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Identifying And Predicting Climate Stress For Agricultural Practices In The North West Region Of Syria

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Abstract

Climate changes affect all sectors of life, especially the agricultural sector, where rising temperatures and drought have caused a decrease in many types of agricultural crops, which poses a threat to global food security. Here we examine potential changes in climate variables (precipitation and temperature) over the freed areas of northern Syria, with the aim of developing a new prediction system for multi-year agrometeorological risks (i.e. drought and extreme heat) over the freed areas of northern Syria. We first conducted interviews, highlighting that regional practitioners do adapt their practices depending on weather/climatic forecast, switching to crops that are more resilient to drought, or adapting their agricultural calendar, but that stressing the need for more reliable forecast of agrometeorological risks. Using ERA5 data between 1979 and 2021, we indeed found an increase in drought risks, which is strongly related to an increase in maximum temperature, enhancing evapotranspiration. We thus test the benefit of neural network in providing reliable prediction for maximum temperature and drought indices.Preliminary results are promising with minimal errors in the mean, and in the variance of predicted data, as compared to the original data. Therefore, we implemented different sensors over the freed areas of northern Syria to monitor climate variations, and to set a live monitoring system, from which new and accurate prediction for climate stress will be provided on seasonal basis.

Key words: Climate, Corps, Agriculture, precipitation, temperature, Neural network.

1-Introduction

Weather and climate greatly affect most sectors of life, especially the agricultural sector. Smallholder farming is the most common type of agriculture on the earth, supporting many of the world's most vulnerable people (Samberg et al., 2016). According to Ricciardi et al. (2018), smallholder farmers produce 70-80 % of the world's food. The success of smallholder farmers is thus very important for global food security, and consequently for national food security in developing countries (Shiferaw et al., 2011). Unfortunately, recent and sudden changes in weather and climate, such as increasing frequency and intensity of heat waves, floods and droughts, substantially affect the production of smallholder farmers (Hufkens et al., 2019). About 76 % of farmers are expected to suffer economic losses as a result of climate change (Claessens et al., 2012).

The World Meteorological Organization (WMO) established production and verification guidelines for seasonal climate forecasts in 2006, which are now being followed by 12 national and multinational forecast centers across five continents, known as Global Producing Centers (GPC; "Global Producing Centers of Long-Range Forecasts," 2016). Thus, the role of meteorological centers is to develop guidelines and warnings, when necessary, for farmers to take measures to determine the types of agricultural crops they wish to grow according to the expected weather (Pulwarty and Sivakumar, 2014). Establishing a relationship between crop selection and meteorology through weather forecasts has many challenges (Cantelaube and Terres, 2005) and climate conditions must be an integral part of decision-making (Kamatchi and Parvathi, 2019).

A large amount of evidence shows the potential utility of increasingly complex and accurate weather and climate forecasts for agricultural production (Westra and Sharma, 2010). In the future decades, crop resilience to climate change will be important for global food security, as decrease in crop productivity is currently observed, as a result of a changing climate (Ahmed et al., 2015). This will be particularly important over the Mediterranean Region, where climate is on average hot and dry, and characterize by very specific morphologic, geographical, historical, and societal properties (Lionello et al., 2006). By 2050s, eastern Mediterranean countries are expected to experience a warming up to 2-2.75 ^{o}C, and a decrease of about 20-25% in winter rainfall (Ragab and Prudhomme, 2002). Many studies have been undertaken to examine the regional climate of several Southwest Asian nations, such as Bahrain (Elagib and Addin Abdu, 1997), as well as the Arab world (Abahussain et al. 2002). The outcomes of these studies show the impact of climate variability is stronger in the recent decades, as a result of human activities (Elagib and Addin Abdu, 1997; Abahussian et al. 2002; Modarres and de Paulo Rodrigues da Silva, 2007). In particular, Ibrahim et al, (2018) showed a decrease in rainfall in most climatic stations, especially in the north and western parts of Syria. However, during the last decade, due to the civil war in Syria, no applied research was conducted in the freed areas, and farmers related to weather forecast only. In addition, there is an urgent need to know the amount of rainfall over the area, as an important factor in assessing the amount of water available to meet the various demands of agriculture, industry and other human activities (Ibrahim et al, 2018). This will have a crucial importance in improving human livelihood over the region.

