climate

MDPI

Article

Crop Coefficients and Irrigation Demand in Response to Climate-Change-Induced Alterations in Phenology and Growing Season of Vegetable Crops

Nadine Schmidt and Jana Zinkernagel *

Department of Vegetable Crops, Hochschule Geisenheim University, 65366 Geisenheim, Germany; nadine.schmidt@hs-gm.de
* Correspondence: jana.zinkernagel@hs-gm.de; Tel.: +49-6722-502-511

Abstract: This study investigates the effects of climate change on the irrigation demand of vegetable crops caused by alteration of climate parameters affecting evapotranspiration (ET), plant development, and growing periods in Central Europe. Utilizing a model framework comprising two varying climate scenarios (RCP 2.6 and RCP 8.5) and two regional climate models (COSMO C-CLM and WETTREG 2013), we calculate the daily crop water balance (CWBc) as a measure for irrigation demand based on reference ET and the temperature-driven duration of crop coefficients until 2100. Our findings for onion show that rising temperatures may shorten cultivation periods by 5 to 17 days; however, the irrigation demand may increase by 5 to 71 mm due to higher ET. By reaching the base temperatures for onion growth earlier in the year, cultivation start can be advanced by up to 30 days. Greater utilization of winter soil moisture reduces the irrigation demand by up to 21 mm, though earlier cultivation is restricted by frost risks. The cultivation of thermophilic crops, however, cannot be advanced to the same extent, as shown for bush beans, and plants will transpire more strongly due to longer dry periods simulated for summer. The results underscore the need for adaptive crop and water management strategies to counteract the simulated changes in phenology and irrigation demand of vegetable crops. Therefore, special consideration must be given to the regional-specific and model- and scenario-dependent simulation results.

Keywords: regional climate models; greenhouse gas emission scenarios; crop water balance; thermal growing season; irrigation scheduling

check for updates

Citation: Schmidt, N.; Zinkernagel, J. Crop Coefficients and Irrigation Demand in Response to Climate-Change-Induced Alterations in Phenology and Growing Season of Vegetable Crops. *Climate* **2024**, *12*, 161. https://doi.org/10.3390/cli12100161

Academic Editor: Sisay Debele

Received: 4 September 2024
Revised: 9 October 2024
Accepted: 9 October 2024
Published: 11 October 2024

1. Introduction

Climate change is the primary global challenge in the 21st century, particularly for vulnerable horticultural systems. The effects of climate change are location-specific and show large variations, which are associated with significant consequences for living beings and the environment [1,2]. Vegetable crops are highly sensitive to variations in temperature and precipitation [3]. While warming trends may extend growing seasons in some regions, increased occurrences of extreme heat and erratic rainfall patterns jeopardize vegetable production and quality [4]. These challenges are exacerbated by the specific water and temperature requirements of different vegetable types [5,6]. For instance, high temperatures can accelerate development in thermophilic crops like tomatoes and cucumbers, potentially leading to shorter growing periods and reduced yields. Conversely, cool-season vegetables such as leafy greens and broccoli are vulnerable to heat stress, which disrupts essential physiological processes and ultimately impacts productivity. Irregular precipitation patterns, including both excessive moisture and drought, can adversely affect crop growth and quality [7]. Excessive moisture can lead to root diseases and poor crop quality, while drought can reduce seed germination and yield [8,9]. Understanding how these changing climatic conditions will affect vegetable production at a regional scale is crucial for developing effective adaptation strategies and ensuring food security [10,11].

While global climate models project an overall increase in annual precipitation by 2100, regional and temporal variations are anticipated. Specifically, regions like the Mediterranean, southern Africa, and parts of Australia and Central America may experience drier conditions, while increased precipitation is predicted near the equator, in the Indian subcontinent, and northern China [12]. Furthermore, many regions face the threat of more frequent and severe precipitation events interspersed with longer dry periods, highlighting the need for regionally adapted irrigation strategies [13]. Advanced irrigation scheduling systems and incorporating dynamic crop models, weather forecasts, and soil moisture data offer potential solutions for mitigating both water and heat stress [14–16].

The widening gap between agricultural water demand and natural water supply, driven by shifting precipitation patterns [3], can be assessed using climate water balance (CWB). This metric considers precipitation and air temperature in relation to evapotranspiration (ET). Crop-specific CWB calculations further incorporate the FAO56 Penman–Monteith reference ET (ET_0) and crop coefficients (Kc) that reflect the evolving water needs of different crop growth stages [17,18]. Critically, future irrigation requirements are influenced by both CWB fluctuations and the duration of these temperature-dependent Kc-stages [19]. Previous studies underscore the significant impact of climate change on CWB variables, particularly precipitation, air temperature, and evapotranspiration. These findings emphasize the importance of locally calibrated models, integrating ET_0 calculations, for accurately simulating crop responses and informing effective irrigation strategies in diverse horticultural settings [20–22].

Accurate estimation of evapotranspiration is crucial for determining crop water requirements and optimizing irrigation management. Inaccurate ET estimations can lead to inefficient water use, reduced yields, and heightened vulnerability to climate change impacts [23,24].

Advanced modeling techniques, particular hybrid models integrating mechanistic and machine learning approaches, offer improved accuracy and robustness in ET prediction. These models leverage diverse data sources, such as remote sensing and meteorological data, and employ sophisticated algorithms to enhance predictive capabilities. For instance, the ANFIS–FA model, a hybrid approach, has demonstrated superior performance compared to standalone models in ET_0 estimation [25,26]. While these advanced models hold significant promise for informing irrigation strategies and crop selection under changing climate conditions, their computational demands and data requirements may pose challenges for widespread adoption, particularly in resource-limited horticultural settings [27].

Temperature fluctuations directly influence crop development, as numerous plant physiological processes are temperature-dependent [10]. This sensitivity to temperature varies throughout a plant's life cycle, with certain phenological stages triggered only after exposure to a minimum accumulation of heat, quantified as growing degree days above a specific base temperature, known as temperature sum (T_{Sum}) [28]. This temperature-driven annual cycle of plant growth, known as the thermal growing season, is projected to shift under climate change, altering the timing of key phenological events [29]. Adjusting sowing or planting dates, a key element of crop management, offers a potential strategy for adapting to these [30]. For instance, earlier cultivation starts, coupled with potentially shorter growing seasons, could capitalize on redistributed precipitation patterns, enhancing water availability during critical germination and early growth [28]. However, any shift in cultivation timing requires careful consideration of crop-specific thermal requirements for germination and growth. Simulating the potential range of changes in thermal growing seasons, crop development, and water demand under various climate and cultivation scenarios can inform the development of more resilient irrigation strategies, particularly in the face of increased risks of dry periods [15]. This study proposes a temperature-sum-based approach, offering a robust and straightforward method for predicting crop phenological development and water needs across diverse climate scenarios, effectively balancing accuracy with simplicity and accessibility.

This research aims to evaluate the impact of climate change on the vulnerability of open-field vegetable crops in temperate climates. To achieve this, we utilize a modeling framework that integrates dynamic and statistical models at both global and regional scales. Our analysis focuses on two contrasting greenhouse gas emission (GHG) scenarios: Representative Concentration Pathways (RCPs) 2.6 and 8.5, representing a range of potential future climate conditions. We employ two distinct regional climate models, the COnsortium for Small-scale MOdeling (COSMO)—Climate Limited-area Modeling Community (abbreviated as C-CLM) and the WEtterlagen-basierte REGionalisierungsmethode (abbreviated as WR13), both driven by the global climate model MPIESM-LR (Max Planck Institute Earth System Model—Low Resolution). While both are driven by the same global model, they employ different modeling approaches, allowing for a more comprehensive assessment of potential climate change impacts. Plant-specific data are utilized to simulate the crop-specific development and water demand in response to climate parameters in a high temporal and spatial resolution. This approach allows us to (1) simulate future changes of climate parameters driving the crop responses and (2) identify temporal patterns of dry periods and assess their potential impact on crop water stress. Furthermore, we can (3) simulate the impacts of climate change on thermal growing seasons and phenological development, ultimately (4) exploring future CWB_C, irrigation water demands, and their temporal variability under different climate scenarios. Finally, to (5) evaluate the sensitivity of our model framework and highlight the importance of crop-specific responses to climate change, we compare the results for two contrasting vegetable crops: onion and bush bean, which differ significantly in their phenology, temperature, and water requirements.

2. Materials and Methods

2.1. Simulation Framework

2.1.1. Climate Models and Data

The RCP scenarios serve as the basis for simulating potential future climate conditions in our study. The RCPs describe different possible climate futures depending on the volume of greenhouse gas concentrations emitted and are consistent with certain socio-economic assumptions. The RCPs are labeled after a possible range of radiative forcing values in the year 2100—2.6, 4.5, 6.0, and 8.5 W/m^2, respectively [31]. We chose RCP 2.6 and 8.5, with the former being an 'optimistic' and the latter a 'pessimistic' pathway. The RCP 2.6 requires that carbon dioxide emissions begin to decline by 2020 and approach zero by 2100. In RCP 8.5, emissions continue to rise throughout the 21st century, and this represents the worst-case scenario for climate change [32].

Projections of possible future climate were derived from output data of two regional climate models: COSMO-CLM (C-CLM) and WETTREG 2013 (WR13). The C-CLM is a dynamical and WR13 an empirical statistical downscaling [33,34]. Both RCMs are driven by the global climate model (GCM) MPIESM-LR. The MPI-ESM couples the atmosphere, ocean, and land surface through the exchange of energy, momentum, water, and carbon dioxide [35]. Climate variables derived from simulation data output of the RCMs are simulated on a daily basis. The selection of C-CLM and WR13 was based on their complementary strengths in capturing regional climate dynamics. C-CLM, with its dynamical downscaling approach, is well-suited for simulating complex atmospheric processes and providing detailed spatial resolution, while WR13, through empirical statistical downscaling, efficiently captures local climate variability and extremes. This combination ensures a comprehensive assessment of potential climate impacts on crop cultivation. For this study, datasets were obtained from the ReKliEs-De project [36], specifically selecting grid points that cover the model area. In the ReKliEs-De project, regional climate projections for Germany were developed by systematically evaluating EURO-CORDEX simulations, supplemented with additional dynamic and statistical methods; model validation was conducted using high-resolution observational data, with results standardized for comparative analysis [36,37].

Precipitation-free periods refer to consecutive days without any measurable rainfall and are used as an indicator to highlight the frequency and duration of dry spells, and therefore to assess potential irrigation needs. While precipitation-free periods do not necessarily equate to agricultural drought, which is defined as insufficient soil moisture to meet crop needs, they can contribute to soil moisture deficits and stress on crops, particularly during critical growth stages [38].

2.1.2. Study Area and Model Crops

The Hessian Reed (49.55° to 49.95° latitude/8.15° to 8.75° longitude) is located in the south of the federal state Hesse, Germany and represents an important vegetable growing region. It is approximately 60 km long and 15 to 20 km wide and covers an area of ca. 110,000 ha. The annual average of precipitation is about 600 mm and of temperature 10 °C. The region is characterized by predominantly sandy soils.

Approximately 5100 ha of the Hessian Reed are dedicated to vegetable production, with onions (*Allium cepa* L.) and bush beans (*Phaseolus vulgaris* L.) being the most significant crops by area, reflecting their economic importance and widespread cultivation in local agricultural practices. Onion is used as the model crop for estimating the impact of climate change on growth and water demand, while bush bean—a thermophilic plant—provides data to assess how various crops respond to climate change. Agro-meteorologically, the crops differ in temperature requirements and frost sensitivity. Onions are adapted to a wide range of temperatures and are frost-tolerant. Leaf, root, and bulb development occurs in cool temperatures between 10 and 20 °C with a growth threshold of 15 °C. Optimal leaf growth of onion occurs at 20 to 25 °C. Once bulbing has begun, onion easily tolerates temperatures higher than 25 °C [39]. For onions, a T_{max} of 35 °C was chosen, as growth rates decline significantly above 30 °C and can be detrimental beyond 35 °C [40]. The progression of these developmental stages can be predicted by calculating the T_{Sum} (in °Cd), which is the accumulated temperature above a base level at which growth occurs over a period of time. As bush beans do not tolerate cold temperatures, sowing should be done not before the end of frost risk. Optimum soil temperature for germination ranges between 21 and 32 °C. A mean air temperature (T_{mean}) of 20 to 25 °C is optimal for overall growth and yield, with a threshold of at least 12 °C for germination. Temperatures below 10 °C during the flowering period may affect fertilization or result in small and misshapen pods [41]. For bush beans, a T_{max} of 30 °C was used, since optimal growth conditions range between 20 and 25 °C, with growth inhibition occurring above 30 °C. Furthermore, bush bean is characterized by shorter growth duration and less water demand (69 mm) compared to onion (194 mm) [42].

