**Processing tomato production is expected to decrease by 2050 due to the projected increase in temperature**

Davide Cammarano1\*, Sajad Jamshidi2, Gerrit Hoogenboom3, Alex C. Ruane4, Dev Niyogi5, Domenico Ronga6

1Department of Agroecology, Aarhus University, Tjele, Denmark

2Department of Agronomy, Purdue University, West Lafayette, USA

3Department of Agricultural and Biological Engineering, University of Florida, Gainesville, USA

4NASA Goddard Institute for Space Studies, New York, New York, USA

5Department of Geological Sciences, Jackson School of Geosciences, The University of Texas at Austin, TX, United States of America

6Department of Pharmacy, University of Salerno, Fisciano, Italy.

\*Corresponding author email: [davide.cammarano@agro.au.dk](mailto:davide.cammarano@agro.au.dk)

**Abstract**

*The global processing tomato production is concentrated in a small number of regions where climate change will have a significant impact on the future supply. Process-based tomato models project that the production in the three main producing countries (the United States, Italy, and China, representing 65% of global production) will decrease 6% by 2050, compared to the baseline period of 1980-2009. The predicted reduction in processing tomato production is due to a simulated increase in air temperature. Under an ensemble of projected climate scenarios, California and Italy might not be able to sustain the current levels of processing tomato production due to water resources constraints. Cooler producing regions, such as China and the northern parts of California, stand to improve their competitive advantage. The projected environmental changes indicate that the main growing regions of processing tomatoes might change in the coming decades.*

**Introduction**

Tomato is one of the world’s most important vegetables by cultivation area, production, commercial use, and consumption1{WPTC, 2021 #1529}. Tomato is grown in many countries due to its adaptability to a wide range of soil and weather conditions and it also has been recognized for its positive health benefits being rich in antioxidants. There are two types of cultivated tomato, i.e., the one for fresh consumption (e.g., salad tomatoes), usually grown under controlled environments and the one used for industrial transformation known as processing tomato (e.g., canned tomatoes), which is usually grown under field conditions2. Processing tomatoes are important because they are used for tomato paste/tomato sauce/ketchup and other tomato derived products. In fact, about 40 million tons are processed yearly, making it the world leader for vegetable processing by weight1. The main production areas are located in temperate zones around both the 40th northern and southern latitude. Worldwide processing tomato production is concentrated in eleven major “tomato baskets” that produce 85% of the global processing tomato. Among the ten countries three of those, i.e. USA (with the majority of production in California), Italy (in Foggia and Emilia-Romagna) and China (mainly in Gansu, Inner Mongolia, and Xingjian), account for 65% of the global production1 (Supplemental Figure 1).

Most of the climate change impact studies on agricultural crops have been mainly concentrated on wheat, maize, rice, and potato3-7, while fruits and vegetables have not received sufficient attention. The four main agricultural crops address food security, but not nutrition security for essential vitamins and micronutrients, fiber, and phytochemicals that individually or in combination may benefit human health8. The World Health Organization Global Strategy on Diet, Physical Activity and Health9 recommends that per capita fruit and vegetable consumption (excluding tubers) should exceed 400 g/day9.

Most of the published research on the impacts of climate change on processing tomato has been done at regional or local level and they included agronomic and/or technological adaptations10,11. However, each study adopted different scenarios, GCMs and different crop modeling approaches12, making it challenging to compare results. A study that assessed the impact of climate on processing tomato supply chain for the United States found that adaptation will offset the negative impact of climate change on processing tomato yield11. However, other studies on the impact of climate change on water and nutrient use efficiency on tomato in Southeastern Italy reported a net negative impact on processed tomato yield2,10,13,14. There is thus a growing need for an up-to-date biophysical assessment of climate change impacts in the three main processing tomato production countries using an ensemble of the latest climate projections and a protocol that makes the results comparable with the results from other global efforts like the Agricultural Model Intercomparison and Improvement Project (AgMIP)7,15 and the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)16. Those communities are building efforts to systematically link different types of agricultural models, with emerging work on fruits and vegetable modeling and dietary demand scenarios.

