil depth (various by locations) respectively and aggregate them to two soil depths for corn (0-30, 30 to maximum rooting depth) and one soil depth (0 to maximum rooting depth). For example, in Fig. 10 when the user creates a corn field, there are three soil depths for this specific soil, the algorithm will grab the 0 – 13 and 13 – 30 cm, and the 30 – 74 and 74 – 150 cm (150 cm is maximum rooting depth the user set) as two groups, then use 35*13/30 + 35*(30-13)/30 for the weighted clay percent at 0 – 30 soil layer. And the algorithm uses the same manner to calculate weighted clay percent for 30 – 150 cm, and so on. Note that the sum of weighted clay, sand, and silt percent at 0 - 30 cm will be 100 percent, and so as the 30 – maximum rooting depth. 3) The final 0 – 30 cm and 30 cm – maximum rooting depth percent of clay, sand, and silt will be passed to USDA soil triangle algorithm(http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_054167), which will return the defined soil texture class for 0 - 30 cm and 30 cm - maximum rooting depth, respectively. Those two values will be passed to the next web page as the default soil texture settings (Fig. 3). After creating the field, it will be shown on the Google Map of Home page with color icons to indicate crop types (corn or soybean) and water stress status (green no stress, red has stress) (Fig. 6). The map services in Fig. 7 mean the Google Map provides service in the Add field information page (Fig. 2).

Third, after the user clicks the Proceed button on the Add a new field page, the app will jump to the next page and asks the user to provide the field specific crop management information (Fig. 3). The required information includes hybrid relative maturity (days), 2) date of planting, 3) plant population (*1000/ha), 4) maximum soil rooting depth, 5) soil surface residues coverage (%), and 6) soil water balance of top 30 cm and below at planting, respectively. All the information is stored in the user database after finishing all the forms. Note that the user can choose to overwrite the auto-loaded soil texture by his/her own choice. We made a design change to attach the irrigation page on the result page in the new version of the app, but this change is subject to the designer. It makes more sense to have irrigation page follow cropping management information page in case the user has already started to irrigate and the updated irrigation information will provide more accurate results.

Fourth, between Add a new field page (and irrigation page) and the Crop projection page for selected field, the app calls the weather database for data from the selected weather station. The weather data comes from two sources. One is from AWDN hosted by HPRCC (http://www.hprcc.unl.edu/awdn.php), which provides the up-to-yesterday daily weather data and historical average weather data to our weather database (Fig. 9). Another source is apixu (https://www.apixu.com/) which provides a 10-day weather forecast. We merge the data from those two sources to meet our model simulation requirement. For the AWDN weather data, we fetch the historical weather data for each available year from all activated AWDN weather stations and stored them in our weather database under wdarane table (Fig.7, Fig. 9). We also calculate historical average weather data for each weather station, respectively, and store them under normdatane table. When the historical weather data is less than 20 years, we flag the normdatane table for the purpose of quality of the historical average weather data. The historical weather data is only used by soybean simulation and serves as a backup when the apixu weather forecast is not available. Every night at 12 am, the HPRCC updates the previous date's weather data, and pushes the new record to our server and stores the data in a text file (dynamic file in Fig. 7). The app grabs the new weather record and updates the weather database. A similar mechanism is applied to update the weather data from Michigan, but instead of grabbings the new data from the text file, we wrote a script to grab it from their website directly. Meanwhile, we use the web API provided by apixu to retrieve 10 days forecasting weather data (including today because AWDN doesn't provide today's data) and store them in the same weather database. By passing the coordinates of the respective weather stations, we retrieve the apixu weather forecasting data of those coordinates. Note that apixu does not provide reference ET, which is pre-calculated by HPRCC and included in the AWDN weather data source. Thus, we wrote a script to calculate it using the forecasted weather data. The ET calculation requires Tmax, Tmin, relative humidity, wind speed, and solar radiation. Because apixu does not provide solar radiation forecast, we use the average of last three days' solar radiation from the corresponding AWDN weather station to calculate the apixu actual ET for the next 10 days. Whenever AWDN updates the yesterdays' weather data, it will be automatically stored in the weather database, and the weather data from the apixu forecasting weather data at the same date is replaced. We also wrote quality control procedure to screen the weather stations data from AWDN. Sometimes, the weather stations from AWDN may be down, so we need to know if the station is discontinuous or gives us null data when we retrieve weather data. When this happen, the app will use the second nearest weather station for model simulation instead.

Fifth, after getting the weather data, the app will gather the crop management data including soil type and weather data and send it to the model for the simulation (Fig. 7). If the crop is corn, the corn model is called. The corn model uses the Hybrid-Maize as the "engine". The Hybrid-Maize model is written in Delphi. In order to efficiently run the model without rewriting the model in PHP due to the complexity, we compiled the source code to a binary executable file. The source code was compiled by Lazarus IDE v.1.2.2 (http://www.lazarus-ide.org/) running under Ubuntu 14.04 LTS Linux environment at 64 bit (https://www.ubuntu.com/). By compiling the source code, the model will be able to run under Linux server environment seamlessly. Here are several steps to show how to convert the source code to a binary executable file:

(6/18/2015)

1. Turn on Ubuntu Linux 64bit system on the laptop.
2. Use Firefox Brower to access the dropbox link from the source and download the whole CornWater project as a .zip file.
3. Move the .zip file to the desktop and put it in a new created fold. Name the fold by the binary version and what problem has been resolved in this version.
4. Unzip this file.
5. Open Lazarus in Linux.
6. Open the new folder. Select the file type all type.
7. Open $Binary.drp. The Lazarus will ask you "The file… seems be a program. Lose current program and create a new program, click "yes". You want to click Yes.
8. Choose application, click ok.
9. At the top bar of Lazarus, click the "play" button.
10. Click ok when "Execution stop". You will see another message box showed Project "$Binary" successfully built.
11. Go back to the new folder, find the generated binary file named "$Binary".
12. In the new folder in desktop, test it by setting up a field name in userlist.txt. For example in userlist.txt, write userA/
13. This will allow the binary read userA.inp and produce results in userA.out.
14. Backup old binary in server hprcc-agron0 at a home directory ~./CornWaterV5Linux32bit
15. Replace the old binary CornWater by the new binary CornWater by copy and paste. If the server did not allow, delete the old binary on server and copy paste the new binary in the same location as the old one located.
16. Change the properties of the binary ConrWater to 755. Basically, for all check boxes only group write and other write are unchecked, other boxes are checked.
17. Test if the output is correct by running CornSoyWater web or mobile app.

There are two parameter files as **statistic files** (parameter.hmf and parameter2.hmf) (Fig. 7). These two files contain parameters for corn model simulation. There is another text file called userlist.txt. Whenever the page jumps to Crop projection page for selected field page (Fig. 8), the app will pass a unique field id to create a string in the userlist.txt file. Meanwhile, the cropping management information is written in a field_id.in file through the user database and the corn model will read that file. The model reads the specific weather data for that field from a ".wth" file generated by the app through the weather database. After the simulation has been completed, the outputs are written in a field_id.out file. The Crop projection page for selected field page then displays the results accordingly. If the user updates the irrigation form under the results and save the updates, the simulation will re-run and new results will be plotted on the page. If the crop is soybean, the **soybean model** will be called. Because we modified the SoyWater code, the soybean model can directly retrieve weather data from the weather database and produce results. Note that both corn and soybean model use a dynamic root growth mechanism to define the total available soil water. It means if the root does not reach a certain soil depth yet, the soil water beneath that depth is not accessible by the crop. This is different from the mechanism used by Hybrid-Maize model which defines the total available soil water to the maximum rooting depth starting from the planting date. This modification lowered the risk for overestimation of total available soil water. Here is the algorithm of soybean model dynamic rooting depth:

(6/22/2016)

Unit: depth in inch, temperature in F

At initiation of simulation, calculate root growth rate (RGR) from user-set maximum rooting depth (maxRD, in inch):
RGR = maxRD /1422

Calculation scheme for Day 1

1. Calculate GDD (growing degree days) from temperature of that day:
   - Calculate mean temperature (Tmean) from the maximum (Tmax) and minimum temperature (Tmin): Tmean = (Tmax + Tmin) /2
   - Calculate daily thermal time (DTT): DTT = Tmean – 50. If DTT > 27 then DTT = 27, else if DTT < 0 then DTT = 0.
   - Calculate GDD up to today: GDD = GDD + DTT. Note that GDD must be set to 0 at initiation of simulation.
2. Calculate root depth (RD, inch): RD = GDD * RGR. If RD < 12 inches then RD = 12 inches; if RD > maxRD then RD = maxRD
3. Calculate Threshold for irrigation: Threshold = RD * (FC - PWP) * 0.5
4. Calculate water content of the root depth (thetaRD) at end of the day:
   - thetaRD = (thetaRD*RD + WaterInput – ET) / RD;
     if thetaRD > FC, then:
       Overflow = (thetaRD – FC)*RD;
       thetaRD = FC;
5. If overflow > 0, then calculate water content of below root depth (thetaBRD) at end of the day:
   - thetaBRD = [thetaRD *(maxRD – RD) + Overflow]/ (maxRD – RD); if thetaBRD > FC, then thetaBRD = FC
6. Calculate total available water (TAW) in the root depth: TAW = RD *(thetaRD – PWP)
7. Plot TAW and Threshold, both in inch

Abbreviations:
RD: root depth, inch
RGR: root growth rate, inches/GDD
GDD: growing degree day
DTT: daily thermal time

Tmax, Tmin, Tmean: daily maximum, minimum, and mean temperature, respectively
FC: field capacity (constant)
PWP: permanent wilting point (constant)
thetaRD: water content (in fraction) of root depth
thetaBRD: water content (in fraction) of below root depth
ET: evapotranspiration (i.e., crop water use)

Sixth, after seeing the results, if the user clicks the Field list and goes back to the home page, he/she can see the up-to-date stress status of the fields on the Google Map from the auto-simulation that is conducted every morning at 6 am Central Time (Fig. 6). The icon pictures (corn/soybean) and colors (green/red) indicate the crop type and whether the crop is or will potentially experience water stress in the next 10 days, respectively.

Seventh, the user may have created a field or multiple fields in the CornSoyWater account in the previous years, if he/she wants to use the old fields information in a new year, he/she can simply click the “Corn fields” or “Soybean fields” under the last years’ fields tab on the field list at the home page and select the field he/she which want to change and update the field information. The app will update the user database so the next time when he/she visit this field, a current year simulation would be presented.

Future Recommendations

The improvement of the app design in the next iterations could be:

1) Add parallel computation for the models. Because we have not had a large amount of simulation requests at a short period of time, we do not know if the binary executable file would be able to handle hundreds of simulation calls at the same time. Add a parallel computing process or rewrite the source code of model into a web script language could resolve this potential issue.

2) Move the server to a commercial cloud service. The Amazon AWS or Digital Ocean would be a good choice as the maintenance efforts of the server would be minimized.
3) Rewrite the code in an MVC fashion and use API if needed. The old code was disorganized. Newly organized app structure and coding fashion are necessary.
4) Move the irrigation page (form) in between Add a new field page and Crop projection page for selected field (Fig. 8). But also keep the irrigation form under the results graph.
5) Add new feature such as a shapefile layer for the field area. In that case, the user can define their own field area.
6) Add parallel simulations for different soil types for a single field. For each soil type in the field, the model should be able to simulate separately by the soil types.
7) Add user input precipitation option. Thus a user can input onsite precipitation by the rain gauge measurement.
8) Add printout button and email option. Thus a user can print out the results page, or receive a notification email for the stress fields in the morning.
9) Add "Try it" option. Thus a user can try the app without registering an account. This new feature can encourage a first time user to try the app out.

