MEF UNIVERSITY

SMART PRECISION AGRICULTURE WITH AUTONOMOUS IRRIGATION SYSTEM USING RNN-BASED TECHNIQUES

Capstone Project

Timuçin Anuşlu

İSTANBUL, 2017

MEF UNIVERSITY

SMART PRECISION AGRICULTURE WITH AUTONOMOUS IRRIGATION SYSTEM USING RNN-BASED TECHNIQUES

Capstone Project

Timuçin Anuşlu

Advisor: Prof. Dr. Özgür Özlük

İSTANBUL, 2017

EXECUTIVE SUMMARY

SMART PRECISION AGRICULTURE
WITH AUTONOMOUS IRRIGATION SYSTEM USING RNN-BASED TECHNIQUES

Timuçin Anuşlu

Advisor: Prof. Dr. Özgür Özlük

OCTOBER, 2017, 35 pages

The study presents a solution to improve freshwater usage for irrigation in the agriculture by building a neural network model to predict soil moisture at 20cm level with time series data from environment sensors, crop, and irrigation system. The Long Short-Term Memory network, a type of recurrent neural networks, is used to cover track of ecosystem data over longer periods of time. The data is collected from environment sensors labeled as Internet of Things, crop records by staff and timetable of the automatic irrigation system in Tabit - Vodafone Akıllı Köy separately. After that, the datasets are joined, cleaned and interpolated to create a dataset for inputs of the model.

Since agriculture has a huge rate of freshwater consumption and also excessive irrigation reduces the crop yield due to damage to the plant roots, the aim of this study is to use the water effectively by predicting necessary freshwater for the plant.

Key Words: Long Short-Term Memory Networks, Recurrent Neural Network, Smart Precision Agriculture, Irrigation System, Internet of Things

ÖZET

YAPAY SINIR AĞLARINA DAYANAN TEKNİKLER KULLANAN
OTONOM SULAMA SISTEMLERİ ILE
AKILLI HASSAS TARIM

Timuçin Anuşlu

Tez Danışmanı: Prof. Dr. Özgür Özlük

EKİM, 2017, 35 Sayfa

Bu çalışma, tarımda sulama için kullanılan temiz su tüketimini iyileştirmek için tarım sahasında algılanan ve kayıt altına alınan veriler girdi olarak kullanılarak yapay sinir ağları modellemesi ile toprak nem miktarını tahmin eden bir çözüm sunmaktadır. Algılanan ve kayıt altına alınan verilerin bitkinin kök toprak nemindeki uzun süredeki etkileri kapsamak için; Yinelenen Yapay Sinir Ağlarından biri olan Uzun Kısa-Vadeli Hafıza (Long Short-Term Memory - LSTM) ağı model kurmak için kullanılmıştır. Modelde kullanılan veriler, Tabit - Vodafone Akıllı Köy'de bulunan Nesnelerin İnterneti konsepti ile sahaya kurulmuş çevre sensörlerden, personelin hasat kayıtlarından ve otomatik sulama sisteminin çalışma zaman çizelgesinden ayrı ayrı toplanmış. Veri birleştirme, veri temizleme ve veri tamamlama işlemleri yapıldıktan sonra veri seti hazır hale getirilmiştir.

Temiz su tüketiminde tarımın yüksek orana sahip olduğu bilinmektedir. Ayrıca, fazla sulamanın bitki köklerine zarar verip, bitkinin hasat miktarını düşürmektedir. Sulamadaki bu durumlar göz önüne alınarak, bu çalışmanın amacı bitki için gerekli olan su miktarını tahmin edip temiz suyu verimli kullanarak tüketimi azaltmaktır.

Anahtar Kelimeler: Uzun Kısa-Vadeli Hafıza Ağları, Yinelenen Yapay Sinir Ağları, Akıllı Hassas Tarım, Sulama Sistemleri, Nesnelerin İnterneti

TABLE OF CONTENTS

ABBREVIATIONS

CCF: Cross-Correlation Function

EDA: Exploratory Data Analysis

ET: Evapotranspiration

IoT: Internet of Things

LSTM: Long Short-Term Memory

RMSE: Root Mean Square Error

RNN: Recurrent Neural Network

1. INTRODUCTION

Nowadays, Machine Learning and Neural Networks as predictive analytics can be used to make smarter decision on agriculture with using stored and real-time data related to environment variables such as sensor data of weather, soil and air quality and process variables such as seed selection, planting, fertilization, irrigation, cultivation and harvest techniques to reduce risk as protection and increase yields as improvement. The ultimate goal of the predictive analytics approach is to optimize the global food production.

1.1. Objective

The autonomous irrigation system using RNN-based techniques is one of the Machine Learning approaches on agriculture. Besides, the aim of this system is to optimize the crop yields with minimizing water usage for irrigation. It is important to minimize water usage for irrigation since 92% of the world's freshwater is used for irrigation (Hoekstra. and Mekonnen, 2011) and also excessive irrigation reduces the crop of the plant due to damage the plant roots.

1.2. Literature

Up to today, lots of precision automated (not autonomous) irrigation systems with remote sensing approaches have been designed and used. However, the systems use the traditional algorithms to decide irrigation time with inadequate observations and the agriculture is a sector that is not open to innovation. In the past, On&Off automated mechanism with weather and sensor data (Bandara, 2016) and the system using crop water stress index (CWSI) over Decision Support System for Agrotechnology Transfer (Barnes, 2000) and the irrigation system controlled by remote control interface (Roham, 2015) are some examples of irrigation innovations. Nowadays, the most effective research (Adeyemi, 2017) includes model predictive control approach with artificial neural networks and fuzzy logic control.

2. ABOUT THE DATA

2.1. Data Provider & Project Environment

Tabit Company aims to increase the efficiency and profitability of the people who live in rural areas and work in agricultural production field and increase their life quality by encouraging the use of technology and its facilities.

The Vodafone Akıllı Köy has been constructed at Aydın/Turkey as a laboratory for smart agriculture by Tabit. At this smart village, some kind of plants such as tomato, pepper, aubergine, melon, watermelon etc. are being planted with different methods either in the greenhouse or in the opened area. The growing cycles and crop yield of the plants and changes of the environment are being monitored and stored in real time.

2.2. Ecosystem

For autonomous irrigation system for the tomato plant which is an eco-friendly solution, the agronomic cognitive predictive model will be built by using neural networks with practice data, environment sensing data and crop yield monitoring data mentioned in the dataset section shown as the ecosystem map in Figure 1.