**Results and Discussions**

**Global and Regional production impacted by projected climate**

The global processing tomato production of the main production areas will decrease by 6% in 2050 (Figure 1). The difference among SSPs is minimal up to 2050 but for further projections to 2100 there is a divergent response depending on the SSPs. The variability of the mean production patterns increases after 2050 as well (Figure 1). Globally, SSP5-8.5 is a scenario that from 2050 onwards shows the highest drop in the projected global production. This is due to an increase in mean air temperature within tomato-producing regions of about +2.6°C for the 2040-2069 and +5°C for the 2070-2099 period with respect to the baseline period (1980-2009) (Supplemental Figures 2 and 3). All five GCMs report an increase in tomato growing region mean air temperature for each RCP due to an increase of both minimum and maximum air temperature. However, the variability among GCMs’ was significant, with GCM2 (IPSL-CM6A-LR) and GCM5 (UKESM1-0) being the most pessimistic (Supplemental Figures 3 and 4).

It is worth noticing that the projected median yield of the global processing tomato production among the three SSPs is somewhat similar; the mean yield decreased by 5.6% when comparing the SSP1-2.6 projections with the SSP5-8.5 projections (Supplemental Figure 5). This decrease is driven by a shift of the tail distribution towards a lower yield level (Supplemental Figure 5). While this pattern is similar for California and Italy, in China there is an increase of both median and mean yield when comparing the SSP1-2.6 projections with the SSP3-7.0 projections, while the SSP5-8.5 projections show similar yield levels when compared with the SSP1-2.6 projections (Supplemental Figure 5). Different GCMs resulted in different simulated yield distributions for each location and each SSP (Supplemental Figure 6). For example, in the USA two GCMs resulted in a decrease in the mean yield while for the other GCMs there were small or no changes. This resulted in a mean global processing tomato yield that for different SSPs is similar for the mean values for three out of five GCMs (Supplemental Figure 6).

The future viability of processing tomato production is different for each region. China will be one of the regions that is projected to be able to maintain a viable production of processing tomato, with only the Xinjiang province is projected to have a slight decrease in production starting in 2075 and continuing until the end of the Century (Figure 1). On the other hand, the other two provinces, i.e., Gansu and Inner Mongolia, show an increase in tomato production for each SSP with an evident increase for SSP3-7.0 and SSP5-8.5 (Figure 1). California and Italy will be negatively impacted by the projected environmental changes, especially for the two most sensitive climate models (GCMs 2 and 5; see Supplemental Table 2) and SSP3-7.0 and SSP5-8.5. In one region of Italy, Foggia, the decrease in the simulated tomato yield in this study (18%) under future climate conditions is slightly higher compared to previously published studies2,10,13,14 with only one study considering adaptation options13. In those studies, the simulated yield decreased between 5 to 15% and this depended on the GCM and the period that was considered2,10,13,14. A recent study for California using only SSP5-8.5 demonstrated how agronomic adaptations and technology trends can reverse the negative impact of climate on tomato production with a yield increase of 15%11. In Foggia, adaptation option like irrigation and fertilization had a positive effect in minimizing the negative climate impacts13. The results from our study suggest that even under current agronomic and technological conditions, without adaptation, tomato yield in California might not be subject to a significant reduction in yield as it depends on the GCM that is being considered for future projections. For example, the results from this study show that even under SSP5-8.5 in 2050 the tomato yield could be reduced by only 2% if only GCMs 1,3, and 4 are considered, versus a reduction in yield of 13% if all the five GCMs are considered. This discrepancy highlights the importance of using multiple GCMs and SSP-RCPs to inform stakeholders about the uncertainty of the potential impact of climate change on tomato production.

