

Article

A Case Study of Bias Correction and the Dynamical Downscaling of CFSv2 S2S Forecasts Using a WRF Model: Heatwave in 2018 over South Korea

Jiwon Oh , Jaiho Oh * and Morang Huh

Nano Weather Co., Ltd., Seongnam 13449, Republic of Korea

* Correspondence: jjho2023@gmail.com

Abstract: Extreme weather events caused by climate change affect the growth of crops, requiring reliable weather forecasts. In order to provide day-to-season seamless forecasting data for the agricultural sector, improving the forecasting performance of the S2S period is necessary. A number of studies have been conducted to improve prediction performance based on the bias correction of systematic errors in GCM or by producing high-resolution data via dynamic detailing. In this study, a daily simple mean bias correction technique is applied on CFSv2 (~100 km) data. We then use case studies to evaluate how beneficial the precision of the high-resolution RCM simulation is in improving S2S prediction performance using the bias-corrected lateral boundary. Based on our examination of 45-day sequences of WRF simulations with 27–9–3 km resolution, it can be concluded that a higher resolution is correlated with better prediction in the case of the extreme heatwave in Korea in 2018. However, the effect of bias correction in improving predictive performances is not significant, suggesting that further studies on more cases are necessary to obtain more solid conclusions in the future.

Keywords: S2S; climate model downscaling; bias correction; high resolution; heatwaves



Citation: Oh, J.; Oh, J.; Huh, M. A Case Study of Bias Correction and the Dynamical Downscaling of CFSv2 S2S Forecasts Using a WRF Model: Heatwave in 2018 over South Korea. *Atmosphere* **2022**, *13*, 2086. <https://doi.org/10.3390/atmos13122086>

Academic Editors: Seung-Jae Lee and Ji-Sun Kang

Received: 31 October 2022

Accepted: 7 December 2022

Published: 11 December 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Over the last decades, extreme weather events such as heatwaves and droughts that impact the growth of crops have increased, and are expected to continue to increase [1–3]. In this respect, weather and climate forecast information is important for the agricultural sector to inform agricultural practices, planning, and projects, ensure reliable crop yields, and aid in managing the stability of the food crop market [3–5]. A sub-seasonal to seasonal (S2S) forecast range (more than 2 weeks and less than a season) is particularly useful for end users in the agricultural application sector, and is useful for managing water resources, energy, unexpected disasters, etc., in order to respond quickly to weather-related hazards; thus, the demand for seamless forecasts is continually growing [6,7]. Kim et al. [8] have verified that machine learning algorithms for storage rate forecasting using 30 years of weather station data are sufficiently applicable, and the management of water is possible with highly reliable meteorological data.

At the S2S time range, however, the prediction skill decreases because of the effect of the initial atmospheric conditions being progressively reduced; moreover, the influence of the ocean's state does not strongly feed into the forecasted field [9–11]. Improving this sub-seasonal to seasonal prediction skill has been a challenging mission. To overcome the difficulty of S2S prediction, global and national research projects have been conducted involving efforts to improve forecasting on the S2S time scale. The WMO (World Meteorological Organization) has developed a database containing available S2S forecasts produced by operational centers, helping the research community to better understand and advance S2S forecasting [6]. The NCEP (National Centers for Environmental Prediction) has developed a climate forecasting system (CFS), the first quasi-global and fully coupled

atmosphere–ocean–land model for seasonal prediction [12]. It provides open-access forecasting data with various time scales for the public. The second version of CFS (CFSv2) has significantly enhanced many aspects of predictability compared to the earlier version [13]. The CFSv2 has great potential to produce skillful temperature or precipitation forecasts at the sub-seasonal time range, because its forecasts are influenced jointly by the conditions of the atmosphere, land, and ocean [14]. Tian et al. (2016) [14] evaluated CFSv2 probabilistic sub-seasonal forecasts of the temperature and precipitation indices over the contiguous United States (CONUS). The indices of both temperature and precipitation extremes for 7-, 14-, and 30-day forecasts were skillful depending on seasons and regions; in particular, the forecasts for the 7- and 14-day temperature indices even showed skill at weeks 3 and 4. Despite development and efforts to improve S2S predictions, there is a limitation of GCMs when applying these models' results to agriculture. Global circulation models (GCMs) have spatial resolutions that are too coarse; for example, CFSv2 has grid resolutions of nearly 100 km for driving dynamical crop model simulations at local scales, where agriculture practices are mostly managed [4,15,16]. Dynamic downscaling with regional climate models (RCMs), which are forced by initial and lateral boundary conditions from GCMs, can transfer global predictions from the GCMs to regional scales [17,18]. Several studies have shown that RCMs can improve regional climate variability and extreme episodes compared to GCMs. Hari Prasad et al. (2021) [17] conducted dynamical downscaling of CFSv2 hindcasts using WRF up to 38 km resolution. In their results, dry biases over Indian land regions were reduced to 16% after downscaling, compared to 44% in CFSv2-T126. Regarding temperature, Hari Prasad et al. (2014) [19] evaluated extreme temperature weather events, such as heat and cold waves, using a 25 km resolution WRF model with NCEP 2.5 degree analysis for the initial and boundary conditions. The regional climate simulations showed the occurrence of about 80% of the total heatwaves in the 1970–2010 period for Europe; however, the results were relatively poor over complex topographical areas. Im et al. (2021) [4] demonstrated that the dynamic downscaling of CFSv2 operational forecasts using the WRF model leads to significant improvements in extreme heatwave years. They evaluated the performance of CFSv2 and WRF-nested simulations for monthly temperatures during a 10-year summer season compared with in situ observational data, and concluded that dynamic downscaling with RCM resolved the regional variability with topography better and reduced cold biases over the Korean Peninsula, which is a characteristic of CFSv2. Even though WRF cannot capture extremely hot summers, such as the summer of 2018, because of the limitations of drawing the initial and boundary condition from the global model, in their study, the downscaled results show reasonable performance in terms of agro-meteorological indices.

Similar to the the cold bias over the Korean Peninsula in the CFSv2 model, GCMs have systematic biases that affect RCM results [5,20]. In other words, in addition to the initial conditions and lower boundaries, RCMs are dependent on the provision of realistic simulations of the GCMs transferred via the lateral boundary conditions [21]. Bruyère et al. (2014) [20] suggested that the application of bias correction to GCM's boundary conditions for RCM may suit many regional climate applications. They conducted six sensitivity experiments with different bias correction components (zonal and meridional wind, geopotential height, temperature, relative humidity, sea surface temperature, and mean sea level pressure) and used these to correct the mean error in the GCM for regional climate simulations. The non-bias correction experiment resulted in substantial regional cooling compared to the 20-year mean daily maximum 2 m temperature observation. The experiment with all boundary condition corrections provided the greatest improvement in relation to the maximum temperature, tropical cyclones, and precipitation. Rocheta et al. (2017) [21] compared three approaches for correcting the lateral boundary biases, including the mean, variance, and modification of the sample's moments through the use of a nested bias correction method. Their study involved the method of modifying the mean field, which is more simple than other methods. The results showed the most improvement with

respect to the low-frequency variability attributes of simulated precipitation, demonstrating that more complicated techniques do not necessarily lead to more skillful simulations.

The purpose of the present study is to examine whether the forecasting performance of the S2S period can be improved when both dynamical downscaling and bias correction are conducted with respect to CFSv2. We apply the simple mean bias method relative to CFSv2 operational data and design a case study using this application as the boundary condition for the WRF model. The WRF simulations were run twice, both with and without bias-corrected boundary conditions for two cases in heatwave episodes over South Korea, using one-way downscaling from 27 km to 3 km. To evaluate the performance, the root mean squared error and correlation coefficient were used for the daily temperature. Moreover, the agro-meteorological indexes related to heat stress were calculated from WRF simulations and evaluated, as the study aims to provide S2S forecasting data for the agriculture sector.

2. Materials and Methods

2.1. Data

The second version of CFS (CFSv2) significantly enhanced many predictability aspects compared to the earlier version. CFSv2 runs four times in a day of simulations for at least 45 days and up to 9 months; therefore, sub-seasonal to seasonal forecast data can be used for the agricultural sector as the operational purpose. Due to the coarse grid resolution of CFSv2 operation forecasts, dynamic downscaling over the regions of interest should be considered before applying the data to agricultural application tools. The CFSv2 initial conditions are made in real-time; thus, it is possible to use them for sub-seasonal forecasting [13]. Here, we focus on the S2S daily forecasting service for the agricultural sector; therefore, we use the CFSv2 45-day operational forecast data in this study. The atmospheric model of CFSv2 has a horizontal resolution of nearly 100 km and 64 sigma-pressure vertical levels. There are two different sets of CFSv2 hindcasts and climatology. The 9-month hindcasts have the initial conditions of the 00Z, 06Z, 12Z, and 18Z cycles every 5 days during 1982–2010. The first season and 45-day hindcasts have initial conditions from every cycle of every day over the 12-year period from 1999 to 2010. NCEP provides smoothed calibration climatologies in time series for both full periods (1982–2010) and the 12-year period (1999–2010). However, the climatologies for the forecasted daily mean from every 6 hour cycle in a calendar day (including 29 February) are available up to the seasonal/45-day time scale. Because the forecast temporal range that is finally used is stated in days, daily climatologies over a 12-year period have been adopted to conduct bias correction in this study.

The ECMWF (European Centre for Medium-Range Weather Forecasts) ERA5 reanalysis for the same 12-year period (1999–2010) has been used to correct biases. It has a regular latitude–longitude grid of 0.25 degrees for atmospheric variables. For the verification of bias-corrected regional climate model results, the observations for 94 stations from the KMA (Korea Meteorological Administration) are used.

