EVALUATION OF FUZZY LOGIC SYSTEMS TO ASSESS CLIMATE SUITABILITY OF ITALIAN RYEGRASS

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ABSTRACT

Assessment of climate suitability for a crop would provide information to develop adaptation options to climate change in a region. A climate suitability index at a site of interest can be determined using a fuzzy logic system, which makes use of expert knowledge or existing data to develop a model. The hierachical fuzzy logic system that depends on rule statements and logical operation between them has been developed to assess climate suitability of forage crops. In the present study, alternative operators and rules for the fuzzy logic system were explored to improve reliability of the climate suitability assessment model. Annual yield data of Italian ryegrass were compared with climate suitability index under the assumption that climate suitability index would represent potential yield. The fuzzy logic system was modified applying standard union, standard intersection, bounded sum, and bounded difference to the logical operation that combines suitability of temperature and precipitation. A simple form of the fuzzy logic system was also developed using the rule statements that characterize suitability of temperature and precipitation based on the duration of optimum temperature condition and precipitation amount under a favorable temperature condition, respectively. It was found that the use of standard union resulted in greater coefficient of determination (0.68) between yield and the climate suitability index for given seasons than the original model (0.53), which suggested that application of an alternative logical operator could improve reliability of the model. Application of an alternative rule statement also resulted in a reasonable assessment of climate suitability. In particular, application of a boundary regression analysis indicated that the *climate suitability index obtained from the simple form of the fuzzy logic system could be compared with the potential yield at a given site. For example, the root mean square error of the simple model was relatively small for Italian ryegrass when the climate suitability index was compared with yields near the boundary line, e.g., within 95% confidence limit, which would represent the potential yield at a site. The climate suitability model based on the fuzzy logic system explained a large variation (70.3 %) of average yield for an extended period. The alternative model was also useful to identify countries where climate suitability was gerater for alfalfa in Europe. This suggested that the variants of fuzzy logic system would be useful to assess climate suitability of a production area, which would provide information on decision making and adaptation planning under a given climate condition. These models can be applied to climate change scenario data in a region, which would provide reliable information for small scale farmers who attempt to introduce crops to their farms under a future climate condition.*

Keywords: Species distribution model, fuzzy logic, uncertainty, minor crop, climate change adaptation

INTRODUCTION

Changes in a cropping system have been suggested as an adaptation option to minimize the negative impact of climate change on crop production (Butt *et al.*, 2005; Chen *et al.*, 2012; de Jong *et al.*, 2001; Howden *et al.*, 2007; Lobell *et al.*, 2008; Robert *et al.*, 2003). For example, cropping practices such as planting date could be shifted depending on future climate conditions (Alexandrov *et al.*, 2002; Tubiello *et al.*, 2002). New cultivars that have more tolerance to environmental stress could be used in the future (Beebe *et al.*, 2011; Nyabako *et al.*, 2012). Practices in tillage, irrigation, and fertilizer application could also be used as an option for climate change adaptation.

Forage crops can be introduced into a cropping system as an additional option for climate change adaptation (Howden *et al.*, 2007). Cultivation of forage crops would have various effects on ecosystem services including a negative impact on soil erosion, reduction of greenhouse gas emission through enhancement of the biogeochemical cycle (Cavigelli *et al.*, 2013; Davis *et al.*, 2012; Lugnot and Martin, 2013; Lemaire *et al.*, 2014). Forage crops would be less affected by environmental stress (Olesen *et al.*, 2011), which would help stable primary production under changing climate conditions. Still, assessment of climatic suitability for a forage crop would be desirable before it is introduced into a cropping system in a region.

Considerable efforts have been made to develop a model to predict the productivity of forages. For example, Johnson *et al.* (2003, 2008) developed a model to support decision-making on pasture management, such as DairyMod and SGS Pasture models. Models that determine the daily growth of crop have also been used to predict yields of forage crops (Kiniry *et al.*, 1995; Ojeda *et al.*, 2016) and to assess climate change impacts on pasture systems (Cullen *et al.*, 2009). Such models are often dependent on local management information, e.g., variety, fertilizer application rate, and irrigation, which is often limited to specific sites (Abraha and Savage, 2008).

Alternatively, a climate suitability model can be used to assess the environmental feasibility of forage and minor grain crops in a region (Ramirez-Villegas *et al.*, 2013). In particular, a fuzzy logic system would facilitate development of a climate suitability model for forage crops of which exact or specific information is limited (Okeke and Karnieli, 2006; Zadeh, 1965). Center and Verma (1998) suggested that fuzzy logic would be useful for modeling in biological and agricultural systems. Kim *et al.* (2018) developed a fuzzy logic system to predict climate suitability of three forage crops.