Currently, 95% of the agricultural land is irrigated, covering around 30,000 ha and requiring an average of 18 million m^3 of water annually. Most irrigation water is sourced from groundwater. Onions represent 14% of the irrigated area in the Hessian Reed [43]. The irrigation season extends from late March to early October. Due to insufficient regional precipitation, an average annual irrigation of 70 mm is necessary, leading to increasing demands on irrigated areas and water supply [44].

2.2. Thermal Growing Season

Thermal growing season is defined as the part of the year during which temperatures are consistently high enough for horticultural activity [45]. The length of thermal growing season accounts for the number of frost-free days between the first day with average temperatures above 5 °C and the first day with temperatures below 5 °C, in which temperature-driven growth processes occur. The beginning (Equation (1)) and the end (Equation (2)) of the thermal growing season within a calendar year were simulated as follows:

Start of thermal growing season
$$\sum_i (Ti - 5\,^\circ\mathrm{C}) > 0\,^\circ\mathrm{C}\ (i = 2,\ 3,\ \ldots,\ 30) \tag{1}$$

End of thermal growing season
$$\sum_i (Ti - 5\,^\circ\mathrm{C}) < 0\,^\circ\mathrm{C}\ (i = 2,\ 3,\ \ldots, \text{end of year}) \tag{2}$$

Both the start and end of the thermal growing season of each year within the corresponding 30-year periods 1971–2000 (reference), 2031–2060, and 2071–2100 were simulated.

2.3. Determination of Sowing Dates and Crop Phenological Growth Stages

To assess the impact of climate change on sowing dates and the duration of crop phenological growth stages, we compared two cultivation scenarios based on different sowing dates (SD). In the first scenario, termed 'standardized SD', traditional sowing dates from the reference period were used: 15 March for onion and 15 May for bush bean. In the second scenario, 'thermal SD', sowing dates were determined by the first day within the simulated thermal growing season when the specific thermal threshold was exceeded. For onion, this threshold was set at 5 °C, while for bush beans it was 12 °C. These thresholds were calculated using Equations (3) and (4), which identify the day of year (DOY) when these temperature conditions are met. Additionally, to ensure plant growth without frost damage, a frost-free period of up to 30 days was required following the thermal threshold exceedance.

$$\text{Sowing date of onion} \quad \mathrm{n}\ (\mathrm{DOY_i} = (\mathrm{T_i} \geq 5\ ^\circ\mathrm{C}))\ \text{with n = 1 and i} = (1, 2, 3, \ldots) \tag{3}$$

$$\text{Sowing date of bush bean} \quad \mathrm{n}\ (\mathrm{DOY_i} = (\mathrm{T_i} \geq 12\ ^\circ\mathrm{C}))\ \text{with n = 1 and i} = (1, 2, 3, \ldots) \tag{4}$$

We employed a T_{Sum} approach to determine the onset, duration, and end of phenological growth stages. This method calculates growing degree-days and pauses T_{Sum} accumulation when daily temperatures exceed predetermined T_{max} or fall below T_{min} values, resuming only when temperatures return within these thresholds. This ensures accurate modeling of phenological stages under varying climate conditions. The T_{Sum} thresholds for each growth stage were derived from 12 years of phenological and meteorological data from open-field trials in Geisenheim, Hesse, Germany (49°59′ N, 7°58′ E). These data provide information on sowing and harvest dates, individual phenological stages, and daily weather conditions. The FAO 56 approach [17] was used to categorize crop development into four main stages: initial, development, mid-season, and late season. For onions, the stages are as follows: (i) sowing (bare ground); (ii) initial stage (after emergence); (iii) development stage (until ≥five leaves); (iv) mid-season stage (until ≥eight leaves); and (v) late-season stage (bending leaves). Bush bean is described by the following five stages: (i) sowing (bare ground); (ii) initial stage (after emergence); (iii) development stage (after flowering); (iv) mid-season stage (pod development); and (v) late-season stage (full-length pods). T_{Sum} calculations started at sowing date and continued throughout the thermal growing season until harvest. The average T_{Sum} for each phenological stage was calculated over multiple trials to establish mean threshold values for progression to subsequent stages. These values formed the basis for simulating future cultivation periods and predicting growth stage durations for both model crops under 'standardized SD' and 'thermal SD' scenarios. The simulations utilized the model framework described in Section 2.1.1, which outlines the climate models and data used in this study.

2.4. Computing Reference Evapotranspiration, Crop-Specific Evapotranspiration, and Crop-Specific Climate Water Balance

Daily reference evapotranspiration (ET_0) is calculated with daily means of climate variables from RCMs output by using FAO-56-modified Penman–Monteith equation. For crop-specific evapotranspiration (ET_C), ET_0 is adjusted by a the 'single-crop coefficient approach' that expresses both plant transpiration and soil evaporation combined into a single Kc [17]. The ET_C over the growing period was calculated (Equation (5)) by gradually adjusting Kc according to the simulated phenological stage.

$$ET_C = ET_0 K_c \tag{5}$$

The balance of the calculated ET_C with simulated precipitation (P) in daily increments over cultivation period represents the crop-specific climate water balance (CWB_c) and is equivalent to crop water requirements (Equation (6)).

$$CWB_c = ET_C - P = ET_0 K_c - P \tag{6}$$

Each phenological stage and the corresponding K_c value are assigned to a specific rooted soil depth, based on [46], to allow the calculation of irrigation thresholds for each plant growth stage (Table 1).

Table 1. Crop coefficients (Kc) of the FAO 56 guidelines as a function of temperature sum (°Cd) for the phenological stages of onion and bush bean based on BBCH code with corresponding root zone.

Phenological Stage	Bush Bean			Onion			Root Zone
	Kc Stage						
Stage 0	after sowing (bare ground) 0.15						0–30 cm
Stage 1	initial (after emergence)	0.4	171 °Cd	initial (after emergence)	0.7	269 °Cd	
Stage 2	development (after flowering)	0.65	816 °Cd	development (≥five leaves)	0.85	1036 °Cd	0–60 cm
Stage 3	mid-season (pod development)	1.05	985 °Cd	mid-season (≥eight leaves)	1.05	1475 °Cd	
Stage 4	late season (full-length pods)	0.9	1210 °Cd	late season (bending leaves)	0.75	1909 °Cd	0–90 cm

2.5. Statistical Analysis

Statistical analysis of temporal climate trends and crop-specific climate water balance trends was conducted using analysis of variance (ANOVA) in the Comprehensive R Archive Network (CRAN) [47], facilitated by the user interface RStudio [48]. The Shapiro–Wilk test was used for normality, and Levene's test assessed homogeneity of variances. For non-parametric data, the Kruskal–Wallis test was employed instead of ANOVA. Additionally, we utilized the ggplot2 package [49] to generate visualizations, including plots and heatmaps.

3. Results

3.1. Temperature, Precipitation, and Dry Periods

Mean air temperature (ΔT_{mean}) is simulated to increase across most months, with a slight decrease observed in May under the C-CLM-RCP 2.6 scenario for the period 2071–2100 (Figure 1). Under C-CLM-RCP 2.6, winter months exhibit more pronounced warming compared to summer (Figure 1a). The model framework C-CLM-RCP 8.5 exhibits substantial temperature increases, particularly during summer months, reflecting a strong response to higher emissions (Figure 1b). Temperature increases by up to 1.5 °C under RCP 2.6 and 4.5 °C under RCP 8.5, indicating considerable differences between emission scenarios rather than between regional climate models. The combination WR13-RCP 2.6 shows consistent warming with less pronounced seasonal variation. Under WR13-RCP 8.5, significant warming is simulated across all months, with peaks observed in late summer and early autumn, respectively. The range of temperature changes spans from 0.4 °C to 2.3 °C for 2031–2060 and −0.1 °C to 4.5 °C for 2071–2100, reflecting substantial variability across both time periods and model framework. Overall, the data reveal a clear trend of increasing temperatures over time, with the most significant changes occurring under higher-emission scenarios and with evident seasonal variations.

Changes in monthly precipitation (ΔP_{sum}) in 2031–2060 and 2071–2100 compared to the reference period of 1971–2000 have been projected (Figure 2). Under C-CLM-RCP 2.6, there is a slight increase in summer precipitation, while winter and spring months tend to be drier. The model combination C-CLM-RCP 8.5 shows the most significant decrease in precipitation, particularly in September, with reductions up to 29 mm. Simulations with WR13-RCP 2.6 indicate minimal differences across the three time periods, suggesting stable precipitation patterns. In contrast, WR13-RCP 8.5 demonstrates a redistribution of precipitation towards winter months, with increases up to 8.5 mm from October to December. Overall, for the three periods, the data reveal variability in precipitation trends across both RCPs and RCMs: the range of ΔP_{sum} differs between WR13 and C-CLM models, independent of the RCP used, with WR13 showing a broader range of changes compared to C-CLM.

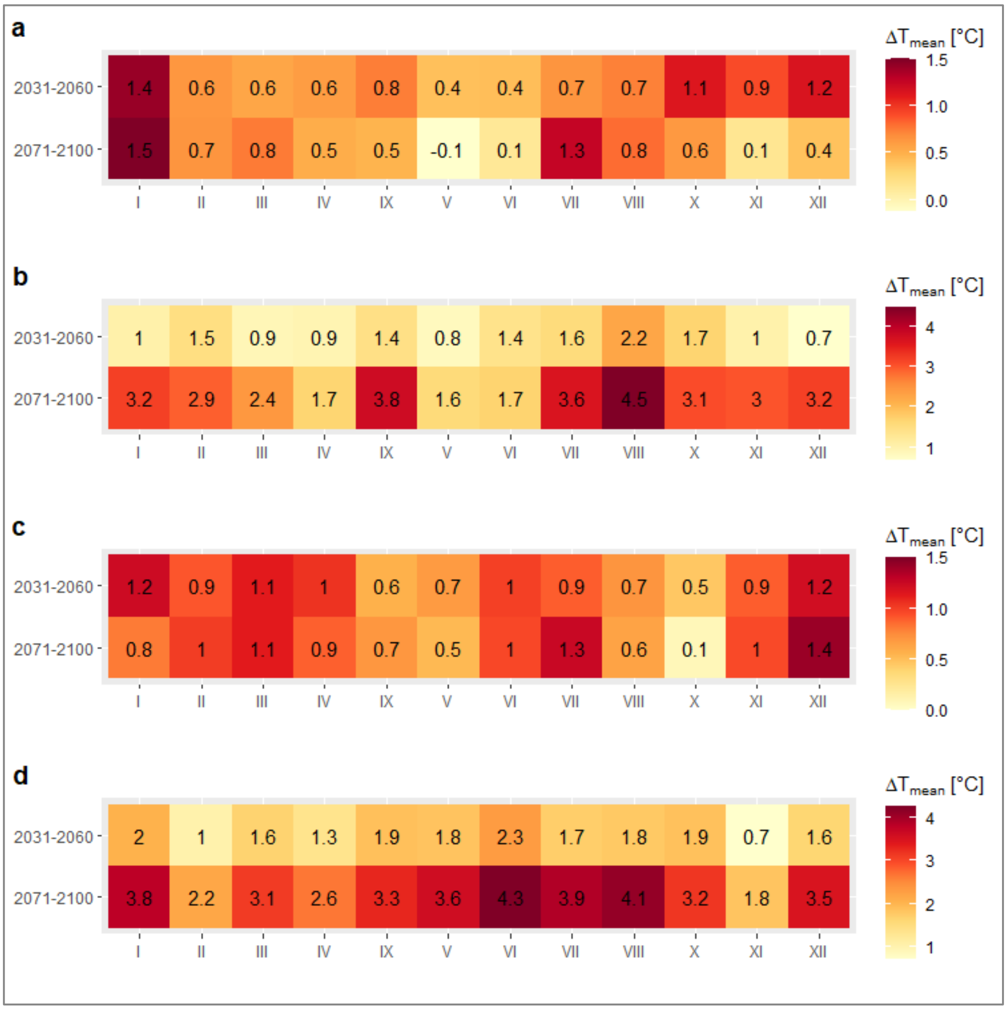

Figure 1. Predicted difference of monthly (I to XII) air temperature (ΔT_{mean}) in the 30-year time periods 2031–2060 and 2071–2100 compared to 1971–2000 in the model region, simulated with (**a**) C-CLM-RCP 2.6, (**b**) C-CLM-RCP 8.5, (**c**) WR13-RCP 2.6, and (**d**) WR13-RCP 8.5.