2.2. Method of Bias Correction

In this study, the word ‘bias’ refers to the systematic errors of the GCM model as described in Bruyère (2014) [20]. Figure 1 shows the 45-day mean temperature difference between the CFSv2 12-year period climatology and the ERA5 reanalysis climatology for the same period over the Korean Peninsula. In the study area, the CFSv2 model tends to simulate lower temperatures compared to observations regardless of the initial date, with the exception of winter. In particular, in the interior of the Korean Peninsula there are negative values that appear in the summer season. In the winter, a positive temperature bias appears in parts of the northern region and in the southern and eastern regions of the Korean Peninsula. Because the center of the biased region is in the highlands, it can be said that the CFSv2 model tends to simulate warmer temperatures with respect to the highlands than the actual temperatures observed in winter. The resolution of CFSv2 is lower than that of ERA5, meaning that it does not reflect the terrain properly, and differences may occur. In

order to remove this bias, a simple mean bias correction method was modified to reflect the time series and applied to the operational data. The simple mean bias correction [22] is described by the following equation:

$$x_{i,corr}^f = x_{i,raw}^f - \widehat{Bias}(\mu^p) = x_{i,raw}^f - (\overline{x_i^p} - \overline{y_i^p}) \quad (1)$$

In Equation (1), $x_{i,raw}^f$ denotes the simulated future time series, x_i^p denotes the mean of the uncorrected model over the chosen present period (1999–2010), and y_i^p denotes the corresponding real mean, where i denotes the calendar date. The bias of the present period is calculated using CFSv2 hindcast and ERA5 reanalysis, as shown in Figure 1, and the CFSv2 operational products are used as future simulations. Then, $x_{i,corr}^f$ can be defined as the bias-corrected future time series.

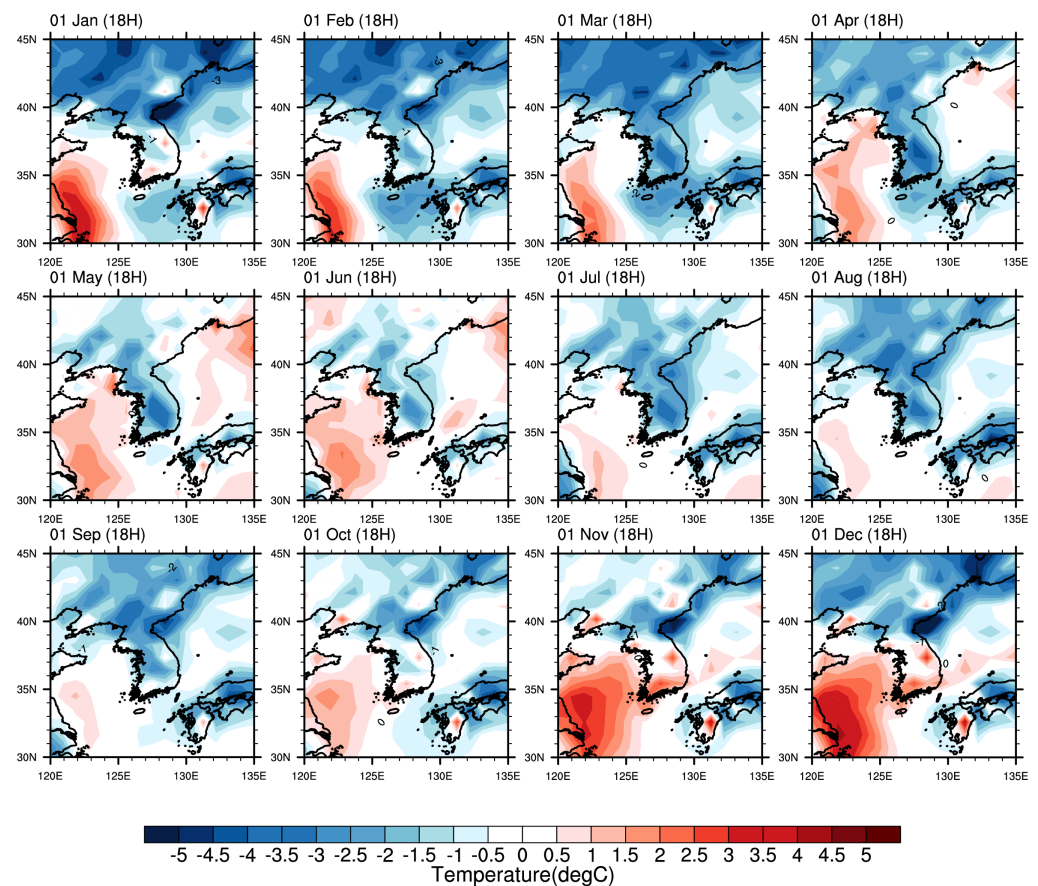


Figure 1. Twelve -year (1999–2010) mean bias (CFSv2–ERA5) during 14–45 days for 2 m temperature, where the initial time is the first day of each month.

2.3. Experimental Design

In this study, the Weather Research and Forecasting (WRF) model version 4.4 was adopted to produce high-resolution simulations over South Korea using CFSv2 data. The model was run in one-way nesting mode with three domains. The mother domain had a 27 km spatial resolution (D1), and the nested domains were 9 km (D2) and 3 km (D3), reducing it by a factor of 3. Figure 2 shows the domain configuration for the simulation; all simulations had a 50 hPa model top and 45 vertical levels. The center of the mother domain was at 36.5° N, 127.5° E, covering northeastern Asia with 150 × 130 grid points. The second domain (D2) consisted of 220 × 214 grid points, the center latitude was 36.49955° N, and the center longitude was 127.191° E. The inner domain with 3 km resolution was nested for the focus over South Korea with 271 × 271 grid points. The center of the inner domain was at 35.46627° N, 127.6521° E.

For the physical configuration, we decided to refer to the sensitivity test from Qui et al. (2020) [23], which consists of the following parametrization schemes: the WSM3 microphysics scheme [24], the RRTMG longwave and shortwave radiation scheme [25], the revised MM5 surface layer scheme [26], the Noah land surface model scheme [27], the Yonsei University planetary boundary layer scheme [28], and the Kain–Fritsch cumulus convection parameterization scheme [29]. The convection parameterization scheme was conducted for 27 km and 9 km simulations and switched off for the 3 km simulations.

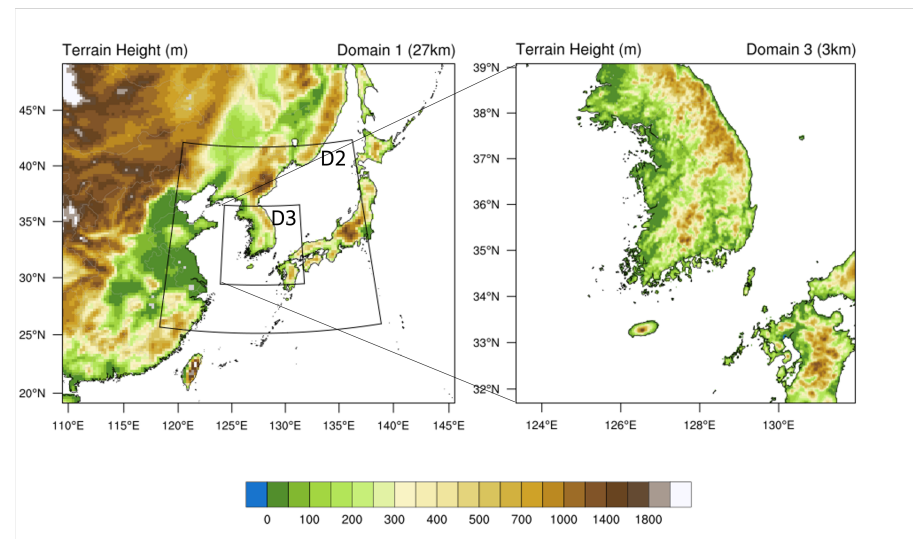


Figure 2. Topography used for the Domain 1 simulation with 27 km resolution (**left**) and nested Domain 3 simulation with 3 km resolution (**right**). The inner solid boxes in Domain 1 mark the nested Domains 2 and 3.

There are 16 operational datasets in a day that can produce an ensemble forecast; however, as this study is the first to evaluate the dynamic downscaling of the daily bias-corrected CFSv2, only one member of the operational forecast was adopted. To examine the applicability of bias-corrected CFSv2 data during the S2S period, an extreme heat wave case that caused significant damage to crops, human life, etc., in Korea was selected. In the summer of 2018, extreme heatwave events occurred in South Korea, causing an estimated 44,060 cases of heat-related illness and 929 excess mortality cases [30]. Figure 3 shows the monthly average temperature anomaly in July and August 2018 against the climatology from 1981 to 2010 at the 72 observation stations. At all stations, the monthly temperature anomalies showed positive values, especially in the inland area with a value of 3 °C or higher. According to the national average daily maximum temperature data from June to August 2018, it exceeded 33 °C, which is the heatwave warning standard. The heatwave started on July 14 and lasted until August 9. Based on the maximum temperature, the initial and boundary conditions comprised the case where the heatwave gradually strengthened during the S2S forecast period (CASE 1) and the case where the heatwave gradually weakened (CASE 2). Simulations were conducted for the two cases. The first was carried out from 1800 UTC, 15 June, to 1200 UTC, 29 July (CASE 1). For the second case, the simulation was carried out from 1800 UTC, 17 July, to 1200 UTC, 30 August (CASE 2). Each case was simulated twice with the same physical configurations and was either fed by bias-corrected boundary conditions (BC) or not (NOBC). The initial and boundary conditions were obtained from CFSv2 operational forecasts. Equation (1) was applied to the 6-hourly 2 m temperature of CFSv2 S2S data to generate lateral boundary conditions for the WRF model. The bias-corrected 2 m temperatures at 00, 06, 12, and 18Z are shown in Figure 4. The 45-day mean field relative to 2 m temperature, initialized on 15 June, increased over the Korean peninsula and Southeast China. The bias-corrected temperature on the initial date of 17 July, not shown here, increased as well. The simulations were run

with 6-hourly SST updates from the CFSv2's data. The earliest 72 h had to be excluded as a model spin-up time, and we analyzed the remaining days.

