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Research Article

Calculated Damage of Italian Ryegrass in Abnormal Climate Based World Meteorological Organization Approach Using Machine Learning

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ABSTRACT

This study was conducted to calculate the damage of Italian ryegrass (IRG) by abnormal climate using machine learning and present the damage through the map. The IRG data collected 1,384. The climate data was collected from the Korea Meteorological Administration Meteorological data open portal.The machine learning model called xDeepFM was used to detect IRG damage. The damage was calculated using climate data from the Automated Synoptic Observing System (95 sites) by machine learning. The calculation of damage was the difference between the Dry matter yield $(DMY)_{normal}$ and $DMY_{abnormal}$. The normal climate was set as the 40-year of climate data according to the year of IRG data (1986~2020). The level of abnormal climate was set as a multiple of the standard deviation applying the World Meteorological Organization (WMO) standard. The DMY_{normal} was ranged from 5,678 to 15,188 kg/ha. The damage of IRG differed according to region and level of abnormal climate with abnormal temperature, precipitation, and wind speed from -1,380 to 1,176, -3 to 2,465, and -830 to 962 kg/ha, respectively. The maximum damage was 1,176 kg/ha when the abnormal temperature was -2 level (+1.04℃), 2,465 kg/ha when the abnormal precipitation was all level and 962 kg/ha when the abnormal wind speed was -2 level (+1.60 ㎧). The damage calculated through the WMO method was presented as an map using QGIS. There was some blank area because there was no climate data. In order to calculate the damage of blank area, it would be possible to use the automatic weather system (AWS), which provides data from more sites than the automated synoptic observing system (ASOS).

(Key words: Abnormal climate, IRG damage, Machine learning, World Meteorological Organization (WMO))

Ⅰ. INTRODUCTION

Italian Ryegrass (IRG) is a winter forage crop with early growth, high forage production and feed value, and high palatability (Choi et al., 2018). Like these characteristics, IRG is a representative forage crop, accounting for 83% of winter forage crops cultivated in Korea (MAFRA, 2022).

According to the National Institute of Meteorological Sciences (NIMS, 2018), Korea has reported that temperatures have increased by 1.4℃ and precipitation has increased by 124mm over the past 30 years (1990-2018) from the beginning of the 20th century (1912-1941). These climate changes can have an impact on changes in agricultural ecology, such as the growth period and growth characteristics of crops (Lee et al., 2008). In addition, due to these climate changes, abnormal climate tends to increase the occurrence frequency (Shim et al., 2008), which is judged to affect the forage production.

The study on the calculated damage considering abnormal climate was conducted by applying the World Meteorological Organization (WMO) standard using the machine learning model (Jo et al., 2021; Kim et al., 2022). This calculated only the damage to whole crop maize, a representative summer forage crop in Korea (Jo et al., 2021; Kim et al., 2022). So, it is necessary to calculate the damage to IRG, a winter forage crop that accounts for most of the domestic forage supply. In addition, it is believed that the calculated damage can be visually presented through a map and effectively show the damage amount of IRG to the user.

Therefore, this research was conducted to calculate the IRG damage consideration of the abnormal climate caused by the

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WMO scenario using a machine learning model, and the predicted damage was presented as a map.

Ⅱ. MATERIALS AND METHODS

1. Data collection

A total of 1,384 data sources of IRG were collected from the research papers in Journal of the Korean Society of Grassland and Forage Science (KSGFS), an adaptability test of imported varieties of grasses and forage crops operated by National Agricultural Cooperative Federation (NACF), the research reports on livestock experiments operated by Korean National Livestock Research Institute, and the Journal of Korean Society of Crop Science (Table 1). Table 2 shows The IRG data collected from 1986 to 2020 were the cultivation area, sowing date, harvest date, and the Dry matter yield (DMY).

The climate data used in this study collected data from 102 Automated Synoptic Observing System (ASOS) from the Weather data service-Open MET data portal (data.kma.go.kr) of the Korea Meteorological Administration. The collection of climate data is a 40-year period from 1979 to 2018 when the matched IRG data and data were collected on an hourly basis from January to December every year.