Changes in the frequency of precipitation-free periods, categorized into 5-day intervals, are simulated for the two future periods compared to a reference period across different RCP/RCM model combinations (Figure 3). For C-CLM under RCP 2.6, there is a decrease in shorter dry periods (1 to 10 days) with a notable reduction of 18 occurrences for the 1- to 5-day category by 2071–2100. For longer dry periods (26 to 30 days), little change is simulated. Under WR13 and RCP 2.6, similar patterns are observed, with a decrease in shorter periods and minimal change in longer ones. For C-CLM under RCP 8.5, there is a significant decrease in shorter dry periods, particularly a reduction of 116 occurrences for the 1- to 5-day category by 2071–2100. For longer dry periods (26 to 30 days), however, an increase is calculated by up to 31 occurrences. WR13 under RCP 8.5 shows a similar trend, with a decrease in shorter periods and an increase in longer ones by up to 35 occurrences. Especially under the scenario of higher emissions, shorter dry periods become less frequent and longer dry periods more frequent. In contrast, longer precipitation-free periods (26 to 30 days) do not occur significantly more frequently compared to the reference, contrary to initial expectations. This suggests that precipitation-free intervals will become longer in future climate scenarios.

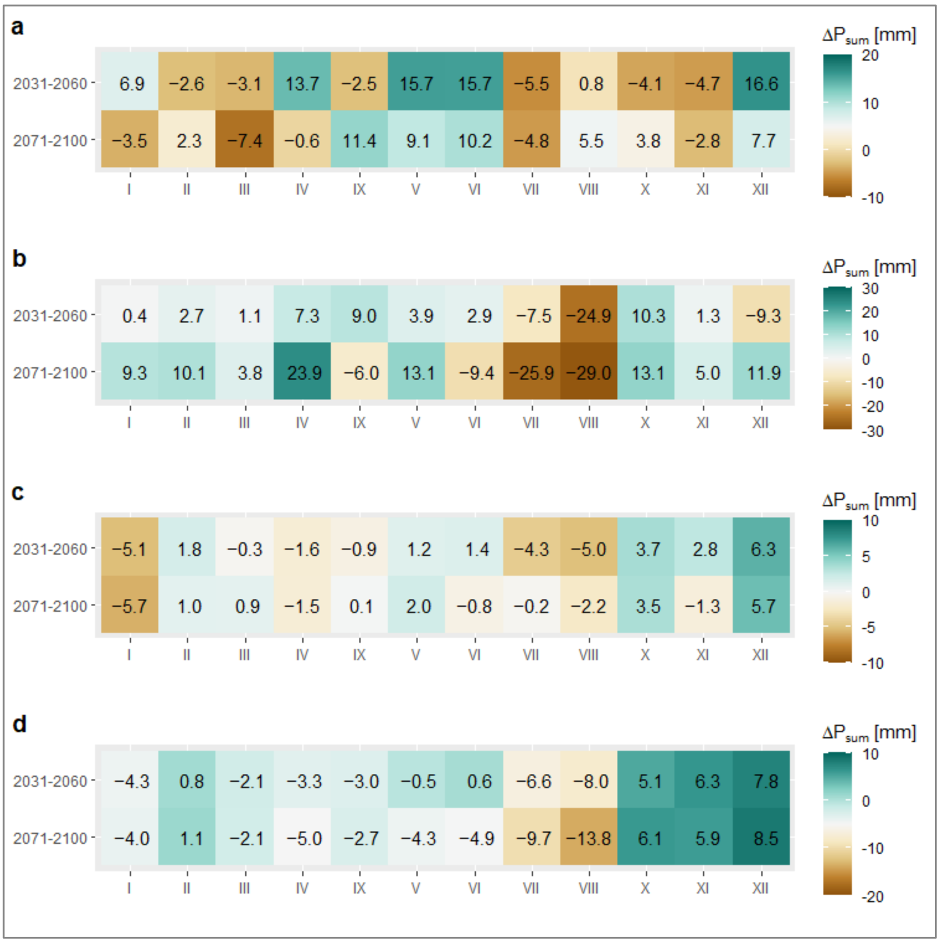

Figure 2. Predicted difference of monthly (I to XII) precipitation sum (ΔP_{sum}) in the 30-year time periods 2031–2060 and 2071–2100 compared to 1971–2000 in the model region, simulated with (**a**) C-CLM-RCP 2.6, (**b**) C-CLM-RCP 8.5, (**c**) C-WR13-RCP 2.6, and (**d**) WR13-RCP 8.5.

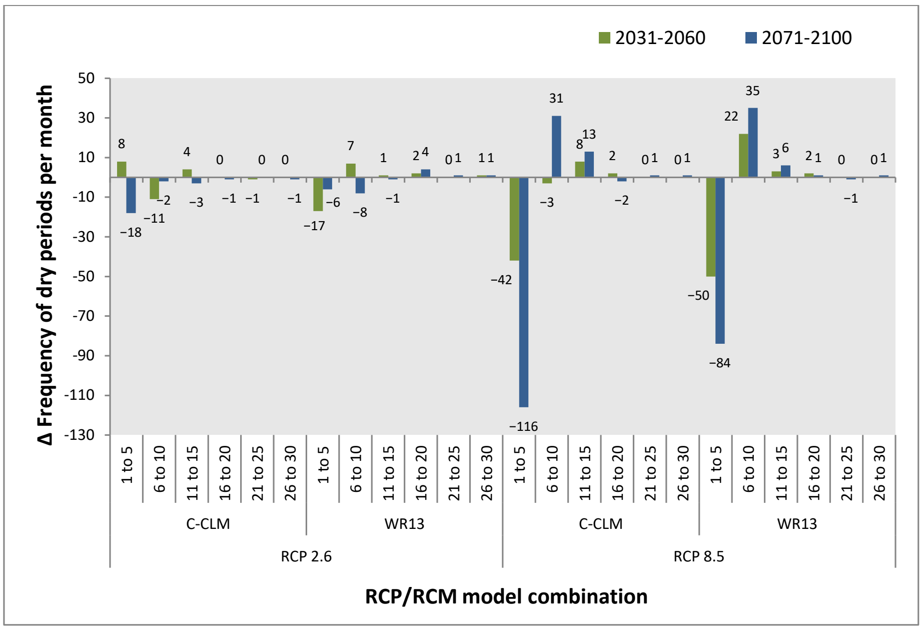

Figure 3. Predicted differences in the frequency of dry periods per month (in days) for the 30-year periods 2031–2060 and 2071–2100 compared to the reference period during growing season from March until October in the model region. Periods are grouped in 5d-classes.

3.2. Thermal Growing Season

Higher T_{mean} during the thermal growing season may accelerate plant development, while temperature above the threshold, particularly during spring and winter months (Figure 1), may induce both earlier onset and delayed end of plant growth. The latter alters the duration of thermal growing seasons. Simulations of thermal growing seasons, using Equations (1) and (2) (Section 2.2), result in longer thermal growing seasons in 2031–2060 and 2071–2100 compared to 1971–2000 for all RCPs and RCMs, respectively. This is attributed to an earlier start and later end of the thermal growing season.

Using RCP 2.6, the thermal growing season lasts longer compared to the reference period, with 18 d (C-CLM) to 21 d (WR13) in 2031–2060 and 11 d (C-CLM) to 27 d (WR13) in 2071–2100. With RCP 8.5, the thermal growing season is prolonged by 22 d (C-CLM) to 26 d (WR13) in 2031–2060 and by 60 d (WR13) to 68 d (C-CLM) in 2071–2100. Overall, the largest differences are observed between the RCPs in the period 2071–2100 (Table 2).

Table 2. Predicted changes in start, end, and length of thermal growing seasons in days in the 30-year periods 2031–2060 and 2071–2100 compared to 1971–2000 for the four climate model combinations.

GHG Emission Scenario	Regional Climate Model	Period 2031–2060			Period 2071–2100		
		Δ Start	Δ End	Δ Length	Δ Start	Δ End	Δ Length
RCP 2.6	C-CLM	−9	9	18	−9	2	11
	WR13	−12	9	21	−14	13	27
RCP 8.5	C-CLM	−12	10	22	−37	31	68
	WR13	−16	10	26	−32	28	60

3.3. Plant Phenological Development Stages

The duration of onion phenological stages (Figure 4) reveals distinct impacts of the climate signal of the C-CLM and WR13 models under both RCP scenarios when comparing the periods 2031–2060 and 2071–2100 with the reference period. The duration of all stages is slightly shorter under RCP 2.6 (Figure 4a). The C-CLM model simulates a decrease in the initial stage from 36 to 32 days, with similar trends observed in subsequent stages. The WR13 model follows this pattern, with reductions from 31 to 28 days. More pronounced changes in the phenological characteristics occur with the C-CLM model under RCP 8.5: the initial stage remains stable, while later stages become significantly longer (Figure 4b). The WR13 model shows an increase from 41 to 48 days for the initial stage and similar extensions for subsequent stages. These findings suggest that while the thermal growing season may generally extend, all phenological stages are influenced by temperature dynamics, albeit to different extents. This can be explained by the fact that it takes longer for temperatures to accumulate (T_{Sum}) sufficiently to reach the threshold for transition between stages, particularly in spring. The entire cultivation period is shortened to varying degrees: by 5 d (C-CLM) and 6 d (WR13) under RCP 2.6, and by 14 d (C-CLM) and 17 d (WR13) under RCP 8.5. Earlier start of cultivation may lead to prolonged phenological stages due to slower temperature accumulation in spring in the period 2071–2100.

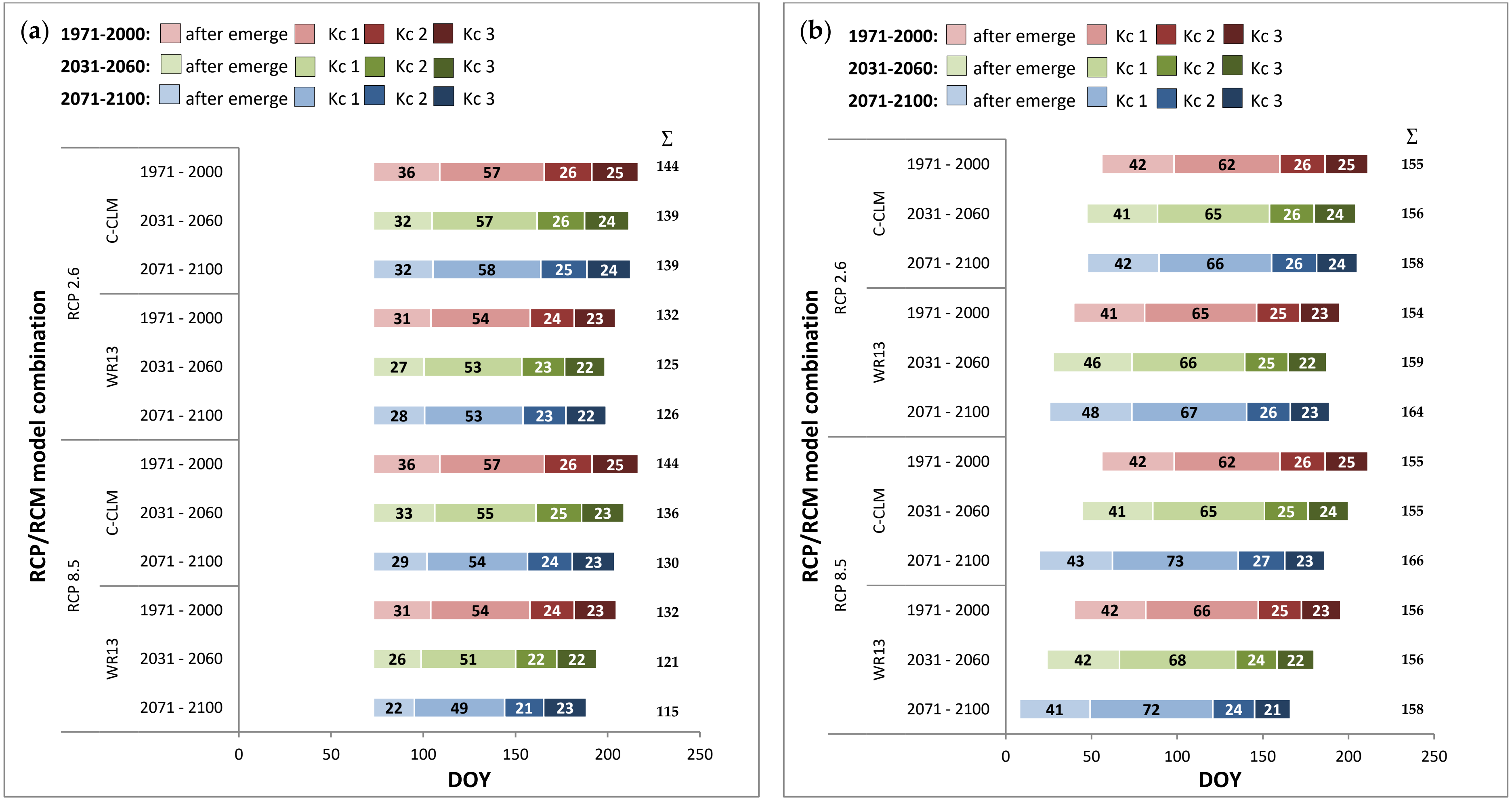

Figure 4. Predicted duration of cultivation period and length of single growing stages of onion (**a**) with standardized SD on 15 March and (**b**) varying thermal SD based on temperature sum in the 30-year periods 1971–2000, 2031–2060, and 2071–2100 for all climate model combinations, calculated in days of year.