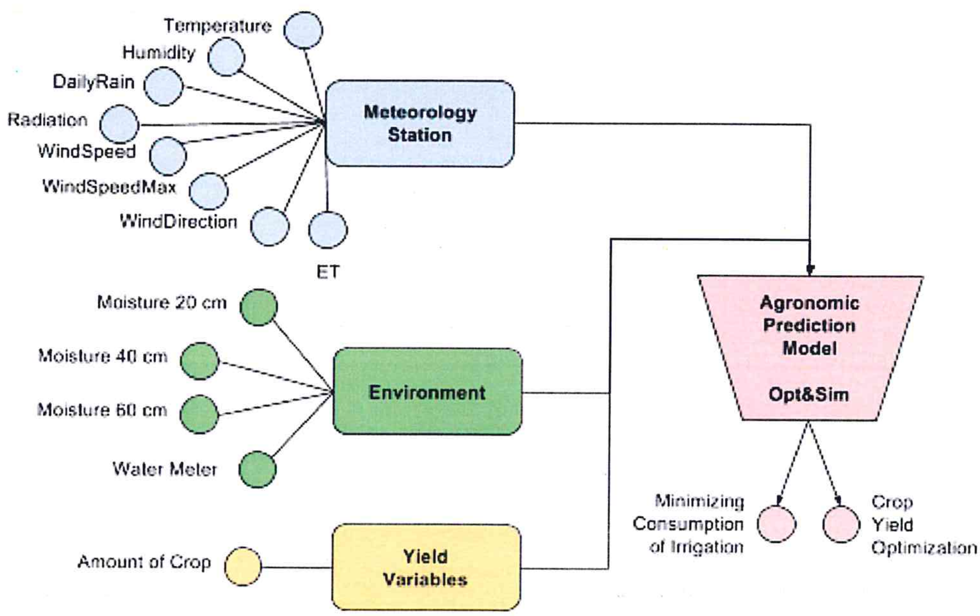

Figure 1 - Ecosystem of the Model

2.3. Description of Data

At the smart village, the 187 seedlings of tomato were planted in 175 m^2 area of Greenhouse in 04.27.2017. After vegetative, growth, reproductive and flowering cycles of tomato, the crop started in 07.15.2017 and then the end time of the cropping is 08.15.2017. In this study, the tomato is analyzed with sensor data of greenhouse and meteorology station, record data of irrigation system and yield data between seedling planting time and crop end time.

The data has been gathered from meteoSense_7b2 (meteorology sensor kit), rsense_00ec4 (greenhouse sensor kit), crop records by staff separately and then the dataset is created by jointing, clean and interpolating these data in 15 minute time intervals and the dataset contains 10384 samples.

The data of meteoSense_7b2 (meteorology sensor kit) includes sensed Temperature, Humidity, DailyRain, Radiation, WindSpeed, WindSpeedMax, WindDirection and ET (Evapotranspiration) variables. Also, the data of rsense_00ec4 (greenhouse sensor kit) includes below sensed NetaSense20cm, NetaSense40cm, NetaSense60cm and WaterMeter variables.

In Figure 2, the soil sensors located at each level of soil sense temperature and moisture of the soil. The sensor groups are embedded in places of farmland where the best measurements can be made.

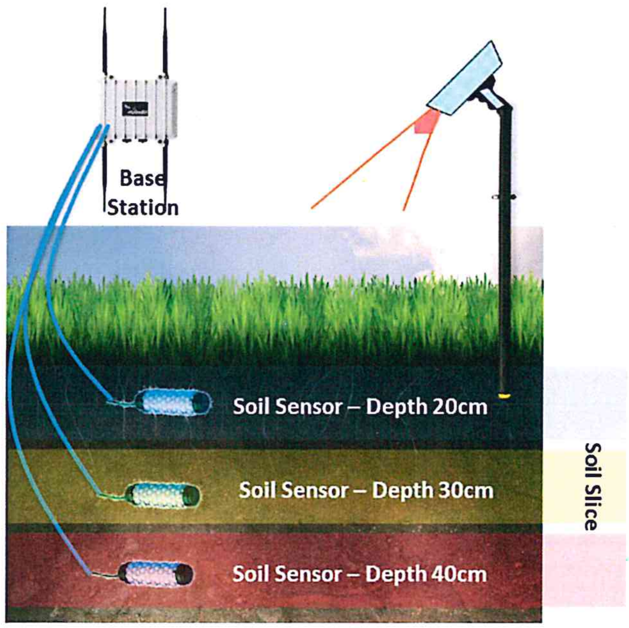

Figure 2 - Soil Sensor Located at Each Level of Soil

In finally, the yield monitor data consists of the total amount of crop for this yield season. The data is split into week parts.

According to the data gathered from the ecosystem, the variables with own units are as in Table 1.

Table 1 - All Variables of the Ecosystem

	Label	***Variable***	***Unit***	***Data Type***
1	date	Date	-	Ordinal
2	temperature	Temperature	celsius	Categorical
3	humidity	Humidity	% RH	Continuous
4	daily_rain	DailyRain	mm	Continuous
5	radiation	Radiation	W/m2	Continuous
6	wind_speed	WindSpeed	m/s	Continuous
7	wind_speed_max	WindSpeedMax	m/s	Continuous
8	wind_direction	WindDirection	degree	Continuous
9	et	ET (Evapotranspiration)	mm	Continuous
10	moisture_20cm	NetaSense20cm	%vol	Continuous
11	moisture_40cm	NetaSense40cm	%vol	Continuous
12	moisture_60cm	NetaSense60cm	%vol	Continuous
13	irrig	WaterMeter	liter	Discrete
14	crop	Crop	gram	Discrete

3. PROJECT DEFINITION

In this section, the problem will be stated and the objectives to overcome the problem will be defined. Following that, it will be specified what the scope of this study covers and what does not.

3.1. Problem Statement

The agriculture irrigation process has a huge proportion of freshwater consumption with the %92 ratio. Moreover, over-irrigation causes roots to decay and so decreasing crop field of the plant (Irmak, 2014). The aim of this study is to minimize the freshwater consumption by focusing water as much as the tomato seedling needs.

The moisture value at 20 cm soil level is the most important role for plant growth because the largest proportion of tomato roots was found between the plant row and 40 cm of the soil. (Oliveira, Calado and Portas, 1996). When the amount of water the plant needs (neither little nor much) is provided to the capillary roots, the plant grows healthy and gives as maximum crops as it can give. Therefore, to provide the amount of water the roots of the plant at 20 cm soil level needs, the irrigation system can be controlled by a prediction model built with all samples of all variables.

3.2. Objectives

The objective of this study is building a model to predict the moisture at 20 cm soil level which the plant needs with both samples of other variables and the previous sample of the moisture at same soil level.

3.3. Scope

The scope of this study is only to build the best model to predict moisture at 20 cm soil level with current and previous sample values of all variables. Next steps of this study may be moisture simulation with different water amount of irrigation system to detect the effects of the irrigation system in the specific environment in the future. Namely, it is out of the scope of the study for now.

4. METHODOLOGY

This section consists of the definition of variables as dependent and independent, Exploratory Data Analysis (EDA), data manipulation, model validation, and model deploying. Moreover, the detailed technical information about the model and techniques such as LSTM Neural Network is given.

4.1. Independent & Dependent Variables

As mentioned in project statement subsection, the dependent variable of the ecosystem is moisture at 20 cm soil level. In meanwhile, the other variables are independent variables. The relationship between variables are shown as below:

moisture_20cm ~ temperature + humidity + daily_rain + radiation + wind_speed + wind_speed_max + wind_direction + et + moisture_40cm + moisture_60cm + irrig + crop

It is assumed that the protection of the water at 20 cm depth of soil depends on the amount of moisture in the 40cm and 60cm depth of soil. So, if water is available at 40 cm and 60 cm depth of soil during irrigation, the water does not go deep, and it is preserved at 20 cm depth of soil where the roots of tomato are. For this reason, moisture_40cm and moisture_60cm variables are incorporated with other variables in the study.

In next section, each variable will be examined individually and then cross-correlation between the dependent variable and each independent variable will be analyzed to make calculation easier as inputs for LSTM. After that, the model will be built with all dependent and independent variables.

4.2 Exploratory Data Analysis

The descriptive statistics of all variables are shown in Table 2.