A fuzzy logic system is often implemented using rules derived from current knowledge. This would help prediction of climate suitability for a forage crop in a region with minimum sets of data, e.g., monthly temperature and precipitation. Still, rules can be modified to determine the values of climate suitability index for greater efficiency. For example, a simple form of rules can be used to calculate climate suitability index without penalty in reliability.

The objectives of this study were to develop and to evaluate the variants of a climate suitability model for Italian ryegrass, which is an important forage crops in Korea and Japan (Koizumi *et al*., 1993; Sugawara *et al*., 2006; Valan *et al*., 2014). Evaluation of such models would provide an insight to make the best use of fuzzy logic system for reliable assessment of climate suitability in a region. This would help identify crop production areas under a given climate condition, which would aid the climate smart agriculture.

MATERIALS AND METHODS

Yield and climate data

Yield data of Italian ryegrass were used to compare the climate suitability index obtained from different types of fuzzy logic systems. The yield dataset includes annual yield data at 18 sites in three countries including the USA, Belgium, and Australia. Daily weather data including daily minimum and maximum temperatures, and precipitation were collected at those sites from weather databases. For example, weather data at the sites in the US and

Belgium were obtained from the Utah Climate Center (https://climate.usurf.usu.edu/). Daily weather data at Australian sites were collected from the Bureau of Meteorology, Australia (http://www.bom.gov.au/). Daily weather data were summarized by month to prepare input data to the fuzzy logic system for calculation of climate suitability index. Detailed description of these data sets can be found in Kim *et al.* (2018).

A fuzzy logic system to assess climate suitability of Italian ryegrass

Kim *et al.* (2018) developed the hierarchical fuzzy logic system that evaluates rules associated with climate conditions for growth and survival of a crop (Fig. 1). The fuzzy logic system consists of a fuzzy set and logical operation between fuzzy sets. The fuzzy set converts a crisp value of a variable into a degree of membership using its membership function. For example, a given precipitation, e.g., 200 mm, is translated into a degree of membership, e.g., 0.2, using a fuzzy set of "suitable" for precipitation. A detailed description of fuzzy sets can be found in Ahamed *et al.* (2000).

The membership function of a fuzzy set is defined using parameter values that can be determined using experimental data. The parameter values can also be determined using existing knowledge. For example, Kim *et al.* (2018) used the EcoCrop database to determine those values (Table 1). This approach would require no calibration process to identify parameter values that result in the least difference between observation and prediction through iteration. In particular, it would be challenging to calibrate a climate suitability model beacause only a small set of data would be available for minor crops such as forage crops.

Alternative logical operation to the fuzzy logic system

The hierarchical fuzzy logic system has been designed to evaluate the rule statements of suitability of temperature and precipitation for a crop, respectively (Fig. 1). The rule statement is combination of sub-rule statements such as "temperature is suitable" and "precipitation is suitable". The sub-rule statement takes into account detailed conditions for temperature and precipitation such as the range of temperature and precipitation, which would affect survival and growth of a crop.