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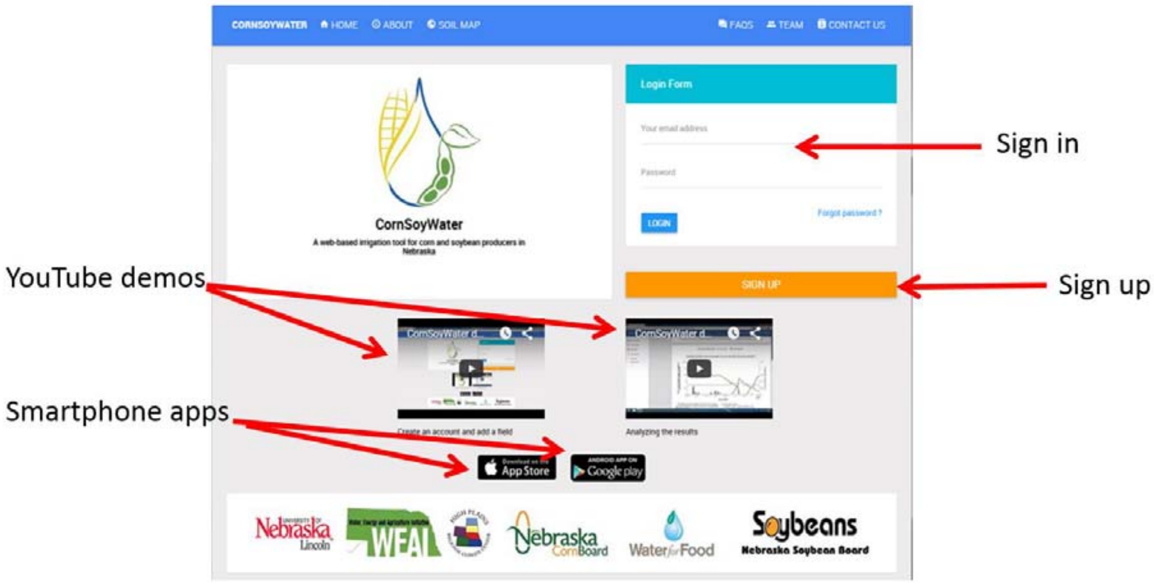


Fig. 1 The home page of CornSoyWater at http://cornsoywater.unl.edu

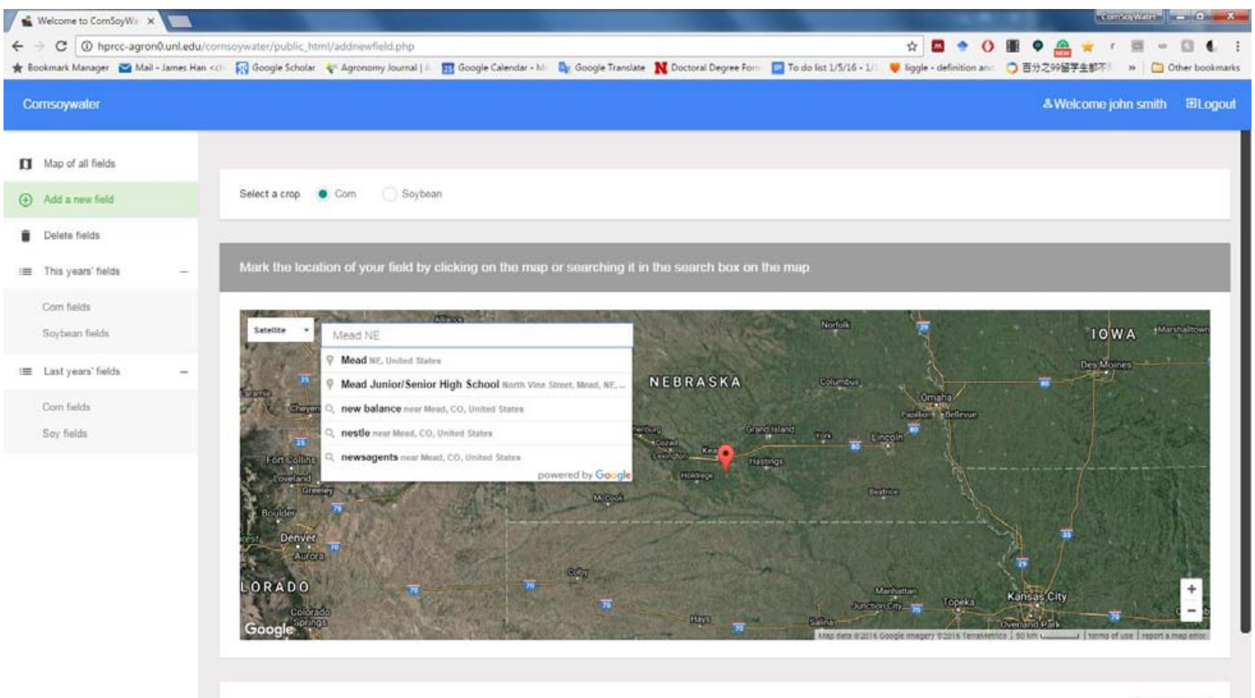


Fig. 2 The homepage of CornSoyWater after login. Field list is on the left site of the page; crop type option on the top of the Google Map, and the Google Map for searching and marking a field

location of the user.

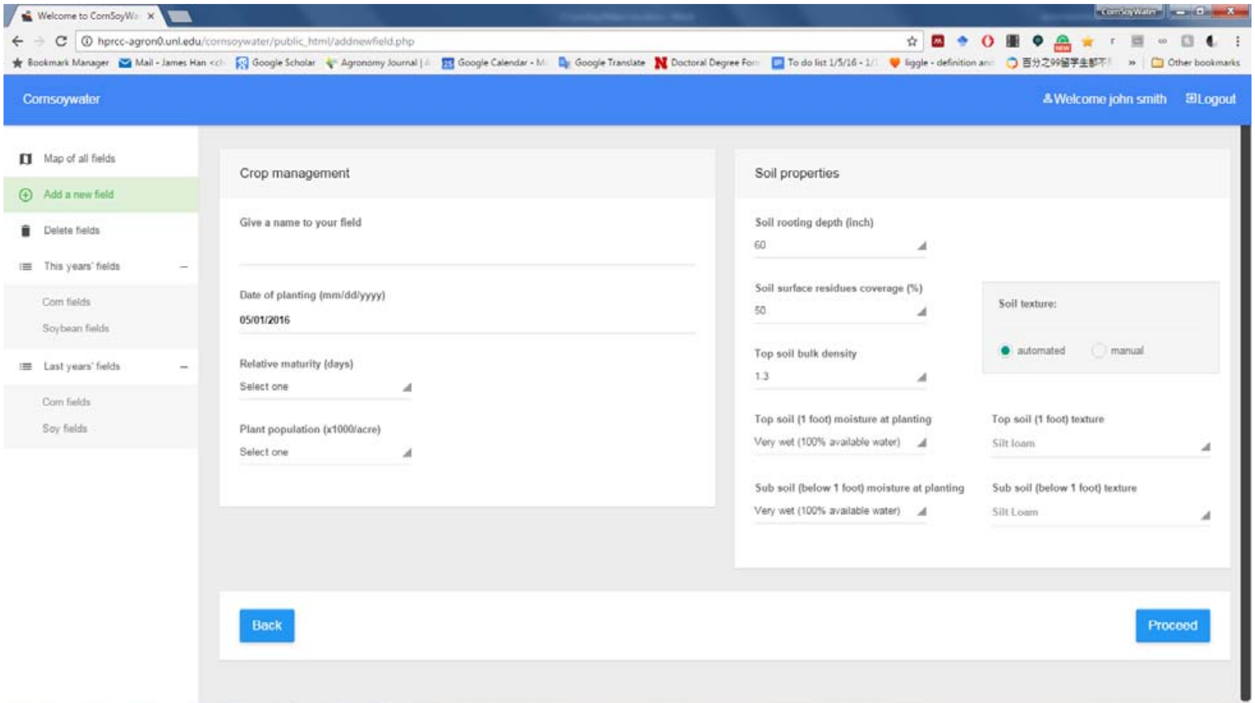


Fig. 3 Adding a new corn field page in CornSoyWater. A user will fill out the crop management information on this page, including 1) hybrid relative maturity (in days), 2) date of planting, 3) plant population (*1000/ha), 4) maximum soil rooting depth, 5) soil surface residues coverage (%), and 6) soil water balance of top 30 cm and below at planting, respectively.

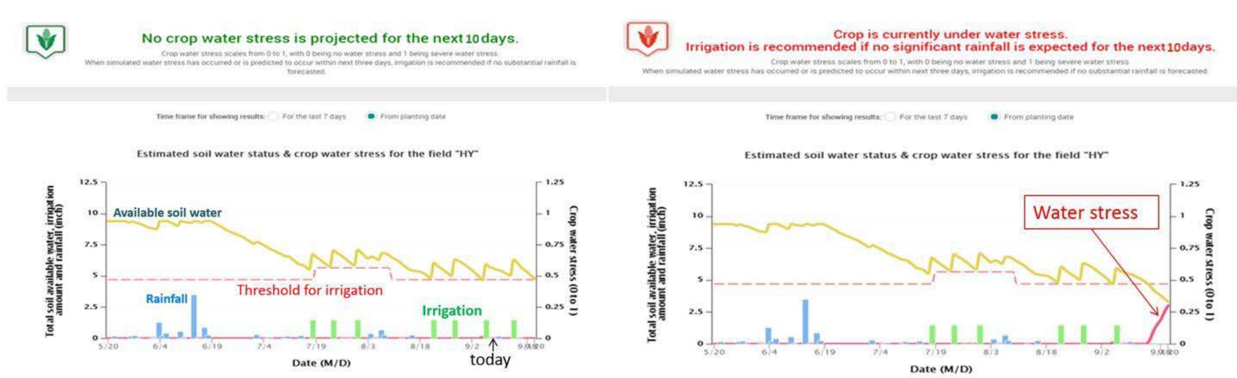


Fig. 4 Left: when the app predicted no water stress, the available soil water (solid yellow line) is above the threshold line (red dash line), the notification message shows green, and no irrigation

is recommended. Right: when the app predicted water stress, the available soil water is below the threshold line, the notification message shows red and irrigation is recommended if no significant rainfall occurs.

Results Summary	
3.3	Current available water balance down to the maximum soil rooting depth (inch)
9.4	Initial available water down to the maximum soil rooting depth at planting (inch)
11.0	Total rainfall amount since planting (inch)
9.0	Total irrigation amount (inch)
20.0	Water consumption (i.e., total crop ET) since planting (inch)
6.0	Water losses, including canopy interception and drain below the maximum soil rooting depth (inch)

Fig. 5 The summary table of the output graph shows current available water balance down to maximum soil rooting depth, initial water down to the maximum soil rooting depth at planting, total rainfall amount since planting, total irrigation amount, water consumption such as ET since planting, water losses, including canopy interception and drain below the maximum soil rooting depth. All unit are in inches.

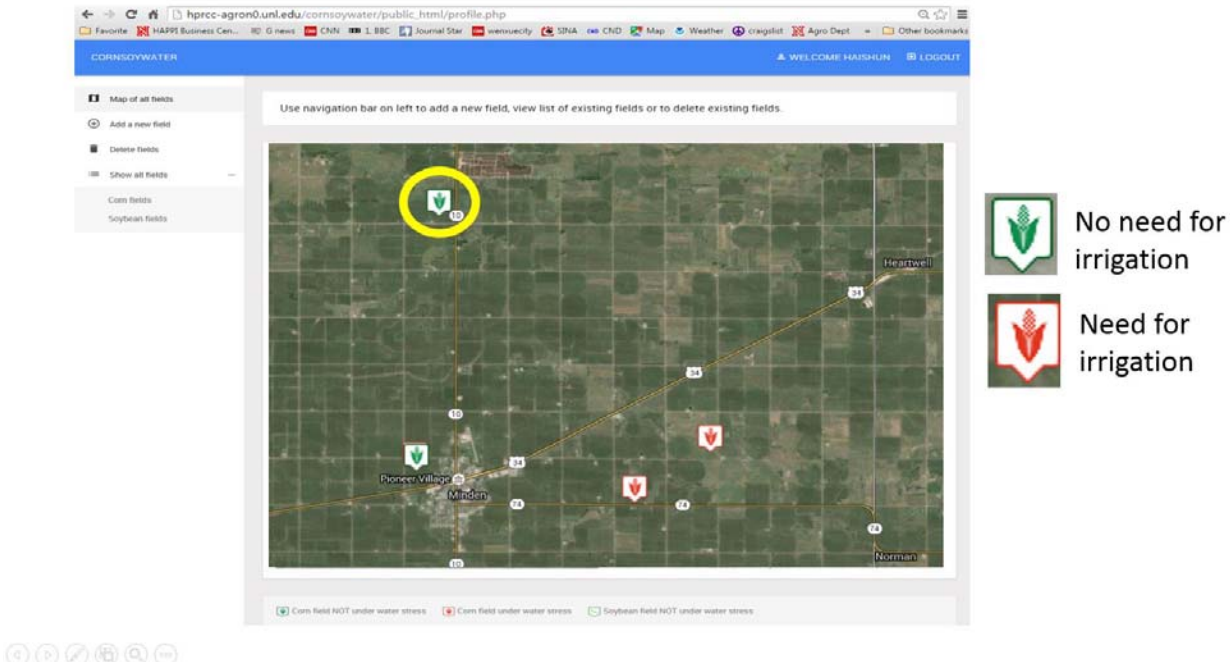


Fig. 6 Field map showing all fields of a user using icons of corn and soybean to indicate. Icons in green mean no water stress predicted while icons in red indicate water stress or will likely experience water stress in the next 10 days if there is no significant rainfall occurs.