Table 2 - Descriptive Statistics of All Variables

Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
moisture_20cm	10,384	22.8	4.9	16.3	36.6
moisture_40cm	10,384	17.5	1.5	14.8	19.8
moisture_60cm	10,384	21.0	1.7	18.8	24.1
irrig	10,384	3.2	19.4	0.0	155.4
crop	10,384	0.1	5.6	0.0	256.2
wind_speed	10,384	1.7	1.3	-0.000	5.4
wind_speed_max	10,384	3.0	1.6	-0.000	7.5
wind_direction	10,384	164.3	83.2	-0.000	354.0
daily_rain	10,384	0.2	1.6	0.0	31.8
temperature	10,384	25.5	5.8	9.2	42.2
humidity	10,384	55.0	18.6	15.1	110.5
radiation	10,384	280.4	314.3	-0.02	1,418.6
et	10,384	5.8	0.6	4.2	7.1

For each variable, the time diagram and the histogram are plotted as in Figure 3. As you can see in this histogram diagram, the variables have no skewness so the variable does not need the transformation to the normal distribution.

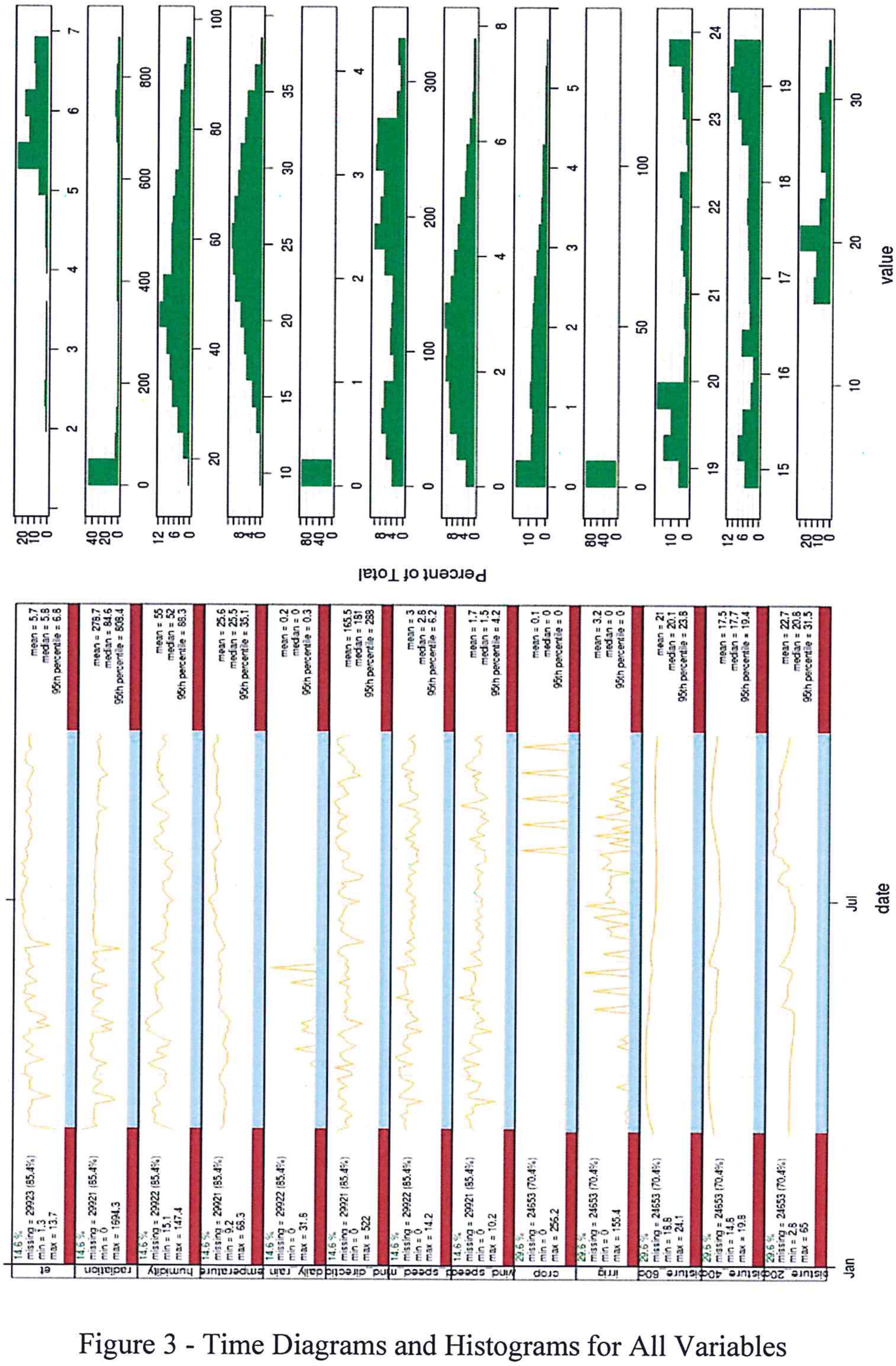

Figure 3 - Time Diagrams and Histograms for All Variables

Moreover, it is not necessary to create the corrgram plot at this point because it is assumed that there will be crosscorrelation between variables in terms of timing. The correlation of variable pairs will be examined after the convenience lag value between two variables is determined in terms of cross-correlation.

After examining the cross-correlation between dependent and independent variables and lagging some independent variables, the corrgram in Figure 4, shows that when the time series effects are excluded, moisture_20cm has a positive correlation with temperature and negative correlation with moisture_60cm. So that, the effects of the previous samples of all variables on the current sample of dependent variables have to be analyzed.

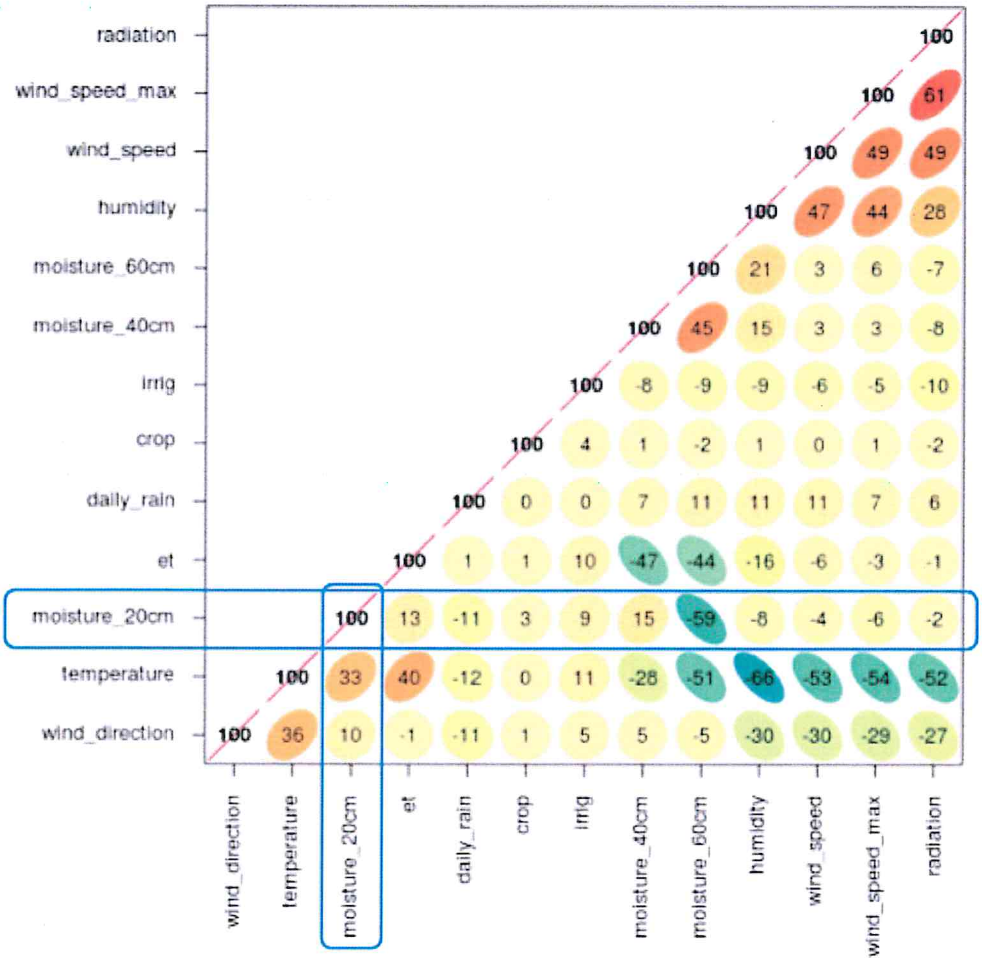

Figure 4 - Correlation Between Dependent Variable and Each Independent Variable

Moreover, the calendar mapping which is used to display continuous data over a period of time (Gohil, 2015) in Figure 5, the sum liter of irrigation can be shown and examined day by day easily. According to the map, the farm was mostly irrigated on June 12th and June 30th. This information from the map also leads us to understand the story of the dataset.