2. Processing climate data

The climate data processing for use in the yield prediction model excluded two regions (Daegu(Gi) and Gangjin-gun) with

Table 1. Italian ryegrass data source and sample size

Reference	Data
The Korean Society of Grassland and Forage Science	597
Nonghyup	343
Rural Development Administration	268
National Institute of Animal Science	137
Journal of Crop Science and Biotechnology	39
Total	1,384

Table 2. Numbers of data on italian ryegrass by cultivation area

Cultivation area	Numbers of data	Cultivation area	Numbers of data
Boseong-gun	6	Haenam	46
Buan	5	Imsil	41
Buyeo	5	Jangheung	3
Cheonan	248	Jeju	159
Cheorwon	6	Jeongeup	3
Chuncheon	14	Jinju	3
Daegu	70	Miryang	24
Daegwallyeong	9	Mungyeong	25
Daejeon	26	seosan	3
Dongducheon	123	Sokcho	2
Gangneung	2	Suncheon	9
Gochang	2	Suwon	328
Gumi	32	Wonju	15
Gunsan	125	Yeonggwang-gun	3
Gwangju	35	Yeongju	12
Total		1,384	

hour-unit data did not exist; five regions (Gwanaksan, Muan, Bukchuncheon, Sejong, and Hongseong)with operating under 5 years from 1986 to 2020; 8 regions (Bukgangneung, Bukchangwon, Juam, Cheomchalsan, Gochang-gun, Gosan, Seongsan, and Seongsanpo) applied close to City Hall and county offices area due to existing over 2 station in same regions. The 87 weather station data were used out of a total of 102 weather station data (Table 3).

Among the IRG cultivation areas, the data from the nearest cultivation site were applied to the place where there was no cultivation site. The climate data were used from September 1 to May 31 considering the growth period of IRG. The climate

Table 3. Climate data used under the non-existing automated synoptic observing system

Region of non-existing ASOS	Applied ASOS*	Region of non-existing ASOS	Applied ASOS
Anseong	Suwon	Iri	Jeonju
Asan	Cheonan	Jinbu	Gangneung
Chilgok	Gumi	Pyeongchang	Wonju
Dangjin	Seosan	Seocheon	Boryeong
Gimje	Buan	Seonghwan	Cheonan
Gunwi	Uiseong	Seongju	Gumi
Gwangju (Gyeonggi-do)	Seoul	Uijeongbu	Seoul
Gwangsan	Gwangju (Jeollanam-do)	Yeoju	Icheon
Gyeongsan	Daegu	Yeongam	Haenam
Hwaseong	Suwon	Yuseong	Daejeon

*ASOS : Automated Synoptic Observing System.

Table 4. Temperature, precipitation, and wind speed by region under hourly normal climate data for experimental period

Region	Temperature (℃)		Precipitation (mm)		Wind Speed (m/s)	
	Mean	SD	Mean	SD	Mean	SD
Andong	19.30	0.61	0.22	0.06	2.17	0.25
Baengnyeongdo	17.65	0.58	0.27	0.09	3.37	0.48
Boeun	18.26	0.89	0.19	0.06	2.31	0.22
Bonghwa	17.09	0.63	0.19	0.05	1.82	0.15
Boryeong	19.24	0.66	0.18	0.03	1.25	0.31
Boseong-gun	20.59	0.35	0.21	0.05	2.52	0.38
Buan	19.44	0.76	0.21	0.06	1.42	0.15
Busan	20.39	0.63	0.23	0.06	1.15	0.21
Buyeo	19.48	0.65	0.21	0.05	1.84	0.17
Changwon	20.89	0.52	0.19	0.06	1.55	0.11
Cheonan	19.20	0.65	0.23	0.06	1.28	0.15
Cheongju	20.10	0.74	0.22	0.06	1.68	0.25
Cheongsong-gun	18.23	0.37	0.23	0.06	1.05	0.21
Cheorwon	18.14	0.54	0.26	0.07	1.59	0.17
Chuncheon	19.01	0.65	0.22	0.05	1.7	0.21
Chungju	19.14	0.89	0.24	0.06	1.08	0.26
Chupungryeong	18.69	0.53	0.23	0.06	1.13	0.19
Daegu	21.02	0.64	0.23	0.07	1.64	0.12