Seasonal forecast are most commonly done using regression techniques (Agbo, 2021). More recently, the scientific community highlighted the added-value of machine learning techniques in providing more reliable seasonal forecast, as such non-linear prediction system allows the systems to learn and grow from their experiences (Rushing et al., 2005; Hasan et al., 2016; Pandy and Singh, 2019). In addition, machine learning does not require a detailed understanding of weather characteristics and parameters, but requires long climatic records to robustly calibrate the model and predicted its future evolution at seasonal to inter annual scales (Salman et al., 2015). Specifically, in this study, after highlighting recent trends in drought and extreme temperature and identifying end-users' need, we aim at developing a prediction system for multi-year agrometeorological risks (i.e. drought and extreme heat) over the freed areas of northern Syria.

This paper is organized as follow. In section 2, we describe the context of the study region, the data and methodology. In section 3.1-2, we present the results of our interviews, before to examine recent trends in agrometeorological risks. In section 3.3, we demonstrate the robustness of neural network in predicting agrometeorological risks over multiple years, before introducing how this approach will be combined to a live monitoring system in the coming month (section 3.4). Finally, in section 4, we summarize our results and discuss their wider implications.

2. Context, Data and Methodology

2.1. Study Region

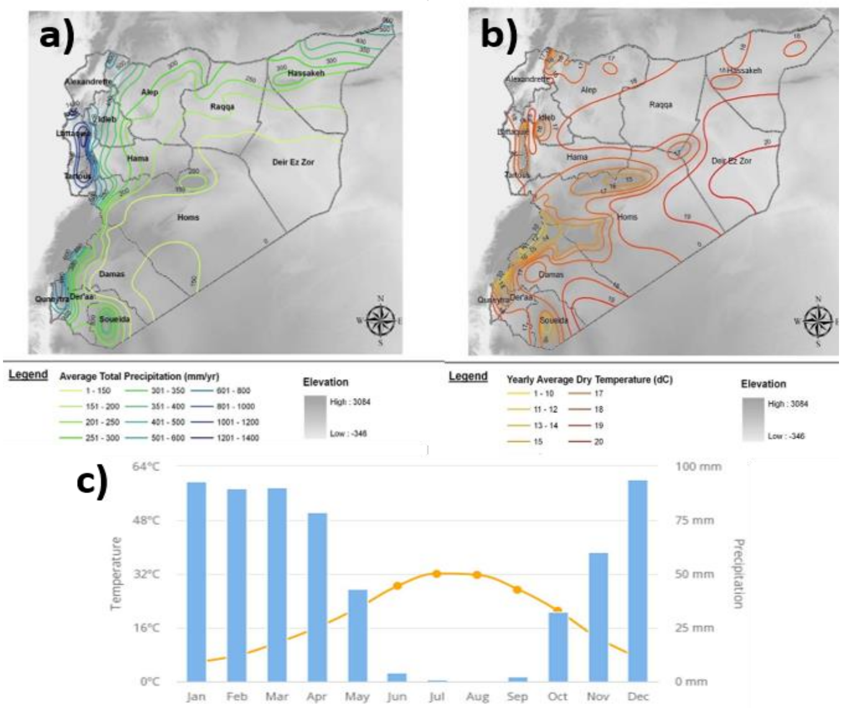

Figure (1) Summary of climate conditions over Syria:

a) annual precipitation (mm.yr^{-1}); b) annual temperature (°C); c) seasonal cycle for precipitation (blue histograms) and temperature (orange lines).