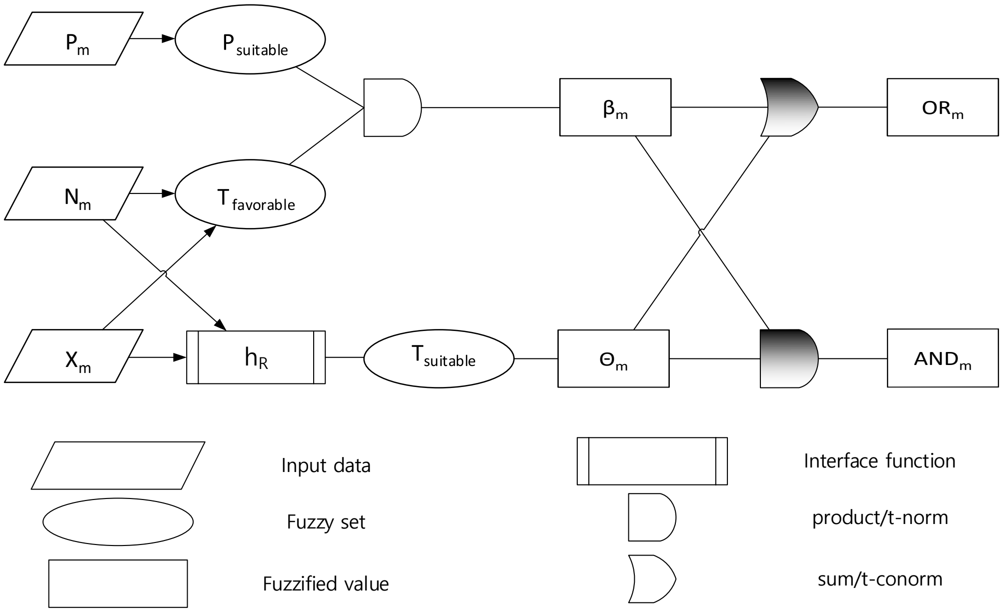

Fig. 1. The structure of the hierarchical fuzzy logic system to assess climate suitability of a crop in a month. The operator in gradient color indicates a logical operator used to combine the outcome of rule statements. P_m, N_m and X_m indicate precipitation, minimum temperature and maximum temperature in a month m, respectively. $P_{suitable}$, $T_{favorable}$, and $T_{suitable}$ are fuzzy sets of precipitation and temperature, respectively. β_m and Θ_m represent suitability index of precipitation and temperature, respectively. OR_m and AND_m are climate suitability index in a given month using t-conorm and t-norm, respectively. The symbols in a gradient color represent the logical operator between fuzzy values.

The rules of temperature and precipitation can be connected using logical operations including OR and AND, which are called t-conorm and t-norm, respectively. In the orginal model, the logical operation of rule statements including t-conorm and t-norm were defined using algebraic sum and algebraic product as follows (Klir and Yuan, 1995):

$R_x \text{ or } R_y = R_x + R_y - R_x \cdot R_y$ and (Eq. 1)

$R_x \text{ and } R_y = R_x \cdot R_y$. (Eq. 2)

In fuzzy logic, alternative operator can be used to define t-conorm and t-norm. For example, bounded sum and bounded difference can be used to quantify the logical connection between two statements. These alternative operators are defined as follows (Klir and Yuan, 1995):

$R_x \text{ or } R_y = \min(1, R_x + R_y)$ and (Eq. 3)

$R_x \text{ and } R_y = \max(0, R_x + R_y - 1)$. (Eq. 4)

Table 1. Climate and management conditions for Italian ryegrass

Abbreviation	Description	Value[a]
G_{min}	minimum growing period (d)	90
G_{max}	maximum growing period (d)	270
T_{kill}	killing temperature (°C)	-4[b]
T_{min}	Minimum absolute temperature (°C)	2
T_{max}	maximum absolute temperature (°C)	38
T_{OPmin}	minimum optimal temperature (°C)	14
T_{OPmax}	maximum optimal temperature (°C)	30
R_{min}	minimum absolute rainfall (°C)	200
R_{max}	maximum absolute rainfall (°C)	1800
R_{OPmin}	minimum optimal rainfall (°C)	500
R_{OPmax}	maximum optimal rainfall (°C)	900

[a]The values of crop parameters were obtained from the EcoCrop database (http://ecocrop.fao.org), which is operated by Food and Agriculture Organization (FAO).
[b]The hierarchical fuzzy logic system was dependent on the parameter values of -11°C for T_{kill}.

It is possible to make use of standard union and standard intersection to determine the values of t-conorm and t-norm, respectively, which are defined as follows (Klir and Yuan, 1995):

$R_x \; or \; R_y = \max(R_x, R_y)$ and (Eq. 5)

$R_x \; and \; R_y = \min(R_x, R_y).$ (Eq. 6)

No calibration process would be needed for logical operators because they require no parameter, which would minimize the need for the observation data. However, these logical operators would cause variation in the values of climate suitability index. Evaluation of alternative operators would provide a hint to develop a reliable climate suitability model.

Climate suitability indices derived from each logical operator were examined if they could represent variation of yield by site. Eqs. 3-6 were used to determine the values of climate suitability index. These values were compared with yield data at site-years as well as those of the original model. A climate suitability index would be an indirect indicator for crop yield. Thus, the coefficient of determination was calculated between the climate suitability index and crop yield at sites of interest to examine reliability of climate suitability index obtained from the variants of the fuzzy logic system.

Alternative rule to the fuzzy logic system

In the present study, it was attempted to calculate climate suitability index using alternative rules. For example, the original model had the rule statements to evaluate a moisture condition for a prolonged period. Assessment of extreme conditions was also applied to determine the values of climate suitability index. These terms would be useful to evaluate conditions that would occur infrequently. Still, monthly data were used as inputs to the model to determine the climate suitability index, which would have limitation to represent such an extreme condition.