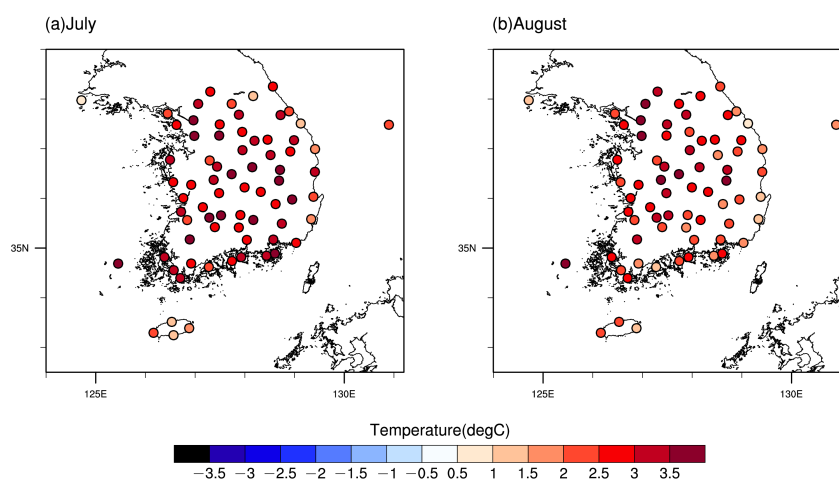


Figure 3. The monthly temperature anomaly in July and August 2018 against the climatology from 1981 to 2010. Each circle over the map indicates the KMA observation stations (ASOS); the color means the difference between monthly temperature and climatology.

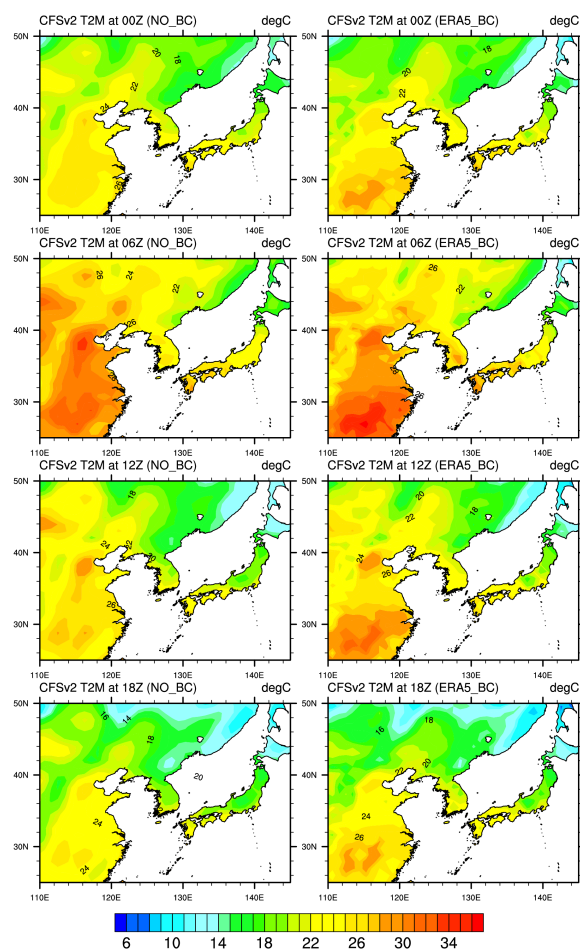


Figure 4. Mean 2 m temperature(NOBC, left) and bias-corrected temperature(right) at 0000, 0006, 0012, and 0018 Z of the CFSv2 initialized during 1800 UTC, 15 June (CASE 1).

3. Results

3.1. Analysis of Simulation Results

3.1.1. Weekly Mean of 2 m Temperature

Figures 5 and 6 show the weekly mean of the 2 m temperature of the ERA5 reanalysis, CFSv2 operational forecast, and the downscaled forecast without bias corrections using the WRF model at 27 km resolution for each case. CFSv2 simulated temperatures lower than the reanalysis during the heatwave period over South Korea. WRF forecasts, which are downscaled dynamically from CFSv2 data, showed a higher temperature than CFSv2 overall, although it did not capture the actual temperature. The WRF forecast showed more realistic temperature patterns on land because high-resolution topographies were reflected. According to the reanalysis data, the temperature at the mountainous terrain in the central and southern regions of the Korean Peninsula, where Mt. Jiri and Mt. Deogyu are located, is relatively low. CFSv2 could not capture this pattern, whereas the WRF simulation shows a high-temperature pattern appearing in the east–west direction centering upon low temperatures in the mountainous terrain. In both cases, the WRF model simulated higher temperatures near Seoul and lower temperatures over the sea and on Jeju Island compared to the reanalysis and CFSv2. It seems to be a characteristic of the WRF model that appears consistently in this study, although it is necessary to perform more cases and physical process experiments to confirm this.

In the first case, which was initialized at 1800 UTC on 15 June, the average 2 m temperature gradually increased from Week 1 to the highest value at Week 6 in ERA5; however, the CFSv2 model showed a decreasing temperature trend after four weeks. The WRF simulation using CFSv2 data as the initial and boundary fields showed that the temperature for 5–6 weeks was 25 degrees or less.

3.1.2. Synoptic Analysis

The mechanisms of heatwave events over Korea are related to the higher pressures observed at the upper levels. When the Tibetan High (TH) and North Pacific High (NPH) expand to the upper level of the Korean Peninsula and form a large high-pressure belt, a solid high-pressure belt forms from the lower layer to 100 hPa, leading to an effect in which heat cannot escape. In the case of the 2018 heatwave, the TH and NPH caused downdrafts over all of South Korea, and heat generated by strong solar radiation and warm advection could not be released to the outside environment due to substantial blocking effects, resulting in severe high temperatures [31]. In CASE 1, TH did not appear near the Korean Peninsula in either WRF simulation (NOBC or BC) from week 1 to 6, which was affected by CFSv2 (not shown); in contrast, the 2 m temperature increased every week (Figure 5) as TH and NPH gradually approached South Korea in the reanalysis data. Because the upper and lower air pressure patterns of the NOBC and BC experiment were very similar, the NOBC experiment is analyzed here. Figure 7 shows the weekly mean geo-potential height at 100 hPa and 500 hPa in CASE 2. The TH stretches eastward, and the center of the NPH is located above the Korean Peninsula (Figure 7a,d,g). The CFSv2 and WRF simulations showed a similar distribution in the first week due to the influence of the initial field. From the second week, the TH and NPH rapidly weakened in CFSv2 (Figure 7b,e,h). On the other hand, the WRF simulation maintained a relatively strong expansion to the east of the TH, and the NPH was widely distributed in the east–west direction, unlike ERA5 (Figure 7c,f,i). Figure 8 shows the weekly mean of wind (vector) and geo-potential height (contour) at 850hPa. During the heatwave, the anti-cyclonic circulation clearly appears in the lower atmosphere where the TH and NPH overlap (Figure 8a,d,g), and high temperatures of 33°C or more are found in the center of the circulation (Figure 6). However, in the case of the CFSv2 (Figure 8b,e,h) and WRF simulations (Figure 8c,f,i), the anti-cyclonic circulation in the lower level does not appear, and the incoming hot and humid air is able to escape.