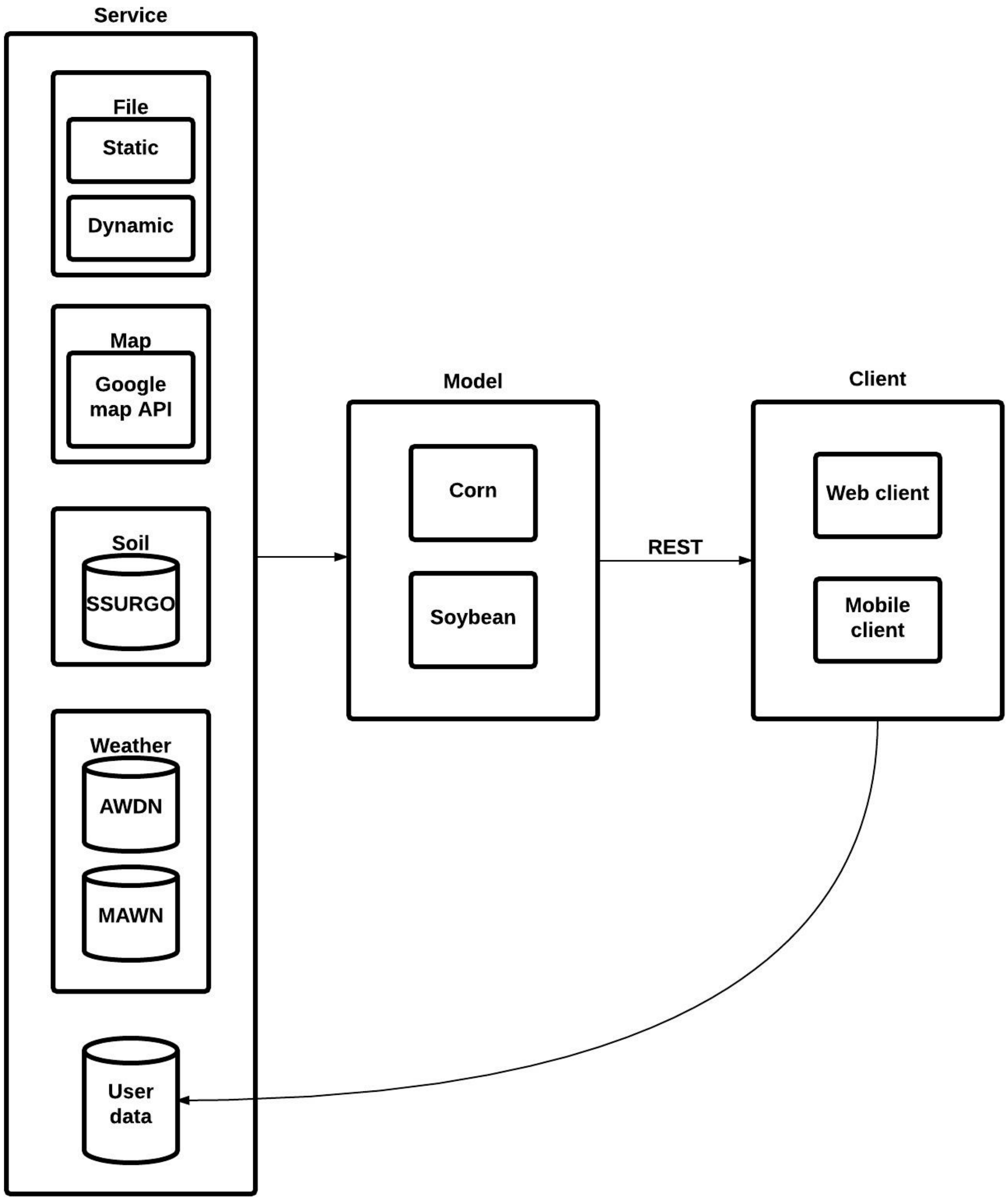


Fig. 7 Components and structure of CornSoyWater. The rectangle indicates service (input) from

Google Map API, SoilWeb, weather data from AWDN and MAWN. With the statics and dynamic fields in our server and our user database, the model will simulate and generate outputs. The output will be showed on the client side. The arrow indicates the direction of flow of the information between components. REST, representational state transfer.

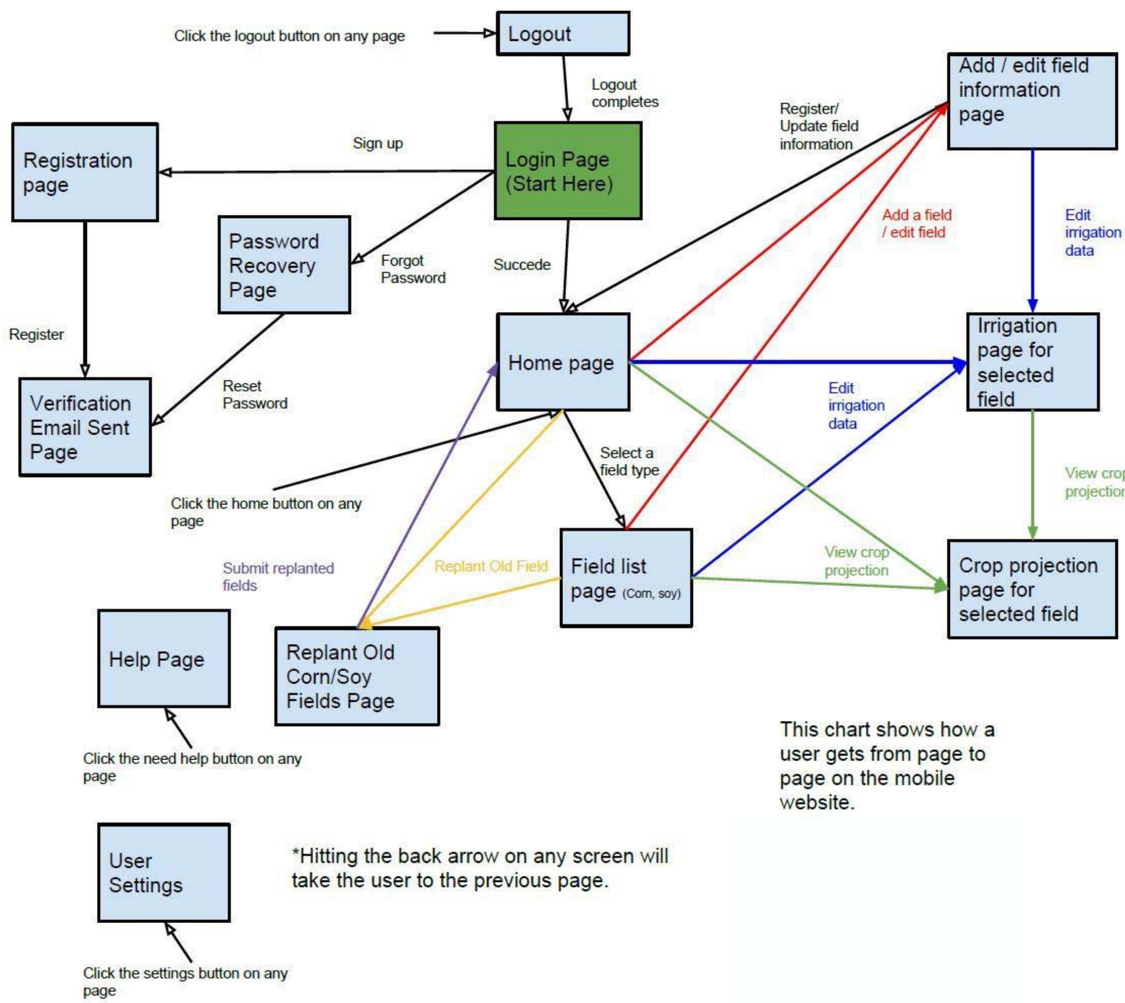


Fig. 8 The workflow of CornSoyWater, starting Login page. The arrow indicates the direction of flow of the information between components. The workflow is subject to change.

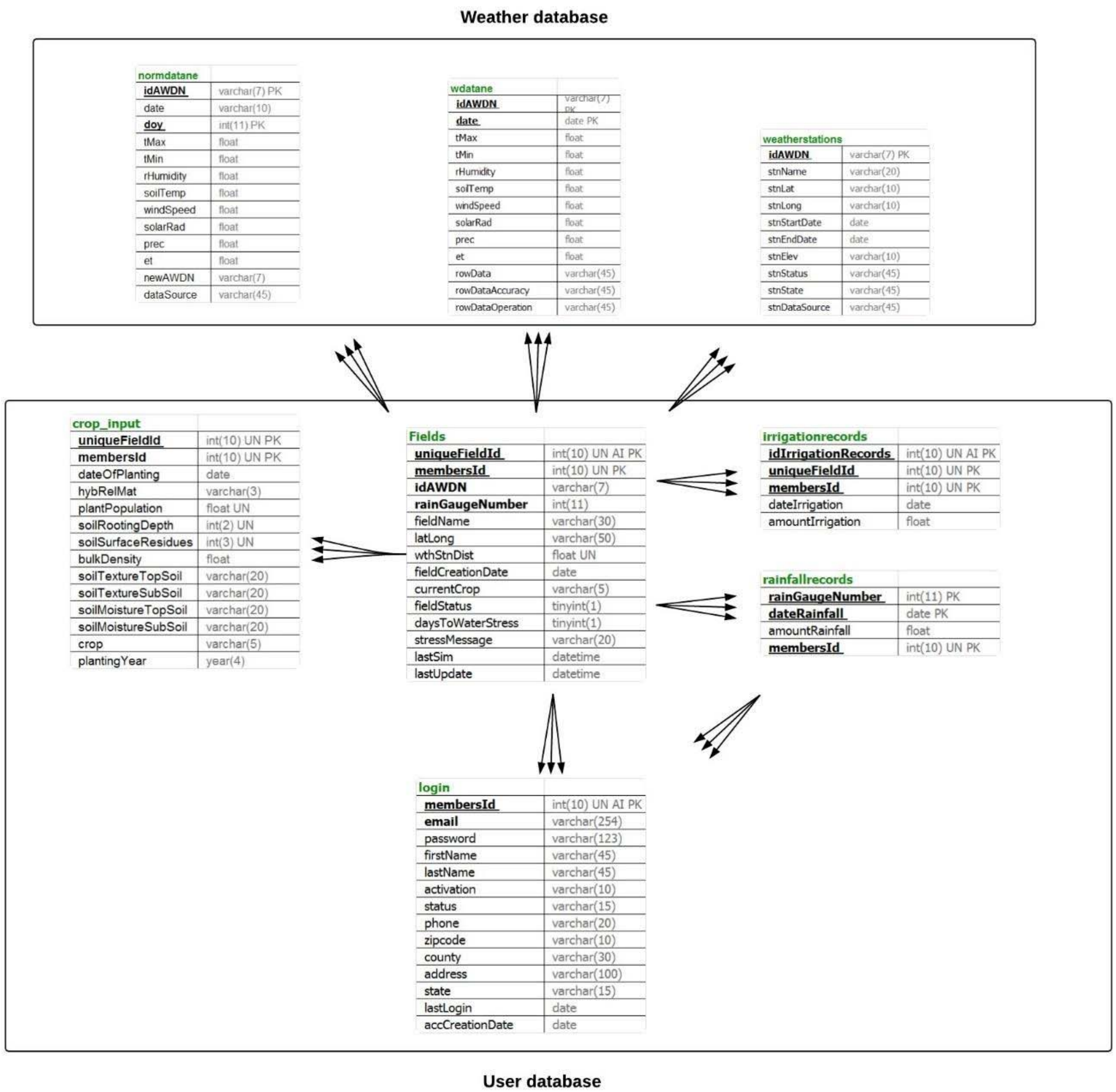


Fig. 9 The databases of the server for hosting CornSoyWater. The top box is the weather database, and the bottom box is user databases. The weather database includes normdatane: historical average weather data, wdatane: AWDN and MAWN weather data, apixu weather data, weather stations: weather station information. The user database includes crop_input: the crop information for each unique fields users creates, Fields: the field information, irrigation records: irrigation records for each field, rainfall records: rainfall records for each field, login: the login information for each user.

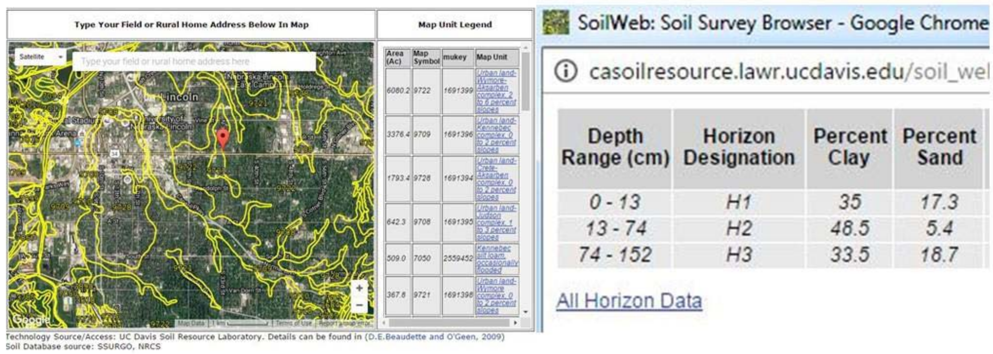


Fig. 10 Left: SoilWeb data layer on a google map. The map shows each soil type, keys, and areas. Right, the soil texture of one soil type at different soil depths.

Chapter 5

Scientific Summary and Discussion, and Ispagtech Business Plan

Scientific Summary

With the fast improvement of internet coverage and speed worldwide, crop model and web based apps like CornWater and CornSoyWater can remotely predict crop development, soil water balance in the field and possible water stress using real-time weather data and increasingly reliable weather forecast.

This study showed that with user specified crop management information and major soil properties, the irrigation apps could estimate overall daily soil water balance of the entire rooting depth and predict future crop water stress reasonably well for the purpose of irrigation scheduling. Although the performance of the maize model in CornSoyWater may not be as accurate as we desired for a specific soil depth, we suspect the cause of the inaccuracy was due to the use of the tipping bucket method for the water redistribution process. Modifying the algorithm by the Richards equation, which is a better representation of unsaturated soil water movement, is likely to improve the model performance.

Furthermore, we tested other components of the model, including crop growth and development. We found the model simulated maize phenology, LAI, and yield reasonably well under different irrigation conditions in Nebraska. However, the model has the tendency of predicting crop stage earlier, and underestimating maize grain yield for the two years' experiment. Deficit irrigation and rainfed conditions have less influence on simulation accuracy for soil water balance, but more influence on biomass and yield simulations. Climate difference from one year to another had more effect on simulation quality than water input.