A simple form of rule statements was used to focus more on ordinary climate conditions for growth of crops. The rule statement for temperature suitability was defined to take into account the length of time during which the optimum temperature occurred. Amount of precipitation and temperature condition during the given period were included in the rule statement to determine suitability of precipitation. The climate suitability in a given month m was determined using alternative rules as follows:

$$\Theta_m = T_{suit}(X_m, N_m) \text{ and} \qquad \text{(Eq. 7)}$$
$$\beta_m = P_{suit}(P_m) \cdot T_{fav}(X_m, N_m). \qquad \text{(Eq. 8)}$$

where Θ_m and β_m represent the degree of suitability for temperature and precipitation in m, respectively. Monthly suitability index can also be determined as follows:

$$OR_m = \Theta_m + \beta_m - \Theta_m \cdot \beta_m \text{ and} \qquad \text{(Eq. 9)}$$
$$AND_m = \Theta_m \cdot \beta_m. \qquad \text{(Eq.10)}$$

where OR_m and AND_m are suitability index in m using t-conorm and t-norm, respectively.

For the given planting date at each site-year, the seasonal suitability index was determined from a group of suitability indices by a potential growing season. Because the length of a growing season would differ by region, it was assumed that a crop would be grown during one of the potential growing seasons. In the EcoCrop database, there is a record such that growing periods for Italian ryegrass would range from 3 - 9 months. In each potential growing season, seasonal suitability index G_s was calculated as follows:

$$G_s = \sum_m \mathrm{M}_m / l_s, \qquad \text{(Eq.11)}$$

where M_m and l_s indicate monthly suitability index, e.g., OR_m or AND_m, and the number of month in a potential growing season s, respectively. To determine the seasonal suitability index, the median of the G_s values was used.

Comparison between yield and climate suitability index

The distribution of yield and climate suitability index obtained from the variants of the fuzzy logic system was examined with visual inspection. The outcomes of fuzzy logic system using the alternative logical operator were also compared with yield data at sites where no disease risk was reported. Sites where diseases have caused problems in forage production were excluded in the analysis to take into account potential yields under a given climate condition. For example, crown rust (*Puccinia coronate*) is the most serious foliar disease of ryegrass species (Takahashi *et al.*, 2005; Reheul and Ghequiere, 1996). White and Lemus (2014) suggested that crown rust would occasionally occur at sites near the coastal regions in the US including Poplarville and Beaumont.

For the variants derived from alternative rules, the distribution of yield and climate suitability index was examined with a boundary line analysis. A climate suitability index would represent the impact of climate conditions on crop yield. Thus, climate suitability would indicate the potential yield rather than an actual yield (Watsons, 1963), which would be affected by crop management and soil conditions as well as climate conditions. In particular, yield data obtained under field conditions would be affected by biotic and abiotic stresses, e.g., diseases or a spell of extreme weather, which can not be assessed using monthly climate data. A boundary line would be a reasonable approach to examine the reliability of climate suitability indices for the potential yield instead of a conventional regression analysis, e.g., linear regression (Cade and Noon, 2003; Vaz *et al.*, 2008). A quantile regression analysis was performed to obtain a boundary line between climate suitability index and yield at site-years. To minimize the impact of an outlier from yield data, the 0.95 quantile was applied to obtain boundary lines. SAS 9.3 (SAS Institute Inc., Cary, NC, USA) was used to perform the quantile regression analysis.

The degree of agreement between observed and estimated yields was analyzed for site-years at which yields were near the boundary line. A reliable climate suitability model would have a small variation of yields along the boundary line obtained from quantile regression analysis because such a model would be able to predict the potential yield accurately under different conditions, e.g., at different sites. As a result, it is likely that the degree of agreement statistics between observed and estimated yields near the boundary line, e.g., within a confidence interval at 95%, would be greater for a reliable model compared with the other models. Site-years at which observed yields were within the confidence interval of the boundary line at 95% were selected by models. Then, the coefficient of determination and root mean square error (RMSE) were determined using estimates of yield for climate suitability index values and observed yields at those site-years.

Averages of yield reported for an extended period were compared with those of climate suitability index by site. Climate suitability in a region would be associated with a long-term yield rather than an annual yield. It was assumed that periods more than or equal to three years would represent an extended period. Yield averages and climate suitability index were calculated for the sites where yield data were available at least for three years.