Syria is located on the eastern of the Mediterranean region, and is divided geographically into mountainous regions, coastal areas, the Badia and the interior areas, which include many plains, such as Damascus, Aleppo, Homs, Daraa and Hama (Fig. 1a-b). It has a Mediterranean influenced climate characterized by long, hot and mostly dry summers (Fig. 1c; Ghaleb et al, 2010). In addition, as illustrated in Figure 1, the coastal region is wetter than others are, whereas Badia is dryer and warmer. The study area is located in the plains of Aleppo, where temperatures above 30 °C in summer and approach zero in winter, and the rainy season extends from October to May, with amount of seasonal rains ranges between 300-500 $mm.yr^{-1}$

2.2. Identifying end-users need:

To identify end-users need, we create a questionnaire targeting the people in the freed areas of the north of Syria. The questionnaire was then presented to farmers, some academics and some university students, working in the agricultural sectors. The total number of participants in the questionnaire was 50.

The questionnaire consists of 12 questions, helping us to identify local practice, such as is the system using irrigated or rain-fed agriculture, cultivating one or several crops throughout the year (Table 1). These questionnaires have also been used to identify potential needs from the farmers themselves (Table 1), e.g.: i) how much does the farmer depend on the weather forecast; and ii) Are weather forecasts impacting the farmer's decision to change the crop.

1	The person who fills out the survey.
2	Where do you live?
3	How many years have you been practicing agricultural work?
4	Does your agriculture depend on weather/climatic forecast?
5	Do you grow a single crop or several?
6	Is the amount of rain sufficient, or do crops need to be supported by irrigation?
7	Do you depend in your activity on growing annual crops such as wheat or cotton, or on growing seasonal vegetables?
8	Do you change the crop if the climate was predicted before planting?
9	Do you look for aids if drought is predicted?
10	Do you care about the weather forecast for farming?
11	Do you trust weather forecasts?
12	why you don't trust weather forecast? What do you need?

Table (1): The questionnaire pattern.

We then analyzed the questionnaire results to determine the participants' interests in weather forecast.

2.3. Testing a non-linear climate prediction system

To provide climate prediction over northern Syria, we used ERA5 data for precipitation and temperature. ERA5 reanalysis has produced by ECMWF (Hans et al, 2020), It provides hourly estimates of a large number of atmospheric, land and oceanic climate variables. The data cover the Earth on a 30km grid, and resolve the atmosphere using 137 levels from the surface up to a height of 80km. ERA5 includes information about uncertainties for all variables at reduced spatial and temporal resolutions. In this study, precipitation, temperature, sea-level pressure and wind data were extracted over northern Syria, and were interpolated at the location of a selected farm, for the period 1979-2021 (cf. Figure 2), using bilinear interpolation techniques. Using these long-term climatic data, we calculated the standardized precipitation index (SPI) to monitor the relative wetness and dryness of our study region over multiple timescales (Mckee et al. 1993; Qaisrani et al. 2012). SPI can be used over 1–36-month timescale, and can be interpreted as the number of standard deviations by which the observed anomaly deviates from long-term mean. Since SPI is not conducive to climate change associated with evapotranspiration, we also calculated the standardized precipitation minus evapotranspiration index (SPEI; Vicente-Serano et al. 2010). We use the SPEI to ensure that the limited ability of SPI to capture the effect of increased temperatures is overcome. In addition to analyze drought indices, we also examine the time-evolution of extreme temperature using maximum temperature, as drought and heat stress are both strongly affecting agricultural production (Zampieri et al. 2017; Solaraju-Murali et al. 2021).

Finally, we used a neural network algorithm, which is a field of artificial intelligence, to develop a prediction system for extreme temperature and drought. By applying Neural Network techniques a program can learn by examples, and create an internal structure of rules to classify different inputs, such as recognising images, Neural networks must be trained before they can solve problems (Mijwel et al , 2019), and this is particularly interesting for risk forecasting (Zhang et al., 2014). It consists of inputs, which are multiplied by weight, and then computed by a mathematical function, which determines the activation of the neuron. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron, we can obtain the output we want for specific inputs. Back-propagation neural networks (BPNNs) are a class of feed-forward neural networks with supervised learning rules, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error is calculated as difference between actual and expected results. The idea of the backpropagation algorithm is to reduce this error, until the ANN learns the training data (Gershenson, 2003).