A series of university extension exhibits and marketing promotion helped the apps reach 1200 registered users. As a prototype, we achieved the app's capability of providing a near real-time estimation, with 10-day predictions, of soil water balance, crop stage, water stress, and recommendation for timely irrigation to avoid possible crop water stress. Moreover, we are satisfied with the performance of the app and concluded that it has its market potential. Producers would be more confident in making irrigation decisions for their corn and/or soybean fields if they use this app.

Scientific discussion

If we want to develop a crop model app that not only is guided by scientific principles but also meets industry production demand, we need to come out with creative approaches to combine scientific sophistication with industry efficiency. For example, if the purpose of the irrigation app is primarily for irrigation scheduling, the accuracy of simulating soil water content for the top 0-60 cm soil may be critical. Currently, we used the tipping bucket method for water recharging process which may not as precise as when using the Richards equation to describe water movement. However, due to the complexity involved in Richards equation for more input information from users (for example, in the case of RZWQM2 model) compared with a simple model, one alternative approach is to modify the tipping bucket method to allow partial water input to move to the lower soil layer before upper soil layer reaches field capacity. In this case, the water movement in the soil profile will be closer to reality. Moreover, this approach will avoid the burden of asking more information from users.

The performance of a crop model app is the key to determining whether the app will be used by the broad audience. As the crop growth and biomass simulation interacts with soil water balance, the quality of model on simulating crop growth and biomass is important. Although we found the climate difference in the two years in Lincoln had effects on the simulation quality on crop growth and biomass, the performance variation in different years can be caused by other abiotic factors which we may not be aware of. In future studies, the key of the model validation and calibration under different environmental conditions should focus on finding the real causes of errors in the model components. For example, one of the key factors is GDD, which affects the crop growth duration and crop stage. If the model cannot predict precisely how long the crop is going to grow, other intermediate results such as biomass accumulation in each organ will be off the target.

One of the benefits of solely relying on crop model apps for agricultural practices is cost effective. However, for agricultural practices that need high precision, sensors are more reliable for many tasks. A combination of sensors with crop models may be an alternative solution for balancing cost and precision requirements. For example, when soil moisture sensors are installed in the field, the representation of the sensor measurements is limited to the installation point. Although the measurement can be accurate, when it comes to scaling up the service of sensors to a larger area, the cost of sensor and installation can become a serious concern. On the other hand, although the accuracy of the crop model still needs to be improved, the models can be a good supplement to sensors when using them side by side with the model's capability of scaling up and forecasting.

The remaining critical issues are how we can deliver such an app to more producers' hands and increase adoption. As described in the introductory chapter, the answer is utilizing startups to bridge the gap between such an app and its target users. Following is the business plan on how the startup will provide the answer.

Ispagtech Business Plan

Executive Summary

Product & Service

Ispagtech is a Business-to-Business (B2B) data analytics company that provides forecasting of water stress, crop growth, grain yield, and nitrogen requirement and leaching via REST application program interface (API) in the JSON format for agricultural decision support platforms. By leveraging a deep understanding of crop modeling science, Ispagtech provides customized real-time forecasting analytics down to the acre scale. Using machine learning technology, Ispagtech enables self-improving forecasting service through an accumulation of a customer's field data.

Competitive Edge

At large scale, there are more than 20+ AgTech companies in the market today that provide integrated agricultural decision support platforms covering 90% of US crop production land. Most of them provide current and historical field data service, but few provide forecasting analysis for their customers. Such a company which uses Ispagtech API service can create business insight on risk management and resource optimization for their end users. Ispagtech can scale up in the market instantly by partnering with individual AgTech companies with accessing user basis. By analyzing a company's customers' ground truth data, Ispagtech can keep improving its forecasting service accuracy by using machine learning technology.

Market Opportunity

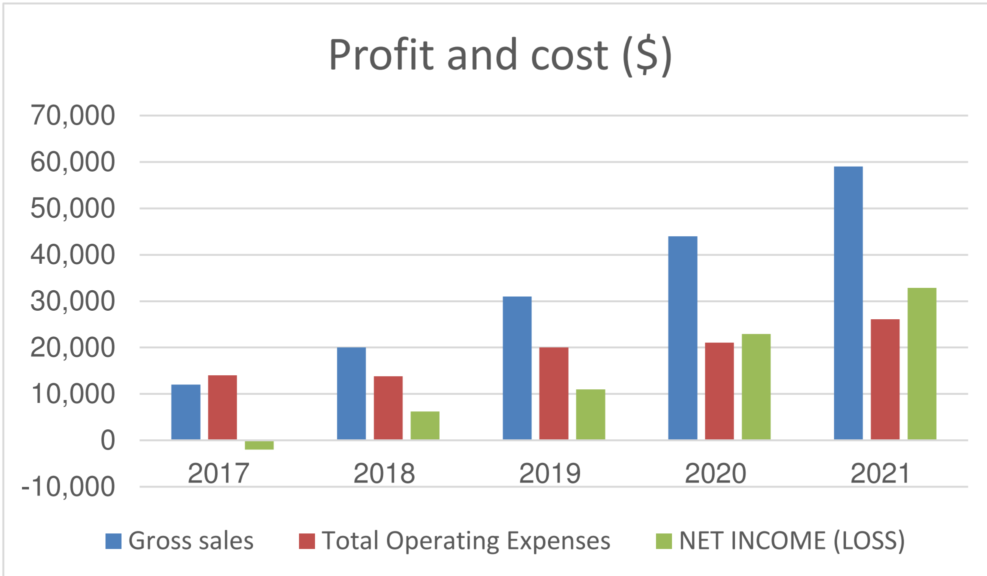
Ispagtech's addressable market includes decision support technology business that utilizes precision agriculture technologies, enterprise resource planning technologies, smart sensors, weather, irrigation and water technologies and app developers. Most of those technologies have an engineering team or engineers themselves that can easily implement Ispagtech API service into their platforms. The average annual investment in decision support technology companies is 246 million with an increase every year since 2014. The platforms provided by these enterprises will collect, connect, and manage a disproportionally large amount of agricultural data in the next decade compared with all the agronomic data collected before in the world. Ispagtech helps those companies to make sense of those data by providing API forecasting analytics.

Sale and Distribution Strategy

Ispagtech sells their API service solely on the online channel. Ispagtech uses Facebook ads and different social media to advertise their product. Ispagtech offers different annual premium plans of $0, $60, $180 for developers, and for the enterprise price Ispagtech will charge $1,000 and $0.01 per call of the API.

Sales Growth and Revenue Projections

Ispagtech expects an average $16,000 sales with a profit of $6,200 which can be used for maintenance of server and Hadoop and Spark for machine learning and 3scale for API management in the second year. We expect 50% annual growth on sales with $11,000 net profit from year 3, $23,000 in year 4, and $33,000 in year 5. In all, a 70% annual growth in net profit is expected after the second year.



	2,017	2,018	2,019	2,020	2,021
Gross sales	12,000	20,000	31,000	44,000	59,000
Total Operating Expenses	14,000	13,800	20,000	21,075	26,108
NET INCOME (LOSS)	(2,000)	6,200	11,000	22,925	32,892

Fig. 1. Profit and cost projection of Ispagtech in the first five years.

The Management Team

James Han (Founder, CEO, CTO), 4 years' data science, modeling, and agriculture production experience. Haishun Yang (Advisor, Board of Director), 27 years' crop modeling and agriculture production experience.

The Exit Strategy

Sell to potential partners, AgTech companies, irrigation companies, and smart agricultural device companies. Provide UNL free access and use for educational purposes.

Mission & Vision

Mission Statement

Ispagtech's mission is to help companies in providing ultimate forecasting service for their crop producers.

Core Purpose

Ispagtech's core purpose is by answering the question of how the plant **will** grow in different environments on earth; Ispagtech will help Elon Musk to make human species a multi colony species by inhabiting Mars and growing crops on Mars.

Core values

"Doing the right thing is always the right thing. - Gary Vaynerchuk".

"Ideas are shit, execution is the game. - Gary Vaynerchuk"

"Rule # 1, don't lose; rule # 2, see rule # 1. - Warren Buffett"

Product and Service Description

Overview of product and service

Ispagtech is a Business-to-Business (B2B) data analytics company that provides forecasting of water stress, crop growth, grain yield, and nitrogen requirement and leaching via REST API in the JSON format for agricultural decision support platforms. Ispagtech focuses on AgTech companies instead of individual crop producers for the purpose of scalability in the market.

Ispagtech provides REST API services in JSON format to companies as leverage in exchange for analyzing customer's field data via either companies' agricultural decision support platforms or data box. Use Open Ag Data Alliance (OADA) JSON format to import field data from companies, Ispagtech provides continuous improvement of forecasting accuracy of the API service by machine learning algorithm.

Ispagtech API service delivers real-time forecasting analysis, with which companies can implement this service seamlessly in their platform portfolio by calling out the API through unique secure authentication. Ispagtech makes the implementation process so easy that any software engineer can finish the task within hours.

Initial, the quality of the API forecasting for specific customers can be compared with the benchmark data provided by the end customers (e.g. crop producers, crop consultants, insurance agents, research institute, government, etc.) of the company through the platforms or data box. Ispagtech establishes partnerships with companies and gives a further in-depth forecasting uncertainty qualification by comparing forecasting with ground truth data from companies' end users. Ispagtech will use a secure pipeline for accessing, analyzing, and sending a report back to the companies on the cloud via an OADA JSON format and update the improved API for the companies. With more end users of companies and more ground truth data, Ispagtech will be able to scale up even further and create multiple forecasting data layers mapping through the majority of U.S. crop production land based on user fields coverage. The expected data layers include national soil water balance, crop stress risk, nitrogen requirement and leaching, and grain yield potential. The advantage of this scaling up is the benefit of the volume of companies' existing users with the low cost of marketing.

The main direction of Ispagtech is to transform from solely providing API as a service to a big data cloud computing company. By its reliable forecasting capability on crop production, Ispagtech uses initial API service as a gateway drug to attract partnership specifically with AgTech companies who are willing to explore their agricultural data. However, the key is to develop a sustainable pipeline to keep improving Ispagtech's service by machine learning. The quality of Ispagtech API service will keep improving by massive ground truth data feed to the deep learning optimization algorithm (Fig. 2). Along the way, Ispagtech will be able to accurately predict how any crop will respond to various abiotic components within a given time frame for a given crop in a given region. This keeps improving the competitive edge for Ispagtech and creating a branding effect in the market.

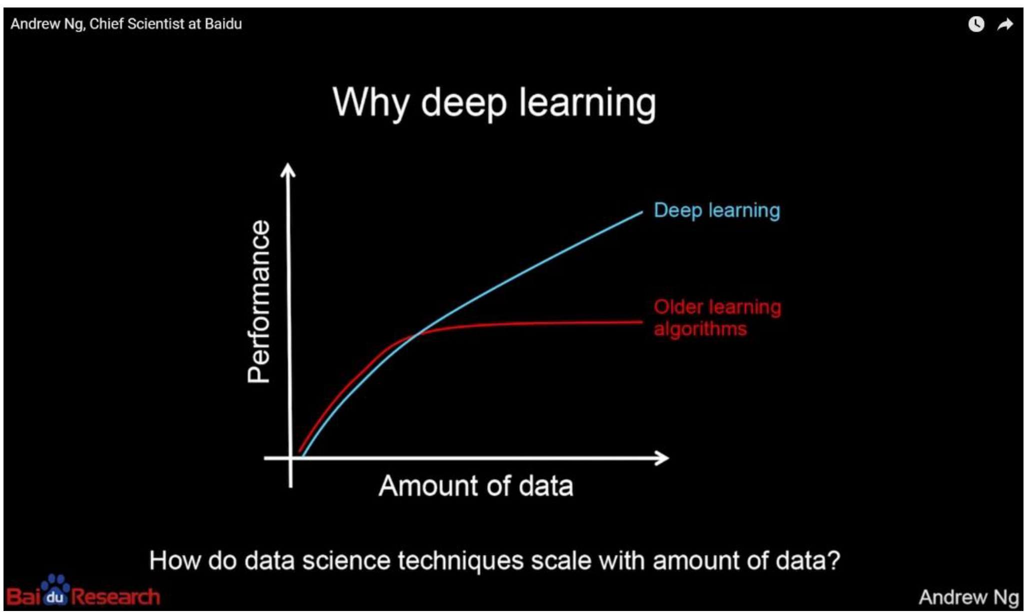


Fig. 2. Baidu chief scientist Andrew Ng showed deep learning (one of the many machine learning algorithms) would outperform traditional algorithm by feeding it more dada.

Ispagtech strategy for a winnable API service is to analyze low cost and massive volume of data by existing scientific algorithms and bringing the analysis to a large scale. This requires collaboration with university research teams which Ispagtech favors. Usually, the people who know how to use the data from the academic sector are not involved with the industry. By collaboration with university research teams, Ispagtech will create a win-win situation by actualizing the existing algorithms of University and providing the university with more business opportunities.

The current algorithm is restricted by the area such as Nebraska and fragments of the nearby states. Ispagtech will modify the algorithm and make it usable in the entire U.S. (Fig. 3) without decreasing the current forecasting accuracy.