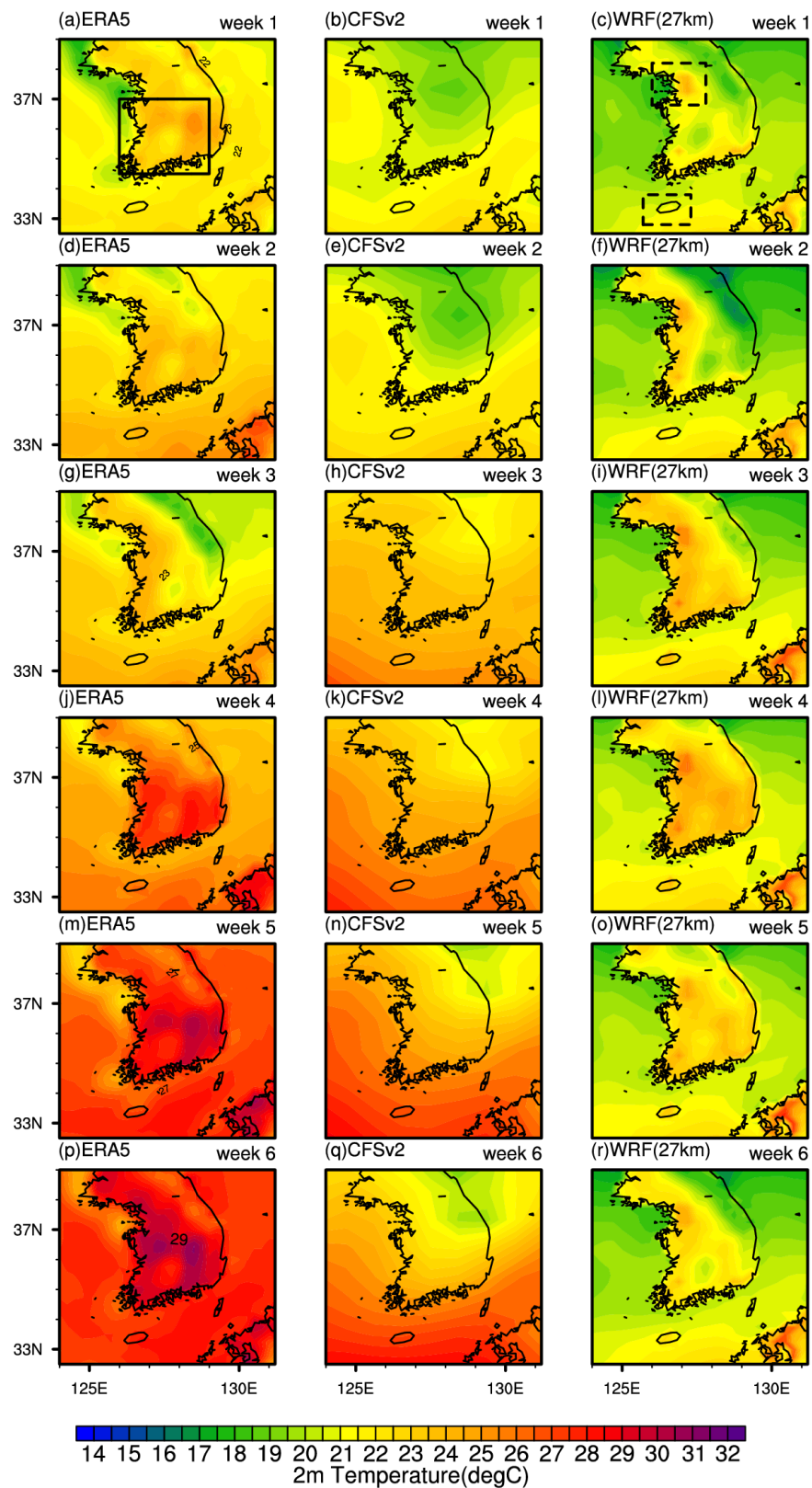


Figure 5. The weekly mean of the 2 m temperature in the ERA5 reanalysis and the CFSv2 and WRF forecasts initialized at 1800 UTC on 15 June. The solid box indicates the central and southern region in Korean Peninsula. The dotted box near 37 N represents Seoul, and the other box represents Jeju Island. From the top to the bottom of the figure (Week 1 to Week 6), the leftmost area represents the reanalysis data, the middle of the row represents CFSv2, and the rightmost area represents the WRF 27 km data.

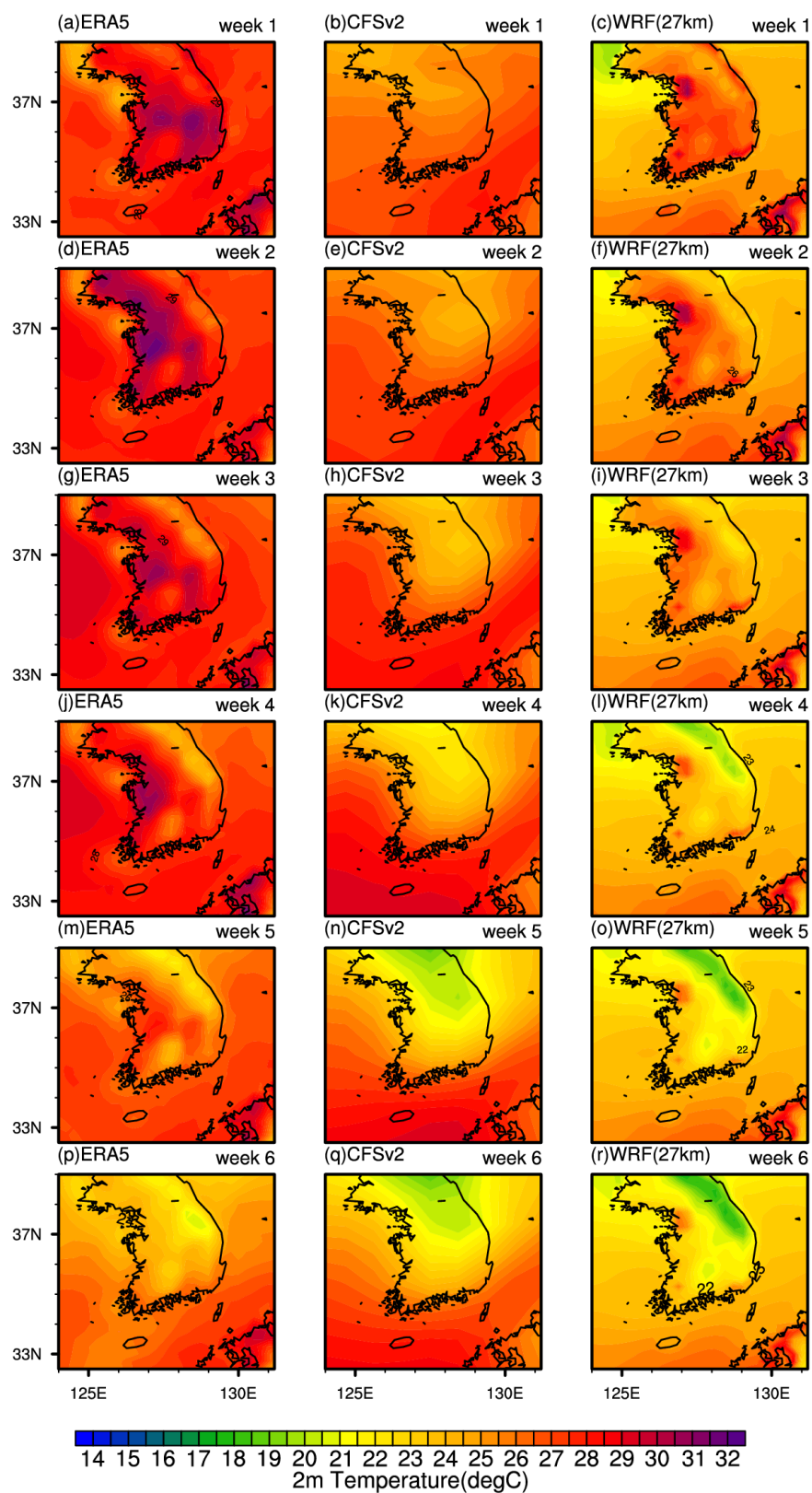


Figure 6. Same as Figure 5, except that CFSv2 and WRF were initialized at 1800 UTC on 17 July.

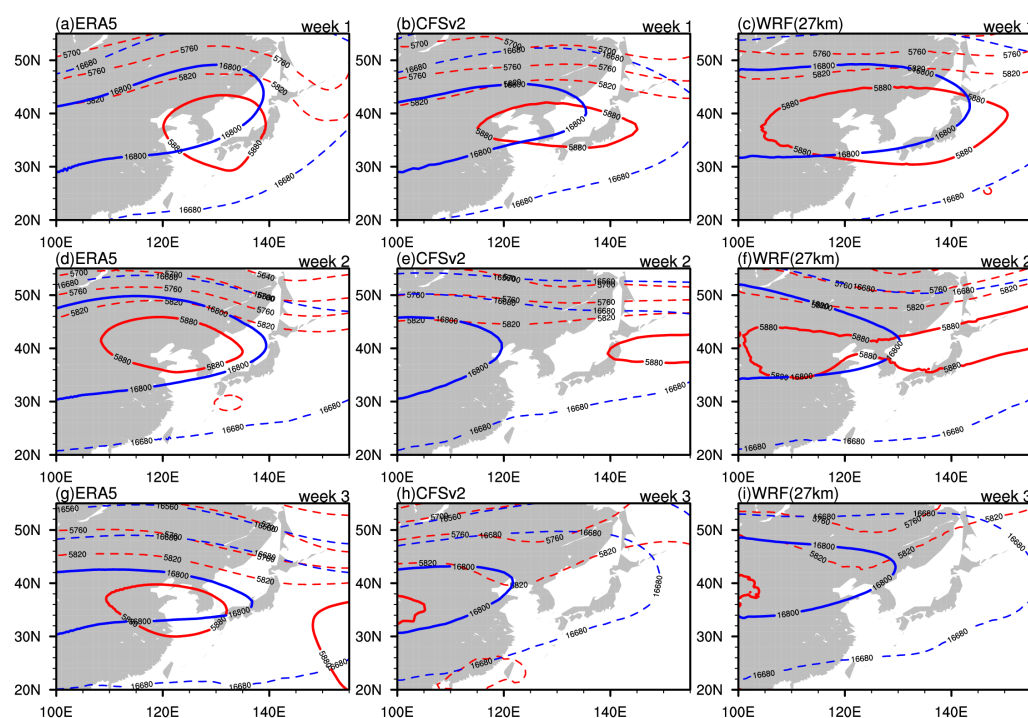


Figure 7. Spatial patterns of the mean geo-potential height (m) at 100 hPa (blue contour) and 500 hPa (red contour) during Weeks 1–3 in CASE 2. The blue bold line represents the Tibet High and the red line represents the North Pacific High.

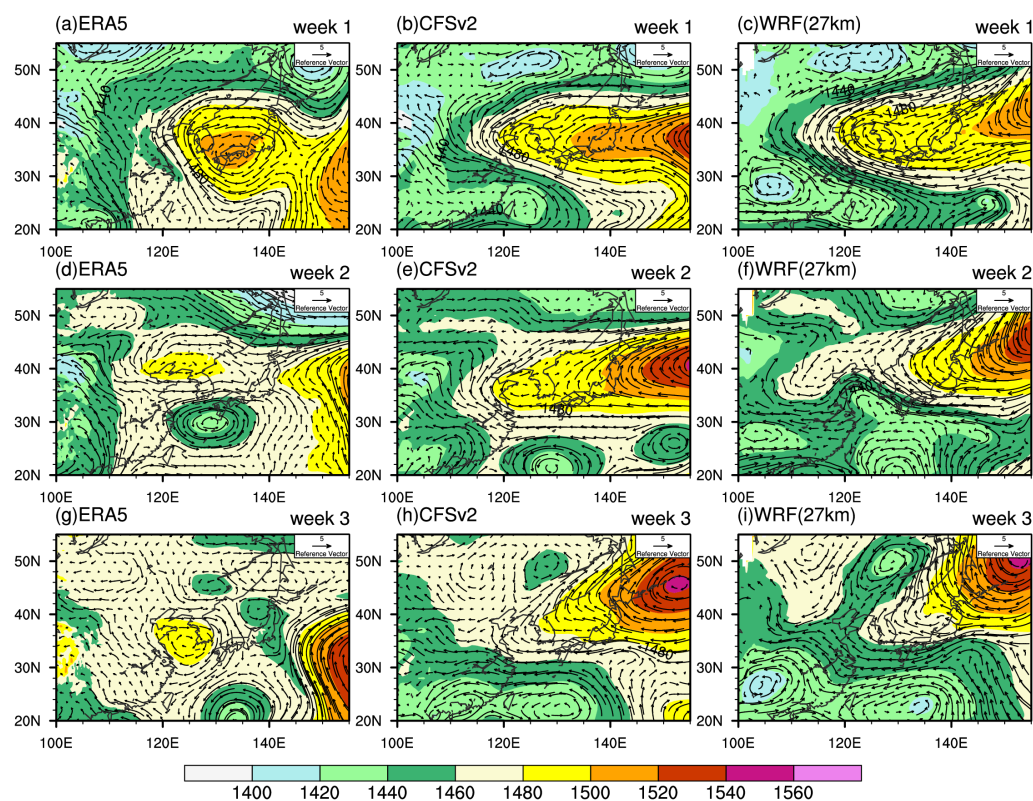


Figure 8. Spatial patterns of the mean geo-potential height (shaded contour, m) and wind vector (vector, m/s) at 850 hPa during Weeks 1–3 in CASE 2.