Independent of each GCM, the differences in simulated yield for each region is due to the fact that the predicted increase in air temperature does not have the same negative effect everywhere; rather, it is dependent on current temperatures and proximity to temperature thresholds that govern plant growth. It is known that an increase in air temperature accelerates the developmental processes, resulting in a shorter duration for biomass accumulation and, therefore, final yield17. All crops have an optimal temperature (defined as cardinal temperature) during which development is optimal. However, such this threshold temperature there is an acceleration in the senescence processes that has a negative impact yield17,18. In the crop modeling approach that was used in this study, the cardinal temperatures for optimal developmental processes are between 22 and 28°C for vegetative and early reproductive development and between 26 and 28°C for late reproductive development17,19. The upper optimal threshold for vegetative and reproductive stages in the model is similar (28°C) and the projected mean temperature exceed such threshold under projected climate. For example, for the 1980-2009 period at a latitude of 37°N, Gansu has a mean air temperature of 11°C and California of 25°C; for the 2040-2069 period California’s temperature will be pushed beyond the optimal temperature threshold (28°C), which impacted developmental, and expansive growth processes as well as canopy photosynthesis, and, thus, caused a reduction in the predicted tomato yield (Supplemental Figure 7).

Warming in areas below optimal temperatures can lead to a future that is more suitable for tomato production compared to current conditions, as is seen in China. In other regions where warming pushes beyond (or further away from) optimal conditions, the increase in air temperature will be detrimental for sustaining the current production levels, which is the case for southern Italy and parts of California.

The relationship between mean air temperature and simulated yield for each location and each SSP is shown in Figure 2. It is evident how the simulated tomato yield decreases when the mean air temperature is above 28°C (Figure 2). For the three provinces of China, the high density is concentrated in the 20 to 28°C ranged for all the SSPs, only a low density is located above 28°C for which the model simulates a reduction in yield. This is particularly evident for SSP5-8.5 for Xinjiang and Inner Mongolia. On the other hand, in California the majority are located near the upper optimal threshold of 28°C, and, therefore, the projected increase in air temperature only has a negative effect on the simulated yield (Figure 2). No matter the SSPs, tomato yield tends to be higher for the Chinese locations (36 to 38°N) and northern Italy (44°N) (Figure 5).

For each location, there are also sub-regional differences in terms of yield response under climate change. Overall, not all the areas within a region show a significant change in yield response per °C of increase in air temperature. For the Xinjiang province, there is a positive response of +0.6 t DM ha-1 °C-1 in yield per each °C in the western part of the province, while there is a negative response (-0.12 t DM ha-1 °C-1) for the eastern part of the province. This difference is due to different GCMs and SSPs responses across the region, with the warmest GCMs (GCM2 and GCM5) showing the most negative yield response (Supplemental Figure 8a). This translated into a +0.5 t DM ha-1 decade-1 in the west and -0.4 t DM ha-1 decade-1 in the east (Supplemental Figure 8b). For the Gansu and Inner Mongolia provinces, there is an average positive response of +0.60 t DM ha-1 °C-1 increase in yield under each SSPs and each GCM, which translates into a +0.5 t DM ha-1 decade-1 increase in yield (Supplemental Figures 9 and 10).

For Italy, SSP1-2.6 and SSP3-7.0 show a mild to non-significant yield trend per year and per °C, except for GCM2 and GCM5 (Supplemental Figure 11). For the Foggia province, GCM1 and GGCM4 show a positive yield change under the SSP1-2.6; and GCM2 and GCM5 slight negative yield changes. For the Emilia-Romagna province, GCM2 and GCM4 for SSP1-2.6 show a significant positive trend in yield, but only for the western portion (Supplemental Figure 11).