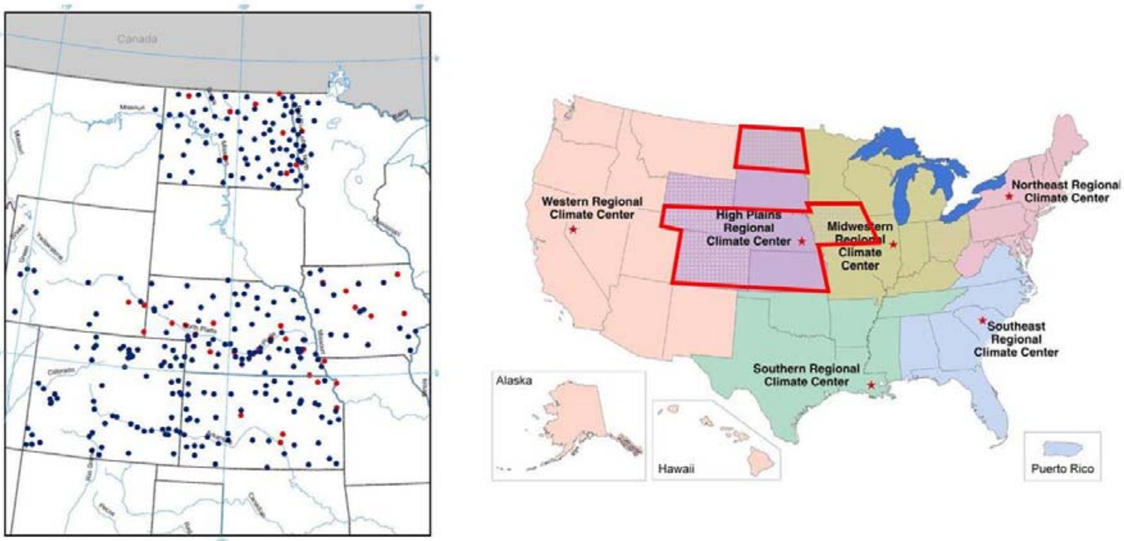


Fig. 3. Left: coverage of current UNL algorithm indicated by dots. Right: coverage of Ispagtech modified algorithm indicated by color areas. The red polygon area indicates the UNL algorithm coverage.

Because of the expanded coverage where Ispagtech API service can be applied, the geographic limitation for Ispagtech's potential customers is removed. Below are the examples of potential users, desired actions, and rewards.

Table 1. Potential users of the service, what the potential users want to do with their current products but have not been able to do so, and what are the potential rewards by using Ispagtech service.

Potential company	Potential desired actions	Potential rewards
Enterprise resource planning companies	Provide forecasting analytics before starting farming practice	New portfolio on facilitating decision-making process
Weather data companies	Use of their data, partnership	Share of revenue
Irrigation companies	Not just forecasting of weather, but forecasting water, precision irrigation guide	Provide forecasting water and stress
Third party app developers	Develop ag-related apps	Provide source for the app development, revenue

After a company implements Ispagtech API service, it can open this service through its platform to users with premium package. The API service will provide forecasting of what will happen in the field for the next 7 days. Furthermore, if those happened, what it will cause for end season will be predicted.

Water related:

- Recommendation message whether irrigate or not based on water stress
- Irrigation amount
- Water stress
- Soil water balance
- Todays' available soil water balance
- Water consumption since planting
- Water losses by drainage and canopy interception

Crop related

- Crop stage
- In season potential grain yield

Nitrogen related

- In-season nitrogen needed
- Potential nitrogen leaching

Weather related

- Maximum and Minimum temperature
- Relative humidity
- Wind speed
- Solar radiation
- ET

Ispagtech API service gives quantified forecasting results for each of the items listed above and provides a likelihood analysis from the most possible to the least possible scenarios so the end users can take action accordingly. For the advanced feature, Ispagtech API can also provide historical analysis on demand.

Problems, Cause, Solutions, and Benefits

The main problems and causes in the current market, and Ispagtech solutions are presented below (Table 2):

Table 2. Problems, causes, solutions, and benefits of the market.

Problems	Causes
Companies are not aware of the existence of available API in the market	So far there is few crop related forecasting API exists in market
Not clear ideas of the ROI of a forecasting service	Most agriculture-related forecasting service is for stock/bond price or weather, but this API service is new
Skeptical of the reliability of such kind of API and potential risk	Never had such product before in the market
New AgTech companies want to develop such technology by themselves	Much investment of money and time, but unknown return due to lack of core technology available: crop modeling, and quality control
Not widely used	Old product from **academic sectors which is not scalable**
Face climate change and global warming	Warmer temperature and more frequent extreme climate affect the traditional crop growth pattern and make it more difficult to predict

Table 2 (continued). Problems, causes, solutions, and benefits of the market.

Solution: API service	Benefits
Ispagtech directly markets the API to the companies	Add values to the current existing platforms

Create new business opportunities for companies such as weather companies	Help companies' end users optimize resource allocation, improve risk management, and reduce energy costs
We have already run test on the reliability Results: reliable Risk: can be qualified	The more data the company provides us, the more accurate the API will be
Provide API directly	Reduce the hassle and investment by bringing simplicity
Ispagtech API is built for scale	Fill the gap between precision ag monitors (Micro) and national drought forecasting (Macro) for the companies
Predict how crop will be affected by warmer temperature and less water	Optimize farming resources allocation at the field

Product and Service Advantages

- Quantify uncertainties, give users piece of mind
- Fill the gap in forecasting capability of ag decision support technology
- Scalable up and down easily
- Precise to a quarter section field
- Real-time forecasting
- Create new business leads for interrelated AgTech and Agribusiness
- Reduce the cost of R&D for Ispagtech customers

Industry Analysis

Industry Overview

The investment in agtech startup has started to boom since 2014. According to the AgFunderNews, in the first half of 2016, there was 1.6 billion investment in the AgTech sector with 307 deals (https://research.agfunder.com/2016/AgFunder-Agtech-Investing-Report-Midyear-2016.pdf). Although the total investment of ag startups pulled back after 2015, the total trend of investment showed an increase from 2014 to 2016. Within the total investment in 2016, precision ag startups raised 333 million at first half year, and 47% of them involved software, irrigation, and weather technologies.

The main reasons of the booming of AgTech investment are that the storage of data (for examples, satellite and drone imagery, weather data, sensors measurement, etc.) has become cheaper, and computational capability of the computer is getting better. Nowadays, the data generated daily is about 90 years of high-definition video (Fig. 4) (*http://www.northeastern.edu/levelblog/2016/05/13/how-much-data-produced-every-day/*). In the next 10 years or so, this volume could be the daily collected agricultural data.

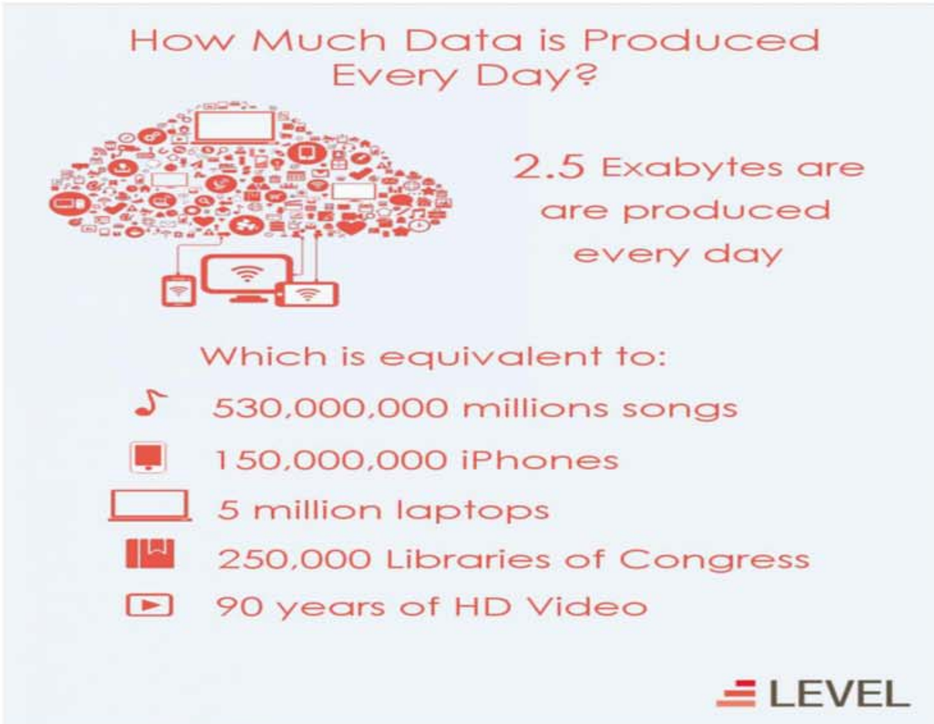


Fig. 4. How Much Data is Produced Every Day in 2016?

However, how to use massive data to forecast the future and create business leads in the agriculture sectors becomes a new challenge. In fact, this forecasting analytics has existed and has been used in the stock market for decades due to its high ROI. In contrast, the same technology has not been used in agriculture because of the cost of data collection in the past. With the increasing volume of agricultural data and the computational ability of cloud computing, to analyze agricultural big data by advanced computer algorithm to create business opportunities will be the next agricultural revolution.

Cloud Computing Industry

Forbs reported the worldwide cloud computing market grew 28% to $110 billion in revenues in 2015. In 2016, the spending on public cloud Infrastructure as a Service (IaaS) hardware and software is forecast to reach $38 billion, and will grow to $173 billion in 2026 (http://www.forbes.com/sites/louiscolumbus/2016/03/13/roundup-of-cloud-computing-forecasts-and-market-estimates-2016/#349377774b07). The public cloud IaaS regards as cloud service when you buy a piece of server in a cloud computing environment that is shared with a number of other clients or tenants (http://www.onlinetech.com/resources/references/public-vs-private-cloud-computing). IDC predicted Software as a Service (SaaS) would remain the dominant cloud computing type, capturing more than 115 billion of all public cloud spending through most of the forecast period. SaaS provides the point of access to software running on servers, so-called cloud service (https://www.computenext.com/blog/when-to-use-saas-paas-and-iaas/). A company like Ispagtech provides application program interface as a service (APIaaS), is one type of cloud service. API can be imagined as the service given by a waiter who directly interacts with a customer (an end user) who wants to order a dish in a restaurant and the waiter pass the order to the kitchen (the algorithm on the cloud).

SaaS is a main potential client of API service, because the essential of SaaS is to build cloud service for clients based on different API services. For example, smaller AgTech companies have certain resource but do not have all the resources to develop applications and web interfaces from scratch. They have the ideas and the capabilities to develop graphical entry points for the front-end of the website or program, but are a lack of knowledge of the science theory to support the new programs at the back-end. This is the time when APIaaS start to fill this gap. (https://cloudcomputingvirtualization.wordpress.com/2012/12/24/api-as-a-service-apiaas/). One success example of APIaaS is Moz.com which individuals or companies use their search engine ranking algorithms to build their own applications, programs or software, and they have to pay licensing fees per the number of calls to the hosted API.

Industry Trends and Key Factors

In the AgTech sectors from 2014 to the first half of 2016, the total investment on precision ag was 1.27 billion. Three main categories took 85% of the total investment, which are drone imagery and platform service, Ag Enterprise Resource Planning (ERP) platform, and smart sensors. Table 3 shows the companies' name list. Among them, drone-related precision ag is listed as the number one, followed by ERP and the last is smart sensors. Note that there is some crossover between drone imagery & service and Ag ERP, and between Ag ERP and smart sensors.

Table 3. List of companies in the three top precision AgTech categories. Note the table only contains precision businesses with annual revenue more than 10 million, or received equivalent pre-seed, serials A, B, C, and D run funds which are close to this number, or have equivalent assets. Hundreds of startups in those three categories are not listed.

Drone, Imagery & Platform Service	Ag Enterprise Resource Planning Platform	Smart Sensors & Irrigation Platform
3DR, Skycatch, Mavrx inc, DroneDeploy, Precision Hawk, AirMap, Sentera, DJI, Parrot, Resson, Slantrange, Delair, Prioria Robotics,	FarmLink, FieldView, Farmlogs, AgriCharts, Farmers Business Network, Farmers Edge, ClearAg, Cropio, OnFarm, Agworld,	CropX, BaseStation3, FieldNET, John Deere Field Connect, Hortau, HydroBio

Airwave, Xaircraft, Kespry, Cyphy Works, Planet, Orbital Insight, Airphrame, Swiftnav, Intelescope Solutions, Pulse Aerospace, Ehang	Granular, Conservis, Agrimap, Farmerp, CropTrack, Fairport, Cengea, aWhere	

With the trend of SaaS product getting popular, new AgTech and some traditional agricultural companies are going to focus on cloud computing. Ispagtech must develop innovative solutions within the three categories above in order to establish itself at the forefront of APIaaS and cloud-based consolidation in agricultural business:

- Build easy to implement and cost-effective API front-end and back-end.
- Use API management platform to track leads, such as 3scale or apigee.
- Ensure security for API back-end
- API service enriches and emphasizes on the mobile end for developers
- Good customer service and technical support

Competitive Analysis

Competitive Overview

So far, the direct competitors are smart sensors & irrigation platform. Below is the comparison table.