3.2. Evaluation of Daily Temperature Forecast

To evaluate the effect of dynamic downscaling and bias correction quantitatively, we used the root mean squared error (RMSE), correlation coefficient (CC), and normalized RMSE (NRMSE) for the daily average and maximum and minimum temperatures during the analysis period. The RMSE and correlation coefficient at 94 observation stations over South Korea were calculated using Equations (2) and (3). In these equations, M_i represents the model's forecast temperature at forecasting day i , O_i represents the observation value at the same time, and $\bar{M}$ and $\bar{O}$ represent the mean value of forecasts and observations for all periods, respectively, which in this case is 42 days:

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

$$CC = \frac{\sum_{i=1}^n [(O_i - \bar{O})(M_i - \bar{M})]}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (M_i - \bar{M})^2}} \quad (3)$$

$$NRMSE = \frac{RMSE}{\bar{O}} \quad (4)$$

Tables 1, 2 and 3 show the averaged RMSE, normalized RMSE and CC for 94 stations, respectively. For both performance measures, the WRF simulations with bias-corrected boundary conditions did not improve very much. The higher the spatial resolution achieved by dynamic downscaling, the lower the RMSE. The RMSEs of the daily temperatures with 3 km resolution (D3) were lower at 1.361 °C according to the 27 km resolution (D1). The bar graphs in Figure 9 show the RMSE difference between D3 and D1 and the RMSE difference between the BC and NOBC experiments in the 3 km domain. The model's performance improvement with downscaling is clear, although the difference in values is not dramatically large; furthermore, the prediction of extreme values such as the maximum temperature improves as the resolution increases. However, the correlation coefficient according to each experiment to which downscaling and bias correction were applied is inconsistent. In other words, the daily temperature change during the S2S period is not significantly improved by the model's resolution or bias correction, and it can be understood that it was not able to escape the influence of the CFSv2 data used as the input.

Table 1. Averaged RMSE (°C) for 94 stations.

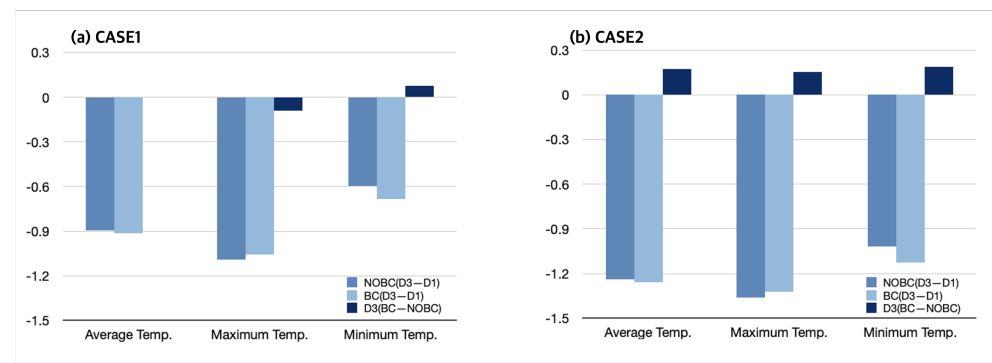
CASE #	Variables	NOBC (27 km)	NOBC (9 km)	NOBC (3 km)	BC (27 km)	BC (9 km)	BC (3 km)
CASE 1	Tavg	4.926	4.392	4.030	4.949	4.398	4.034
	Tmax	6.595	6.002	5.506	6.474	5.911	5.416
	Tmin	4.075	3.659	3.481	4.243	3.769	3.558
CASE 2	Tavg	3.858	3.073	2.618	4.051	3.276	2.792
	Tmax	5.348	4.562	3.987	5.465	4.734	4.141
	Tmin	3.629	2.908	2.609	3.927	3.138	2.798

Table 2. Averaged normalized RMSE (°C) for 94 stations.

CASE #	Variables	NOBC (27 km)	NOBC (9 km)	NOBC (3 km)	BC (27 km)	BC (9 km)	BC (3 km)
CASE 1	Tavg	0.217	0.198	0.182	0.213	0.195	0.179
	Tmax	0.193	0.172	0.158	0.194	0.173	0.158
	Tmin	0.189	0.170	0.162	0.197	0.175	0.166
CASE 2	Tavg	0.164	0.140	0.123	0.167	0.145	0.127
	Tmax	0.140	0.112	0.095	0.147	0.119	0.102
	Tmin	0.155	0.125	0.112	0.167	0.135	0.120

Table 3. Averaged correlation coefficient for 94 stations.

CASE #	Variables	NOBC (27 km)	NOBC (9 km)	NOBC (3 km)	BC (27 km)	BC (9 km)	BC (3 km)
CASE 1	Tavg	0.196	0.162	0.164	0.124	0.147	0.145
	Tmax	0.046	0.058	0.092	0.058	0.100	0.105
	Tmin	0.367	0.303	0.294	0.253	0.244	0.249
CASE 2	Tavg	0.521	0.581	0.574	0.518	0.549	0.559
	Tmax	0.437	0.491	0.472	0.432	0.450	0.451
	Tmin	0.371	0.440	0.444	0.401	0.448	0.459

**Figure 9.** The difference in RMSEs between Domain 1 (27 km, D1) and Domain 3 (3 km, D3) and between the NOBC and BC experiments at D3.

Regarding RMSE, the improvement in bias correction does not appear in the averaged measures; however, there are certain stations of improvement in the spatial distribution for each point. The distribution of RMSE for Tavg, Tmax, and Tmin shows that the bias-corrected results further improve at the same resolution in the southern and western areas over the Korean Peninsula (Figures 10 and 11). The simulated Tmin is better than Tmax (as indicated by the RMSE). In CASE 2, the distribution of red dots in Figure 11a–d increases overall, meaning that the RMSE is below 3 °C. For the maximum temperature, as shown in e–h, the measures from 6 to 8 °C at the 27 km resolution decrease, ranging between 3 and 6 °C in the BC experiment with 3 km resolution.

3.3. Evaluation of Agro-Meteorological Indexes

Because of on the purpose of this study to provide S2S forecasts for agriculture, the agro-meteorological indexes produced related to the mean and maximum temperature were evaluated. We calculated the accumulated heat stress index as the threshold 24 °C of the mean temperature [32] according to the equation introduced in Im et al. (2021) [4].

$$AccumulatedHeatStress = \sum_{i=1}^n (Tmean_i - 24), \text{ if } Tmean_i > 24^{\circ}\text{C} \quad (5)$$

In Figure 12, the averages of the accumulated heat stress index for 94 stations derived from observations and NOBC and BC simulations are shown in the bar graph. Although the analysis period for calculating the index is different, as in a previous study [4], the index calculated by the WRF's simulation was found to be less than half of the actual level in extreme heatwave cases, such as the case in 2018. Similar to the underestimation of the average 2 m temperature in Figures 5 and 6, the heat stress index showed a lower value than the actual one.

In CASE 1, which had poor RMSE and correlation coefficient evaluation results, the heat index of the WRF simulation at 27 km resolution was only 6% of the actual level. In that case, the heat index increased to about 28% after downscaling. For the same reason, in CASE 2, dynamical downscaling had an important role in terms of improving the index. With respect to the increasing RMSE in CASE 2, the accumulated heat stress index was

worse in the BC simulation than NOBC. The heat stress index of simulation BC with a 3 km resolution was 63% of the actual level, and the NOBC simulation rose slightly to 68%.

For the maximum temperature, we calculated the number of days when the maximum temperature exceeded 30 °C. This is the plant heat stress (PHS) index introduced in Piticar (2019) [33]; we adopted a threshold of 30 °C in this study based on Im et al. (2021) [4]. The number of days when the daily maximum temperature exceeded 30 °C at 94 stations in both cases is shown in Figures 13 and 14. As we expected based on previous results, the number of days derived from the WRF simulations was lower than observations, especially because the simulations for CASE 1 could not capture the maximum temperatures. However, the number of days with respect to BC simulations increased at the inland stations. Even though it was lower than the observations, it was possible to confirm the improvement by the bias correction. In CASE 2, NOBC simulations could not capture the maximum temperatures along the sea shores well, although the domain 3 with 3 km resolution showed better estimations for the plant heat stress index. The difference in the number of days between the BC and NOBC simulations in CASE 2 was generally minimal. At a few stations, the BC simulations showed better estimations for the plant heat stress; however, there were no significant patterns among the resolutions.