3.4. Crop-Specific Water Demand

To explore the impact of climate change on crops' water demand, the crop-specific climate water balance is calculated taking the simulated impact on crop growth into account. By comparing simulation results of CWB_C between adjusted and non-adjusted cultivation period to 'thermal shift' of growing seasons, a common pattern of CWB_C development was observed irrespective of the simulation framework (Figure 5). Regardless of cultivation with or without thermal shift, the simulated CWB_C of onion differs significantly between the RCMs and RCPs. Under RCP 2.6 without thermal shift, the CWB_C using C-CLM is positive, whereas it is negative under WR13. Nevertheless, comparing ΔCWB_C in 2031–2060 and 2071–2100, C-CLM simulates an increasing water deficit, while WR13 simulates a decrease by 2100. Under RCP 8.5, both C-CLM and WR13 show an increasing water deficit due to more negative CWB_C from 2031–2600 until 2100. In detail, WR13 simulates negative CWB_C for all growth stages and C-CLM for all growth stages except stage 2 in the 30-year periods compared to reference.

The shift of sowing date results in ΔCWB_C moving into a more positive value range and increasing in future (Figure 5b), compared to cultivation without thermal shift (Figure 5a). Regardless of model and scenario, mainly the CWB_C of stage 3 becomes increasingly positive until 2071–2100, leading to an overall decrease in the future water deficit. The deficit of growing stages 1 and 2 decreases by 2071–2100, implying that the combination of higher spring precipitation (up to 7% on average), lower evapotranspiration due to lower spring temperatures, and the shift in the growing season by up to 37 days results in lower negative CWB_C and thus lower crop water deficit.

Adjusting the sowing date of onion to growth temperature requirements ('thermal SD') will result in less negative CWB_C in future. Overall, the shift in the cultivation period may lower water requirements compared to the standardized cultivation period. The model combination C-CLM-RCP 2.6 is an exception. Although the CWB_C values with thermal SD are more positive than with standardized SD, shifting the cultivation period does not prevent an increasing deficit from 2031–2060 until 2100 compared with the reference.

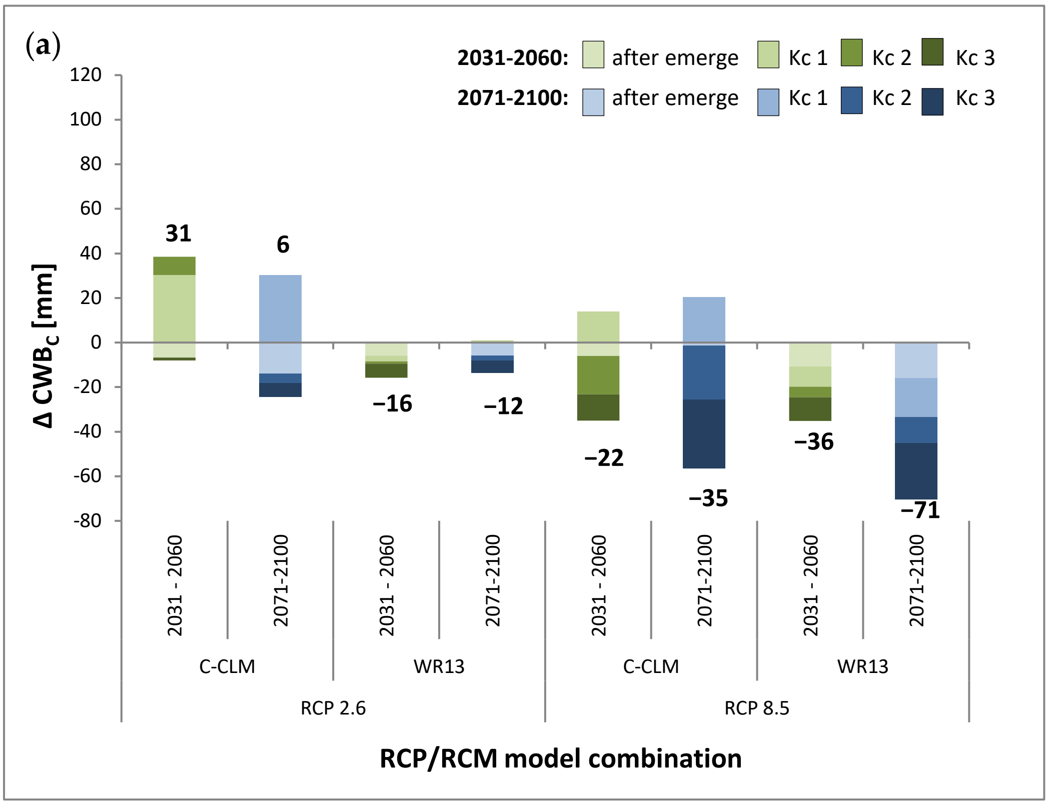

Figure 5. *Cont.*

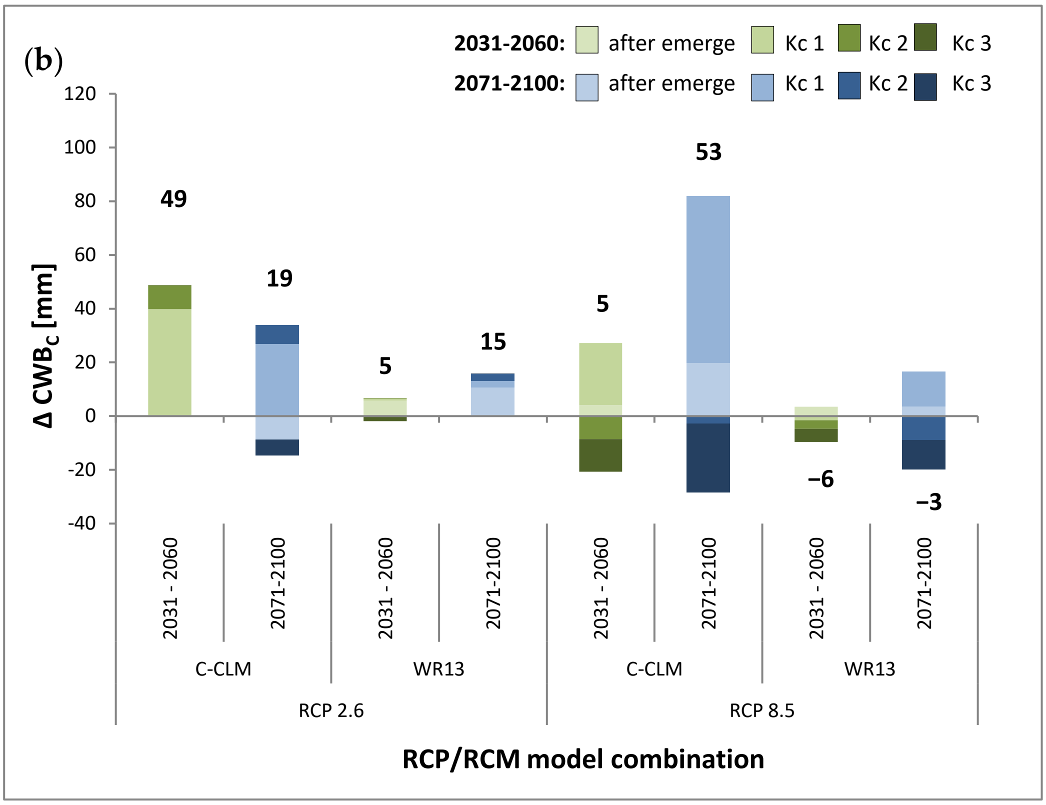

Figure 5. Predicted changes in the specific climate water balance (ΔCWB_C) of onion for cultivation (**a**) with 'standardized SD' and (**b**) with 'thermal SD' in the 30-year periods 2031–2060 and 2071–2100 compared to reference 1971–2000 for the four climate model combinations, calculated in mm.

3.5. Model and Crop Importance for Climate Signal

To test the importance of the model framework against crop-specific responses to climate change projections, we compare our key findings for onion with simulations for bush bean, a species with plant traits and climatic requirements different to onion. Considering higher base temperature and frost sensitivity, we demonstrate whether and how a thermal shift in the growing season affects the phenology, growing conditions, and consequently irrigation demand of bush bean differently to onion. As a result of the future shift of the thermal growing season, the length of the cultivation period for bush bean is prolonged, but not to the same extent in percent as for onion until 2100 compared to the reference period, irrespective of the simulation framework (Figure 6). Differences in the extension of the growing season are more attributed to the regional climate model and GHG emission scenario than to the crop. With WR13, the extension of the growing period increases more compared to C-CLM. The RCPs show different extensions of the cultivation period in 2071–2100, which are due to higher temperatures under RCP 8.5.

In all model combinations across both future periods (Figure 7), the cultivation start of bush bean is later than that of onion. The climate signal associated with the more severe RCP 8.5 scenario has a more pronounced impact than that of the less severe RCP 2.6 scenario. The regional climate model exerts varying influences on the timing of cultivation start across different crops. For onion, all model combinations project an increasingly early start of cultivation. In contrast, no consistent pattern emerges among the four model combinations for bush bean. Consequently, while the magnitude of the change in day of year (ΔDOY) differs between the crops, the trend variations across the four model combinations are similar for both.

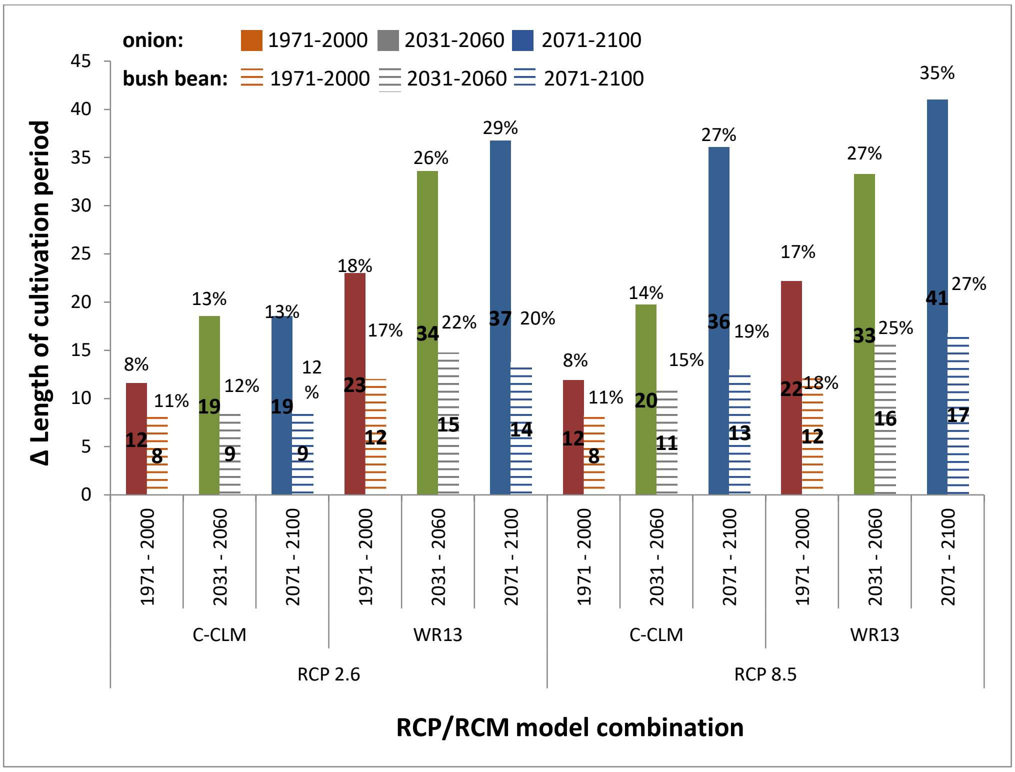

Figure 6. Predicted differences in length of cultivation period with 'standardized SD' and 'thermal SD' for onion (**bold colors**) and bush bean (**striped**) in the 30-year periods 1971–2000, 2031–2060, and 2071–2100 for all used climate model combinations, shown in days and percent (%).