Table 4. Direct Competitors of Ispagtech

	Ispagtech	aWhere	Cropx	Lindsay	Valley
Owner/CEO	James Han	John Corbett	Isaac Bentwich	Rick Parod	Len Adams
Year founded	2017	1997	2013	1950	1946
Headquarter	Lincoln, NE	Broomfield, CO	San Francisco Bay Area	Omaha, NE	Valley, NE
Website	Ispagtech.com	aWhere.com	Cropx.com	Lindsay.com	Valleyirrigaiton.com
Type of Entity	Private	Private	Private	Private	Private
Product Overview	API service	Agricultural Intelligence, API	Smart moisture sensor with platform	FieldNET, weather station, moisture sensor	Irrigation Exchange, weather station, moisture sensor
Key Feature	Forecast crop water stress	Use weather data to provide Agricultural Intelligence	Send moisture reading to phone	Send moisture reading to PC/phone	Send moisture reading to PC/phone
Pricing	$0, $60, $180 for	Unknown	$275, $600,	Come with the	Come with the center

	developers and $1,000 for company + $0.01/call		$700 / sensor **per user** depends on subscribed years	center pivot	pivot
Strength	Forecasting	Weather data	Platform, sensor	Platform, sensor	Platform, sensor
Weakness	Lack of platform and ground truth data	Short of models	Lack of forecasting capability, Costly when scale up	Lack of forecasting capability, Costly when scale up	Lack of forecasting capability, Costly when scale up

Besides competitors, Ispagtech has indirect competitors some of which are products from the academic sector and others that can potentially develop similar API services.

Table 4 (continued). Indirect Competitors of Ispagtech.

	Smart-Irrigation apps	**eRAMS**	**DSSAT API**	**ApSim API**	**SWATShare**
Owner	University of Florida	Colorado State University	Many universities in	Universities of Australia	USDA and Texas A&M

			the US		AgriLife Research
Year founded	2014	2014	2015	2015	2016
Headquarter	Florida	Colorado	N/A	N/A	N/A
Website	smartirrigationapps.org	erams.com	dssat.net	apsim.info	swat.tamu.edu
Type of Entity	Academic	Academic	Academic	Academic	Academic
Product Overview	irrigation app	Online platform for irrigation management	Initialize, run and post-process for DSSAT, Decision support system agrotechnology transfer model	Development tool for APSIM, Agricultural Production Systems Simulator	An online collaboration environment for sharing data, models, and code regards to hydrology
Key Feature	Irrigation management, crop stage, GDD	Irrigation management	Includes irrigation management module	Includes irrigation management module	Includes irrigation management module
Pricing	Free	Free	Free	Free	Free

Strength	Free	Free	Free	Free	Free
Weakness	Cannot scale, Subject to regions, lack of maintenance	Cannot scale, Subject to regions, lack of maintenance	Hard to implement, lack of maintenance	Hard to implement, lack of maintenance	Only data, no implementation

Competitive Advantages

Forecasting is not actual, but close enough for many purposes. Ispagtech creates a piece of mind because it will provide more accurate estimation of what is going to happen in the field, and forecasting results are going to be better compared with historically averaged results.

Portable to different platforms and services. The API service provided by Ispagtech done to the core is algorithm consolidation. It is easy to plug in and out to any new Ag ERP platforms. It is also easy to be used as a foundation for newly development platforms, or as a basic feature of Platforms as a Service (PaaS) business. It immediately stands out from other products either only having sensors, or platform, or field data collection. Ispagtech API service actually can be the glue to connect the three different categorized precision ag businesses together and create more new business leads. The business model of Ispagtech is to generate revenues and increase distribution through strategic partners and/or affiliate.

Scalable. Horizontally, Ispagtech API service can provide customized forecasting down to one-quarter-section field (160 ac or 65 ha) for an end user of a platform. However, it can also be used by two million acres of field and thousands of users through the platform. Vertically, Ispagtech API service currently only supports forecasting for corn and soybean primarily.

However, with the modification, the algorithm can be used for forecasting service for any crop in different growing seasons. Moreover, it also can be adapted to vegetable and garden lawn which has entirely different markets. Horizontally, the flexibility of the API allows Ispagtech API service to be used with much wider geographic areas, compared with the indirect competitors who have geographical limitation and cannot be scaled even they may have more models available. Ispagtech API service instantly adapts to a broader market when is implemented to existing platforms with the user base.

Improvement. By establishing strategic partners and/or affiliates, Ispagtech provides API service in exchange for access to partners' user data, for the purpose of improving the accuracy of forecasting based on machine learning technology. Besides Ag ERP platform, Ispagtech has the potential to partner with Smart Sensors & Irrigation Platform, and Drone, Imagery & Platform Service. For Smart Sensors & Irrigation Platform, Ispagtech can be a continuous projection of the moisture sensor reading to forecast field moisture status. Ispagtech API algorithm can to modified and read the drone or satellite collected imagery to create more accurate forecasting results and benefit the imagery business.

Low cost. The API service is very low cost. The value of having in situ sensors is obvious. For example, a soil water balance may drift over the season compared with historical records, but a soil water sensor does not have that problem to capture this. A drawback of a soil water sensor is that multiple locations are needed to get a good average of the soil water level, and many service providers do not do this. On the other hand, API modeling the soil water balance can be done at a lower cost. For example, the Climate Corporation product FieldView has 13 million acres' field that is paid for premium service in 2016 (http://fortune.com/2016/08/17/monsantos-climate-corp-to-expand-digital-farming-platform/). In the US, one producer has on average 1,000 acres' land (about 10 fields), which is about 13,000 individual paid users. Let us assume if each user calls the API under his/her platform account 1 time per day, the total calls from entire FieldView users will be 130,000 calls per day which Ispagtech only charges Climate Corporation about $10,000 a year (subject to change). Compared with Climate Corporation uses the subscription of Cropx soil sensors service, with each quarter section field installing 3 sensors ($275 / sensor / year), the total cost for FieldView on 13 million acres' land will be 4.29 billion per month. Both Ispagtech API service and Cropx soil sensor can create insight of field soil moisture conditions; Ispagtech only costs 0.000002 % of Cropx's cost. If a similar comparison is applied to John Deere Field Connect (soil moisture sensor), the cost of Ispagtech will be 0.0000003%.

Rare and in demand. There are 78 agricultural API service available on the market (not including weather API). Only a few are crop health related(http://www.programmableweb.com/category/all/apis?keyword=agriculture) so far. Once Ispagtech API service turns farm data collected by Drone, Imagery & Platform Service, Ag ERP platform, and Smart Sensors & Irrigation Platform, to actionable post-process data, it will create an in-demand effect which drives startups or individual developers to use Ispagtech API service more to develop age-related apps and create more business opportunities.

Barriers to entry

- Reliable and cost-effectively weather data source for supporting Ispagtech.

  Candidates: iteris, aWhere, ACIS.

- Gain the trust and establish the first partnership with a company with Ag ERP platform. Since the forecasting of API service is new and the quality is still under testing, it will take the time to have a first company to use it.

  Solution: preliminary testing by university research has shown the algorithm could provide highly accurate one some category such as soil water balance forecasting on common Nebraska soils. More collaboration is needed between Ispagtech and University.
- Strategic partner provides access to their users' data. Ispagtech API service needs data to improve its accuracy.

  Solution: Ispagtech provides a discount for forecasting service in exchange for data access. The improvement of forecasting will gain a competitive advantage in the long run and create a branding effect.

Market Analysis

Addressable Market

Ispagtech' addressable market focuses on companies with 1) ag decision support platforms which intend to expand its current portfolio to crop health forecasting; 2) smart sensor and irrigation control platform which has interests to implement forecasting soil moisture into their platform, and 3) drone and imagery platform which uses indices such as NDVI to represented plant health, and 4) the Ag analytics company. There are 12 ag decision support platforms companies, 9 sensor and irrigation platform companies, 10 drone and imagery platform companies, and 2 Ag analytics company can be Ispagtech potential customers (Table 5).

Table 5. A full list of potential customers of Ispagtech. The tables were created by using

DataFox.

Name	Location	Description
Ag ERP platform		
The Climate Corporation	San Francisco, CA	Agronomic and weather data at the field level for decision-making
AGWorld	West Leederville, Australia	Farm Data gallery
Granular	San Francisco, CA	Farm management software and analytics platform
FarmLogs	Ann Arbor, MI	Forecast and measure farm profits, track farming expenses, manage risk
OnFarm	Fresno, CA	Agriculture data from hardware decision-making platform
SST Software	Stillwater, OK	Geospatial infrastructure for precision ag products and services
Cropio		Amazing field management and vegetation control system
Farmer's Edge	Winnipeg, Canada	Field-Centric Data Management & Analysis
Farmer's Business Network	San Carlos, CA	Agronomic intelligence, market
AgriCharts	Chicago, IL	Agricultural website hosting, management, consulting and agribusiness
Crop Tech Solutions	Gothenburg, NE	Field data management and decision to quickly know break-even
FarmLink	Kansas City, MO	Yield potential and management decision
Ag Data analysis & API		
aWhere	Broomfield, CO	Agriculture analytics, weather, API
Iteris (ClearAg)	Santa Ana, CA	Agriculture analytics, weather, API
Sensor and irrigation platform		
John Deere	Moline, IL	Moisture sensor, cloud
Lindsay Corporation	Omaha, NE	Moisture sensor, cloud
Hortau	San Luis Obispo, CA	Improving crop production with precision irrigation
HydroBio	Denver, CO	Monitor your crop water usage at the sub-acre level and dynamically building the best irrigation prescription
CropX	San Francisco,	Smart moisture sensor with app

	CA	
IRROMETER Company, Inc.	Riverside, CA	Soil tension sensor with cloud
AgSense	Huron, SD	Agricultural control and monitoring, allowing growers to control soil moisture
Valley Irrigation	Omaha, NE	Moisture sensor, cloud
CropMetrics	North Bend, NE	precision irrigation management.
Drone & Imagery		
PrecisionHawk	Raleigh, NC	Algorithm, remote sensing applications and data processing services,
Planet Labs, Inc.	San Francisco, CA	Broad coverage and high-frequency monitoring for Precision Agriculture.
DroneDeploy	San Francisco, CA	To make aerial data accessible to anyone with a drone.
Delair-Tech	Toulouse, France	Drone and platform
Slantrange	San Diego, CA	Accurate, repeatable crop health measurements with advanced sensors and intelligence tools for agriculture drones
Orbital Insight, Inc.	Red Bank, NJ	Understanding global and national trends through advanced image processing and data science at petabyte scale.
Mavrx	Francisco, CA	Imagery and data to bring actionable insights to the global agriculture industry
Airphrame	San Francisco, CA	An end-to-end solution for the capture, management, and analysis of spatial data
sentera	Minneapolis, MN	Drone solutions for NDVI, precision agriculture, aerial photography & inspection.
Resson Aerospace	Fredericton, Canada	Bioinformatics and data analytics company, delivering customized agriculture solutions for large corporate clients.

Table 5 (continued). A full list of potential customers of Ispagtech. The tables were created by using DataFox.

Name	Headcount	URL	Founded	Private Funding	Revenue
Ag ERP platform					
The Climate Corporation	370	climate.com	2006	$108.80m	> $100m

AGWorld	180	www.agworld.co/	2009	$11.63m	> $20m
Granular	60	granular.ag	2014	$24.90m	> $5m
FarmLogs	70	farmlogs.com	2012	$15.83m	> $5m
OnFarm	8	onfarm.com	2012	$1.23m	> $1m
SST Software	180	sstsoftware.com	1994		> $5m
Cropio	20	cropio.com/	2011		
Farmer's Edge	180	farmersedge.ca/	2005	$103.45m	> $20m
Farmer's Business Network	60	Farmersbusin essnetwork.com	2014	$47.20m	
AgriCharts	7	www. agricharts.com			> $1m
Crop Tech Solutions		Croptech solutions.com			
FarmLink	60	farmlink.com/	2000	$64.60m	> $2m
Ag Data analysis & API					
aWhere	40	awhere.com	2007	$14.45m	> $2m
Iteris (ClearAg)	240	iteris.com	1969		> $50m
Sensor and irrigation platform					
John Deere	57000	www.deere.com	1837		> $5b
Lindsay Corporation	1300	lindsay.com	1950		> $500m
Hortau	180	hortau.com	2002	$21.50m	> $20m
HydroBio	40	hydrobioars.com/	2012	$3.10m	> $5m
CropX	20	www.cropx.com/	2013	$10.00m	
IRROMETER Company, Inc.	40	irrometer.com			> $2m
AgSense	40	agsense.net	2003		> $1m
Valley Irrigation		valleyirrigation.com			
CropMetrics	10	cropmetrics.com/	2009	$1.35m	> $1m
Drone & imagery					
PrecisionHawk	100	precisionhawk.com	2011	$29.00m	> $20m
Planet Labs, Inc.	230	planet.com	2010	$183.10m	> $5m
DroneDeploy	50	dronedeploy.com	2013	$31.00m	> $2m
Delair-Tech	40	www.delair-tech.com/en	2011	$14.50m	> $5m
Slantrange	10	slantrange.com	2013	$8.51m	> $2m
Orbital Insight, Inc.	30	orbitalinsight.com/	2013	$28.70m	
Mavrx	30	mavrx.co	2013	$22.50m	
Airphrame	20	airphrame.com	2012	$4.25m	
sentera	10	sentera.com	2014	$9.50m	> $2m
Resson Aerospace	30	ressontech.com/	2013	$13.70m	> $2m

Third party developers

The number of irrigation apps in the app store has increased from 4 in 2014 to 463 in 2016. The volume of irrigation apps increases exponentially with a growth rate of 11500% in just two years. With such demand, the third party developers and startups will be eager to include Ispagtech API web service in their apps. The biggest two weather companies in the market iteris and aWhere have open sourced their weather data so the third party developers can create more agricultural intelligence apps. Meanwhile, public sectors such as ACIS provides integrated weather network data which is free for public use. The weather data is the fuel of our service, which the increase of weather data availability, we expected to have more app developers use our Ispagtech API service for their apps.