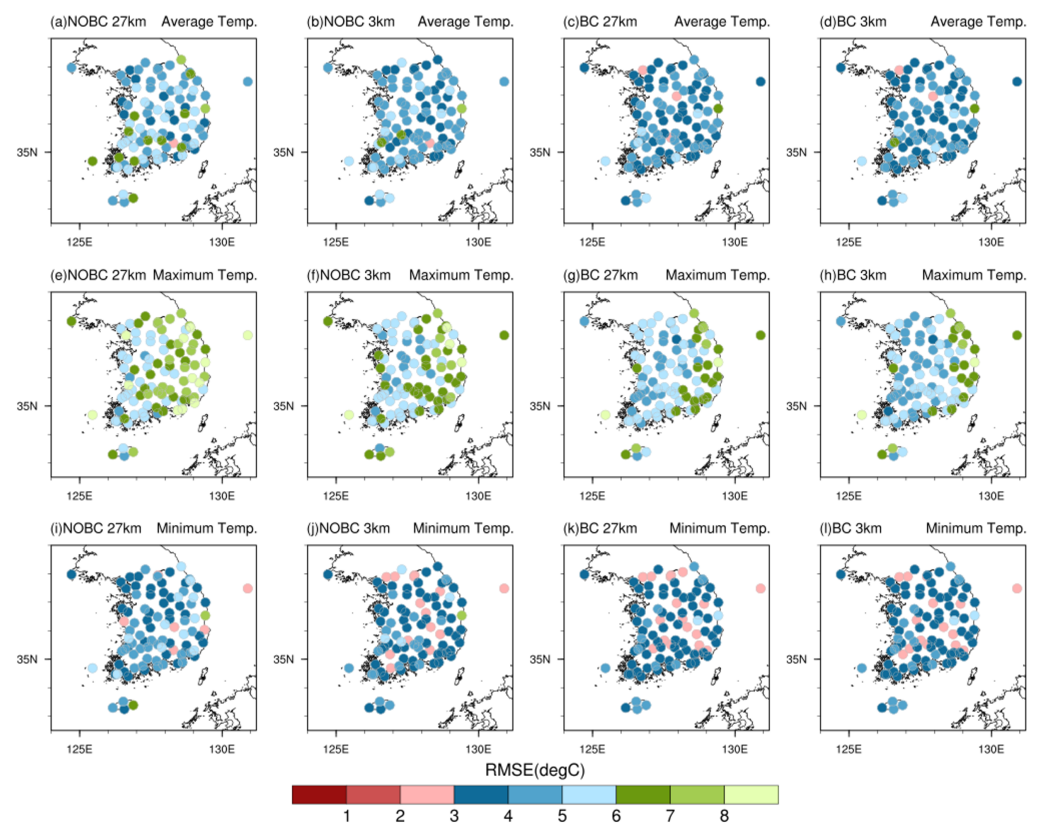


Figure 10. The spatial distribution of the RMSE of the WRF simulation, initialized at 1800 UTC on 15 June (CASE 1), at 94 stations over South Korea. (a–d): RMSE for daily average temperature; (e–h): RMSE for maximum temperature; (i–l): RMSE for minimum temperature. ‘BC’ and ‘NOBC’ denote the WRF simulation using bias-corrected boundary conditions and non-biased conditions, respectively.

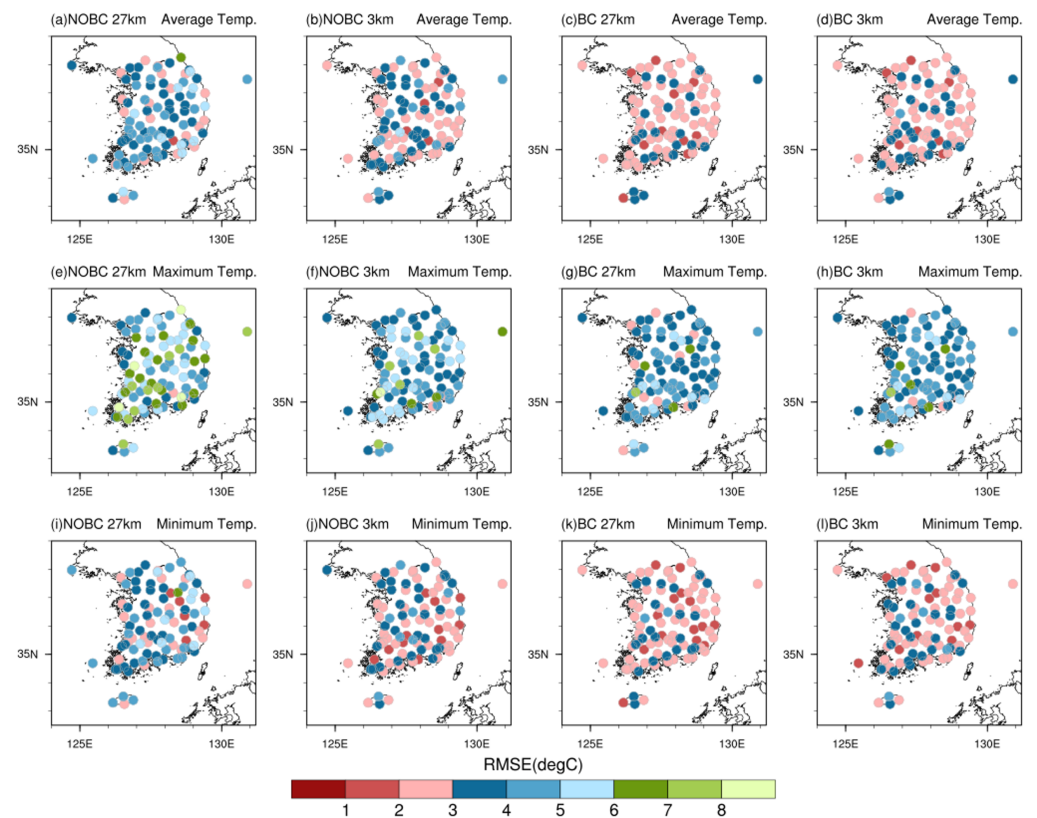


Figure 11. Same as Figure 10, except with WRF initialized at 1800 UTC on 17 July (CASE 2).

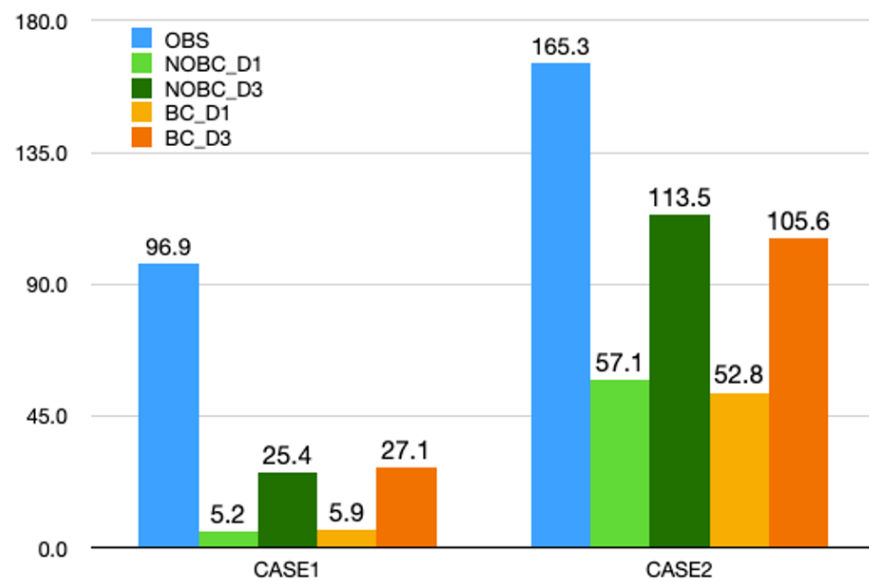


Figure 12. The accumulated heat index averaged for 94 stations derived from observations and the two sets of NOBC and BC simulations.

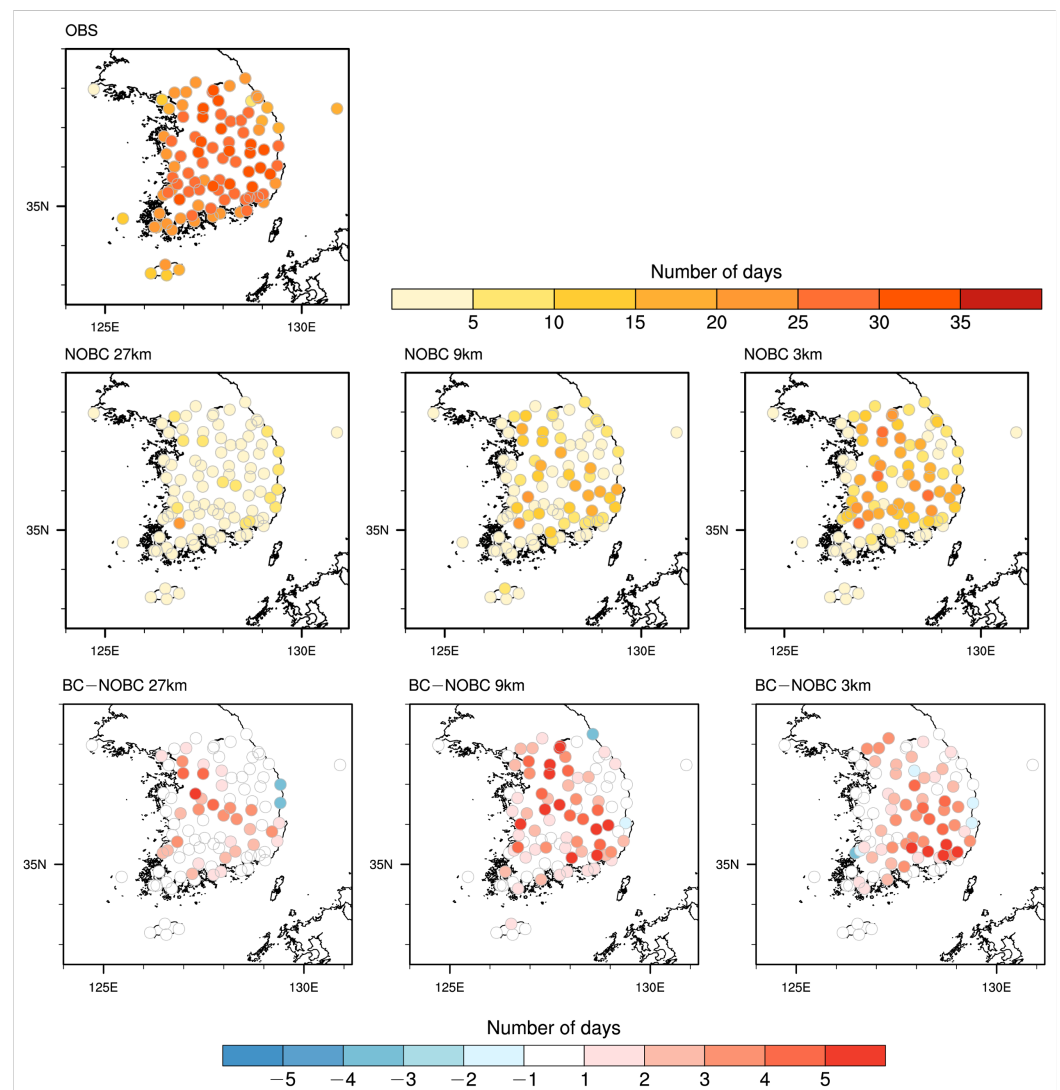


Figure 13. The number of days with T_{max} exceeding 30°C for the 94 stations, derived from observations and WRF simulation in CASE 1. Below, the three figures show the difference in the index between BC and NOBC.