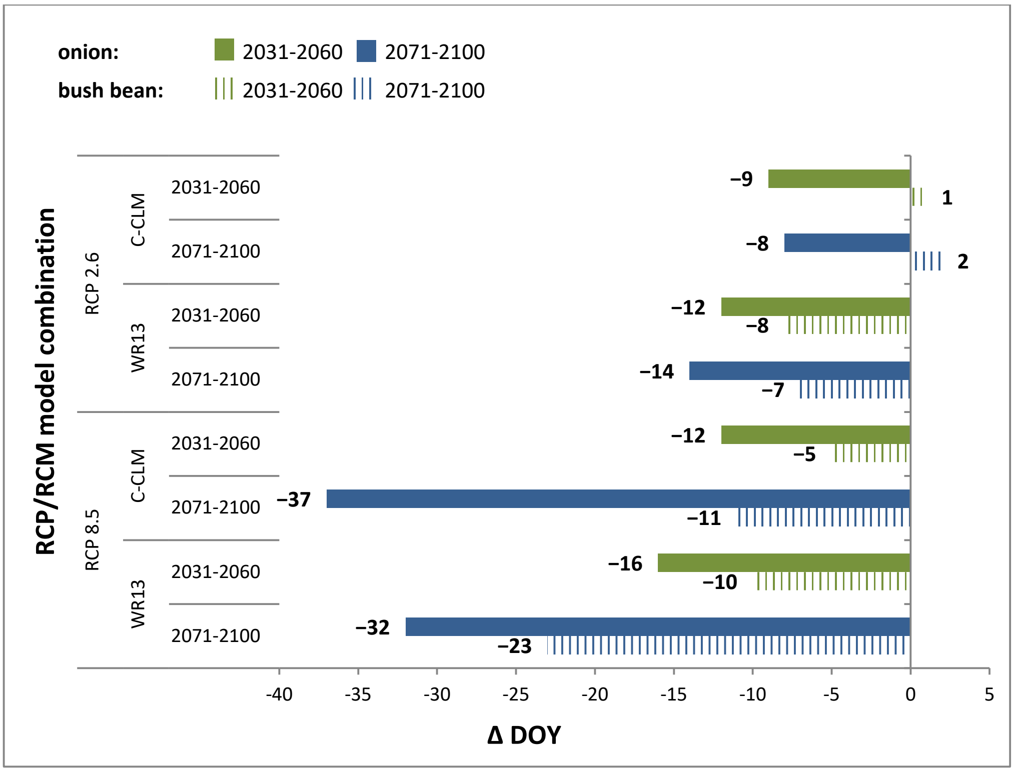

Figure 7. Predicted changes of the cultivation period for onion (**bold colors**) and bush bean (**striped**) using thermal SD in the 30-year periods 2031–2060 and 2071–2100 compared to 1971–2000 for all used climate model combinations, shown as differences in days of year (ΔDOY).

Crop-specific cultivation start and duration are expected to have effects on CWB_C. The climate signal affects the difference in CWB_C using standardized and thermal SD differently for onion and bush bean (Figure 8). For both crops, three of four model combinations simulate an increasing effect of the thermal shift on ΔCWB_C in future. The regional climate models simulate divergent trends for both crops with RCP 2.6. While WR13 shows insignificant change in ΔCWB_C for bush bean, exclusively this model simulates an increase of ΔCWB_C for onion. For both crops, the climate signal of RCP8.5 becomes more apparent with C-CLM than with WR13. Since the effect of the thermal shift on CWB_C is calculated as difference in CWB_C with standardized and thermal SD, these values cannot be interpreted as potential saving of irrigation water demand (Figure 8).

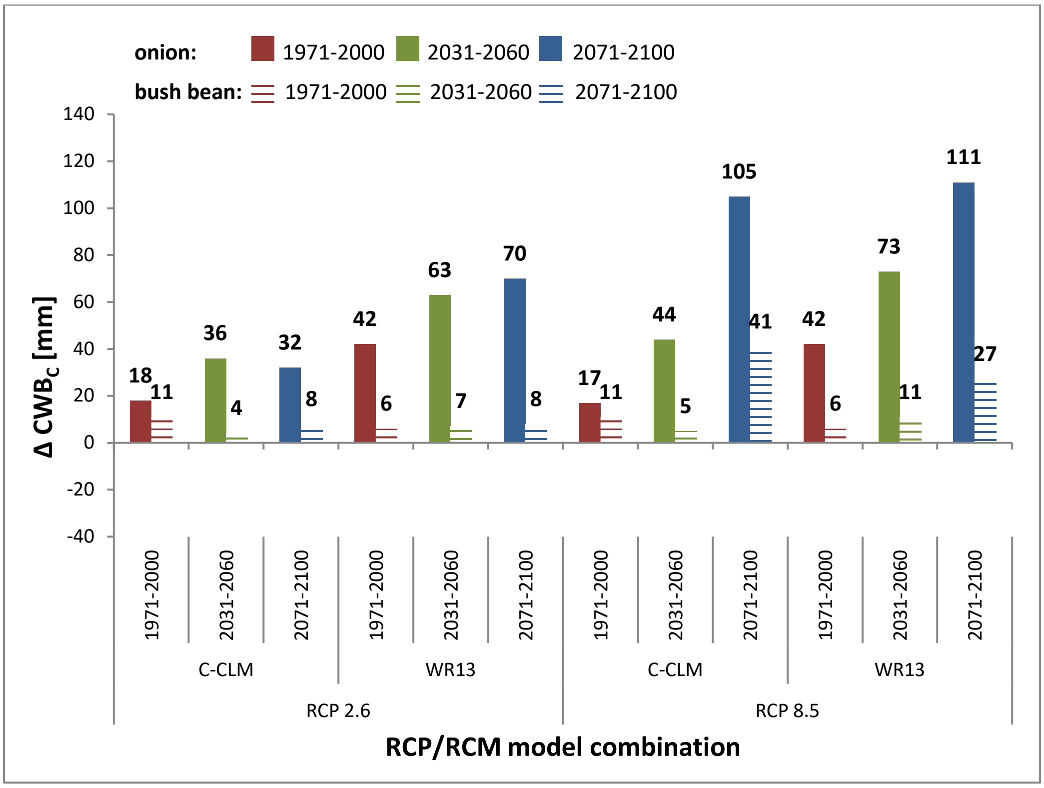

Figure 8. Predicted changes of specific climate water balance (ΔCWB_C) of onion (**bold colors**) and bush bean (**striped**) between standardized and thermal SD in the 30-year periods 1971–2000, 2031–2060, and 2071–2100 for all used climate model combinations, calculated in mm.

The comparison of simulated trends between bush bean and onion across the model ensemble for the three characteristics i. length of cultivation period, ii. start of cultivation period, and iii. climate water balance illustrates that the crop-specific response determines the extent of the simulated climate change impact. Crop-specific differences are due to either frost sensitivity, which is taken into account in the simulation of growing seasons, or temperature requirement of individual phenological stages and thus duration of the crop. As a result, a much wider range of climate-induced temporal adjustment emerges for onion than for bush bean under identical climate signal. This has implications for the crop's resource requirements. Irrigation demand, derived from CWB_C under the thermal shift scenario, is reduced for crops with high earliness potential in the future.

The impact of regional climate models on the change in crop water balance components reveals significant differences beyond the crop-specific responses. The WR13 model indicates a reduction in water demand for onions, but this trend is not observed for bush beans, which show increased demand. Similarly, the C-CLM model predicts increased water demand for both onions and bush beans in future scenarios. This indicates that RCM outcomes are highly dependent on the spatial and temporal characteristics of crop development. Additionally, greenhouse gas emission scenarios do not alter the conclusions for either crops or RCMs due to the uniformly simulated temperature increases.

4. Discussion

This study reveals that impacts of climate change on future crop conditions can be attributed to crop phenology and the selected climate model combination by small-scale modeling with empirical phenological data at high temporal resolution. Temperature-driven duration and onset of Kc-stages vary individually for phenological stages and influence the irrigation demand depending on the simulated cultivation date within the thermal season of onion and bush bean under future Central European conditions.

A significant temperature increase is simulated for the model region, consistent with various studies and climate models. According to the Coupled Model Intercomparison Project Phase 6, a collaborative framework coordinated by the World Climate Research Programme, which uses Shared Socioeconomic Pathways (SSPs) based on the IPCC Sixth Assessment Report [50], land temperatures in Europe are expected to rise further by 1.2 to 3.4 °C under the SSP1–2.6 scenario and by 4.1 to 8.5 °C under the SSP5–8.5 scenario [51]. Recent studies with SSP scenarios affirm an increase in extreme heat across Western Europe, surpassing model predictions and indicating a likely rise in heat waves [52,53]. Our model region shows distinct meteorological patterns across various projected scenarios, particularly for seasonal dynamics of temperature variations, with a consistent trend of overall T_{mean} increases for most months, except May. Winter temperatures are expected to rise more significantly than summer temperatures, especially highlighted in the C-CLM-RCP 2.6 combination. Despite varying regional climate models, all simulate similar temperature trends, though greenhouse gas emission scenarios significantly affect the magnitude of projections, emphasizing the importance of emission pathways.

Significant variations in future precipitation patterns are also identified. All models simulate increased precipitation in spring and winter, with drier summer conditions for our study area. Global projections show that areas in the northern hemisphere may experience more winter and spring precipitation, while areas in the southern hemisphere may become drier [54]. Such shifts may lead to more frequent and longer dry periods during growing seasons, significantly impacting crop cultivation. Dry periods reduce soil moisture [55] and can cause plant drought stress, which inhibits crop growth and lowers yield. Coupling drought stress with elevated temperature may intensify the stress level, particularly during critical growth stages like the reproductive phase, causing significant yield declines as observed in several crops [7,56].

The anticipated rise in precipitation variability and dry periods potentially increases the vulnerability of onion production in the Hessian Reed, due to higher requirements for water supply, leading to a higher and more variable demand for irrigation water in the future. This vulnerability is already evident in the current irrigation demand of 228 mm (for sandy soil) in the period 1991 to 2020, which has risen by 53 mm compared to 1961 to 1990 [42]. This requires both an optimized as well as enlarged irrigation infrastructure to accommodate these changes [57–60]. Groundwater is the primary source of irrigation in the Hessian Reed, but increasingly limited. In this region, groundwater levels have declined by an average of 0.5–1 m over the past two decades, with some areas experiencing declines of up to 2 m [61]. Current groundwater extraction for irrigation is estimated at 20–25 million cubic meters annually, with projections suggesting that this could increase by 30–40% by 2050 under current climate change scenarios [44]. This increasing demand is likely to exceed local groundwater availability; similar trends of groundwater depletion due to extensive agricultural use have been observed globally [62–64]. While enhanced winter precipitation could recharge aquifers adequately, intensified agricultural irrigation combined with more arid conditions may cause groundwater withdrawal surpassing natural replenishment rates. This imbalance could result in further decreases in groundwater reserves or significant fluctuations in groundwater levels [44]. These scenarios do not yet fully account for future variations in cultivation periods and practices, which could further impact water demand

and availability. Maximum irrigation requirements during peak dry periods may reach up to 40–50 mm per week for onions, placing higher demands on irrigation technology regarding efficiency, frequency, and simultaneity, while also highlighting the importance of inter-farm water management considerations to ensure equitable distribution of limited resources during these critical periods [65]. Research on onion irrigation has demonstrated significant differences in water use efficiency and crop yield between various irrigation techniques. Drip irrigation reduced water consumption by up to 45% compared to furrow irrigation while maintaining or even improving yield [65]. Sprinkler irrigation systems can lead to 20–30% water losses due to evaporation and wind drift in onion fields despite their widespread use, emphasizing the need for more efficient irrigation methods [66]. Drip irrigation is considered more beneficial for onion production due to better water distribution uniformity, reduced evaporation losses, and deep percolation despite requiring higher management levels [67]. It provides precise water distribution directly to the root zone, particularly beneficial for onions with shallow root systems sensitive to water stress, and can increase water use efficiency by up to 90%, compared to less than 50% for surface irrigation methods. Furthermore, it allows for more frequent and smaller irrigation applications ideal for maintaining consistent soil moisture levels crucial for onion bulb development and is able to meet future requirements for irrigation frequency [68]. While drip systems require higher initial investment and management, they can lead to improved onion yield and quality, making them a valuable consideration for addressing future irrigation challenges in the Hessian Reed.