Assessment of climate suitability of alfafa using the alternative rule

The model with alternative rule was applied to assess climate suitability of *Medicago sativa* L. in Europe. Yield data of alfalfa in European countries were obtained from the Eurostat website (http://ec.europa.eu/eurostat). Countries where yield data were available for more than or equal to three years were included in the further analysis. To identify locality where *M. sativa* L. would be grown, occurrence data of *M. sativa* were obtained from Global Biodiversity Information Facility (GBIF) database (http://www.gbif.org). The parameters for *M. sativa* were obtained from the FAO-EcoCrop database.

Climate suitability index for alfalfa was calculated by cell using gridded climate data. Because yield data available by country, it was necessary to calculate climate suitability index within the boundary of countries. Climate conditions would differ by region even in a small country, a gridded calculation of climate suitability index was needed. In the present study, the E-OBS gridded datasets were used as inputs to the model (Haylock *et al.*, 2008).

In gridded calculation, the starting date for a growing season was unknown. Thus, climate suitability index was calculated for each day in a season. The maximum value of climate suitability index was chosen as the final suitability index in the given season. The values of final suitability index were determined for the periods from 2000 to 2014 at each cell. Climate suitability index at occurrence site was averaged within the administrative boundary of countries in Europe.

RESULTS

Application of alternative logical operation

Reliability of the fuzzy logic systems differed by the logical operator (Fig. 2). Application of standard union to the logical operation between rule statements for suitability of temperature and precipitation explained the greater variation of yield using the climate suitability index. In contrast, combination of these rule statements using the standard intersection had the lower coefficient of determination. Overall, t-conorm resulted in higher values of R^2 than t-norm for combination of rules to evaluate suitability of temperature and precipitation.

Application of alternative rule to the existing model

The scattering patterns between climate suitability indices and yield at given site-years were similar to a triangular shape for the fuzzy logic system based on t-conorm (Fig. 3A). Yield tended to increase with increasing climate suitability index obtained from the fuzzy logic system with the alternative rule, which was similar to that of the original model. For example, yields at Gatton in 1994 were lower than 1985. The climate suitability indices from the fuzzy logic system were 0.64 and 0.92 in 1994 and 1985, respectively. Climate suitability index was relatively high at Beaumont in 2005 (0.92) when the yield was considerably low (6,054 kg ha^{-1}). As a result, a clear boundary line was obtained between climate suitability for the fuzzy logic system based on t-conorm and yield at site-years. In contrast, such a trend was less evident in the distribution of yield for climate suitability index obtained from t-norm (Fig. 3B).