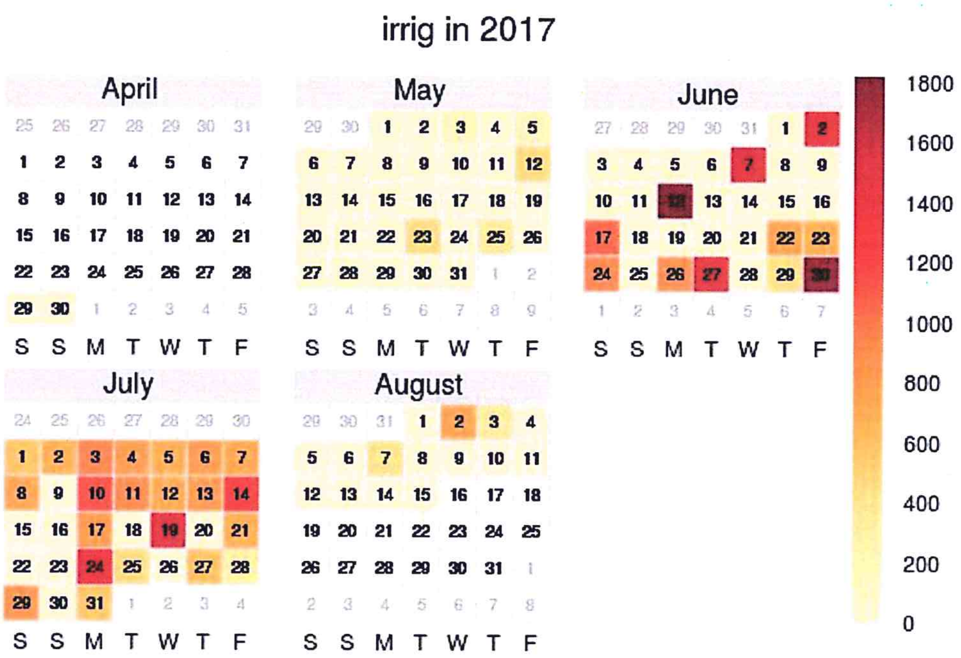

Figure 5 - Calendar Map of Irrigation System

4.3. Data Manipulation

4.3.1. Data Cleaning

The aim of this pre-processing step is increasing data quality. The reason for the need to increase the quality of the data is that the data has noise and/or outliers. To determine whether the data cleaning is required or not, exploratory data analysis methods are applied for each variable and the outliers and/or noises can be detected via the methods. To detect outliers and/or noises, the box plot should be created with outliers. If a variable of a sample has any outliers, this sample should be removed from the data completely.

Sometimes, sensors are able to be misdiagnosed due to sensor failure and it causes outliers. To detect the outliers, the boxplots of the variables are plotted in Figure 6.

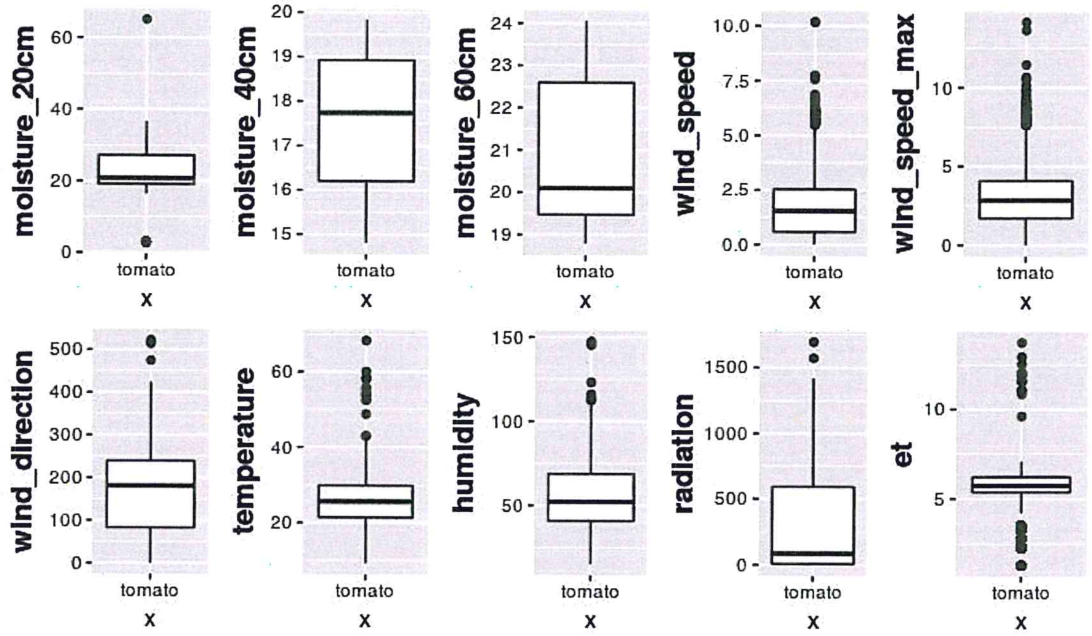

Figure 6 - The Boxplots of Variables to Detect Outliers

The moisture_20cm, wind_speed, wind_speed_max, temperature, humidity, radiation and et variables have outliers so these have to be cleaned by using the 1.5 x IQR Rule for Outliers (Moore, 2010). Moreover, the wind_direction variable must not be higher than 360 so it needs to be updated with this limit.

After this cleaning step, the boxplots of these variables as in Figure 7 and the variables do not contain an outlier anymore.