Our study projects a significant extension of thermal growing seasons in various scenarios, driven by the Representative Concentration Pathway scenarios. Similar changes have been observed, with Central and northern Europe expected to experience prolonged growing seasons. Southern Europe faces more variable lengths, posing challenges despite potential extensions [69,70]. Unpredictability in growing season length can disrupt planting and harvesting schedules, affecting crop planning and yield predictability in southern Europe. While prolonged periods present opportunities and complexities for horticulture [29], increased heat stress and potential water scarcity may compromise these benefits [4]. Thus, impacts of warming scenarios vary across Europe, with northern Europe potentially benefiting from prolonged growing seasons, while southern Europe may suffer from intensified heat and drought [30,71]. Adapting to extended growing seasons will require farmers to modify crop varieties, adjust planting/sowing schedules, and improve irrigation practices. Some farmers have adapted by choosing tolerant varieties and altering planting/sowing dates [72,73]. Evolving strategies, such as breeding heat-resistant crop varieties and precision planting techniques [24,74], remain pivotal for sustaining productivity amidst shifting climate patterns.

Elevated temperatures enhance crop growth and development until they become stress-inducing. For onion, the phenological stages of bulb initiation, bulb development, and maturity are temperature-dependent [39,75]. Higher temperatures accelerate these stages, shortening the cultivation period, particularly under the RCP 8.5 emission scenario, which predicts significant temperature increases. Under the milder RCP 2.6 scenario, only bulb initiation is shortened. Earlier thermal growing seasons extend phenological stages' duration due to later attainment of the temperature baseline for growth, more pronounced under RCP 8.5, significantly shifting bulb initiation, development, and maturity timing. Adjustments in sowing dates may be necessary, potentially advancing by 8 to 37 days in 2071–2100. Aligning the cultivation period with crop-specific temperature requirements generally prolongs phenological stages due to later temperature threshold attainment, as future spring temperatures are expected to remain too low, delaying T_{Sum} attainment.

Shortening of specific phenological stages in onions could reduce associated water consumption but increase vulnerability to water shortages. Elevated temperatures, especially under the RCP 8.5 scenario, accelerate phenological stages such as bulb initiation, development, and maturity in onions. This acceleration is primarily due to temperature changes, which significantly influence crop coefficients by affecting plant physiological processes such as transpiration and photosynthesis in onions. As temperatures rise, the onion crop experiences increased transpiration rates, leading to higher daily water demand. Onion water demand increases gradually during leaf formation and bulb development, peaking at advanced bulb growth stages, especially in hot weather [76]. Stages like emergence, leaf formation, and bulb formation are particularly sensitive to water shortages [77,78]. Under RCP 2.6, the bulb formation stage, with the highest water consumption [76], is shortened, which could potentially reduce overall water demand despite weak climate signals. To address these challenges, future temperature effects on Kc-stage duration should be considered in irrigation scheduling for higher accuracy [17]. Irrigation scheduling according to the accelerated phenological phases with elevated water demand would result in more frequent irrigation recommendations and avoid drought stress. In addition, water amount of the irrigation events must be modified to meet the higher daily requirements resulting from increased evapotranspiration. Overall, these adjustments highlight the need for more frequent and higher irrigation events to support onion growth under changing climate conditions. Effective future water demand of onions will vary greatly depending on location, season, and the agro-climate [9,79]. This variability, coupled with predicted climate change impacts on water availability and precipitation-free periods, underscores the complexity of predicting future crop water demand and the importance of adaptive irrigation strategies in the face of climate change.

Projections of onion's crop water balance under both standardized sowing dates and adapted sowing dates ('thermal SD'), the latter accounting for the thermal shift in growing seasons, reveal significant impacts of model characteristics on water demand estimates [80–83]. The dynamic C-CLM model, which integrates detailed physical processes such as soil–water–plant–atmosphere interactions, photosynthesis, and energy balance, suggests possible decreases in water demand, resonating with the adaptive thermal SD strategy. This aligns with the hypothesis that climate change will exacerbate fluctuations in precipitation and water supply, impacting crop growth [22,84]. In contrast, the statistical WR13 model, extrapolating from historical data, simulates increased water deficits, particularly under thermal SD, highlighting potential challenges posed by climate change. These contrasting projections underscore the models' sensitivity to regional climatic variations and their intrinsic methodological differences [85,86]. Application of thermal SD shows promise in modifying the crop water balance positively [87], especially in the long term, as indicated by the more favorable projections for the period 2071–2100. Adjusting SD has already been observed in various onion-growing areas, where changing rainfall patterns have prompted farmers to postpone cultivation [76,79]. C-CLM's capacity for dynamic simulation may allow for better climate change adaptation, while WR13's dependency on historical data could constrain predictive power when past trends do not match future conditions. The outcomes of these simulations emphasize the importance of model selection in agricultural planning under the specter of climate change. The strengths and limitations of both dynamical and statistical models play a crucial role in shaping results, and the choice between them should be informed by the specific context of the system being modeled, available data, and research objectives. Both models offer important perspectives for horticultural decision-making in the context of climate change, but their respective strengths and limitations should be carefully weighed for informed application.

Our simulations reveal significant variations due to interaction between Regional Climate Model frameworks and Representative Concentration Pathway scenarios. While temperature projections show considerable discrepancies between RCM outputs across Europe, the precipitation patterns exhibit relatively consistent projections [88]. This divergence in variability can be attributed to several factors that each model simulates. Temperature projections can be more variable due to differences in how climate models simulate factors like greenhouse gas concentrations, solar radiation, and atmospheric and oceanic circulation patterns, which can particularly affect smaller-scale regions [89,90]. In contrast, precipitation patterns may show more consistency owing to their dependence on larger-scale factors like atmospheric moisture content and wind patterns, although there can still be notable differences in details at the regional or local level due to factors like convective processes and moisture transport [4,91,92]. The observed changes in temperature and precipitation patterns underscore the sensitivity of crop-specific responses to different climate models and greenhouse gas concentration pathways [93,94]. To address these uncertainties, the use of ensemble modeling approaches, which incorporate multiple models with diverse structures, can help capture a range of potential outcomes and provide a more comprehensive understanding of climate impacts [95].

Adapting irrigation strategies to climate change requires a nuanced understanding of regional climate variations and insights from regional climate models and Representative Concentration Pathways [76]. These models are instrumental in forecasting how climate change could alter temperature patterns and precipitation regimes at a regional level, affecting crop water requirements and irrigation needs [77]. Variability captured by different RCMs and RCPs underscores the complexity of predicting future agricultural water demand [76]. For instance, RCMs can project how regional climate shifts might extend or shorten crop growing seasons, influencing irrigation timing and amounts [77]. Similarly, the choice of RCPs, ranging from milder to more extreme changes, has distinct implications for water management and irrigation scheduling [76]. Integrating temperature-sum-based crop coefficients into irrigation management allows for dynamic adjustment in response to temperature-driven crop growth changes [23]. The effectiveness of such strategies is contingent upon the accuracy and resolution of RCM projections, highlighting the importance of selecting models that reflect specific regional climate dynamics [77]. This approach facilitates more precise and adaptive irrigation strategies, emphasizing the need for ongoing refinement as new climate data and model projections become available. Optimizing irrigation strategies, including advanced scheduling systems that integrate weather forecasts and soil moisture data, is essential for efficient water management [96,97]. The integration of climate models in irrigation scheduling or estimations of regional irrigation requirements enables agricultural stakeholders to develop adaptive strategies that enhance resilience against future climate conditions despite uncertainties.

We believe that our findings highlight the importance of inherent crop characteristics, particularly temperature thresholds in combination with regional climate variations and model framework choices, to determine the degree to which the cultivation period can be shifted under changing climate conditions. This shift can potentially help mitigate increased water demand. The cultivation start of thermophilic crops will generally be later than that of frost-tolerant crops due to higher base temperatures. However, frost-tolerant crops may experience a narrower range of climate-induced temporal adjustment compared to thermophilic crops, as they are already adapted to cooler conditions and may have less flexibility in their growing season. Regional climate variations play a significant role in this context. Changes in crop phenology, including the length and start of the cultivation period, are closely related to regional climate variability and change [98]. This implies that the potential for shifting the cultivation period will vary across different regions due to their distinct climate characteristics, offering opportunities to optimize water use by aligning crop growth with more favorable climate conditions. The model framework used plays a pivotal role in determining how regional temperatures are simulated, which can subsequently shift the timing of crop growth. It was found that the influence of Regional Climate Models (RCMs) and Representative Concentration Pathways (RCPs) on lengthening the cultivation period was more pronounced than the influence of the crop type itself. Despite these differences, the study confirms the broad applicability of the temperature-based cultivation period shifting approach to various crops. This suggests that while the extent of the shift may vary, the method can be applied broadly to account for the impacts of climate change on different crops.

These results emphasize the complexity of modeling climate change impacts and emphasize the crucial consideration of simulation inputs and underlying assumptions. The study underscores that while RCMs are valuable for regional-level insights into future climate conditions, their projections can significantly vary, especially for temperature, at smaller scales due to local influencing factors [99]. Despite these challenges, RCMs remain instrumental in informing adaptation strategies and understanding potential climate changes at the regional and local level [92,100].

5. Conclusions

Rising temperatures will affect crop phenology and water demand, leading to significant changes in agricultural practices. Our findings suggest that shorter cultivation periods and extended thermal growing seasons may allow for more crop cycles, but this also increases vulnerability to water scarcity and higher irrigation needs. The differing adaptation potentials among crops indicate potential shifts in crop distribution and selection. Farmers will need to adjust their strategies to optimize production under changing climate conditions. Regional climate variations will significantly influence these changes, highlighting the importance of localized adaptation strategies. Increased water demand due to higher evapotranspiration rates and more frequent droughts will require advancements in irrigation technologies and efficient water management practices. These consequences call for a transformative approach in agricultural research and policy, focusing on developing climate-resilient crop varieties and validating adaptation strategies across diverse contexts.

Author Contributions: Conceptualization, J.Z.; methodology, N.S.; validation, N.S.; formal analysis, N.S.; writing—original draft preparation, N.S.; writing—review and editing, J.Z and N.S.; visualization, N.S.; supervision, J.Z.; project administration, J.Z.; funding acquisition, J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Edmund Rehwinkel Foundation of the Landwirtschaftliche Rentenbank. We acknowledge support by the Open Access Publishing Fund of Geisenheim University.

Data Availability Statement: The data supporting the reported results are not publicly available. For further inquiries, please contact the corresponding author.

Conflicts of Interest: The authors declare no conflicts 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. Dawson, T.P.; Perryman, A.H.; Osborne, T.M. Modelling impacts of climate change on global food security. *Clim. Chang.* **2016**, *134*, 429–440. [CrossRef]
2. Lee, H.; Calvin, K.; Dasgupta, D.; Krinmer, G.; Mukherji, A.; Thorne, P.; Trisos, C.; Romero, J.; Aldunce, P.; Barret, K.; et al. *Synthesis Report of the IPCC Sixth Assessment Report (AR6), Longer Report. IPCC*; Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland, 2023.
3. Monteleone, B.; Borzí, I.; Bonaccorso, B.; Martina, M. Quantifying crop vulnerability to weather-related extreme events and climate change through vulnerability curves. *Nat. Hazards* **2023**, *116*, 2761–2796. [CrossRef]
4. Elias, E.H.; Flynn, R.; Idowu, O.J.; Reyes, J.; Sanogo, S.; Schutte, B.J.; Smith, R.; Steele, C.; Sutherland, C. Crop Vulnerability to Weather and Climate Risk: Analysis of Interacting Systems and Adaptation Efficacy for Sustainable Crop Production. *Sustainability* **2019**, *11*, 6619. [CrossRef]
5. Krug, H.; Liebig, H.-P.; Stützel, H. *Gemüseproduktion: Ein Lehr- und Nachschlagewerk für Studium und Praxis*; Verlag Eugen Ulmer: Stuttgart, Germany, 2003; ISBN 978-3800135844.
6. Zinkernagel, J.; Weinheimer, S.; Mayer, N. Wasserbedarf von Freilandgemüsekulturen. Available online: https://www.hortigate.de/bericht?nr=73862 (accessed on 26 September 2024).
7. Cohen, I.; Zandalinas, S.I.; Huck, C.; Fritschi, F.B.; Mittler, R. Meta-analysis of drought and heat stress combination impact on crop yield and yield components. *Physiol. Plant.* **2021**, *171*, 66–76. [CrossRef] [PubMed]
8. Kondinya, A.; Palash, S.; Pandit, M.K. Impact of Climate Change on Vegetable Cultivation—A Review. *Int. J. Agric. Environ. Biotechnol.* **2014**, *7*, 145. [CrossRef]
9. Schmidt, N.; Zinkernagel, J. Model and Growth Stage Based Variability of the Irrigation Demand of Onion Crops with Predicted Climate Change. *Water* **2017**, *9*, 693. [CrossRef]
10. Hatfield, J.L.; Prueger, J.H. Temperature extremes: Effect on plant growth and development. *Weather Clim. Extrem.* **2015**, *10*, 4–10. [CrossRef]
11. Oyebamiji, Y.O.; Abd Aziz Shamsudin, N.; Asmuni, M.I.; Yusop, M.R. Heat Stress in Vegetables: Impacts and Management Strategies—A Review. *Sains Malays.* **2023**, *52*, 1925–1938. [CrossRef]