For California, the yield changes per °C show differences due to the SSPs and the GCMs considered. In terms of regional response for California, the southeastern part of the state is projected to have the significant reduction in yield reduction (-0.96 to -1.4 t DM ha-1 °C-1), while for the western part of the state yield changes ranged between -1.18 and +0.14 and t DM ha-1 °C-1 depending on the GCM (Supplemental Figure 12). For SSP5-8.5, all GCMs reported a decrease in yield per °C for the eastern parts of the growing regions, while GCM1 and GCM4 showed a slight positive change for the western part of the area with an increase in yield of +0.14 t DM ha-1 °C-1 (Supplemental Figure 12). The decadal yield change for SSP1-2.6 and for GCM1, GCM3 and GCM4 is not significant for most parts of eastern California and is positive for the southwest part of the state with +0.1 t DM ha-1 decade-1 (Supplemental Figure 12). On the other hand, it is interesting to note how for SSP3-7.0 the western part of California shows an increase in yield of 0.1 t DM ha-1 decade-1 for the GCM1, GCM3 and GCM4, while for GCM5 it shows a decrease in yield of 0.8 t DM ha-1 decade-1 (Supplemental Figure 12). In a recent study, two GCMs (representing hot-and-dry and cool-and-wet storylines) were used to quantify land suitability for tomato production in California; and showed that only 34 to 87% of the land might be suitable in the future20. However, the results from our study show that depending on the GCM and the SSP, some of the temperature increase per year might not be statistically significant and that there is, therefore, no or little impact on yield and total production, e.g., SSP1-2.6. Most of the negative impact due to the projected changes in air temperature mainly occur in the eastern part of California (Supplemental Figure 12).

**Production stability**

There is an increase in frequency of extremely low production years for the later decades with differences across locations and SSPs (Figure 3). The patterns of low frequency yield, along with the spatial yield response to the increase air temperature, also cause a change in frequency of yield distribution across the different countries, with Italy and California show a shift and a flattening of the yield distribution from the baseline (1980-2009) to the end of the Century (2070-2099). On the other hand, for China the overall patterns of the density distribution of simulated yield tend to move towards higher yield values (Figure 3a) and by the end of the century the yield variability compared to the baseline would increase for SSP3-7.0 and SSP5-8.5 (Figure 3a). However, for the period 2070-2100 and for the SSP3-7.0 and SSP5-8.5 the yield distribution showed two peaks, one with broad yield failures and one with a high yield. This is due to the different response to projected temperature changes for each Chinese province, with Xinjiang showing a negative relationship between mean air temperature and yield for these SSP3-7.0 and SSP5-8.5 (Figure 2).

SSP1-2.6 simulations showed a lower number of low yielding years, defined as the yield in t DM ha-1 that are below the 10% quantile) per decade for each location, with, on average, two years of low yield per decade (Figure 3b). In contrast, SSP5-8.5 showed an increase in the frequency of low yielding years per decade with a steep increase towards the last two decades of the century (Figure 3b). For locations such as Italy’s’ Foggia province and California, the projections indicate between 6 and 8 low yielding years per decade under the very high greenhouse gas emission scenario, i.e., SSP5-8.5, causing a higher reduction in tomato yield (Figure 3b). However, for Gansu and Inner Mongolia provinces of China, there is an overall decrease of low yielding years per decade with no evident reduction in yield. For China’s Xinjiang province, the increase of low yielding years per decade is notably in one part of the province that drives down the projected yield changes for Xinjiang for the SSP5-8.5 scenario (Figures 1 and 3, Supplemental Figure 8). The increase in frequency of low yielding years is mainly caused by GCM2 and GCM5 for all three countries, except for Inner Mongolia and Gansu where all the GCMs show a similar number of low yielding years (Figure 3).