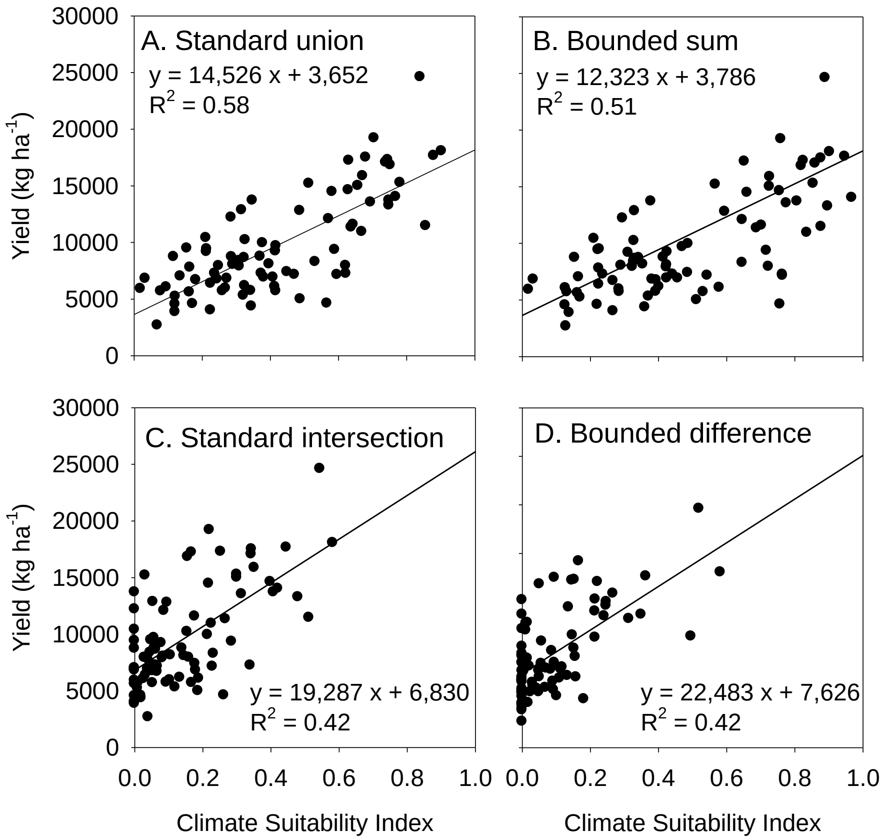

Fig. 2. Distribution of observed yields at site-year for climate suitability index values obtained using (A) standard union t-conorm, (B) bounded sum t-conorm, (C) standard intersection t-norm, and (D) bounded difference t-norm. The names of t-conorm and t-norm were used after Klir and Yuan (1995).

The degree of agreement between yield data estimated and reported at site-years of which yield were near boundary line was considerably high for the fuzzy logic system based on t-conorm (Fig. 4). For example, the R^2 value for the fuzzy logic system was 0.95. The root mean square error (RMSE) for the model was relatively small (1,297 kg ha^{-1}), which was about 11% of average yield at sites of interest. However, the fuzzy logic system based on t-norm had climate suitability index values that clustered together for a certain range of yield.

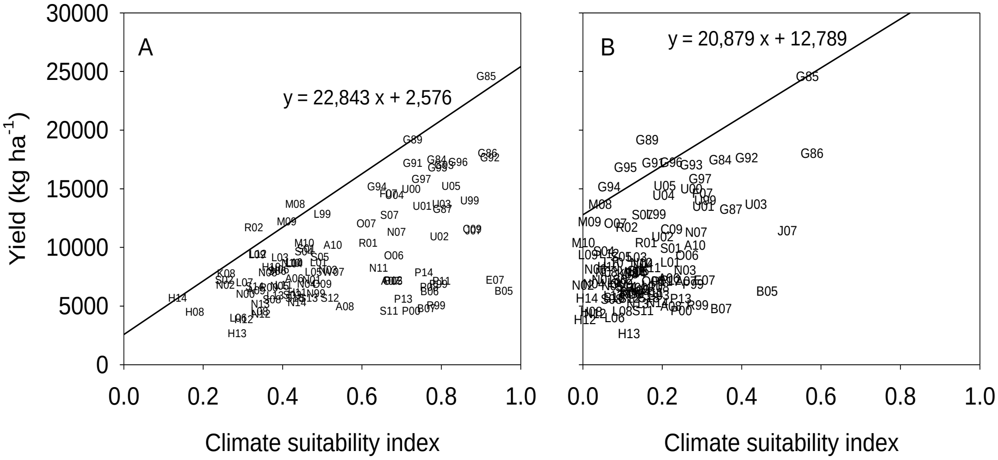

Fig. 3. Distribution of observed site-year yield for climate suitability index of the fuzzy logic system based on the alternative rule using (A) t-conorm and (B) t-norm. A line in each plot represents boundary lines at 0.95 quantile for corresponding models. Individual site-year was denoted by the first letter of site name and a season.

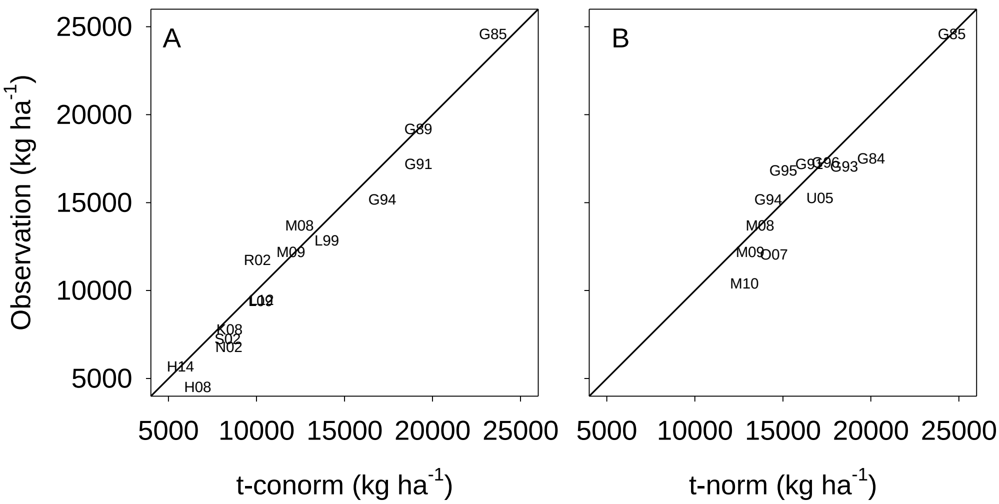

Fig. 4. The relationship between reported and estimated yields at site-years of which yields were within the 95% confidence limit of the boundary line for the alternative fuzzy logic system using (A) t-conorm and (B) t-norm. Individual site-year was denoted by the first letter of the site name and a season. The line in the plot indicates 1:1 line.