12. IPCC. *Climate Change 2022—Impacts, Adaptation and Vulnerability*; Cambridge University Press: Cambridge, UK, 2023; ISBN 9781009325844.
13. Tabari, H. Climate change impact on flood and extreme precipitation increases with water availability. *Sci. Rep.* **2020**, *10*, 13768. [CrossRef]
14. Mirás-Avalos, J.; Rubio-Asensio, J.; Ramírez-Cuesta, J.; Maestre-Valero, J.; Intrigliolo, D. Irrigation-Advisor—A Decision Support System for Irrigation of Vegetable Crops. *Water* **2019**, *11*, 2245. [CrossRef]
15. Rosa, L. Adapting agriculture to climate change via sustainable irrigation: Biophysical potentials and feedbacks. *Environ. Res. Lett.* **2022**, *17*, 63008. [CrossRef]
16. Tian, X.; Dong, J.; Jin, S.; He, H.; Yin, H.; Chen, X. Climate change impacts on regional agricultural irrigation water use in semi-arid environments. *Agric. Water Manag.* **2023**, *281*, 108–239. [CrossRef]
17. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. Crop evapotranspiration guidelines for computing crop requirements. FAO Irrigation and Drainage. Report modeling and application. *J. Hydrol.* **1998**, *285*, 19–40.
18. Zinkernagel, J.; Maestre-Valero, J.F.; Seresti, S.Y.; Intrigliolo, D.S. New technologies and practical approaches to improve irrigation management of open field vegetable crops. *Agric. Water Manag.* **2020**, *242*, 106404. [CrossRef]
19. Le Page, M.; Fakir, Y.; Jarlan, L.; Boone, A.; Berjamy, B.; Khabba, S.; Zribi, M. Projection of irrigation water demand based on the simulation of synthetic crop coefficients and climate change. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 637–651. [CrossRef]
20. Conversa, G.; Bonasia, A.; Di Gioia, F.; Elia, A. A decision support system (GesCoN) for managing fertigation in vegetable crops. Part II-model calibration and validation under different environmental growing conditions on field grown tomato. *Front. Plant Sci.* **2015**, *6*, 495. [CrossRef]
21. Olberz, M.; Kahlen, K.; Zinkernagel, J. Assessing the Impact of Reference Evapotranspiration Models on Decision Support Systems for Irrigation. *Horticulturae* **2018**, *4*, 49. [CrossRef]
22. Potopová, V.; Trnka, M.; Vizina, A.; Semerádová, D.; Balek, J.; Chawdhery, M.; Musiolková, M.; Pavlík, P.; Možný, M.; Štěpánek, P.; et al. Projection of 21st century irrigation water requirements for sensitive agricultural crop commodities across the Czech Republic. *Agric. Water Manag.* **2022**, *262*, 107–337. [CrossRef]
23. Allen, R.G.; Kilic, A.; Robison, C.W. Current frameworks for reference ET and crop coefficient calculation. In Proceedings of the 6th Decennial National Irrigation Symposium, San Diego, CA, USA, 6–8 December 2021; American Society of Agricultural and Biological Engineers: St. Joseph, MI, USA, 2021.
24. Gao, L.; Kantar, M.B.; Moxley, D.; Ortiz-Barrientos, D.; Rieseberg, L.H. Crop adaptation to climate change: An evolutionary perspective. *Mol. Plant* **2023**, *16*, 1518–1546. [CrossRef]
25. Amani, S.; Shafizadeh-Moghadam, H. A review of machine learning models and influential factors for estimating evapotranspiration using remote sensing and ground-based data. *Agric. Water Manag.* **2023**, *284*, 108324. [CrossRef]
26. Chia, M.Y.; Huang, Y.F.; Koo, C.H.; Fung, K.F. Recent Advances in Evapotranspiration Estimation Using Artificial Intelligence Approaches with a Focus on Hybridization Techniques—A Review. *Agronomy* **2020**, *10*, 101. [CrossRef]
27. Islam, M.N.; Logofătu, D. Machine Learning Models to Predict Soil Moisture for Irrigation Schedule. In Proceedings of the 2022 24th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC), Linz, Austria, 12–15 September 2022; pp. 226–232, ISBN 978-1-6654-6545-8.
28. Peet, M.M.; Wolfe, D.W. Crop ecosystem responses to climatic change: Vegetable crops. In *Climate Change and Global Crop Productivity*; Reddy, K.R., Hodges, H.F., Eds.; CABI Publishing: Wallingford, UK, 2000; pp. 213–243. ISBN 9780851994390.
29. Aalto, J.; Pirinen, P.; Kauppi, P.E.; Rantanen, M.; Lussana, C.; Lyytikäinen-Saarenmaa, P.; Gregow, H. High-resolution analysis of observed thermal growing season variability over northern Europe. *Clim. Dyn.* **2022**, *58*, 1477–1493. [CrossRef]
30. Minoli, S.; Jägermeyr, J.; Asseng, S.; Urfels, A.; Müller, C. Global crop yields can be lifted by timely adaptation of growing periods to climate change. *Nat. Commun.* **2022**, *13*, 7079. [CrossRef] [PubMed]
31. Pachauri, R.K.; Allen, M.R.; Barros, V.R.; Broome, J.; Cramer, W.; Christ, R.; Church, J.A.; Clarke, L.; Dahe, Q.; Dasgupta, P.; et al. *Climate Change 2014: Synthesis Report: [Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*]; Pachauri, R.K., Ed.; IPCC: Geneva, Switzerland, 2015; ISBN 978-92-9169-143-2.
32. IPCC. *Climate Change 2013: The Physical Science Basis: Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*; WMO IPCC: Geneva, Switzerland, 2014; ISBN 9781107057999.
33. Kreienkamp, F.; Spekat, A.; Enke, W. The Weather Generator Used in the Empirical Statistical Downscaling Method, WETTREG. *Atmosphere* **2013**, *4*, 169–197. [CrossRef]
34. Rockel, B.; Will, A.; Hense, A. The Regional Climate Model COSMO-CLM (CCLM). *Meteorol. Z.* **2008**, *17*, 347–348. [CrossRef]
35. MPI fuer Meteorologie Hamburg. MPI-ESM. Available online: https://mpimet.mpg.de/en/science/models/mpi-esm (accessed on 21 July 2024).
36. Hübener, H.; Bülow, K.; Fooken, C.; Früh, B.; Hoffmann, P.; Höpp, S.; Keuler, K.; Menz, C.; Mohr, V.; Radtke, K.; et al. ReKliEs-De—Regional Climate Projections Ensemble for Germany. Available online: https://www.umweltbundesamt.de/en/topics/climate-energy/climate-change-adaptation/adaptation-tools/project-catalog/reklies-de-regional-climate-projections-ensemble (accessed on 24 September 2024).
37. ReKliES-De—English. Available online: https://www.dkrz.de/en/projects-and-partners/projects-1/reklies-de (accessed on 24 September 2024).

38. Lovino, M.A.; Pierrestegui, M.J.; Müller, O.V.; Müller, G.V.; Berbery, E.H. The prevalent life cycle of agricultural flash droughts. *npj Clim. Atmos. Sci.* **2024**, *7*, 73. [CrossRef]
39. Daymond, A.J.; Wheeler, T.R.; Hadley, P.; Ellis, R.H.; Morison, J.I.L. The growth, development and yield of onion (*Allium cepa* L.) in response to temperature and CO_2. *J. Hortic. Sci.* **1997**, *72*, 135–145. [CrossRef]
40. Ikeda, H.; Kinoshita, T.; Yamamoto, T.; Yamasaki, A. Sowing time and temperature influence bulb development in spring-sown onion (*Allium cepa* L.). *Sci. Hortic.* **2019**, *244*, 242–248. [CrossRef]
41. Vargas, Y.; Mayor-Duran, V.M.; Buendia, H.F.; Ruiz-Guzman, H.; Raatz, B. Physiological and genetic characterization of heat stress effects in a common bean RIL population. *PLoS ONE* **2021**, *16*, e0249859. [CrossRef]
42. Zinkernagel, J.; Weinheimer, S.; Herbst, M.; Kleber, J.; Mayer, N. Der Bewässerungsbedarf von Freilandgemüse Steigt. *Berichte Über Landwirtsch.—Z. Agrarpolit. Landwirtsch. Aktuelle Beiträge* **2022**, *100*. [CrossRef]
43. Hessian State Bureau of Statistics. Statistische Berichte: Die Gemüseerhebung in Hessen. CI3 mit CII; 2016. Statistische Berichte: Die Gemüseerhebung in Hessen. Available online: www.statistik.hessen.de (accessed on 15 August 2024).
44. Berthold, G. Sicherstellung der Landwirtschaftlichen Produktion mit Zusatzwasserbedarf bei Veränderten Klimatischen Bedingungen—Maßnahmen für ein Nachhaltiges Grundwassermanagement sowie Anbauempfehlungen für die Landwirtschaftliche Produktion im Hessischen Ried. Integriertes Klimaschutzprogramm Hessen INKLIM 2012. Projektbaustein II: Klimawandel und Seine Folgen, Issue 2, Volume 100, HLNUG. 2008. Available online: https://www.umweltbundesamt.de/themen/klima-energie/klimafolgen-anpassung/werkzeuge-der-anpassung/projekte-studien/sicherstellen-der-landwirtschaftlichen-produktion (accessed on 15 August 2024).
45. Chmielewski, F.-M. Phenology in Agriculture and Horticulture. In *Phenology: An Integrative Environmental Science*; Schwartz, M.D., Ed.; Springer Netherlands: Dordrecht, The Netherlands, 2013; pp. 539–561. ISBN 978-94-007-6925-0.
46. Feller, C.; Fink, M.; Laber, H.; Maync, A.; Paschold, P.; Scharpf, H.C.; Schlaghecken, J.; Strohmeyer, K.; Weier, U.; Ziegler, J. *Düngung im Freilandgemüsebau*; Schriftenreihe des Leibniz-Institutes für Gemüse-und Zierpflanzenbau Großbeeren und Erfurt (IGZ): Großbeeren, Germany, 2011.
47. R Core Team. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2020.
48. RStudio Team. *RStudio: Integrated Development for R*; RStudio, PBC: Boston, MA, USA, 2021.
49. Wickham, H. *Ggplot2: Elegant Graphics for Data Analysis*, 2nd ed.; Springer International Publishing: Cham, Switzerland, 2016; ISBN 9783319242774.
50. Lee, H.; Calvin, K.; Dasgupta, D.; Krinner, G.; Mukherji, A.; Thorne, P.W.; Trisos, C.; Romero, J.; Aldunce, P.; Barrett, K.; et al. *IPCC, 2023: Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Lee, H., Romero, J., Eds.; Intergovernmental Panel on Climate Change (IPCC): Geneva, Switzerland, 2023.
51. European Environment Agency. Global and European Temperatures. Available online: https://www.eea.europa.eu/en/analysis/indicators/global-and-european-temperatures (accessed on 8 January 2024).
52. Pasqui, M.; Di Giuseppe, E. Climate change, future warming, and adaptation in Europe. *Anim. Front. Rev. Mag. Anim. Agric.* **2019**, *9*, 6–11. [CrossRef]
53. Vautard, R.; Cattiaux, J.; Happé, T.; Singh, J.; Bonnet, R.; Cassou, C.; Coumou, D.; D'Andrea, F.; Faranda, D.; Fischer, E.; et al. Heat extremes in Western Europe increasing faster than simulated due to atmospheric circulation trends. *Nat. Commun.* **2023**, *14*, 6803. [CrossRef] [PubMed]
54. Trancoso, R.; Syktus, J.; Allan, R.P.; Croke, J.; Hoegh-Guldberg, O.; Chadwick, R. Significantly wetter or drier future conditions for one to two thirds of the world's population. *Nat. Commun.* **2024**, *15*, 483. [CrossRef] [PubMed]
55. Shiru, M.S.; Shahid, S.; Dewan, A.; Chung, E.-S.; Alias, N.; Ahmed, K.; Hassan, Q.K. Projection of meteorological droughts in Nigeria during growing seasons under climate change scenarios. *Sci. Rep.* **2020**, *10*, 10107. [CrossRef]
56. Becker, R.; Schüth, C.; Merz, R.; Khaliq, T.; Usman, M.; aus der Beek, T.; Kumar, R.; Schulz, S. Increased heat stress reduces future yields of three major crops in Pakistan's Punjab region despite intensification of irrigation. *Agric. Water Manag.* **2023**, *281*, 108243. [CrossRef]
57. Ells, J.E.; McSay, A.E.; Soltanpour, P.N.; Schweissing, F.C.; Bartolo, M.E.; Kruse, E.G. Onion Irrigation and Nitrogen Leaching in the Arkansas Valley of Colorado 1990-1991. *HortTechnology* **1993**, *3*, 184–187. [CrossRef]
58. Leskovar, D.I.; Agehara, S.; Yoo, K.; Pascual-Seva, N. Crop Coefficient-based Deficit Irrigation and Planting Density for Onion: Growth, Yield, and Bulb Quality. *HortScience* **2012**, *47*, 31–37. [CrossRef]
59. Martín de Santa Olalla, F.; Domínguez-Padilla, A.; López, R. Production and quality of the onion crop (*Allium cepa* L.) cultivated under controlled deficit irrigation conditions in a semi-arid climate. *Agric. Water Manag.* **2004**, *68*, 77–89. [CrossRef]
60. Matsunaga, W.K.; Da Silva, V.d.P.R.; Amorim, V.P.; Sales, E.S.G.; Dantas, S.M.; Oliveira, A.B. Evapotranspiration, crop coefficient and water use efficiency of onion cultivated under different irrigation depths. *Rev. Bras. Eng. Agríc. Ambient.* **2022**, *26*, 219–225. [CrossRef]
61. Hessisches Landesamt für Naturschutz, Umwelt und Geologie. *Gewässerkundlicher Jahresbericht*; Hessisches Landesamt für Naturschutz Umwelt und Geologie: Wiesbaden, Germany, 2021; ISBN 9783890267234.
62. Bhattarai, N.; Lobell, D.B.; Balwinder-Singh; Fishman, R.; Kustas, W.P.; Pokhrel, Y.; Jain, M. Warming temperatures exacerbate groundwater depletion rates in India. *Sci. Adv.* **2023**, *9*, eadi1401. [CrossRef]