**Water use**

In this study we focused on irrigated tomato systems given their prevalence in the study regions, although water supply and demand changes remain relevant to meeting water resource needs.The growing season precipitation patterns show more variability among locations than the temperature changes for each of the time windows (Supplemental Figures 2, 13 and 14). Overall, Foggia and Emilia-Romagna show a decrease in rainfall for each SSP that will be severe by the end of the century. In California, the projected changes in rainfall show an increase of 10% by the end of the century for SSP1-2.6 to 5% for SSP5-8.5 (Supplemental Figure 13). The variability of projected rainfall changes among the GCMs is small for 2010-2039, while there is some divergence for 2040-2069, especially for the GCM3 and GCM5. GCM3 showed a high variability of projected rainfall for each SSP with a notable decrease in rainfall for Foggia, while GCM5 showed a distinct pattern of rainfall change for Foggia and Emilia (-10%) compared to the other locations (+15%). At the end of the century (2070-2099) the five GCMs show diverging patterns of rainfall changes, but the two Italian provinces, i.e., Foggia and Emilia-Romagna, are always projected to have less rainfall compared to the baseline period (Supplemental Figure 14).

By the middle (2040-2069) and the end of the century, the amount of water required for irrigation will increase by 5% to 50% compared to the global baseline. This translates into an additional 25 to 150 mm of irrigation water with a high regional variability (Supplemental Figure 15). For example, in locations such as Gansu and Inner Mongolia, irrigation requirements are less under current and projected climate compared to California or Italy. The combination of reduced yield and increased irrigation requirements means a decrease in the water use efficiency from the middle to the end of the century for Italy and California.

The crop simulations assumed that the availability of water for irrigation was none-limiting and that irrigation water would always be supplied to meet the need of the tomato crop. Thus, increasing air temperature corresponds to higher evaporative demand and any changes in rainfall means more or less irrigation to apply to the crop. In California, where there is a projected increase in total rainfall, there is still an increase in the required water for irrigation under the projected climate change because the need for water is partially also driven by the projected increase in air temperature. In comparison, for Foggia both a decrease in total rainfall and an increase in air temperature drive the requirements for water for supplemental irrigation.

Water Use Efficiency (WUE) for dry weight tomatoes in Italy decreases by 3 and 6 kg DM ha-1 mm-1 for the SSP3-7.0 and SSP5-8.5, respectively, when comparing the mid and end of century projections to the baseline (Figure 4). In California, on the other hand, the mean WUE only showed small changes across SSPs out to the 2040-2069 period, where the mean WUE is around 17 kg DM ha-1 mm-1 (Figure 4). In China, the WUE increased by 1.9 and 1.6 kg DM ha-1 mm-1 for the mid of the century for the SSP3-7.0 and SSP5-8.5.

Across all simulated regions, the need for irrigation water will increase from 520,000 ML for the 1980-2009 to 650,000 and 720,000 ML by the end of the century under SSP3-7.0 and SSP5-8.5, respectively (Supplemental Figure 15).

**Future work**

Since the mid-2000 multi-crop model ensembles have been used to evaluate the potential impact of climate change at different spatial scales5,7,12,21-23. While multi-crop model ensembles have been used for major crops like wheat, potato, rice, and maize to assess global climate impacts6,24, specialty crops such as fruits and vegetables have not received sufficient attention. Therefore, mainly single crop models have been used, partially also because for specialty crops the number of available models is limited25. Despite the ability of the CROPGRO-Tomato model18 to capture the crop response to the interannual climate variability and the projected changes, adding more tomato models to create a multi-model ensemble would help to reduce any bias that could be introduced by the choice of a single crop model26.

A further need is to collaborate with horticultural experimentalists in order to obtain datasets that can be useful for model calibration and evaluation for a range of environments where tomatoes are commonly grown. In fact, crop modelers have always relied on limited datasets for model calibration and evaluation models27,28. Recent international collaboration activities, such as the AgMIP project, has helped define the data requirement for crop modeling calibration and evaluation23,24. While the data used for this study in terms of calibration and evaluation were satisfactory and contained all the information needed to run a crop model, extending this work on other tomato-producing countries will require more field data with specific data feature. Additional field experimentation and crop model development could also capture the global warming impacts of more climate conditions that are hazardous to tomato production, as well as the effects of changing conditions related to pests, diseases and surface ozone concentrations29,30.