Table 4. Continued

Region	Temperature (℃)		Precipitation (mm)		Wind Speed (m/s)	
	Mean	SD	Mean	SD	Mean	SD
Daegwallyeong	13.92	0.74	0.3	0.09	1.68	0.27
Daejeon	20.05	0.63	0.22	0.06	1.22	0.28
Dongducheon	19.05	0.60	0.21	0.05	2.01	0.11
Donghae	18.64	0.92	0.3	0.08	1.64	0.33
Ganghwa	18.40	0.55	0.21	0.06	1.44	0.16
Gangneung-si	19.54	0.66	0.23	0.06	1.39	0.11
Geochang	18.58	0.79	0.26	0.08	1.25	0.23
Geoje	20.11	0.81	0.23	0.06	2.62	0.18
Geumsan	18.95	0.65	0.21	0.05	1.2	0.17
Gimhae-si	21.54	0.42	0.25	0.07	1.56	0.3
Gochang	20.02	0.52	0.25	0.08	2.07	0.31
Goheung	19.86	0.73	0.19	0.05	1.04	0.08
Gumi	19.55	1.10	0.17	0.04	2.25	0.16
Gunsan	19.65	0.59	0.18	0.05	1.36	0.18
Gwangju	20.61	0.65	0.21	0.05	1.37	0.20
Gwangyang	21.36	0.28	0.20	0.05	1.21	0.17
Gyeongju-si	19.87	0.62	0.19	0.05	1.35	0.11
Haenam	19.79	0.58	0.18	0.04	1.58	0.13
Hamyang-gun	19.52	0.42	0.17	0.05	2.25	0.41
Hapcheon	19.80	0.84	0.22	0.06	1.74	0.40
Heuksando	18.66	0.42	0.18	0.04	1.62	0.34
Hongcheon	18.32	1.10	0.17	0.06	3.74	0.54
Icheon	19.18	0.99	0.17	0.05	3.34	0.56
Imsil	18.24	0.73	0.17	0.05	1.03	0.15
Incheon	19.25	0.69	0.15	0.02	1.17	0.04
Inje	17.64	0.87	0.18	0.06	2.70	0.39
Jangheung	19.52	0.82	0.22	0.06	2.09	0.25
Jangsu	17.64	0.60	0.18	0.04	2.52	0.39
Jecheon	17.79	1.05	0.23	0.06	1.84	0.28
Jeju	21.07	0.71	0.25	0.07	3.57	0.38
Jeongeup	20.10	0.67	0.24	0.07	2.32	0.26
Jeongseon-gun	18.11	0.53	0.21	0.06	2.01	0.24
Jeonju	20.41	0.63	0.22	0.06	1.75	0.34
Jindo-gun	20.34	0.58	0.13	0.04	4.47	0.49
Jinju	20.03	0.50	0.20	0.06	2.74	0.42
Miryang	19.99	0.97	0.24	0.06	1.88	0.09
Mokpo	20.16	0.54	0.18	0.05	3.44	0.52
Mungyeong	18.83	0.85	0.24	0.04	2.41	0.43
Namhae	20.24	0.92	0.26	0.08	1.57	0.10
Namwon	19.46	0.79	0.24	0.06	3.68	0.30
Paju	18.82	0.62	0.24	0.07	1.66	0.38
Pohang	20.43	0.75	0.26	0.06	1.09	0.16