63. Kirby, J.M.; Mainuddin, M.; Mpelasoka, F.; Ahmad, M.D.; Palash, W.; Quadir, M.E.; Shah-Newaz, S.M.; Hossain, M.M. The impact of climate change on regional water balances in Bangladesh. *Clim. Chang.* **2016**, *135*, 481–491. [CrossRef]
64. An, W.; Xu, C.; Marković, S.B.; Sun, S.; Sun, Y.; Gavrilov, M.B.; Govedar, Z.; Hao, Q.; Guo, Z. Anthropogenic warming has exacerbated droughts in southern Europe since the 1850s. *Commun. Earth Environ.* **2023**, *4*, 232. [CrossRef]
65. Kumar, S.; Imtiyaz, M.; Kumar, A.; Singh, R. Response of onion (*Allium cepa* L.) to different levels of irrigation water. *Agric. Water Manag.* **2007**, *89*, 161–166. [CrossRef]
66. Al-Jamal, M.S.; Ball, S.; Sammis, T.W. Comparison of sprinkler, trickle and furrow irrigation efficiencies for onion production. *Agric. Water Manag.* **2001**, *46*, 253–266. [CrossRef]
67. Enciso, J.; Wiedenfeld, B.; Jifon, J.; Nelson, S. Onion yield and quality response to two irrigation scheduling strategies. *Sci. Hortic.* **2009**, *120*, 301–305. [CrossRef]
68. Enciso, J.; Jifon, J.; Anciso, J.; Ribera, L. Productivity of Onions Using Subsurface Drip Irrigation versus Furrow Irrigation Systems with an Internet Based Irrigation Scheduling Program. *Int. J. Agron.* **2015**, *2015*, 178180. [CrossRef]
69. Calinger, K.; Curtis, P. A century of climate warming results in growing season extension: Delayed autumn leaf phenology in north central North America. *PLoS ONE* **2023**, *18*, e0282635. [CrossRef]
70. Kukal, M.S.; Irmak, S.U.S. Agro-Climate in 20th Century: Growing Degree Days, First and Last Frost, Growing Season Length, and Impacts on Crop Yields. *Sci. Rep.* **2018**, *8*, 6977. [CrossRef]
71. Marklein, A.; Elias, E.; Nico, P.; Steenwerth, K. Projected temperature increases may require shifts in the growing season of cool-season crops and the growing locations of warm-season crops. *Sci. Total Environ.* **2020**, *746*, 140–918. [CrossRef]
72. Acevedo, M.; Pixley, K.; Zinyengere, N.; Meng, S.; Tufan, H.; Cichy, K.; Bizikova, L.; Isaacs, K.; Ghezzi-Kopel, K.; Porciello, J. A scoping review of adoption of climate-resilient crops by small-scale producers in low- and middle-income countries. *Nat. Plants* **2020**, *6*, 1231–1241. [CrossRef]
73. Pixley, K.V.; Cairns, J.E.; Lopez-Ridaura, S.; Ojiewo, C.O.; Dawud, M.A.; Drabo, I.; Mindaye, T.; Nebie, B.; Asea, G.; Das, B.; et al. Redesigning crop varieties to win the race between climate change and food security. *Mol. Plant* **2023**, *16*, 1590–1611. [CrossRef] [PubMed]
74. Shah, I.H.; Manzoor, M.A.; Jinhui, W.; Li, X.; Hameed, M.K.; Rehaman, A.; Li, P.; Zhang, Y.; Niu, Q.; Chang, L. Comprehensive review: Effects of climate change and greenhouse gases emission relevance to environmental stress on horticultural crops and management. *J. Environ. Manag.* **2024**, *351*, 119978. [CrossRef] [PubMed]
75. Brewster, J. *Onions and Other Vegetable Alliums*, 2nd ed.; CABI: Wallingford, UK, 2008; ISBN 9781845936228.
76. Tolossa, T.T. Onion yield response to irrigation level during low and high sensitive growth stages and bulb quality under semi-arid climate conditions of Western Ethiopia. *Cogent Food Agric.* **2021**, *7*, 1859665. [CrossRef]
77. Kalbarczyk, R. The Effect of Climate Change in Poland on the Phenological Phases of Onion (*Allium cepa* L.) between 1966 and 2005. *Agric. Conspec. Sci. ACS* **2009**, *74*, 297–304.
78. Pelter, G.Q.; Mittelstadt, R.; Leib, B.G.; Redulla, C.A. Effects of water stress at specific growth stages on onion bulb yield and quality. *Agric. Water Manag.* **2004**, *68*, 107–115. [CrossRef]
79. Pérez Ortolá, M.; Knox, J.W. Water Relations and Irrigation Requirements of Onion (*Allium cepa* L.): A Review of Yield and Quality Impacts. *Exp. Agric.* **2015**, *51*, 210–231. [CrossRef]
80. Alessi, M.J.; DeGaetano, A.T. A comparison of statistical and dynamical downscaling methods for short-term weather forecasts in the US Northeast. *Meteorol. Appl.* **2021**, *28*, e1976. [CrossRef]
81. Holzkämper, A.; Calanca, P.; Fuhrer, J. Statistical crop models: Predicting the effects of temperature and precipitation changes. *Clim. Res.* **2012**, *51*, 11–21. [CrossRef]
82. Lobell, D.B.; Burke, M.B. On the use of statistical models to predict crop yield responses to climate change. *Agric. For. Meteorol.* **2010**, *150*, 1443–1452. [CrossRef]
83. Manzanas, 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]
84. Drastig, K.; Prochnow, A.; Libra, J.; Koch, H.; Rolinski, S. Irrigation water demand of selected agricultural crops in Germany between 1902 and 2010. *Sci. Total Environ.* **2016**, *569–570*, 1299–1314. [CrossRef] [PubMed]
85. Bettolli, M.L.; Solman, S.A.; da Rocha, R.P.; Llopart, M.; Gutierrez, J.M.; Fernández, J.; Olmo, M.E.; Lavin-Gullon, A.; Chou, S.C.; Rodrigues, D.C.; et al. The CORDEX Flagship Pilot Study in southeastern South America: A comparative study of statistical and dynamical downscaling models in simulating daily extreme precipitation events. *Clim. Dyn.* **2021**, *56*, 1589–1608. [CrossRef]
86. Hernanz, A.; Correa, C.; Domínguez, M.; Rodríguez-Guisado, E.; Rodríguez-Camino, E. Comparison of machine learning statistical downscaling and regional climate models for temperature, precipitation, wind speed, humidity and radiation over Europe under present conditions. *Int. J. Climatol.* **2023**, *43*, 6065–6082. [CrossRef]
87. Zhang, Y.; Zhang, L.; Yang, N.; Huth, N.; Wang, E.; van der Werf, W.; Evers, J.B.; Wang, Q.; Zhang, D.; Wang, R.; et al. Optimized sowing time windows mitigate climate risks for oats production under cool semi-arid growing conditions. *Agric. For. Meteorol.* **2019**, *266–267*, 184–197. [CrossRef]
88. Gao, C.; Booij, M.J.; Xu, Y.-P. Assessment of extreme flows and uncertainty under climate change: Disentangling the uncertainty contribution of representative concentration pathways, global climate models and internal climate variability. *Hydrol. Earth Syst. Sci.* **2020**, *24*, 3251–3269. [CrossRef]

89. Caya, D.; Biner, S. Internal variability of RCM simulations over an annual cycle. *Clim. Dyn.* **2004**, *22*, 33–46. [CrossRef]
90. Gaur, S.; Bandyopadhyay, A.; Singh, R. Modelling potential impact of climate change and uncertainty on streamflow projections: A case study. *J. Water Clim. Chang.* **2021**, *12*, 384–400. [CrossRef]
91. Gampe, D.; Schmid, J.; Ludwig, R. Impact of Reference Dataset Selection on RCM Evaluation, Bias Correction, and Resulting Climate Change Signals of Precipitation. *J. Hydrometeorol.* **2019**, *20*, 1813–1828. [CrossRef]
92. Wing, I.S.; de Cian, E.; Mistry, M.N. Global vulnerability of crop yields to climate change. *J. Environ. Econ. Manag.* **2021**, *109*, 102462. [CrossRef]
93. Bayissa, Y.; Melesse, A.; Bhat, M.; Tadesse, T.; Shiferaw, A. Evaluation of Regional Climate Models (RCMs) Using Precipitation and Temperature-Based Climatic Indices: A Case Study of Florida, USA. *Water* **2021**, *13*, 2411. [CrossRef]
94. Kakouei, K.; Domisch, S.; Kiesel, J.; Kail, J.; Jähnig, S.C. Climate model variability leads to uncertain predictions of the future abundance of stream macroinvertebrates. *Sci. Rep.* **2020**, *10*, 2520. [CrossRef] [PubMed]
95. Aryal, A.; Shrestha, S.; Babel, M.S. Quantifying the sources of uncertainty in an ensemble of hydrological climate-impact projections. *Theor. Appl. Climatol.* **2019**, *135*, 193–209. [CrossRef]
96. Saikanth DR, K.; Kumar, S.; Rani, M.; Sharma, A.; Srivastava, S.; Vyas, D.; Singh, G.A.; Kumar, S. A Comprehensive Review on Climate Change Adaptation Strategies and Challenges in Agriculture. *Int. J. Environ. Clim. Chang.* **2023**, *13*, 10–19. [CrossRef]
97. Gebre, G.G.; Amekawa, Y.; Ashebir, A. Can farmers' climate change adaptation strategies ensure their food security? Evidence from Ethiopia. *Agrekon* **2023**, *62*, 178–193. [CrossRef]
98. Xiao, D.; Zhang, Y.; Bai, H.; Tang, J. Trends and Climate Response in the Phenology of Crops in Northeast China. *Front. Earth Sci.* **2021**, *9*, 811621. [CrossRef]
99. Challinor, A.J.; Ewert, F.; Arnold, S.; Simelton, E.; Fraser, E. Crops and climate change: Progress, trends, and challenges in simulating impacts and informing adaptation. *J. Exp. Bot.* **2009**, *60*, 2775–2789. [CrossRef]
100. Timlin, D.; Paff, K.; Han, E. The role of crop simulation modeling in assessing potential climate change impacts. *Agrosyst. Geosci. Environ.* **2024**, *7*, 20453. [CrossRef]