Our neural network prediction system is then cross-validated using two procedures. First, we estimated the out-of-bag (OOB) error using bootstrap aggregation, where each new neuron is fit from a bootstrap sample of the training observation $z_i = (x_i, y_i)$. The OOB error is the average for each z_i calculated using predictions from the neuros that do not contain z_i in their respective bootstrap sample (Hastie et al. 2009). Second, we employed a split dataset, which consisted in removing three years of the original data, and to predict it from the remaining 39 years. Both cross-validation performances were then quantified using the correlation coefficient between the original and predicted data, and the Mean Absolute Error (MAE), which is given by:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} [observed - predicted]$$

3. Results

3.1. Analysis of the questionnaires.

Based on our interview, 66% of the population in the freed areas of northern Syria depends on rain-fed agriculture, while 34% of them use irrigation systems (Figure 2a), 30% of the person participating in the interview confirmed that rainwater is inadequate for crop liquidity (Figure 2b). Interestingly, most practitioners rely on multiple crops, 60% of the person uses annual crops, such as cotton and wheat, and not seasonal crops, like vegetables (Tomato, Potato, Pepper etc…; Figure 2c).

Since the irrigation depends on precipitation, and the evapotranspiration, when weather/climate forecast suggest no rainfall, most farmers adapted their practice accordingly. For instance, around 70% of practitioners in the area will change the type of crop, depending on the amount of rainfall that is predicted (Figure 2d). More specially, when weather/climate forecast suggest a deficit of rainfall, most practitioners considered switching to drought-resilient crops, or to adapt the sowing season.

When asked how confident they were about weather/climate forecasts, only 40% of practitioners were confident about the forecast, 30% did not have full confidence, and 30% admit not to trust the result of the forecast (Figure 2e). About 74% of participants responded that weather forecasts were useful for farmers in those areas, whereas 36% admitted not to pay attention to weather forecasts, as they were not accurate, or not specific, to their region (Figure 2f).

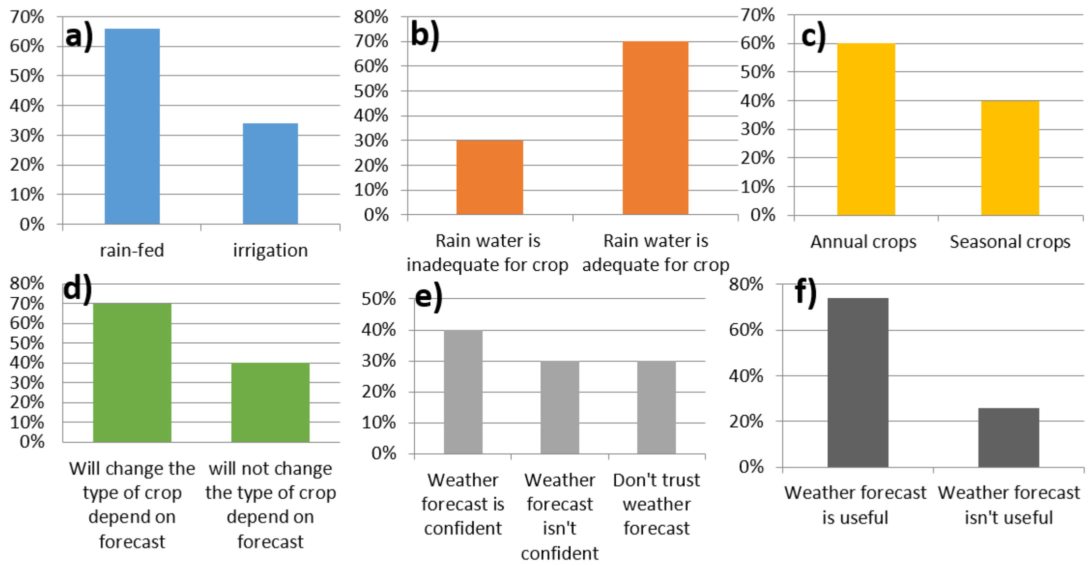

Figure (2): Results of interviews with regional practitioners. a) Rain-fed or irrigation, b) Rainwater is adequate or inadequate, c) Annual crops or Seasonal crops, d) Change the type of crop or no, e) Weather forecast is confident or not, f) Weather forecast is useful or not.