Assumptions on irrigation and land use are not meant to make the study rigid, but allows the analysis to point out the circumstances in which these assumptions break down which would therefore be a major driver of adaptation. In other words, when the assumption of no adaptation leads to bad results, that is an indication that adaptation will be necessary.

Additional socioeconomic information is needed to assess the likelihood of system change and the potential emergence of new tomato basket regions in the future. These will also require shifts in the value chain including processing plants and transportation lines that may be anticipated.

**Methods**

**Processing tomato simulation using the DSSAT.** The crop model used to simulate field-grown processing tomato is Cropping System Model (CSM)-CROPGRO-Tomato, which is part of the Decision Support System for Agrotechnology Transfer (DSSAT, V4.7)18. GROPGRO-Tomato has been tested and applied for a range of climate-change impact studies under different environmental conditions2,10,13,14,17,31. CROPGRO-Tomato model was calibrated for common processing tomato cultivar grown in their specific geographical location. In order to run the model, it requires daily weather data (rainfall, solar radiation, maximum and minimum temperature), soil information for horizons (texture, bulk density, organic carbon), and agronomic management information (e.g. planting time, fertilizer amount and timing, irrigation amount and timing)18. A literature review was conducted to identify studies that contained all the information needed to run a crop model, and to calibrate processing tomato phenology information (flowering and maturity), yield, and any other available output (e.g. aboveground biomass, evapotranspiration, soil water content)2,10,13,14,32-37. Calibration was conducted for two locations in California (North and South), one location in Italy (Emilia-Romagna), and two locations in China (Inner Mongolia and Xinjiang provinces)2,10,13,14,32-37. For the province of Foggia (Italy) the tomato model was calibrated and evaluated in a separate study and those coefficients were used into current simulations2. The results of the calibration are shown in the supplemental material (Supplemental Figure 16).

**Regional model evaluation:** Following calibration and evaluation of the model for specific locations, the CROPGRO-Tomato model was set up to evaluate model performance at a regional level. The observed regional yield data (kg DM ha-1) reported for California (USA), Emilia (Italy), Foggia (Italy), Gansu (China), Inner Mongolia (China), and Xinjiang (China) was obtained from the World Processing Tomato Industry for the period 2005-20191. In order to match the observed yield at the regional level, the CROPGRO-Tomato model was run over a gridded area (see section below for details) covering each region. The crop model was run for 30 years and the aggregated mean yield for each region was compared with the average observed tomato yields the results of the regional evaluation are reported in the supplemental material (Supplemental Figure 17).

**Regional crop model setup:** To quantify the cropped areas a map of tomato-growing regions is not yet available. But, to have an idea where the crops is suited to grow to spatial map of crops and vegetable was used38. Within each cropped area, the soil information was obtained from the Global High-Resolution Soil Profile Dataset that contains a 5 arc-minute grid soil information formatted for DSSAT usage39,40. The soil properties available for this dataset included bulk density, organic carbon, percentage of clay and silt, soil pH, cation exchange capacity, and hydraulic properties (saturated hydraulic conductivity, soil water content at field capacity, permanent wilting point and saturation)39,40. For each geographical area, the gridded weather data were overlaid with the soil data to define the soil and weather combination for the simulation with the CROPGRO-Tomato model. Since there is not a global spatial calendar for transplanting of processing tomato plants, the integration of literature review data, experts’ knowledge, and a sensitivity simulation with the CROPGRO-Tomato model allowed us to identify the mean transplanting date for each region. In terms of agronomic management such irrigation and fertilizer inputs, processing tomatoes are grown under optimal water and nutrient conditions without stresses41,42. Therefore, irrigation water was applied automatically when the soil available water content in the top 30 cm of soil profile dropped below an 80% of the plant available soil water content, while nitrogen was considered to be unlimited to avoid simulating any nitrogen stress. Water use efficiency (WUE) was calculated dividing the tomato dry yield against the growing season evapotranspiration43.