Table 4. Continued

Region	Temperature (℃)		Precipitation (mm)		Wind Speed (m/s)	
	Mean	SD	Mean	SD	Mean	SD
Samcheok	18.36	0.94	0.18	0.04	2.04	0.09
Sancheong	19.46	0.78	0.24	0.06	4.94	0.41
Sangju	19.67	0.59	0.21	0.06	2.07	0.36
Seogwipo	21.57	0.64	0.18	0.04	4.70	0.35
Seosan	19.03	0.53	0.20	0.06	3.24	0.80
Seoul	20.02	0.69	0.22	0.06	1.28	0.27
Sokcho	18.43	0.71	0.20	0.05	1.64	0.16
Sunchang-gun	19.88	0.35	0.23	0.04	1.67	0.09
Suncheon	19.58	0.55	0.22	0.06	1.23	0.20
Suwon	19.58	0.79	0.24	0.06	1.62	0.14
Taebaek	15.66	0.78	0.21	0.05	1.64	0.39
Tongyeong	20.22	0.52	0.21	0.05	1.19	0.25
Uiryeong-gun	19.74	0.72	0.17	0.05	5.52	0.52
Uiseong	18.83	0.84	0.3	0.08	2.73	0.52
Uljin	18.39	0.64	0.29	0.07	2.82	0.47
Ulleungdo	18.11	0.65	0.29	0.08	2.81	0.25
Ulsan	20.31	0.60	0.22	0.07	3.09	0.28
Wando	20.07	0.60	0.21	0.05	1.16	0.13
Wonju	19.14	0.94	0.20	0.05	1.93	0.22
Yangpyeong	19.00	0.93	0.22	0.05	1.26	0.19
Yangsan-si	21.21	0.47	0.21	0.06	2.35	0.30
Yeongcheon	19.35	0.86	0.21	0.05	1.60	0.24
Yeongdeok	19.00	0.82	0.22	0.06	1.22	0.16
Yeonggwang-gun	19.96	0.34	0.28	0.32	1.33	0.22
Yeongju	18.59	0.63	0.21	0.05	1.79	0.21
Yeongwol	18.57	0.61	0.23	0.21	2.12	0.41
Yeosu	20.27	0.54	0.21	0.05	1.31	0.37

factors considered in this study were temperature, precipitation, and wind speed (Table 4). The missing value of the climate factor was supplemented by inputting the average of the time before and after the missing.

3. Yield prediction model construction

The constructed yield prediction model learned the DMY of climate conditions according to the growth period and cultivation area of IRG and can calculate DMY under various climate conditions. Eight machine learning techniques were used to construct yield prediction models: Linear, FM (Factorization Model), Deep, Deep Crossing, Wide & Deep, DeepFM, CIN (Compressed Interaction Network), and xDeepFM.

In this study, the R^2 value was the highest, and the lowest Root Mean Square Error (RMSE) value was chosen to select a yield prediction model.

The climate data increased the number of data by abnormal weather, adjusted to a level similar to the number of data by normal weather, and used in the yield prediction model.

Data by abnormal weather was selected for the year in which the average of climate factors for one year deviated from the standard deviation ± 2 times of normal weather by region. Of the total 408 abnormal weather data, 390 data by abnormal weather were repeatedly learned seven times (n=2,730), which removed overlapping data (n=18), to a similar level to the data by normal weather (n=2,618). Python and Tensorflow were used to constructed yield prediction models through machine learning.

4. Calculating damage by abnormal climate

The DMY damage (Damage) according to abnormal climate was calculated through the difference between the predicted DMY in normal climate (DMYnormal) and in abnormal climate (DMYabnormal) through the yield prediction model. The damage calculation process is as follows.

$$\text{Damage} = \text{DMY}_{\text{normal}} - \text{DMY}_{\text{abnormal}}$$

Where, the normal and abnormal climate for calculating DMYnormal and DMYabnormal of IRG was set in the following way. The normal climate by region was set as the average (40-year average) of weather data by year by the IRG data collection year (1986-2020).

The abnormal climate by region was set by giving fluctuation values to climate factors (temperature, precipitation, and wind speed) in normal weather. The fluctuation value of abnormal weather was calculated after the mean and standard deviation (SD) for each climate factor and set to four levels (-2, -1, +1, and +2 times SD) of ± 1 and ± 2 times SD (Park et al., 2015). The SD by climate factor varied by region, with temperature, precipitation, and wind speed ranging from 0.28 to 1.10℃, 0.02 to 0.32 mm, and 0.04 to 0.80 m/s, respectively.