Averages of climate suitability index for an extended period explained a large variation (70%) in those of reported yield at sites where no disease risk was reported (Fig. 5). The fuzzy logic system that depends on alternative rules had a highly significant correlation between averages of yields and climate suitability ($p = 0.0098$) when t-conorm was used to combine the rule statements. In contrast, no significant correlation between averages of yield and climate suitability index obtained from the fuzzy logic system based on t-norm was found.

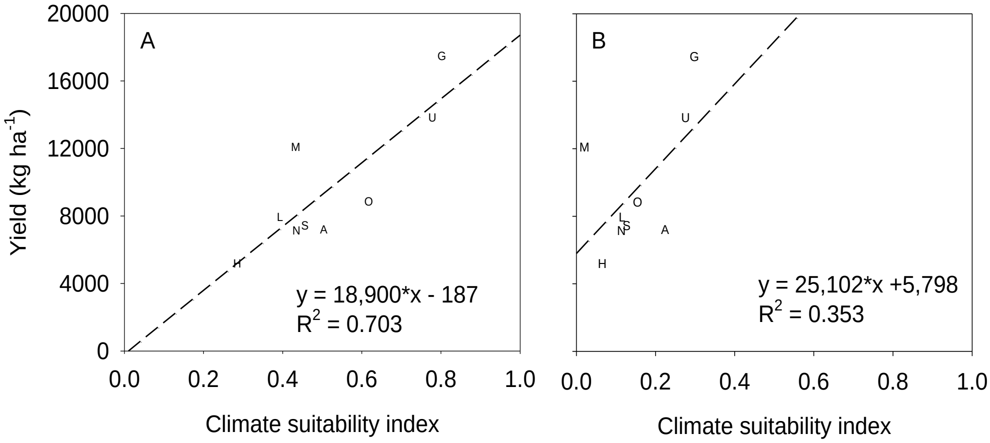

Fig. 5. The relationship between averages of yield and climate suitability index for the fuzzy logic system based on (A) t-conorm and (B) t-norm, respectively. A line in each plot represents a regression lines for corresponding models. Yields and climate suitability index for an extended period, e.g., ≥ three years, were averaged for a given site. The individual site was denoted by the first letter of site name.

Application of alternative model to alfalfa

When the regression coefficient obtained from the analysis of annual ryegrass was used as the slope of a regression line between climate suitability index and average yields of countries, it appeared that these yields were aligned with two regression lines (Fig. 6). There was a group of countries where the yield of alfalfa was considerably higher than other countries for a given climate suitability index. Those countries include Poland, Italy, Denmark, Estonia, Spain, and Croatia. For the second group of countries, the intercept of a regression line between climate suitability index and alfalfa yield was considerably low, e.g., 7,268 kg ha^{-1}. Although climate suitability index was considerably high, e.g., > 0.78, in Serbia and Bosnia and Herzegovina, yield of alfalfa was relatively low, e.g., < 4500 kg ha^{-1}.