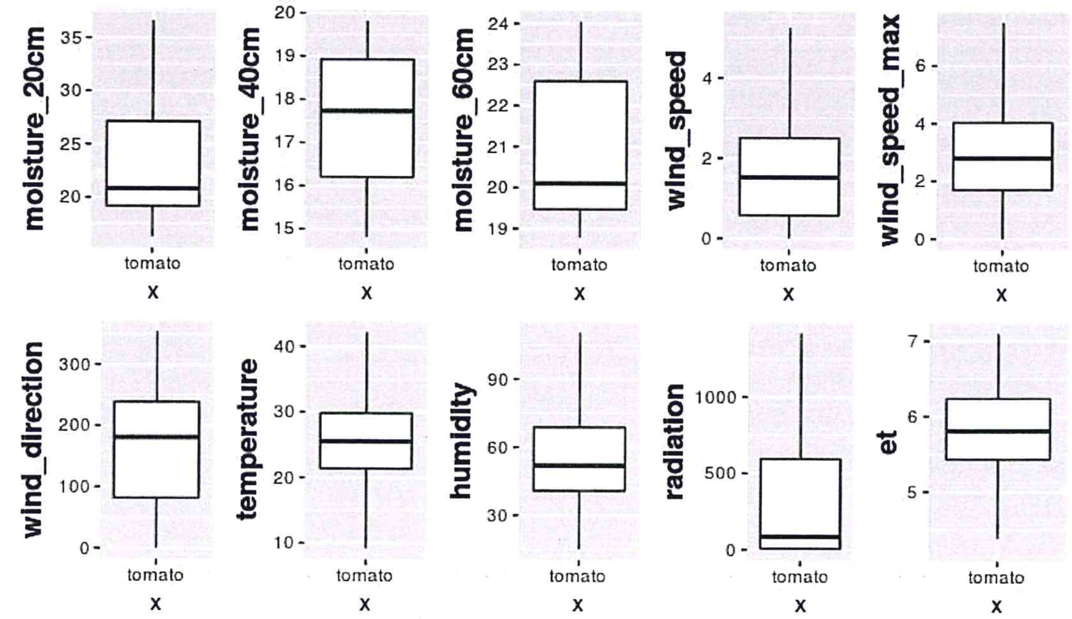

Figure 7 - The Boxplots of Variables After Outlier Cleaning

4.3.2. Data Interpolation

Some variables have missing values due to some reasons such as sensor failure, incompatibility of sample time interval etc. If a variable has some missing value, it is necessary to interpolate the missing values of the variable with convenient interpolation method such as linear, spline, stine, locf, kalman etc. For example, the moisture_20cm has 33 missing values and the missing values are interpolated with linear methods such as in Figure 8. Similarly, wind_speed, wind_speed_max, wind_direction, daily_rain, temperature, humidity, radiation and et variables having missing values due to outliers are interpolated.

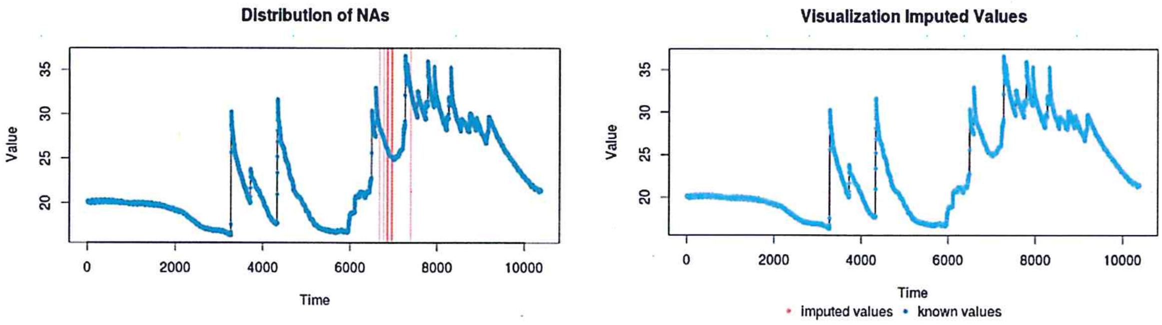

Figure 8 - The Time Diagram of Moisture_20cm Variable with & without Missing Data

4.4. Cross-Correlation

This step is pre-operation to make calculation easier for LSTM. The cross-correlation between the dependent variable and each independent variable is investigated by lagging independent variables over 2 days time domain[1]. The CCF (Cross-Correlation Function) figure shows both the cross-correlation within t=0 and then the cross-correlation within calculated time lagging. Also, the vertical line indicates the max cross-correlation between them.

For example, the cross-correlation between moisture_20cm and irrigation is shown in Figure 9. As you can see, moisture_20cm has the highest correlation with 154 * 15 min lag of irrigation.

[1] It is assumed that the effect of environmental samples is lasts for up to 2 days.

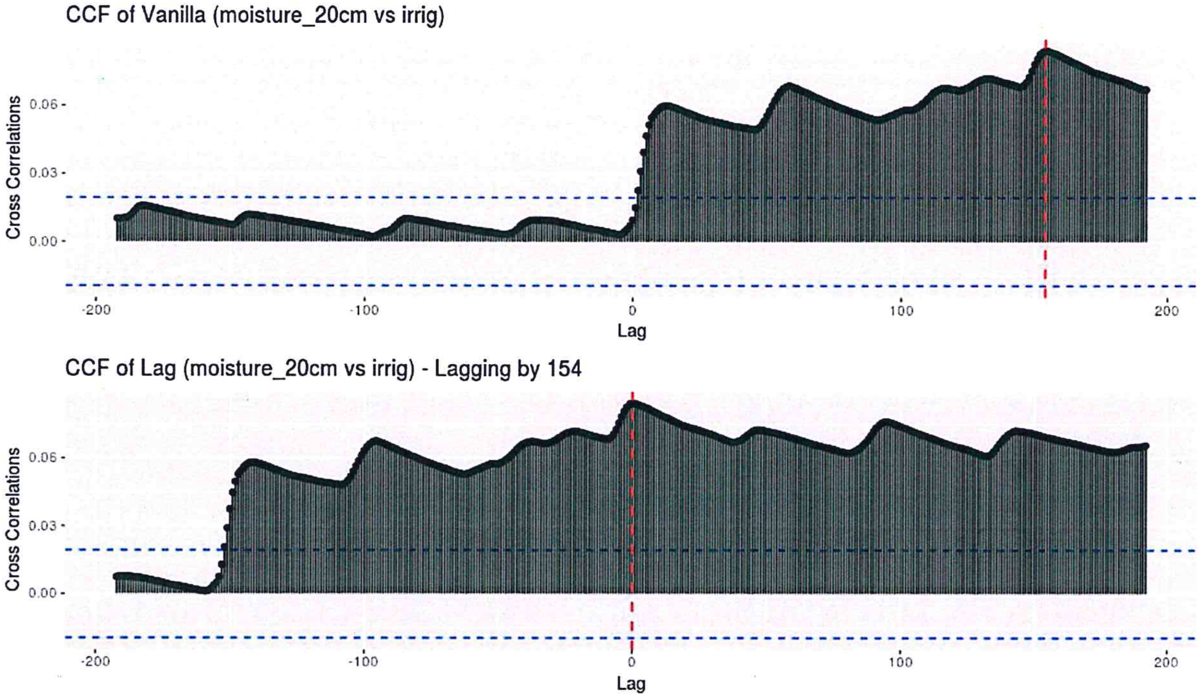

Figure 9 - Cross-Correlation between Moisture_20cm and Irrigation

As the result of this analysis, the below formula is obtained with all variables.

moisture_20cm(t) ~ temperature(t-136) + humidity(t-128) + daily_rain(t+20) + radiation(t-12) + wind_speed(t+185) + wind_speed_max(t-5) + wind_direction(t+163) + et(t-192) + moisture_40cm(t-162) + moisture_60cm(t-192) + irrig(t-154) + crop(t+101)

4.5. Standardization

Often variables are not expressed with the same standard (e.g., the unit of weather temperature is Celsius and the unit of weather humidity is percentage of relative humidity). In such a case, this can potentially add error or distort the experiment when the value as features is combined in modeling. By transforming the values with feature normalization so that they are on a common scale, yet maintain their general distribution and ratios, the better result can be generally obtained when modeling (Fontama et. al., 2015). Normalization serves the purpose of bringing the indicators into the same unit.

After normalization between 0 and 1, the variables are shown as in Figure 10.