Sales and Marketing Plan

Sales and Marketing Goals

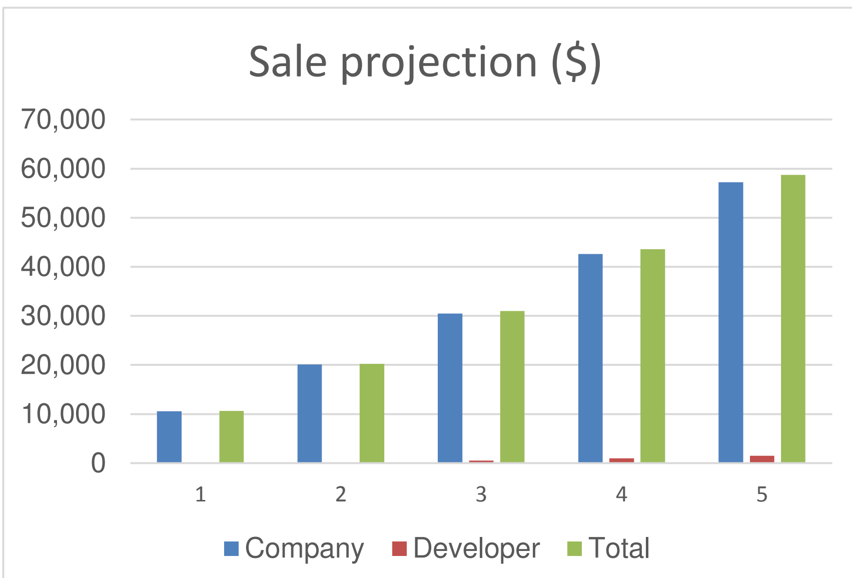
Ispagtech will sell API service solely via online channel due to the nature of the product. Ispagtech will create customized sale pitch for each targeted company and reach out by LinkedIn and email for presentation opportunities. James Han will represent Ispagtech as a sale representative / idea promoter of the API service to travel and meet listed companies.

The charts below provide Ispagtech's marketing goals for online sales based on the following assumptions:

- Each year Ispagtech sells the service to at least one company.
- Each year Ispagtech has 50% growth annually on companies and the third party developers.

- 100% subscription from companies and 50% subscription from developers remains in the following year

Ispagtech expects the average annual sale of $16,000 in the first two years with a breakeven of maintenance of AWS EC2 server and Hadoop and Spark for machine learning and 3scale for API management. We expect 50% of annual growth on sales with $12,000 at the first year from the companies' part. For sales from developers, we expected during first years; it will make a total sale for $3,180. The sale projection is in Fig. 5. Ispagtech will adjust the price according to the usage of the API service through 3scale management platform.



	Year 1	Year 2	Year 3	Year 4	Year 5
Company	$11,940	$19,880	$30,500	$43,000	$57,500
Developer	$60	$120	$500	$1,000	$1,500
Total	$12,000	$20,000	$31,000	$44,000	$59,000

Fig. 5. The sale projection of Ispagtech in first five years.

SWOT

The following chart shows Ispagtech's strengths, weaknesses, opportunities and threats for entering into the business (Fig. 6):

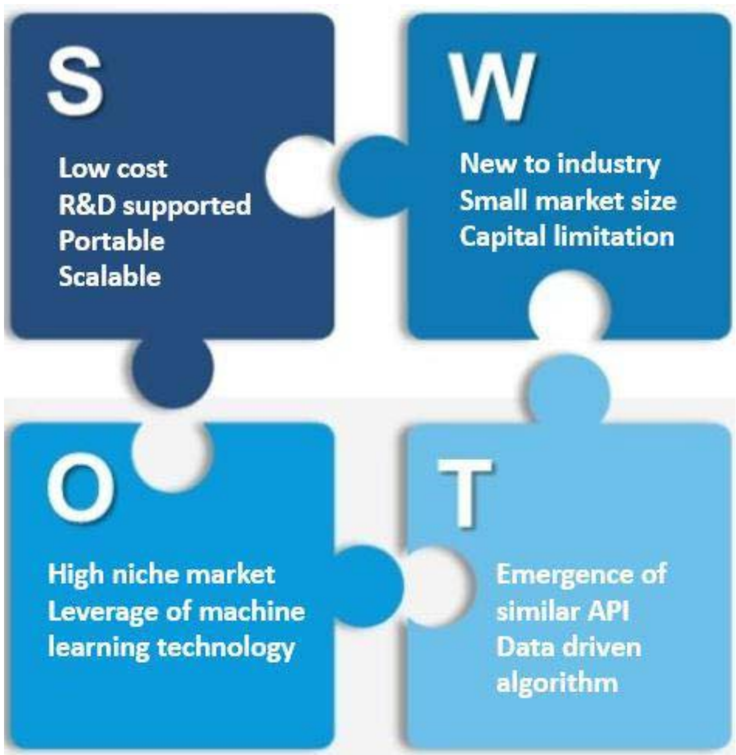


Fig. 6. SWOT matrix of Ispagtech on strengths, weaknesses, opportunities, and threats to get into the business.

Pricing Strategy

Protect the downside and maximimize the upside. Protect Ispagtech's downside by charging a subscription fee for small companies and third party developers. The upside is for when Ispagtech partners with a company who provides Ispagtech user's field data, using machine learning algorithm to provide better-customized forecasting service will strongly boost the API's business value. The data access will enable Ispagtech to create additional business insight. Table

6 is the pricing for Ispagtech API service. Ispagtech offers different premium plans depending on the number of calls per day.

Table 6. Annual plans of Ispagtech API service.

	Entrepreneur	Adventurer	Expert	Enterprise
Price per year	$10 fee + $0/call	$60 fee + $0/call	$180 fee +$0/call	$1,000 fee + $0.01/ call
Calls per day	100	1,000	1,500	>1,500

There is a base fee for Entrepreneur, Adventurer, Expert packages listed above. For Enterprise package, the base fee is $1,000 per year. For more than 1,500 calls per days, we will charge $0.01 per call. For companies providing Ispagtech access of actual ground truth data and forecasting results of the field, we will provide calibration service for the API and a discount for the plan subscribed. For companies which have extra needs on historical analytics, we will provide below price:

Table 7. Historical analytics of Ispagtech API service.

	Starter	Medium	Advanced	Expert
Price per year	$50 fee + $0/call	$120 fee + $0/call	$250 fee + $0/call	$1,000 fee + $0.01/ call
Calls per day	100	1,000	1,500	>1,500
Historical estimation	12 months back	12 months back	24 months back	30 months back

Marketing/Branding Strategy

Ispagtech will heavily depend on social media to create its brand. The strategy of marketing is based on Gary Vaynerchuk's book "Jab, Jab, Jab, Right Hook: How to Tell Your Story in a Noisy

Social World”. Presents values first to users by creating social media contents; have empathy to users; guilt users to buy your product instead of a sale.

First, by creating Ispagtech’s YouTube channel content on a weekly basis and Snapchat contents on a daily basis to provide documentation contents of how to develop an API for AgTech business. Meanwhile, write a blog to explore how the forecasting service can help the end users reduce crop production risk. Ispagtech will raise awareness of the importance of using forecasting service to help farmers to save water, energy, and time.

Second, use Facebook ads to drive online traffic to Ispagtech’s Instagram and YouTube channel. After the potential customers exposing multiple times to the contents which promote AgTech, Precision Ag, data mining, and machine learning which can create new business opportunities from Ispagtech’s social media channels, lead potential customers to Ispagtech homepage and ask them to try it out.

Actively engaging with company’s R&D and management personal by interacting and retweeting their twitter contents, as well as their end customers (for examples, crop producers) to understand what they care about. Create 1-on-1 deep engagement experience with the potential customer (company reprehensive or app developer) by skype calls or meetings until it leads to partnership or sale. Respect the fact that the branding process will take years and be patient because the world of mouth in such a small and niche market is critical.

Operation Plan and Timeline

API development: 12/2016 – 5/2017

Django python framework for REST API

TensorFlow for machine learning

3scale for API management

WordPress for Homepage

Amazon AWS for data storage.

The first year: based on how much call per company has, and adjust the price

Branding: 1/2017 – as long as Ispagtech exists

Facebook Ads, Snapchat, YouTube, Twitter, Instagram, LinkedIn

Establish the first partnership 6/2017 – 12/2017

Customer service

24/7 by James Han

Team management

James Han (Founder, CEO, CTO), PhD in crop modeling, University of Nebraska - Lincoln. 4 years' data science, simulation modeling, and crop production. James' major responsibility is to create the vision and direction for the company, API development, branding, and sale before hiring the first sale representative.

https://www.linkedin.com/in/james-han-4b68493a

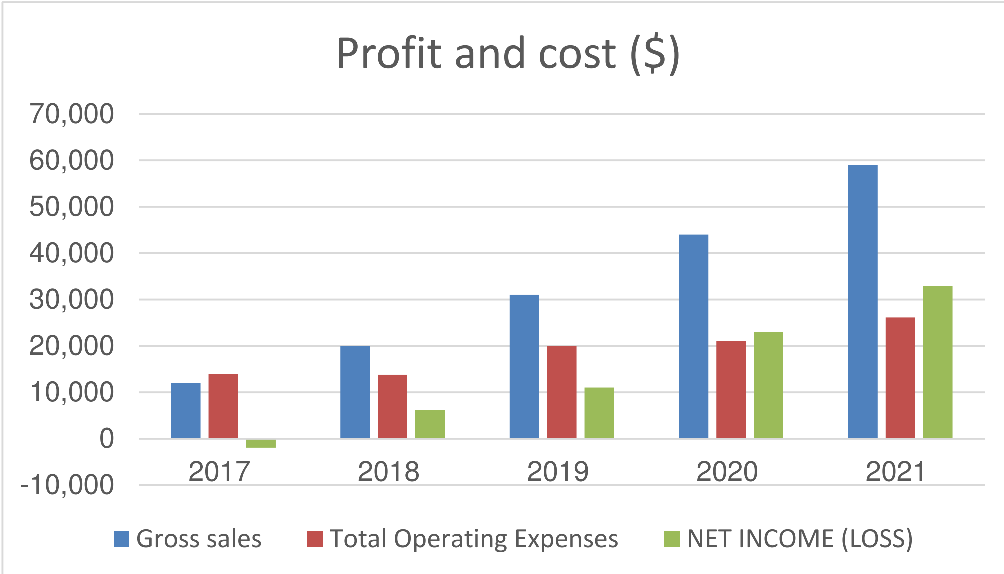
Haishun Yang (Advisor, Board of Director), PhD in soil science, Wageningen University. Associate professor of University of Nebraska - Lincoln. 27 years' crop simulation modeling and crop production experience. Previously worked as a crop modeling scientist for Monsanto Co. Haishun is the algorithm creator of the simulation model CornSoyWater, Hybrid-Maize model, Maize-N, and creators of simulation model software SoySim. The algorithm of the simulation models is the intellectual property ispagtech intends to license. Haishun's major responsibility is to give advice on modeling algorithm optimization and company development direction. http://agronomy.unl.edu/yang

Financial Plan

Financial summary

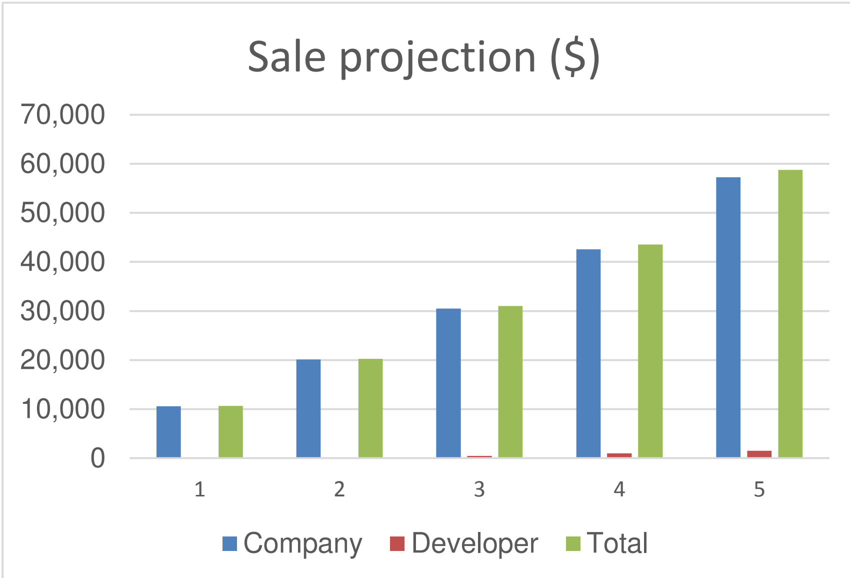
The following indicates the profit and cost, sale projection, profit margins, income statement, cash flow, and balance sheet in the first five years.