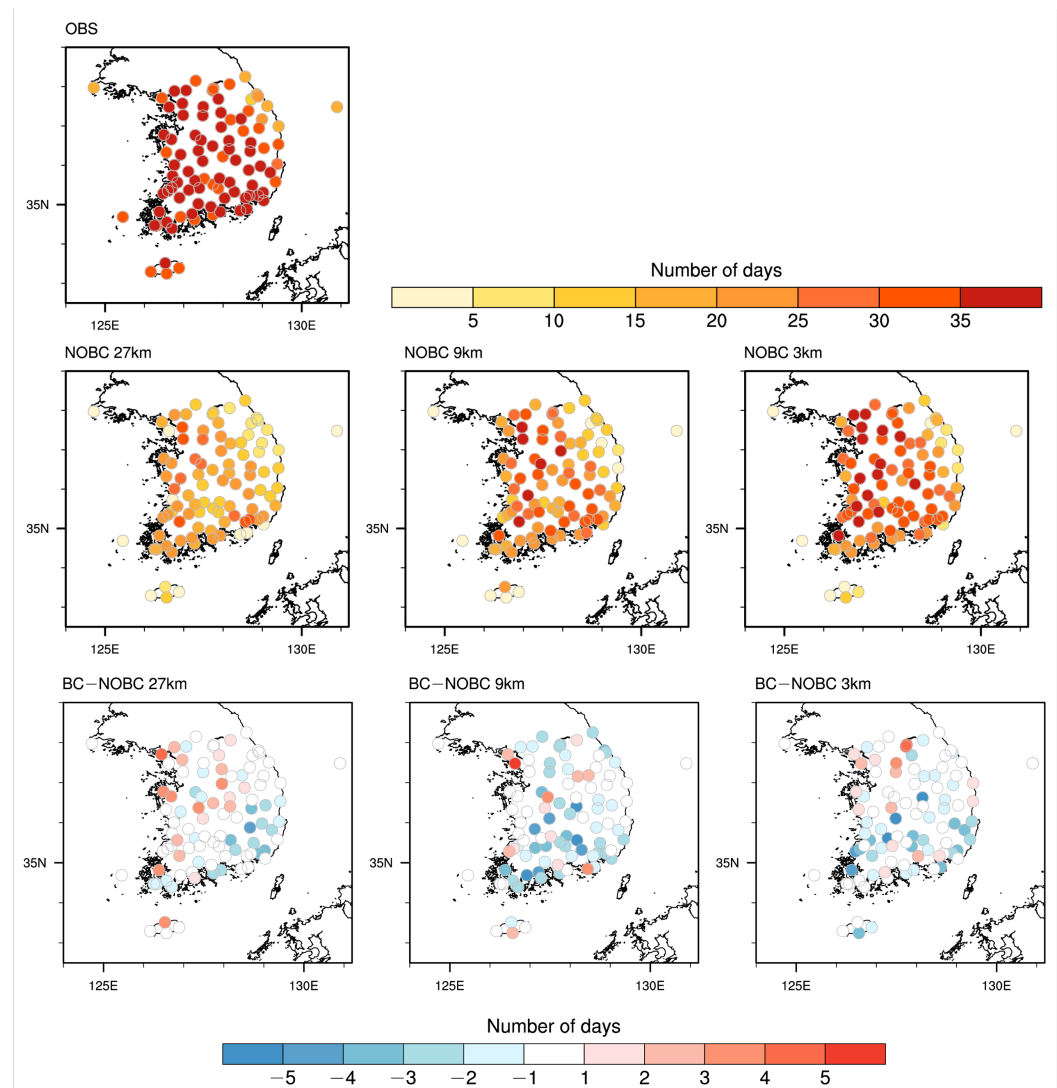


Figure 14. Same as Figure 11, except for CASE 2.

4. Discussion and Conclusions

The starting point of this study was to find out how to improve the performance of S2S predictions for agricultural communities. The simple mean bias correction method [22] was selected at 6-hour intervals for a temperature of 2 m using CFSv2 operational data, which are updated daily. In order to evaluate the reliability of this method, WRF simulations of a sequence of downscaling with 27–9–3 km resolution were conducted in cases both with and without bias correction applied to the boundary fields for the extreme heatwave episode on the Korean Peninsula in 2018.

Then, the effect of downscaling and bias correction was evaluated in terms of the RMSE, correlation coefficient, and agro-meteorological indexes. The CFSv2 model has a tendency to underestimate summer temperatures in the Korean Peninsula, and this tendency improved after dynamic downscaling using the WRF model. Considering the extreme case, which causes difficulty in predictions [4], bias correction improves the model's simulation, though not significantly, as only the 2 m temperature variable was corrected in this study. Heat waves are related to upper anti-cyclones; however, the experiments in this study did not consider the correction of variables such as the geo-potential height, and thus the upper barometer and lower circulation at the time of heat waves could not be simulated well. Because the bias correction technique was not carried out for the other variables, such as zonal and meridional winds, geo-potential height, and humidity, there were imbalances between the boundary conditions, leading to the BC experiments not showing better results

than the NOBC ones. Furthermore, the results were not consistent, as shown in CASE 1 and CASE 2. In CASE 1, the RMSE decreased and the AHS (accumulated heat stress) and PHS (plant heat stress) improved slightly in BC simulations for all resolutions, while the bias correction simulations in CASE 2 did not improve. Twelve-year hindcast data were used to correct the model's systematic bias on a daily scale; however, longer hindcast data are needed in order to mitigate the effects of short-term variations [20].

Robust positive results were obtained for model performance with downscaling using WRF in both cases. For example, the accumulated heat stress index with 3 km resolution showed better results with a 27 km resolution, and the plant heat stress showed similar results with high resolutions in comparison with observations. As for the correlation coefficient of the daily temperature data, however, neither changing the resolution nor bias correction was effective in improving heatwave prediction, where the model seems to be more affected by the CFSv2 input data.

Likewise, the influence of the input data proved very important in the results of agro-meteorological indices, and the performance improved somewhat when resolving the influence via dynamic downscaling using WRF. Even though RCM with downscaling was not possible for representing the observed heatwaves due to the limits of the input data, the spatial distribution of the temperature improved because of the ability to capture complex topography features. Moreover, the downscaling results are more valuable because the CFSv2 model underestimates the temperature over the Korean peninsula, considering the fact that the simulated daily maximum temperature never exceeded 30 °C during the study period. Although there are several limits to discuss, this study demonstrates a possible improvement in S2S predictions using the WRF model with bias correction method. To ensure reliable performance for the WRF model, a future study should consider the following points:

- (1) The two-way nesting option (available in the WRF model) should be considered in order to overcome the uncertainty propagating from the CFSv2 boundary condition.

- (2) The bias correction technique should be applied to the other variables of the lateral boundary condition (zonal and meridional winds, geo-potential height, and relative or specific humidity).

- (3) The 30-year climatology should be built using the WRF model driven by the CFSR reanalysis dataset to calculate the normal values of Tmax and Tmin.

More accurate meteorological forecasts can contribute better results for applications in agriculture, energy, disaster response, and more. Despite the difficulty of S2S forecasting, it is necessary to continue with research to better support the decision-making process in these sectors of application.

Author Contributions: Conceptualization, J.O. (Jaiho Oh) and M.H.; methodology, J.O. (Jiwon Oh); validation, J.O. (Jiwon Oh); investigation, M.H. and J.O. (Jiwon Oh); writing—original draft preparation, J.O. (Jiwon Oh), J.O. (Jaiho Oh) and M.H.; writing—review and editing, J.O. (Jiwon Oh), J.O. (Jaiho Oh) and M.H.; visualization, J.O. (Jiwon Oh); supervision, J.O. (Jaiho Oh). All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Korea Institute of Planning and Evaluation for Technology in Food, Agriculture, and Forestry (IPET) via the Living Lab Project for Rural Issues, funded by the Ministry of Agriculture, Food, and Rural Affairs (MAFRA) (120099-03).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: CFSv2 operational forecast and hindcast (reforecast) data can be found at <https://www.ncei.noaa.gov/thredds/model/model.html>, (accessed on 17 August 2022); ECMWF ERA5 hourly data on single levels from 1959 to present can be found at <https://doi.org/10.24381/cds.adbb2d47>, (accessed on 19 September 2022); ECMWF ERA5 hourly data on pressure levels from 1959 to present can be found at <https://doi.org/10.24381/cds.bd0915c6>, (accessed on 23 November 2022).