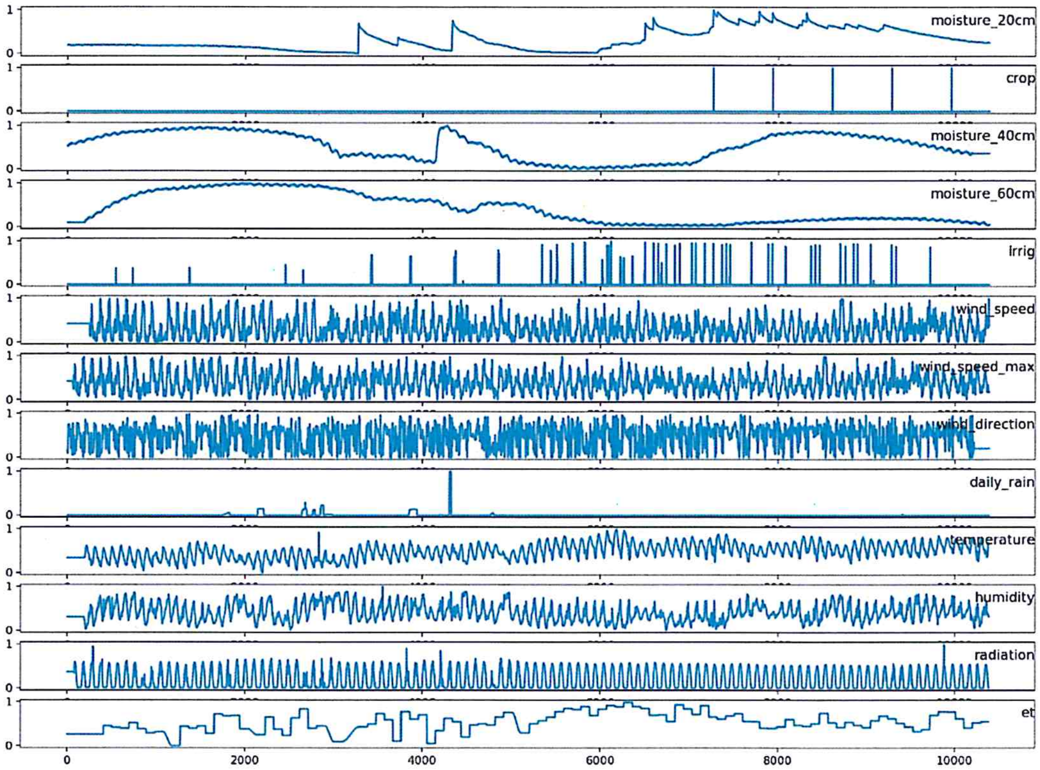

Figure 10 - Time Graph of Normalized Variables

After predicting the future data, the predicted data has to be denormalized to reach real data.

4.6. Model and Techniques

In this study, LSTM Neural Network is used to trace the effects of both current and past sample values on moisture at 20 cm soil level.

Besides, it is noted that we have tried some methods such as linear regression without time series and dynamic panel data analysis methods but we have obtained some unsuccessful results by using these methods.

4.6.1. Long Short-Term Memory - Recurrent Neural Networks

Recurrent Neural Networks (RNN) are used for sequential modeling on datasets where high autocorrelation exists among observations (Rao & Prakash, 2017). A recurrent layer is made up of particular neurons that present recurrent connections so as to bind the state at time t to its previous values. Moreover, RNNs overcome this problem by providing an internal memory which can capture short-term and long-term dependencies (Bonaccorso, 2017).

LSTM Neural Network is a recurrent neural network with LSTM blocks as units in hidden layers (Hirose et. al., 2016). LSTM can store information over more than 1000 time steps (Otte et. al., 2014). The general structure of the transformations in LSTM neuron that are applied to the hidden state at time step t (Gulli & Pal, 2017) is illustrated in Figure 11.

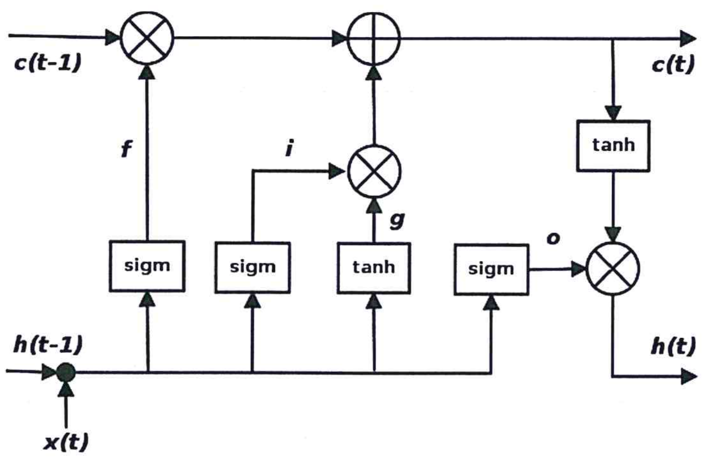

Figure 11 - General Structure of Transformations in LSTM Neuron

Agriculture irrigation system depends on the past samples with high correlations. Therefore, the LSTM model is convenient to predict the future data of moisture amount on the root with environment effects measured by sensors and crop yields recorded by the staffs.

4.6.2. Model Validation

To validate the model, the dataset is split into train and test datasets like 9894 samples and 480 samples with 1+130 variables. 480 samples are referred as one-week data. The reason for one-week selecting for test data is that this week is the last one of the four-week time cycle of cropping. If the test dataset is chosen more, the effect of cropping would be minimal in the model building with train dataset.

4.6.3. Model Deploying

The inputs and output of the model are the following:

The Output of the LSTM (1 variable):

moisture_20cm(t)

The Inputs of the LSTM (130 variables):

moisture_20cm(t-1:10)

temperature(t-136:146)

humidity(t-128:138)

daily_rain(t+20:10)

radiation(t-12:22)

wind_speed(t+185:175)

wind_speed_max(t-5:15)

wind_direction(t+163:153)

et(t-192:202)

moisture_40cm(t-162:172)

moisture_60cm(t-192:202)

irrig(t-154:164)

crop(t+101:91)

The structure of the model is figured in Figure 12. For the train data, the model input shape is [9894, 1, 130] of a matrix and the model output shape is [9894, 1, 1] of a matrix. Also, for the test data, the model input shape is [480, 1, 130] of a matrix and the model output shape is [480, 1, 1] of a matrix.

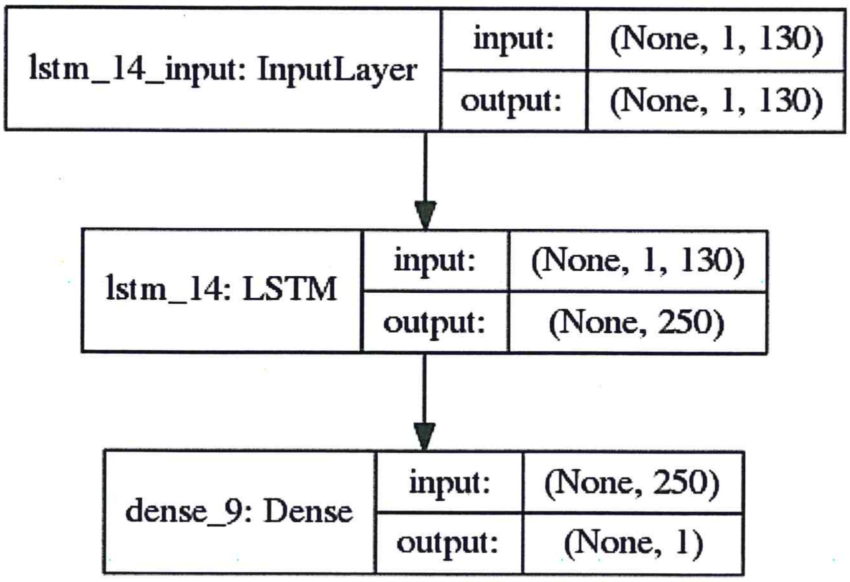

Figure 12 - Neural Network Model

For LSTM layers, the number of neurons is 250 and input shape of the layer is same as input shape of the overall model. Conversely, other values have been tried but the accuracy of the model has decreased. So, the 250 of neurons are best for the model.