**Climate data:** Crop models were configured using daily historical weather data obtained from NASA Power or, as in the case of the calibration dataset for Italy (both Emilia and Foggia), local instrument observations supplied by the authors2,33. For gridded modeling all the baseline climate was obtained from NASA Power. Climate simulations were driven by an ensemble of five bias-adjusted global climate models produced at 0.5° x 0.5° daily resolution by the Inter-Sectoral Model Intercomparison Project (ISIMIP)16 based on simulations conducted within the Coupled Model Intercomparison Project Phase 6 (CMIP644; see Supplemental Table 2). The bias-adjustment method adjusts each quantile of the daily weather variable distribution for each month of the year while preserving trends, and the model subset represents early CMIP6 model outputs available while including a range of high and low climate sensitivities45. Crop model simulations were run from 1980 to 2100 forced by Shared Socioeconomic Pathway and Representative Concentration Pathway (SSP-RCP) scenarios representing low (SSP1-2.6), high (SSP3-7.0) and very high (SSP5-8.5) greenhouse emissions and related socio-economic conditions with resulting increases in surface atmospheric carbon dioxide concentrations46 as shown in Supplemental Figure 18. The mid-point of 30-years period was used as input for the crop model runs7.

**Data Availability**

The DSSAT model is available from the DSSAT website upon request free of charge (<https://dssat.net/>). The Baseline weather data have been obtained for free from NASA Power (<https://power.larc.nasa.gov/>) and the climate projections from (<https://www.isimip.org/>).

**Code Availability**

The codes for generating the Figures and the simulated outputs used to build the figures are available as: *"Replication Data for: Processing tomato production is expected to decrease due to the projected increase in temperature*", https://doi.org/10.7910/DVN/SNDP5W, Harvard Dataverse

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**Authors’ contribution statement**

**D.C.** initiated the study, calibrated and run the baseline of the crop model, write the manuscript and analyzed the data; **S.J.** run the crop model, formatted the data, developed the codes for the Figures, contributed to write the manuscript; **G.H.** supported the model’s calibration/evaluation, contributed to write the manuscript; **A.C.R.** provided the climate data and contributed to write the manuscript; **D.N.** contributed on the crop-climate simulations, and to write the manuscript; **D.R.** contributed in the literature review of the data for tomato calibration and evaluation, and to write the manuscript.

**Competing Interests Statement**

The authors declare no competing interests

**Figure Captions**

**Figure 1.** Simulated trend of processing tomato production (calculated using dry weight yield) for SSP1-2.6(orange line), SSP3-7.0 (red line), and SSP5-8.5 (green line). The red capital letters on the World’s map represent the main region of processing tomato production simulated in this study.

**Figure 2.** Relationship between simulated processing tomato yield and mean air temperature at different locations and for different RCPs. The color of yield-temperature relationship indicates the density of individual model simulations corresponding to a given combination of mean air temperature and yield.

**Figure 3.** Relationship between simulated processing tomato yield and mean air temperature at different locations and for different SSPs. The color of yield-temperature relationship indicates the density of the points. The low yielding are the 0.1 quantiles of the simulated yield.

**Figure 4.** Water use efficiency calculated for SSP1-2.6 (yellow), SSP3-7.0 (purple), and SSP5-8.5 (green) for 1980-2009; 2010-2039; 2040-2069; and 2070-2099, for Italy (top row), United States (middle row), and China (bottom row). For each box-and-whiskers plot, the end of the whisker line represents the 10th and 90th percentiles. The lines of the box represent the 25th, median, and 75th percentiles.

**Figure 5.** Relationship between mean air temperature, latitude and yield for the **(A)** SSP1-2.6; **(B)** SSP3-7.0; and **(C)** SSP5-8.5

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