In summary, Ispagtech projects a net loss of $2,000 in the first year and will breakeven in the second year. Ispagtech projects a net profit of $6,200 in year 2, $11,000 in year 3, $23,000 in year 4, and $33,000 in year 5. In all, a 70% annual growth in net profit after the second year.



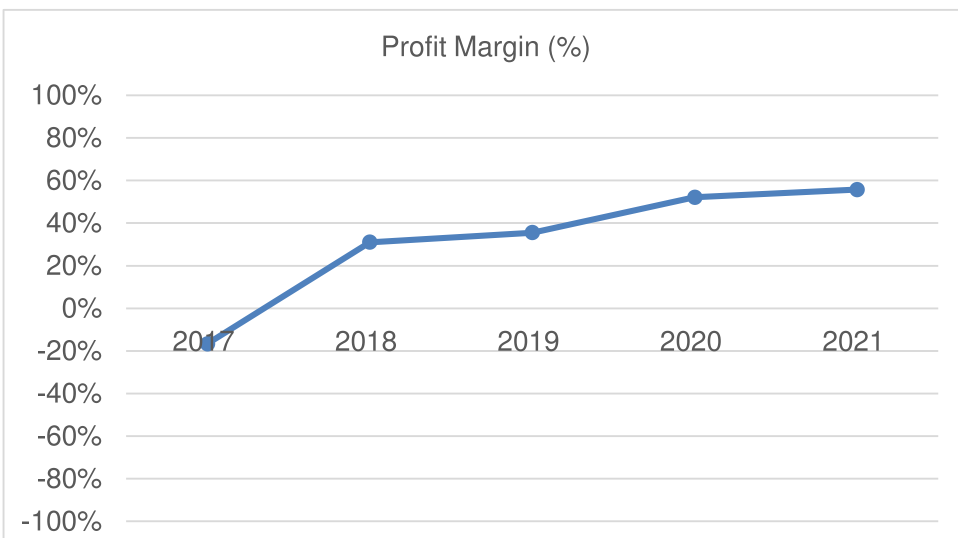
	2,017	2,018	2,019	2,020	2,021
Gross sales	12,000	20,000	31,000	44,000	59,000
Total Operating Expenses	14,000	13,800	20,000	21,075	26,108
NET INCOME (LOSS)	(2,000)	6,200	11,000	22,925	32,892

Fig. 1. Profit and cost projection of Ispagtech in the first five years.



	Year 1	Year 2	Year 3	Year 4	Year 5
Company	$11,940	$19,880	$30,500	$43,000	$57,500
Developer	$60	$120	$500	$1,000	$1,500
Total	$12,000	$20,000	$31,000	$44,000	$59,000

Fig. 5. The sale projection of Ispagtech in first five years.



	2017	2018	2019	2020	2021
Profit Margin	-17%	31%	35%	52%	56%

Fig. 7. The profit margin projection of Ispagtech in first five years.

Table 8. The income statement of Ispagtech in the first five years.

Income Statement

Ispagtech

For 2017 through 2021

REVENUE	2017	2018	2019	2020	2021
Gross sales	$12,000	$20,000	$31,000	$44,000	$59,000
funding support	$0	$0	$0	$0	$0
Net Sales	$12,000	$20,000	$31,000	$44,000	$59,000
OPERATING EXPENSES					
CEO salaries and wages	$0	$0	$10,000	$15,000	$20,000
Advertising	$1,000	$2,000	$2,000	$2,000	$2,000
Cloud server	$0	$100	$200	$500	$500
Employee benefits	$0	$0	$0	$0	$0
Payroll taxes	$0	$0	$1,300	$1,675	$2,058
Health Insurance	$0	$0	$0	$0	$0
Software licence purchase purchased / mar	$0	$200	$0	$350	$0
UNL licence	$0	$1,000	$1,000	$1,000	$1,000
Consulting fee	$500	$500	$500	$500	$500
Sale expense	$10,000	$7,500	$5,000	$0	$0
Field test validation for the application	$2,500	$2,500	$0	$0	$0
Postage	$0	$0	$0	$50	$50
Interest	$0	$0	$0	$0	$0
Total Operating Expenses	$14,000	$13,800	$20,000	$21,075	$26,108
NET INCOME (LOSS)	($2,000)	$6,200	$11,000	$22,925	$32,892

Table 9. The cash flow of Ispagtech in the first five years.

Cash Flow Statement

Ispagtech

For 2017 through 2021

Cash flows from operating activities	2017	2018	2019	2020	2021
Cash received from customers	$12,000	$20,000	$31,000	$44,000	$59,000
Cash received from funding	$3,500	$0	$0	$0	$0
Cash paid for wages and other operating expenses	($14,000)	($13,800)	($20,000)	($21,075)	($26,108)
Cash paid for interest	$0	$0	$0	($574.2)	($198.3)
Cash paid for taxes	$0	$0	$0	$0	$0
Net cash provided (used) by operating activities	$1,500	$6,200	$11,000	$22,350.8	$32,694
Cash received from long-term borrowings	$0	$0	$0	$10,000	$0
Cash paid to retire long-term debt	$0	$0	$0	$5,372.8	$5,372.8
Net cash provided (used) in financing activities	$0	$0	$0	$15,373	$5,373
Increase (decrease) in cash during the period	$1,500	$6,200	$11,000	$37,723.6	$38,067
Cash balance at the beginning of the period	$1,000	$2,500	$8,700	$19,700	$57,424
Cash balance at the end of the period	$2,500	$8,700	$19,700	$57,424	$95,490

Table 10. The balance sheet of Ispagtech in the first five years.

Balance Sheet					
Ispagtech					
For 2017 through 2021					
ASSETS	**2017**	**2018**	**2019**	**2020**	**2021**
Current Assets					
Cash	$2,500	$8,700	$19,700	$57,424	$95,490
Total Current Assets	$2,500	$8,700	$19,700	$57,424	$95,490
Fixed Assets					
Equpment and software	$4,000	$3,000	$2,000	$1,000	$0
Total Net Fixed Assets	$4,000	$3,000	$2,000	$1,000	$0
TOTAL ASSETS	$6,500	$11,700	$21,700	$58,424	$95,490
LIABILITIES					
Loan	$0	$0	$0	$0	$0
Total Liabilities	$0	$0	$0	$0	$0
SHAREHOLDERS' EQUITY					
Retained earnings	$0	-$2,000	$4,200	$15,200	$38,125
Current earnings	($2,000)	$6,200	$11,000	$22,925	$32,892
Total Shareholders' Equity	$6,500	$11,700	$21,700	$58,424	$95,490
TOTAL LIABILITIES & EQUITY	$6,500	$11,700	$21,700	$58,424	$95,490

Exit Strategy

Sell to potential partners, AgTech companies, irrigation companies, and smart agricultural device companies. Provide UNL free access and use for educational purposes.

Supplementary

Ispagtech business canvas

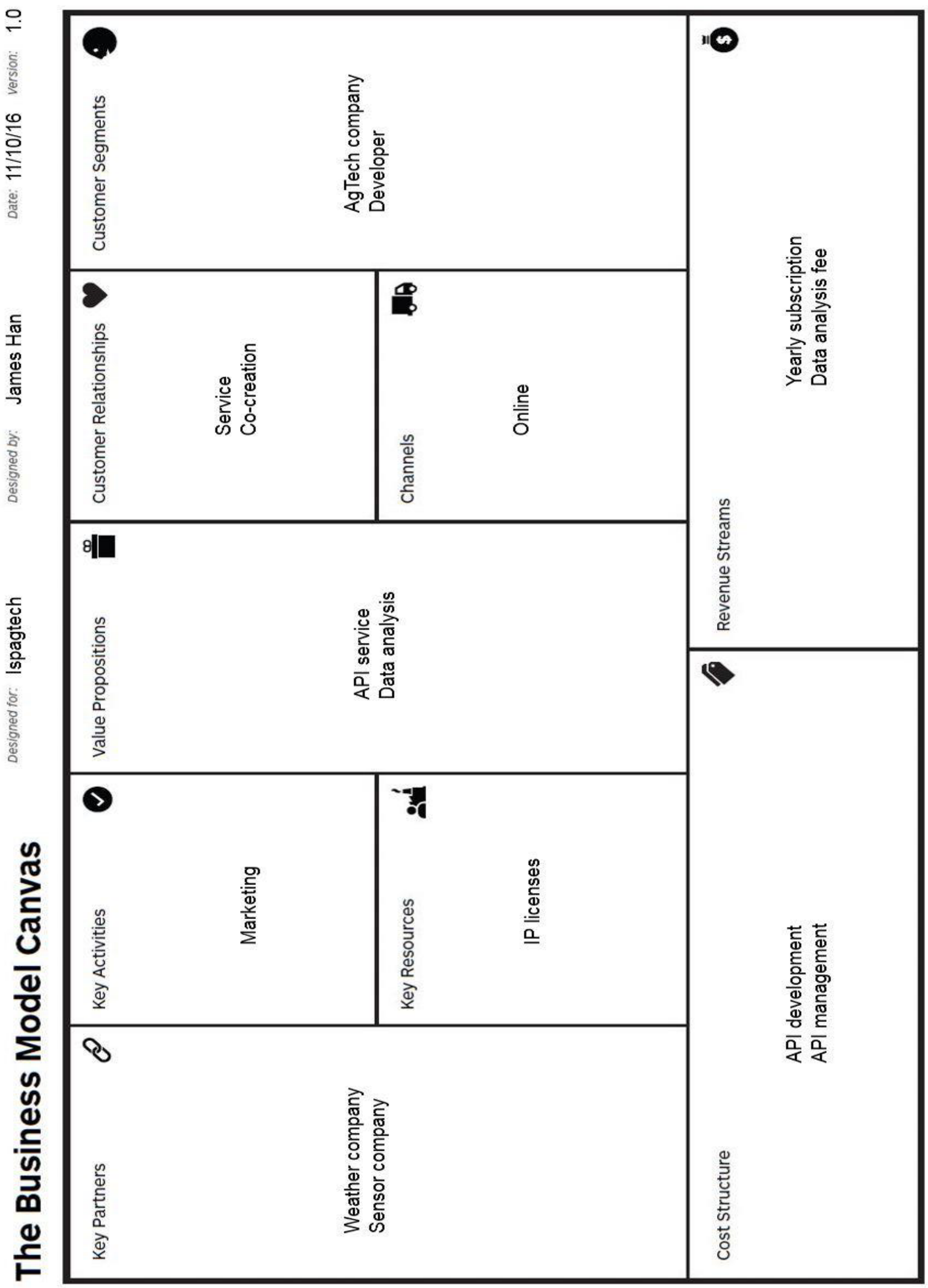


Fig. 8. The business canvas of Ispagtech. The canvas was created by using Strategyzer.

Ispagtech value proposition canvas

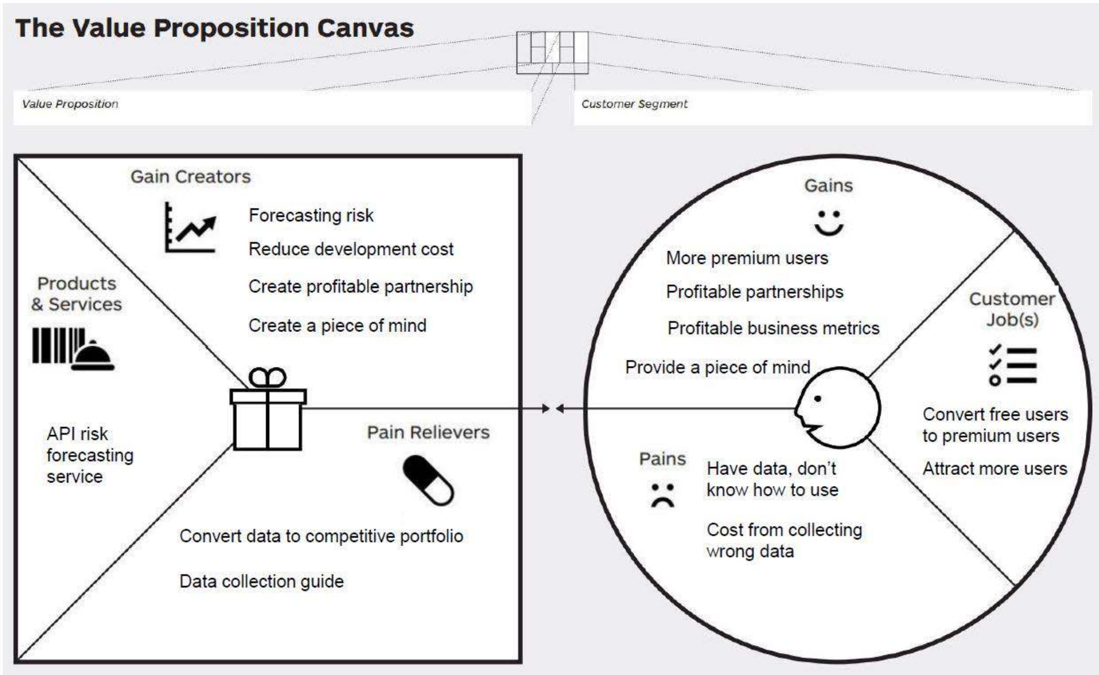


Fig. 9. The value proposition canvas of Ispagtech. The canvas was created by using Strategyzer.