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

References

1. Morales, M.S.; Cook, E.R.; Barichivich, J.; Christie, D.A.; Villalba, R.; LeQuesne, C.; Srur, A.M.; Ferrero, M.E.; González-Reyes, A.; Couvreur, F.; et al. Six hundred years of South American tree rings reveal an increase in severe hydroclimatic events since mid-20th century. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 16816–16823. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Perkins-Kirkpatrick, S.E.; Lewis, S.C. Increasing trends in regional heatwaves. *Nat. Commun.* **2020**, *11*, 3357. [\[CrossRef\]](#)
3. Heinicke, S.; Frieler, K.; Jägermeyr, J.; Mengel, M. Global gridded crop models underestimate yield responses to droughts and heatwaves. *Environ. Res. Lett.* **2022**, *17*, 044026. [\[CrossRef\]](#)
4. Im, E.S.; Ha, S.; Qiu, L.; Hur, J.; Jo, S.; Shim, K.M. An Evaluation of Temperature-Based Agricultural Indices Over Korea From the High-Resolution WRF Simulation. *Front. Earth Sci.* **2021**, *9*, 656787. [\[CrossRef\]](#)
5. Song, C.Y.; Kim, S.H.; Ahn, J.B. Improvement in Seasonal Prediction of Precipitation and Drought over the United States Based on Regional Climate Model Using Empirical Quantile Mapping. *Atmosphere* **2021**, *31*, 637–656.
6. Vitart, F.; Ardilouze, C.; Bonet, A.; Brookshaw, A.; Chen, M.; Codorean, C.; Déqué, M.; Ferranti, L.; Fucile, E.; Fuentes, M.; et al. The Subseasonal to Seasonal (S2S) Prediction Project Database. *Bull. Am. Meteorol. Soc.* **2017**, *98*, 163–173. [\[CrossRef\]](#)
7. Kim, S.W.; Kim, H.; Song, K.; Son, S.W.; Lim, Y.; Kang, H.S.; Hyun, Y.K. Subseasonal-to-Seasonal (S2S) Prediction Skills of GloSea5 Model: Part 1. Geopotential Height in the Northern Hemisphere Extratropics. *Atmosphere* **2018**, *28*, 233–245. [\[CrossRef\]](#)
8. Kim, S.J.; Bae, S.J.; Lee, S.J.; Jang, M.W. Monthly Agricultural Reservoir Storage Forecasting Using Machine Learning. *Atmosphere* **2022**, *13*, 1887. [\[CrossRef\]](#)
9. Brunet, G.; Shapiro, M.; Hoskins, B.; Moncrieff, M.; Dole, R.; Kiladis, G.N.; Kirtman, B.; Lorenc, A.; Mills, B.; Morss, R.; et al. Collaboration of the Weather and Climate Communities to Advance Subseasonal-to-Seasonal Prediction. *Bull. Am. Meteorol. Soc.* **2010**, *91*, 1397–1406. [\[CrossRef\]](#)
10. Mariotti, A.; Rutigliano, P.M.; Rixen, M. Progress in subseasonal to seasonal prediction through a joint weather and climate community effort. *npj Clim. Atmos. Sci.* **2018**, *1*, 4. [\[CrossRef\]](#)
11. Manrique-Suñén, A.; Gonzalez-Reviriego, N.; Torralba, V.; Cortesi, N.; Doblas-Reyes, F.J. Choices in the Verification of S2S Forecasts and Their Implications for Climate Services. *Mon. Weather Rev.* **2020**, *148*, 3995–4008. [\[CrossRef\]](#)
12. Saha, S.; Nadiga, S.; Thiaw, C.; Wang, J.; Wang, W.; Zhang, Q.; Van den Dool, H.M.; Pan, H.L.; Moorthi, S.; Behringer, D.; et al. The NCEP Climate Forecast System. *J. Clim.* **2006**, *19*, 3483–3517. [\[CrossRef\]](#)
13. Saha, S.; Moorthi, S.; Wu, X.; Wang, J.; Nadiga, S.; Tripp, P.; Behringer, D.; Hou, Y.T.; Chuang, H.Y.; Iredell, M.; et al. The NCEP Climate Forecast System Version 2. *J. Clim.* **2014**, *27*, 2185–2208. [\[CrossRef\]](#)
14. Tian, D.; Wood, E.; Yuan, X. CFSv2-based sub-seasonal precipitation and temperature forecast skill over the contiguous United States. *Hydrol. Earth Syst. Sci. Discuss.* **2016**, *21*, 1–24. [\[CrossRef\]](#)
15. Shin, D.W.; Cocke, S. Alternative ways to evaluate a seasonal dynamical downscaling system. *J. Geophys. Res. Atmos.* **2013**, *118*, 13443–13448. [\[CrossRef\]](#)
16. Shin, D.W.; Baigorria, G.A.; Romero, C.C.; Cocke, S.; Oh, J.H.; Kim, B.M. Assessing crop yield simulations driven by the NARCCAP regional climate models in the southeast United States. *J. Geophys. Res. Atmos.* **2017**, *122*, 2549–2558. [\[CrossRef\]](#)
17. Hari Prasad, K.B.R.R.; Ramu, D.A.; Rao, S.A.; Hameed, S.N.; Samanta, D.; Srivastava, A. Reducing Systematic Biases Over the Indian Region in CFS V2 by Dynamical Downscaling. *Earth Space Sci.* **2021**, *8*, e2020EA001507. [\[CrossRef\]](#)
18. Manzananas, R.; Gutiérrez, J.M.; Fernández, J.; van Meijgaard, E.; Calmanti, S.; Magariño, M.E.; Cofiño, A.S.; Herrera, S. Dynamical and statistical downscaling of seasonal temperature forecasts in Europe: Added value for user applications. *Clim. Serv.* **2018**, *9*, 44–56. [\[CrossRef\]](#)
19. Dasari, H.P.; Salgado, R.; Perdigao, J.; Challa, V.S. A Regional Climate Simulation Study Using WRF-ARW Model over Europe and Evaluation for Extreme Temperature Weather Events. *Int. J. Atmos. Sci.* **2014**, *2014*, 704079. [\[CrossRef\]](#)
20. Bruyère, C.L.; Done, J.M.; Holland, G.J.; Fredrick, S. Bias corrections of global models for regional climate simulations of high-impact weather. *Clim. Dyn.* **2014**, *43*, 1847–1856. [\[CrossRef\]](#)
21. Rocheta, E.; Evans, J.P.; Sharma, A. Can Bias Correction of Regional Climate Model Lateral Boundary Conditions Improve Low-Frequency Rainfall Variability? *J. Clim.* **2017**, *30*, 9785–9806. [\[CrossRef\]](#)
22. Maraun, D. Bias Correcting Climate Change Simulations—A Critical Review. *Curr. Clim. Chang. Rep.* **2016**, *2*, 211–220. [\[CrossRef\]](#)
23. Qiu, L.; Im, E.S.; Hur, J.; Shim, K.M. Added value of very high resolution climate simulations over South Korea using WRF modeling system. *Clim. Dyn.* **2020**, *54*, 173–189. [\[CrossRef\]](#)
24. Hong, S.Y.; Dudhia, J.; Chen, S.H. A Revised Approach to Ice Microphysical Processes for the Bulk Parameterization of Clouds and Precipitation. *Mon. Weather Rev.* **2004**, *132*, 103–120. [\[CrossRef\]](#)
25. Iacono, M.J.; Delamere, J.S.; Mlawer, E.J.; Shephard, M.W.; Clough, S.A.; Collins, W.D. Radiative forcing by long-lived greenhouse gases: Calculations with the AER radiative transfer models. *J. Geophys. Res. Atmos.* **2008**, *113*, 13. [\[CrossRef\]](#)
26. Jiménez, P.A.; Dudhia, J.; González-Rouco, J.F.; Navarro, J.; Montávez, J.P.; García-Bustamante, E. A Revised Scheme for the WRF Surface Layer Formulation. *Mon. Weather Rev.* **2012**, *140*, 898–918. [\[CrossRef\]](#)

27. Chen, F.; Dudhia, J. Coupling an Advanced Land Surface–Hydrology Model with the Penn State–NCAR MM5 Modeling System. Part I: Model Implementation and Sensitivity. *Mon. Weather Rev.* **2001**, *129*, 569–585. [[CrossRef](#)]
28. Hong, S.Y.; Noh, Y.; Dudhia, J. A New Vertical Diffusion Package with an Explicit Treatment of Entrainment Processes. *Mon. Weather Rev.* **2006**, *134*, 2318–2341. [[CrossRef](#)]
29. Kain, J.S.; Weiss, S.J.; Bright, D.R.; Baldwin, M.E.; Levit, J.J.; Carbin, G.W.; Schwartz, C.S.; Weisman, M.L.; Droegemeier, K.K.; Weber, D.B.; et al. Some Practical Considerations Regarding Horizontal Resolution in the First Generation of Operational Convection-Allowing NWP. *Weather Forecast.* **2008**, *23*, 931–952. [[CrossRef](#)]
30. Park, J.; Chae, Y. Analysis of heat-related illness and excess mortality by heat waves in South Korea in 2018. *J. Korean Geogr. Soc.* **2020**, *55*, 391–408. [[CrossRef](#)]
31. Hee-Dong, L.; Ki-Hong, M.; Jeong-Ho, B.; Dong-Hyun, C. Characteristics and Comparison of 2016 and 2018 Heat Wave in Korea. *Atmosphere* **2020**, *30*, 1–15. [[CrossRef](#)]
32. Thuy Tran, L.; Lee, C.K.; Jeong, J.H.; Lee, H.S.; Yang, S.Y.; Im, Y.H.; Hwang, W.H. Impact of Heat Stress on Pollen Fertility Rate at the Flowering Stage in Korean Rice (*Oryza sativa* L.) Cultivars. *J. Korean Soc. Crop. Sci.* **2020**, *65*, 22–29. [[CrossRef](#)]
33. Piticar, A. Changes in agro-climatic indices related to temperature in Central Chile. *Int. J. Biometeorol.* **2019**, *63*, 499–510. [[CrossRef](#)] [[PubMed](#)]