3.2. Recent trends in agrometeorological risks

In this section, we discuss historical trends in drought and maximum temperature over northern Syria between 1979 and 2021 (Figure 3).

Looking at the SPI drought indices, which is only based on cumulative rainfall deficit, drought risks appear quite variable over the region. For instance, many prolonged drought conditions were found over different periods (e.g. 2004-2009, 2013-2014, 2015-2018; Figure 3a), highlighting recurrent risks for water scarcity over the region. However, SPI drought indices do not show any particular trends (Figure 3a). Using th SPEI drought indices, which account for the effect of potential warming temperature through increased evapotranspiration, all drought spells previously detected based on rainfall appear more pronounced (Figure 3b). More importantly, a clear trend toward drier conditions is identified from the early 2000s (Figure 3b). As confirmed on Figure 3c, such increasing drought risks found in the SPEI indices is very likely to be associated with an increasing trends in the maximum temperature, suggesting the extreme temperature are also becoming more frequent.

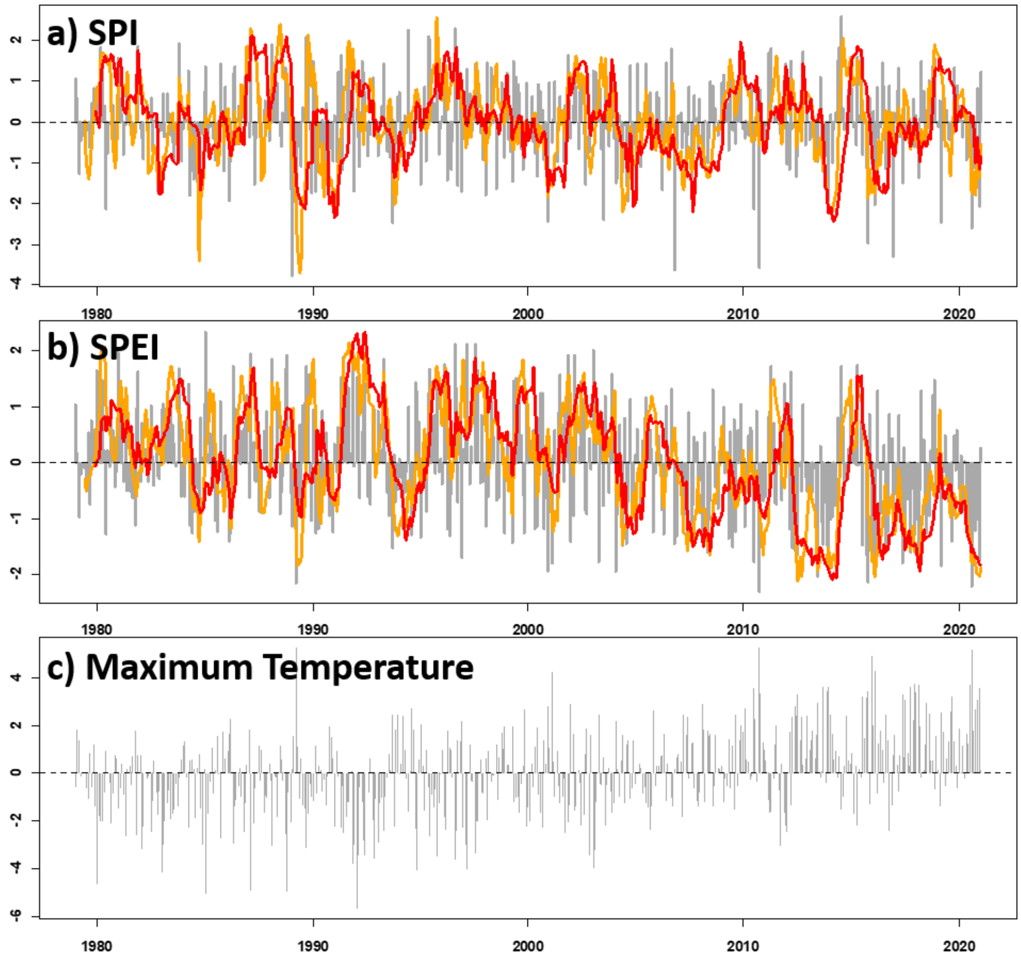

Figure 3: Time-evolution of drought and extreme temperature over Northern Syria between 1979 and 2021. a) SPI-1 (grey), -6 (orange) and-12 red) month; b) SPEI-1 (grey), -6 (orange) and -12 red) month; c) Maximum temperature anomalies.