5. Mapping as damage of abnormal climate

The map was made using the QGIS (Quantum Geographic Information System) and was expressed by dividing it by domestic administrative districts. The amount of damage was divided into five classes by the level, and the more it was, the darker it was.

Among the areas for calculating the amount of damage, areas close to the city hall and county office were applied to areas where administrative districts overlap. In this process, Gosan, Gochang-gun, Bukgangneung, Bukchangwon, Seongsan, Seongsanpo, Juam, and Cheomchalsan were replaced to the Jeju, Gochang, Gangneung, Changwon, Seogwipo, Seogwipo, Suncheon, and Jindo, under map preparation, respectively.

The final area where the map of abnormal climate damage was presented was 87 areas. The damage to IRG by abnormal climate was divided into five classes by standard deviation and shown on the map.

Ⅲ. RESULTS AND DISCUSSION

1. Calculated dry matter yield of IRG by abnormal climate level

Based on the eight machine learning models, the R^2 and RMSE of the yield prediction model varied from 0.6300 to 0.6758 and 0.1581 to 0.1689, respectively (Table 5). The yield prediction model used in this study was xDeepFM, which had the highest R^2 and the lowest RMSE compared to other models. The DMYnormal calculated by xDeepFM ranged from 5,678 to 15,188 kg/ha and varied by region (Fig. 1). In abnormal temperatures, abnormal precipitation, and abnormal wind speed, the DMYabnormal ranged from 5,227 to 15,853 (Fig. 1A), 5,676 to 15,189 (Fig. 1B), and 4,964 to 15,511 (Fig. 1C) kg/ha, respectively, and varied by region and level.

Table 5. R^2 AND RMSE BY MACHINE LEANING MODEL

MODEL	R^2	RMSE
LINEAR	0.6342	0.1680
FM	0.6307	0.1688
DEEP	0.6300	0.1689
DEEPCROSSING	0.6564	0.1628
WIDE&DEEP	0.6392	0.1668
DEEPFM	0.6738	0.1586
CIN	0.6622	0.1614
XDEEPFM	0.6758	0.1581

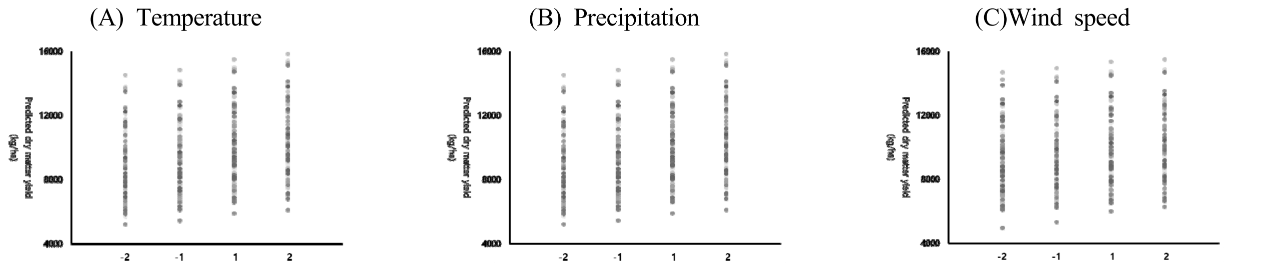

Fig. 1. Predicted dry matter yield of Italian ryegrass according to the level of abnormal temperature (A), precipitation (B), and wind speed (C).