For this recurrent neural network, the objective function (loss) of the model is Mean Absolute Error (MAE) and also the optimizer of the model is Adam which is one of the methods for stochastic optimization. By contrast with this options, it is seen in trials that other objective functions such as logloss, poisson etc. and other optimizers such as Adadelta, TFOptimizer etc. affect the accuracy of the model negatively.

For fitting of this model, the batch size is determined to 97[2] according to the sample size of train data like 9894/102 and the number of times to iterate over the training data (epoch) is selected as 200. With the batch size and epoch value, it is aimed that the memory of computer is used efficiently.

[2] prime multiplier of sample size - the smallest possible part of samples

5. RESULTS

According to model building, the plot showing the train and test loss during the fitting process is in Figure 13.

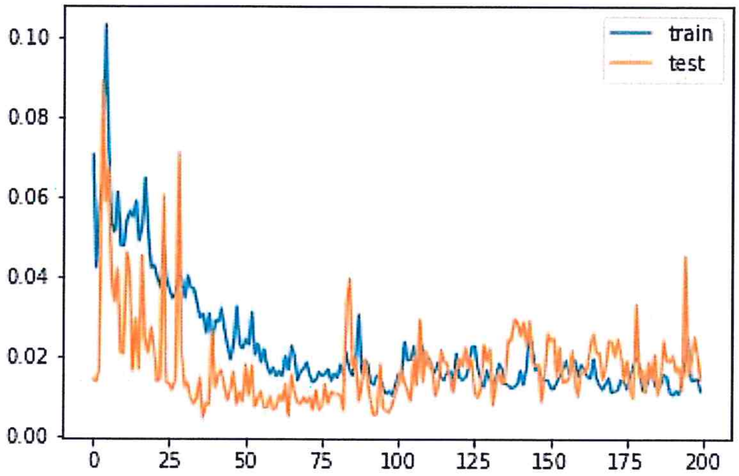

Figure 13 - Loss of Train and Test Datasets

Moreover, the results of RMSE (Root Mean Square Error) which is one of the quality evolution metrics to evaluate the quality of the forecast (Zhao et. al., 2017) for train and test datasets are calculated with predicted and actual values of samples are below. These RMSE results are acceptable for the model of the study.

Train Score: 22.79 RMSE

Test Score: 22.15 RMSE

The actual and predicted values of the dependent variable are plotted over the time scale in Figure 14. As you can see, the errors between actual and predicted values are acceptable.

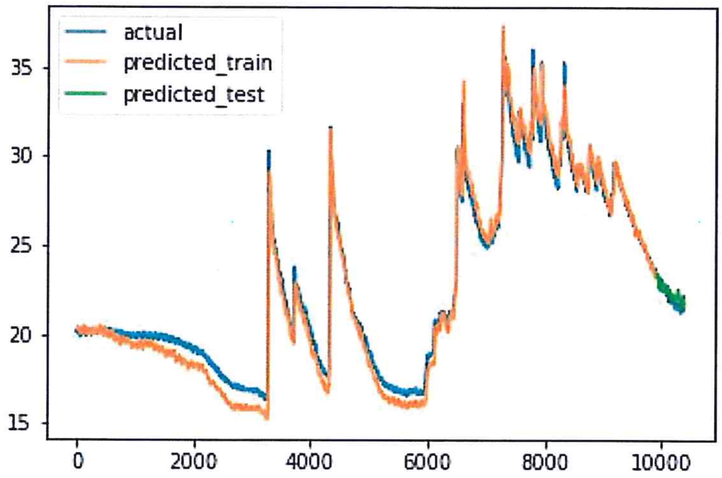

Figure 14 - Time Diagram of Actual and Predicted Values of Train and Test Datasets

When the test partition of the dependent variable is zoomed in, the predicted values are shown as in Figure 15.

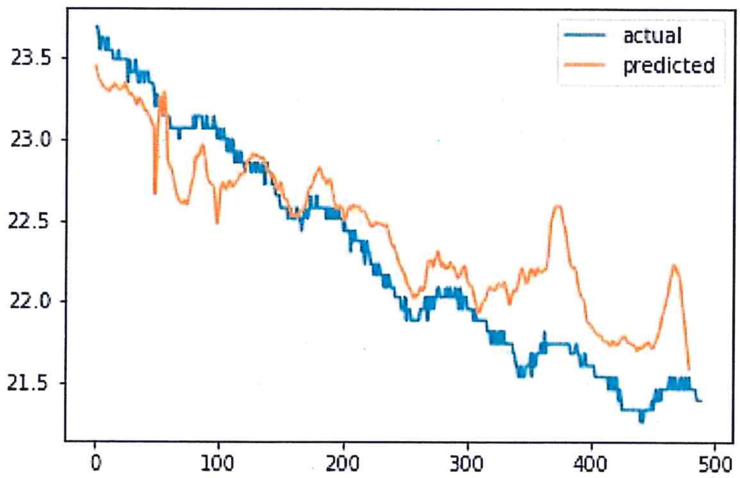

Figure 15 - Time Diagram of Actual and Predicted Values of Only Test Datasets

As you can see with these graphs and the results, the model is compatible with the project statement and the model is ready for a simulation to optimize the freshwater usage for farmland.

6. SOCIAL AND ETHICAL ASPECTS

According to The Organisation for Economic Co-operation and Development (OECD), increased pressure from urbanisation, industrialisation and climate change will provide agriculture with more competition for water resources and climate change could affect water supply and agriculture through changes in the seasonal timing of rainfall and snow pack melt, as well as higher incidence and severity of floods and droughts. On the other hand, sustainable management of water in agriculture is critical to increase agricultural production, ensure water can be shared with other users and maintain the environmental and social benefits of water systems. Governments need to improve the economic efficiency and environmental effectiveness of policies that seek to improve water resource use efficiency and reduce water pollution from agricultural systems.

Moreover, the agriculture sector is often criticized for high wastage and inefficient use of water at the point of consumption (i.e. at farm level) encouraged by subsidized low charges for water use or low energy tariffs for pumping (Turner et. al., 2004)

As mentioned in the beginning sections, the aim of this study is to decrease freshwater consumption for agriculture and to enable plants to give more crops with more effective growing. In this way, it will increase the crop quality and crop yield without damaging the mankind and nature.

Moreover, the autonomous irrigation systems using this model, compared to other systems, further reduce farmers' workload. This is another great gain.

7. VALUE DELIVERED

The value delivered of this study is a built model to predict the moisture at 20 cm soil level with environmental effects and crop amount for the tomato plant. This model can be used to control the irrigation system by simulating by using this model with the environmental effects and the crop amount.

Until today, the automatic irrigation systems which irrigate the farmland with programmable logic control principles. Hereafter, according to environmental changes, the irrigation systems are able to be controlled autonomously.

Finally, this model can only be one of the improvements and models in agriculture. Lots of parameters on agriculture area waiting to be improved exists. Agriculture is Indispensable for humankind, so every modeling and remediation in agriculture are is very important in order to use resources efficiently and to get more products.