Such trends in increasing risks of drought and heat stress is particularly important for agricultural productions and practices, and this emphasizes the need to develop a new prediction system that will be used to inform regional practitioners.

3.3. Calibration and Validation of neural network multi-year prediction system for drought and heat stress.

We therefore developed a new prediction system for maximum temperature and drought risks based on neural network. The results of the validation of this model are presented below for the maximum temperature (Figure 4) and for the SPEI (Figure 5).

As illustrated on Figure 4, after training the data using 10 neurons (first row) and with 40 neurons (bottom row), the MAE was 0.1682, which is suggesting little bias in the mean, based on the OOB cross-validation. Following the same cross-validation technique, the correlation coefficient between the original and predicted data was about 0.95145, suggesting that the variation between the two sets of data are coherent (Figure 5). Using the split dataset cross-validation techniques, predicting recursively periods of three years (Table 2), very similar cross-validation results were found.

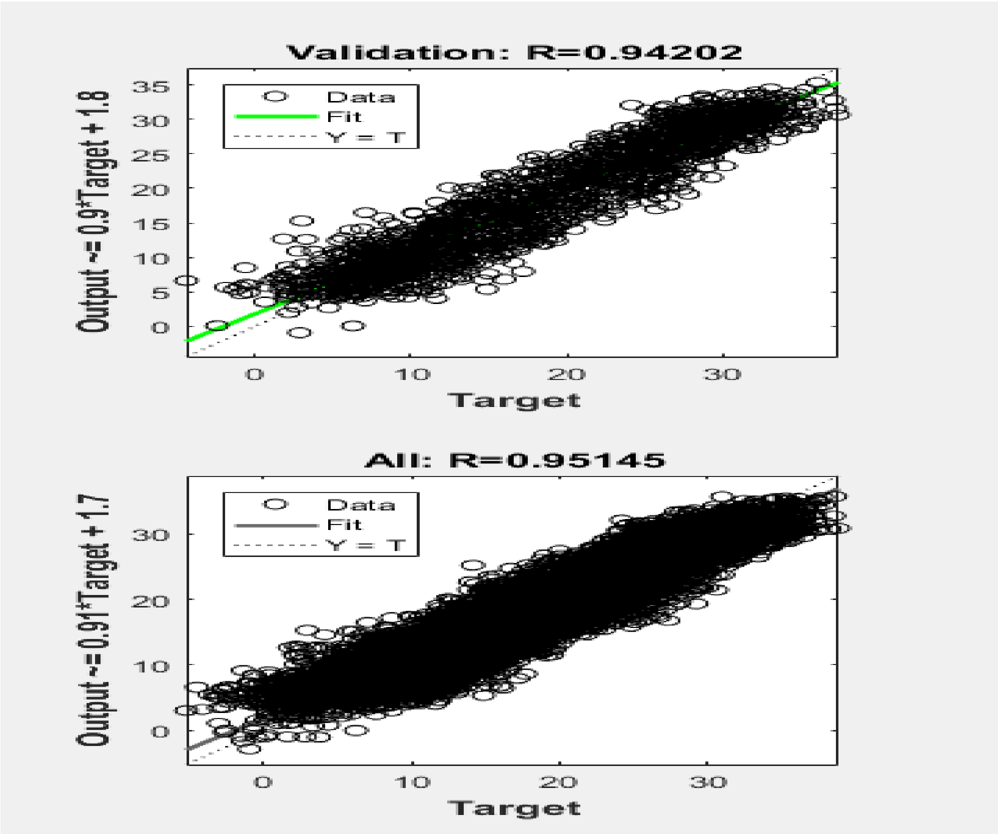

Figure (4): OOB cross-validation for max temperature data. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets.