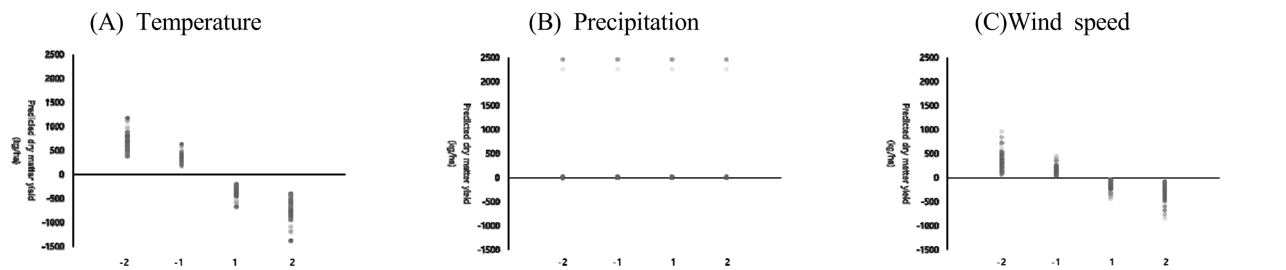

Fig. 2. Damage of Italian ryegrass according to the level of abnormal temperature (A), precipitation (B), and wind speed (C).

2. Calculated damage of IRG by abnormal climate level

The damage of IRG due to abnormal temperature, abnormal precipitation, and abnormal wind speed ranged from -1,380 to 1176, -3 to 2465, and -830 to 962 kg/ha, respectively (Fig. 2). The maximum damage caused by the abnormal temperature level exceeded 1,176 kg/ha when the hourly temperature decreased (-2 level) in Gochang (Fig. 2A). As the temperature increased, the DMY of IRG tended to increase, which was the same result as Jung et al. (2020). IRG is vulnerable to cold (Choi et al., 2005), so it assumes that DMY has decreased because it is hard to over-winter under low temperatures in winter. The maximum damage caused by the abnormal precipitation was 2,465 kg/ha when the hourly precipitation increased and decreased in Daejeon (Fig. 2B). Except for some sites, such as Daejeon and Jangsu, most of the sites suffered no damage. It is judged to have little impact on precipitation when cultivating IRG, which is thought to be similar to Choi et al. (2018).

The maximum damage caused by the abnormal wind speed was 962 kg/ha when the hourly wind speed decreased (-2 level) in Gunsan (Fig. 2C). The tendency of DMY by the level of abnormal temperature and abnormal wind speed increased as the abnormal climate level increased. The amount of precipitation in which the maximum damage occurred was 0% of the DMYnormal in areas other than Jangsu and Daejeon.

It is guessed that the damage in Jangsu and Daejeon was affected by factors other than abnormal climate. In addition, it is necessary to examine whether abnormal climate using the WMO method is a weather condition that damages the DMY of IRG. Therefore, it is judged that abnormal climate needs to

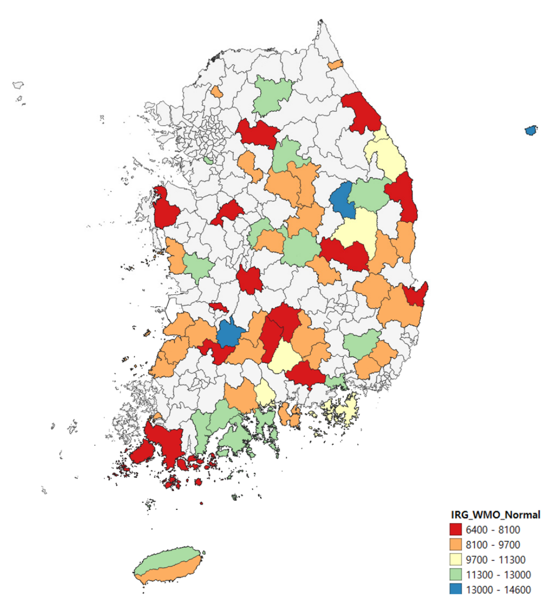

Fig. 3. Mapping on dry matter yield of Italian ryegrass under normal climate.