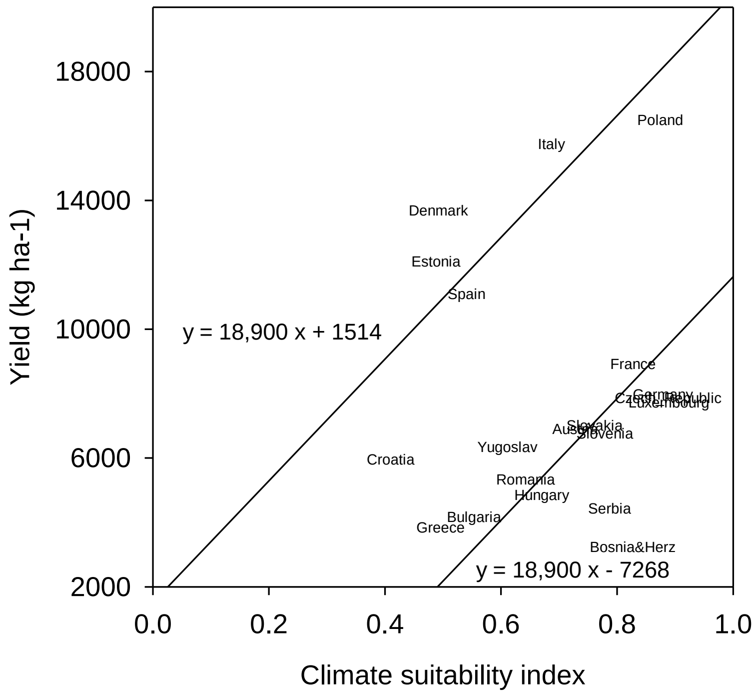

Fig. 6. Distribution of alfalfa yields for climate suitability index during extended periods in European countries. After the slope of the line was fixed to be 18,900, the intercept of lines were obtained from regression analysis for two groups of countries where yields of alfalfa was considerably different for given climate suitability index. Yield data in Bosnia and Herzegovina (Bosnia&Herz) and Serbia were excluded from the analysis. The former Yugoslav republic of Macedonia was denoted by Yugoslav. Yields and climate suitability index were averaged for the period during which yield records were available ≥ three years.

DISCUSSION

This study illustrated that the climate suitability index obtained from the variants of the fuzzy logic system would be useful to estimate the potential yield of Italian ryegrass. Climate suitability would represent the potential yield at a site under given climate condition when the impact of extreme weather events and non-climate factors, e.g., soil and disease, would be minimal. The potential yield based on climate suitability would be greater than or equal to actual yield, which would result in a triangular distribution between actual yield and climate suitability index (Greenberg *et al.*, 2015; Maller, 1990; Vaz *et al.*, 2008). Using the fuzzy logic system, such a distribution was obtained for individual seasons. The fuzzy logic system also had a significant relationship between yields and climate suitability for an extended period at sites with relatively low disease risks.

It appeared that the type of logical operator such as standard union over standard intersection would have a considerable impact on reliability of climate suitability index because the rules of suitability for temperature and precipitation are combined in a different way. For example, the R^2 value of the fuzzy logic system with standard intersection was considerably lower than that of the fuzzy logic system with standard union although difference between these systems was the logical operator between the rule statements. This suggested that an optimum set of logical operator can be found. For example, Genesis and Jonas (2014) used a complex function to combine multiple terms for prediction of yield. Thus, it would be merited to explore additional set of logical operators, which could improve the reliability of climate suitability assessment.

Although the choice of logical operators affected the reliability of the fuzzy logic system to determine climate suitability index, the rule statement of the fuzzy logic system would also have considerable impact on reliability of climate suitability index. In the present study, it was shown that t-norm would be inferior to t-conorm for evaluation of two rule statements on temperature and precipitation. Nevertheless, application of simple rule did not decrease the reliability of climate suitability assessment, which suggested that the simple form of fuzzy logic system would be useful to reduce the computation time. In particular, gridded assessment of climate suitability would help individual farmers who plan to introduce a new crop in their farm in a given region (Zabel *et al.*, 2014).

Climate suitability of a crop has been used to evaluate suitable areas to cultivate certain crop in the future with projected climate scenarios (Ramirez-Villegas *et al*., 2013). In those studies, long-term averages of climate data have been used as inputs to determine climate suitability indices. For example, the time resolution of climate surfaces is usually limited to monthly averages for normal years, e.g., 30 years. Thus, it would be worthwhile to compare the outcomes of climate suitability assessment using long-term averages of climate data as inputs to the model and averages of climate suitability index values for the period. Spatial averages of climate suitability index could also be used for reliable assessment of climate suitability. Thus, further studies would be merited to examine the impact of spatial and temporal characteristics of climate data on the reliability of climate suitability index. Still, spatial assessment of climate suitability index would help growers identify crop production areas with suitable climate conditions, which would aid climate smart agriculture.

CONCLUSION

The fuzzy logic system into which knowledge of ecological envelope for a crop can be formulated has been implemented using a diverse set of options including logical operators and rules. Evaluation of these variations would help reliable assessment of climate suitability for a crop. In particular, forage crops including Italian ryegrass can be benefit from the climate suitability model because few crop models are available for these minor crops. Further studies would be merited to examine climate suitability of other minor crops such as vegetables. Such studies would provide information for small farmers who try to implement the climate smart agriculture.

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