APPENDIX

In this study, the R and Python programming languages are used together for analysis. With the following libraries, exploratory data analysis, data manipulation, cross-correlation have been performed by using R programming language and normalization, model building and predicting steps also has been implemented by using Python programming language.

R Libraries:

- googlesheets
- ggplot2
- lubridate
- readxl
- openair
- gridExtra
- imputeTS
- stargazer
- tibble
- dplyr
- forecast
- astsa
- GGally
- xts
- fpp2
- plotly
- vars

Python Libraries:

- numpy
- math
- sqrt from math
- concatenate from numpy
- pyplot from matplotlib
- read_csv from pandas
- DataFrame from pandas
- concat from pandas
- MinMaxScaler from sklearn.preprocessing
- LabelEncoder from sklearn.preprocessing
- mean_squared_error from sklearn.metrics
- Sequential from keras.models
- Dense from keras.layers
- LSTM from keras.layers
- plot_model from keras.utils

REFERENCES

Aadith Moorthy, (2016). Global custom-tailored machine learning of soil water content for locale specific irrigation modeling with high accuracy. International Journal of Environmental & Agriculture Research (IJOEAR).

Ajit Jaokar and Pragnesh Shah, Reinforcement Learning and the Internet of Things, Retrieved from http://www.kdnuggets.com/2016/08/reinforcement-learning-internet-things.html

A.G.N. Bandara, B.M.A.N. Balasooriya, H.G.I.W. Bandara, K.S. Buddhasiri, M.A.V.J. Muthugala, A.G.B.P. Jayasekara and D.P. Chandima. (2016). Smart Irrigation Controlling System for Green Roofs Based on Predicted Evapotranspiration.

Bonaccorso, Giuseppe. (July 2017). Machine Learning Algorithms. *Packt Publishing.* Retrieved from https://www.safaribooksonline.com/library/view/machine-learning-algorithms/9781785889622/d440880d-c70e-4623-a8a2-10627bb4aa7e.xhtml

Gohil, Atmajitsinh. (January 2015). R Data Visualization Cookbook, *Packt Publishing.* Retrieved from https://www.safaribooksonline.com/library/view/r-data-visualization/9781783989508/ch07s04.html

D.J. Hunsaker a, A.N. Frencha, P.M. Waller b, E. Bautistaa, K.R. Thorpa, K.F. Bronsona, P. Andrade-Sanchezc. (2015). Comparison of traditional and ET-based irrigation scheduling of surface-irrigated cotton in the arid southwestern USA, Agricultural Water Management. *Elsevier*

E.M. Barnes, P.J. Pinter, Jr., B.A. Kimball, D.J. Hunsaker, G.W. Wall, and R.L. LaMorte. (2000). Precision Irrigation Management Using Modeling And Remote Sensing Approaches

Fontama, Valentine, Barga, Roger, Tok, Wee Hyong. (2015). Predictive Analytics with Microsoft Azure Machine Learning, *Apress*

Gulli, Antonio, Pal, Sujit. (April 2017). Deep Learning with Keras. *Packt.* Retrieved from https://www.safaribooksonline.com/library/view/deep-learning-with

Hirose, Akira, Ozawa, Seiichi, Doya, Kenji, Ikeda, Kazushi, Minho Lee, Derong Liu. (September 2016). Neural Information Processing (pp 532). *Springer*. Retrieved from https://books.google.com.tr/books?id=UfUqDQAAQBAJ&pg=PA532

Hussein M. Al-Ghobari, Fawzi S. Mohammad and Mohamed S. A. El Marazky. (2016). Evaluating two irrigation controllers under subsurface drip irrigated tomato crop. Spanish Journal of Agricultural Research.

Irmak, Suat. (April 2014). University of Nebraska - Lincoln, Plant Growth and Yield as Affected by Wet Soil Conditions Due to Flooding or Over-Irrigation, Retrieved from http://extensionpublications.unl.edu/assets/pdf/g1904.pdf

Luigi Occhipinti, University of Cambridge, Giuseppe Nunnari, University of Catania, Synthesis of a greenhouse climate controller using AI-based techniques. Retrieved from https://www.researchgate.net/publication/3659496_Synthesis_of_a_greenhouse_climate_controller_using_AI-based_techniques

Moore, David S. (2010). The Basic Practice of Statistics. (pp. 48) *W. H. Freeman and Company, New York*

Oliveira , Maria do Rosário G., Calado, António M., Portas, Carlos A. Martins.(1996). Tomato Root Distribution under Drip Irrigation. (pp. 644). Journal of the American Society for Horticultural Science. Retrieved from http://journal.ashspublications.org/content/121/4/644.full.pdf

Olutobi Adeyemi, Ivan Grove, Sven Peets and Tomas Norton, (Journal, 2017). Advanced Monitoring and Management Systems for Improving Sustainability in Precision Irrigation. *Sustainability*

Otte, Sebastian, Liwicki, Marcus and Krechel Dirk. (July 2014). Machine Learning and Data Mining in Pattern Recognition (pp. 487). *Springer*. Retrieved from https://books.google.com.tr/books?id=22UqBAAAQBAJ&pg=PA487

Rao, Achyutuni Sri Krishna, Prakash, Dr. PKS. (August 2017). R Deep Learning Cookbook. *Packt Publishing.* Retrieved from https://www.safaribooksonline.com/library/view/r-deep-learning/9781787121089/c8d10427-7296-48a8-aec5-67bcafdf5be7.xhtml

Shivaram Irukula. (December 2015). Reinforcement Learning based on Controller for Precision Irrigation. Retrieved from http://oaktrust.library.tamu.edu/bitstream/handle/1969.1/156129/IRUKULA-THESIS-2015.pdf

S. L. Davis, and M. D. Dukes, (2015). Methodologies for Successful Implementation of Smart Irrigation Controllers. *Journal of Irrigation and Drainage Engineering*

Trifun Savić, Balša Bajagić, Mirko Knežević, Milutin Radonjić. (2017). Method for Measuring Released Amount of Water in Smart Irrigation System. 22nd International Scientific-Professional Conference Information Technology

Turner, Kerry, Georgiou, Stavros, Clark, Rebecca, Brouwer, Roy and Burke, Jacob. (2004), Economic valuation of water resources in agriculture - From the sectoral to a functional perspective of natural resource management. *Food and Agriculture Organization of The United Nations*. Retrieved from http://www.fao.org/docrep/007/y5582e/y5582e04.htm

Vaibhavraj S. Roham, Ganesh A. Pawar, Abhijeet S. Patil, Prasad R. Rupnar. (2015). Smart Farm using Wireless Sensor Network, *International Journal of Computer Applications*.

W.M. Rodriguez-Ortega, V. Martinez, R.M. Rivero, J.M. Camara-Zapata, T. Mestre, F. Garcia-Sanchez. (2016). Use of a smart irrigation system to study the effects of irrigation management on the agronomic and physiological responses of tomato plants grown under different temperatures regimes. Agricultural Water Management. *Elsevier.*

Yue Xu, Recent Machine Learning Applications to Internet of Things (IoT). Retrieved from http://www.cs.wustl.edu/~jain/cse570-15/ftp/iot_ml/

Zhao, Rui, Yan, Ruqiang, Wang, Jinjiang and Mao, Kezhi. (February 2017), Learning to Monitor Machine Health with Convolutional Bi-Directional LSTM Networks, *Sensors.* Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5336098/pdf/sensors-17-00273.pdf

GLOSSARY

ET (Evapotranspiration):

the process by which water is transferred from the land to the atmosphere by evaporation from the soil and other surfaces and by transpiration from plants.