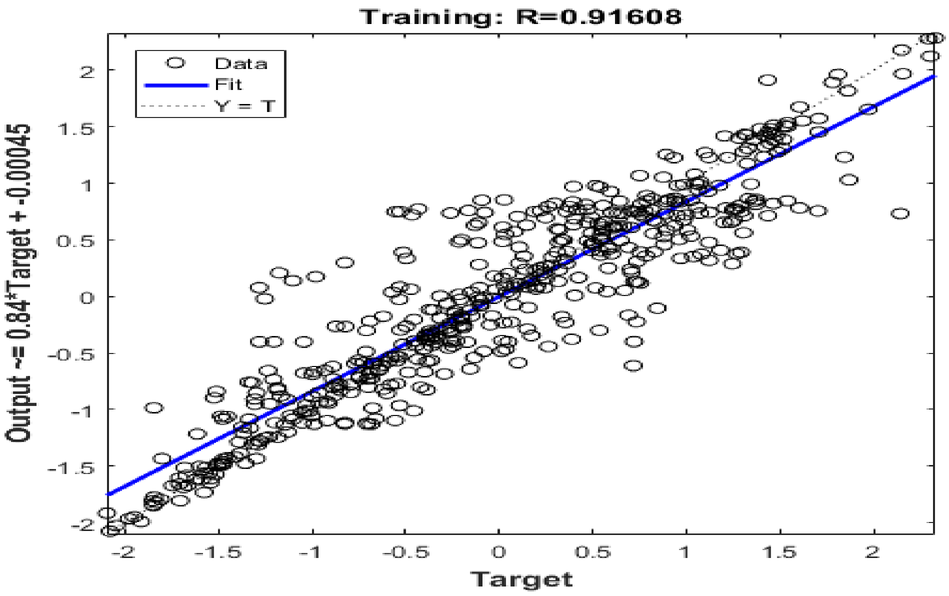

Figure (5): OOB cross-validation for the SPEI index. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets.

	Input Maximum Temperature	MAE	R
Train 1	**1979-2010**	**0.1680**	**0.9514**
Test1	**2011-2015**	**0.1904**	**0.8029**
Train2	**1979 -2010 without 2001- 2002-2003**	**0.1712**	**0.9444**
Test 2	**2001-2003**	**0.1346**	**0.8989**

Table (2): Split-data cross-validation results for maximum temperature.

Regarding the SPEI, the MAE was 0.046, which is suggesting very little bias in the mean, based on the OOB cross-validation. The correlation coefficient between the original and predicted SPEI data was about 0.916, suggesting that the variation between the two sets of data are coherent (Figure 5).

In summary, those results on the validation of our predictive system demonstrate that it is possible to prediction robustly agrometeorological risks using neural network over the region.

3.4. Toward a live monitoring system

As the ERA5 reanalysis data may not be the most reliable climatic information over the region. We installed a weather station, in a farm near Al-Bab city in freed areas north of Syria (Figure 6), to obtain real data that would help us to create more accurate and region-specific agrometeorological risk prediction.

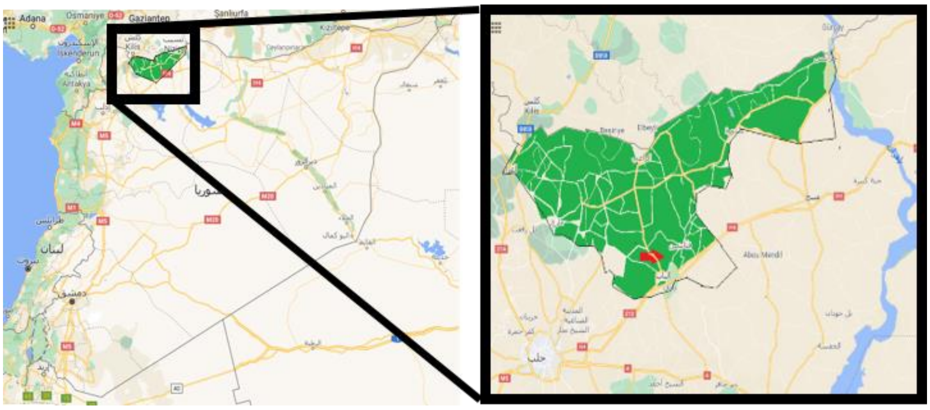

Figure (6) Syria map, Freed Areas in green and the red arrow refer to the position of the weather station in the farm.