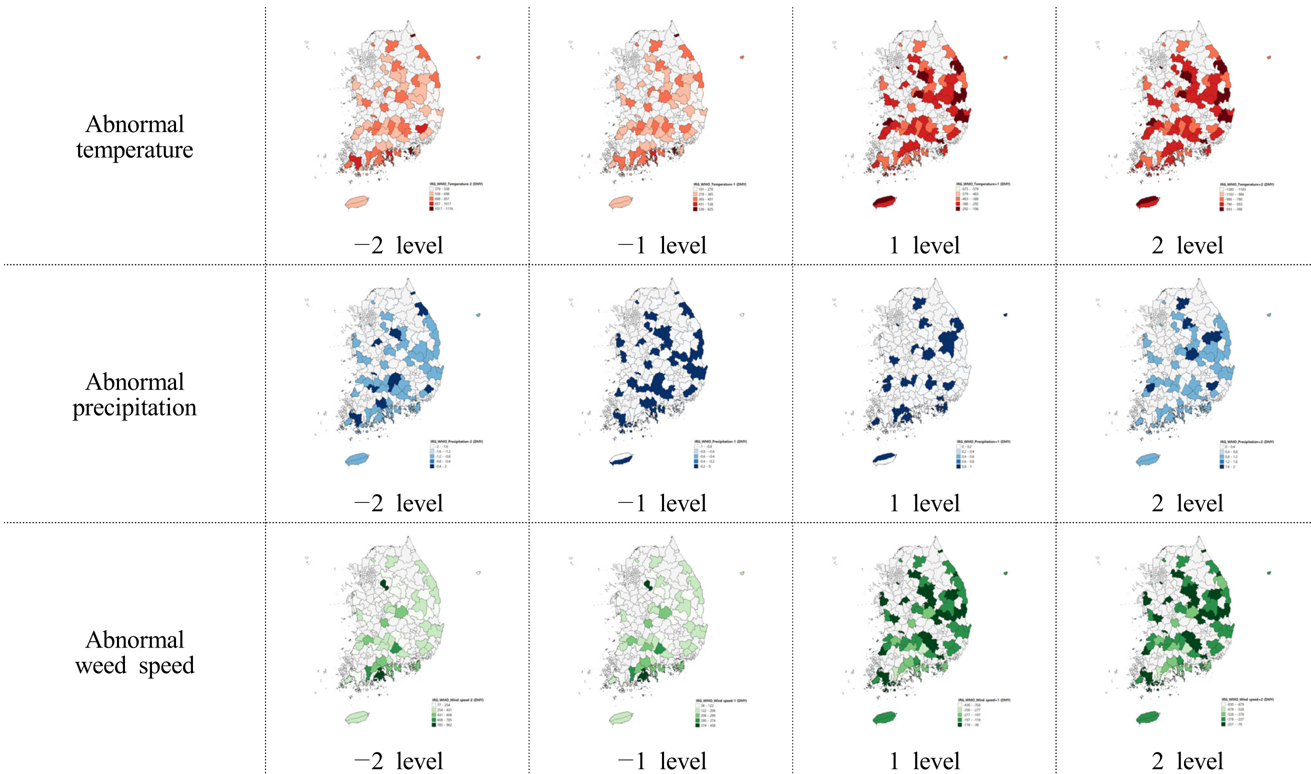

Fig. 4. Mapping on damage of Italian ryegrass under abnormal climate each level.

be set in a different method to compare and evaluate the WMO method.

3. Mapping of the damage by abnormal climate level

The map presented the DMYnormal (Fig. 3) and damage by abnormal climate using WMO methods by the level (Fig. 4). As a result of converting the damage of IRG by abnormal climate in each region into the ratio of DMYnormal, the damage was in the range of 0 to 22%. When the map of the results of this study was presented separately by the administrative district, the damage was not calculated, so there was a blank (white) area. Therefore, the maximum damage in accordance with the WMO scenario calculated by the xDeepFM-based yield prediction model was 2,465 kg/ha. In addition, as the level of abnormal temperature and abnormal wind speed increases, the DMY of Italian ryegrass increases. As for the damage to IRG, administrative districts with ASOS weather data were presented as maps (Fig. 4). In this study, it is required to review whether the damage of IRG caused by abnormal climate is significant. In the future, research on the calculation of damage to IRG needs to be additionally conducted considering the search for more abnormal climate cases and the growth stage of IRG. In addition, to compensate for the gap in the blank area, more detailed damage can be calculated by using the automatic weather system (AWS), which provides more data at points than the ASOS, although there is much-missing data and device malfunction.

Ⅳ. ACKNOWLEDGEMENTS

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