The overall design of our remote measurement system is summarized on Figure 8. The sensors measure climatic parameters, and then send these data via a serial circuit to the Internet connection gateway (Raspberry Pi 4;Figure 7). This Internet connection gateway then store the climatic data on the cloud to be displayed (Figure 7). The climatic data can then be downloaded from the cloud.

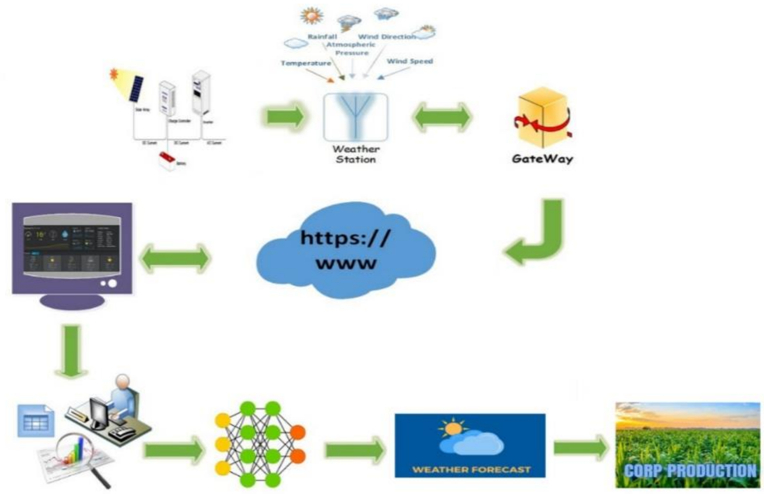

Figure (7): Diagram of the remote measurement system.

Specifically, this system is transferring live information on maximum and minimum temperature, precipitation, sea-level pressure, wind speed and directions at hourly basis. Based on these variables, different agrometeorological indices, such as the SPI, SPEI and maximum temperature anomalies, are then calculated. As demonstrated above, combined with the neural network algorithms, agrometeorological risks can thus be predicted over the coming season, in order to provide live information on upcoming risks to the farmers in the area. Thus, after we get results of multi-year prediction for agrometeorological risks for a specific area, we can share these results with farmers by sending periodic messages to them. These data are currently still being collected, but we aim to provide a full service by the end of 2021. Ultimately, this system could be used to help farmers in determining the type of crop or the timing of plowing commensurate with the predicted weather events.

4. Conclusion

In this study, we aimed at examining recent trends in drought and extreme temperature and at identifying end-users' need, in order to develop a new prediction system for multi-year agrometeorological risks (i.e. drought and extreme heat) over the freed areas of northern Syria. Our results highlight the need for more reliable forecast of agrometeorological risks. This is particularly important over the region, as drought risks are found to increase over the last decades, and most of the population over the area depends on rain-fed agriculture. We found that increasing drought risks is strongly related to an increase in maximum temperature, enhancing evapotranspiration rates.

More importantly, based on the results of our interview, regional practitioners do appear to adapt their practices depending on weather/climatic forecast, switching to crops that are more resilient to drought, or adapting their agricultural calendar. However, many regional practitioners highlighted the need to improve the usefulness of those predictions, and provide specific information on the degree of risks at specific locations and time. To answer this need, we tested the added-value of neural network in providing reliable prediction for maximum temperature and drought indices. Preliminary results are promising with minimal errors in the mean, and in the variance of predicted data, as compared to the original data. To provide more reliable information on specific sites of the freed areas of northern Syria, we implemented a new live monitoring system, from which weather conditions are recorded on hourly basis. We now aim at coupling this live monitoring system with our neural network prediction system for agrometeorological risks over the region. Ultimately, this system could be used to help farmers in determining the type of crop or the timing of plowing commensurate with the predicted weather events.

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