Climate change-induced abiotic stresses for maize crops: modeling integration and adaptation insights

Adaptive Management of Natural Resources and Agricultural Systems

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1 Introduction

Climate change impacts, derived from higher average and maximum temperatures to increased variability in rainfall patterns and more frequent occurrence of extreme events, are increasingly being felt in the field of agriculture around the world. Such impacts have already started to affect significantly agricultural outputs, as the hot and dry period in Europe in the summer of 2022 has painfully shown (Baruth et al. (2022)). Moreover, the interplay between agricultural crops and the water they demand is also likely to be affected, potentially altering the dynamics of the agroecosystems in which they are embedded.
As climate change conditions become more detrimental for crops in certain regions, it is essential to enrich our current knowledge of agricultural production systems' dynamics and evaluate more formally potential damages to crop yields and to agroecosystems. To this end, this paper aligns with others trying to better integrate climate change-induced stresses in existing agroecosystem models (van der Velde et al. (2012)). Specifically, it focuses on the **DPSIR watershed model prototype**, and, after exploring strength and inconsistencies, it proposes improvements based on the inclusion of the following abiotic stresses: heat, drought and waterlogging.
Integration of abiotic stresses into the DPSIR watershed model enables to simulate and test the new model against unusual weather conditions. This is done in the paper using real data for maize crops in Mont-de-Marsan, a town located within the Nouvelle-Aquitaine region in South-Western France, in 2022 Baruth et al. (2022). Moreover, assessment of different potential adaptive management systems is carried out comparing various adaptation options (use of tolerant maize varieties, increased irrigation efficiency, and shifting growing seasons). Thanks to the "alternative reality" provided by the model, relevant insights on the measures are explained and discussed.

The analysis proceeds by a short literature review on heat, drought and waterlogging stresses, a critical examination of the DPSIR watershed model, a section on the methods and data employed and on the model improvements, and two sections on results with and without adaptation.

2 Literature Review

Extreme weather drivers affect crops in numerous ways, from impacts on plant physiological processes to direct physical damages and forced changes on the timing and conditions of field operations. The rudimentary representation of these dynamics in the DPSIR model attempted in this paper is based on the following literature review on the main channels through which crops are affected.

2.1 Heat Stress

Heat stress, manifest in reduced biomass accumulation, lower grain weights and, thus, lower yields, operates in three main ways. Firstly, temperatures above optimum reduce photosynthesis as a result of impaired stomatal conductance and damage to chloroplasts (Rezaei et al. (2023)). Secondly, extreme heat affects pollen availability[1], sterilising it and impairing fertilisation (ibid., Cairns et al. (2012)). Thirdly, and most manifestly, the crop development rate is hastened and the phenological phases become shorter than normal. Abbas et al. (2017), for example, have found that sowing-to-maturity spring maize in Pakistan has experienced a 9.2 days' reduction per every degree of warming.

One relevant uncertainty transpiring from the literature has been on maize's *cardinal* temperatures[2], particularly for critical stages such as before and during anthesis (reproduction). Sabagh et al. (2021) assert that temperatures above 35°C, especially around 40°C during flowering and grain filling, are particularly destructive for maize. Yet, studies like Sánchez et al. (2014) or Lizaso et al. (2018) underline the uncertainty around these thresholds, and recommend the importance of updated parametrizations. This paper builds on the work of Lobell et al. (2011), who have estimated econometrically that maize yields decline with accumulated maximum temperatures above 30°C.

2.2 Drought Stress

Maize is a moderate to high water-demanding crop , particularly during its flowering and grain-filling phases Steduto et al. (2012). Precipitations falling short of historical averages can, especially for rainfed crops, cause drought stress. One way this stress functions is through delayed silking[3], meaning that the ears are not ready to receive pollen at the right time (Cairns et al. (2012)). Tassel-silking mismatch normally leads to poor fertilisation. Another mechanism is through reduced leaf growth rate and/or premature leaf senescence, which can in turn affect canopy cover and thus canopy temperature and transpiration (Steduto et al. (2012)). Studies like Webber et al. (2018) suggest that, in low-yielding years for farmers in Europe, drought stress has contributed much more pronouncedly than heat stress (even though, as explained below, it is difficult to disentangle them).

2.3 Heat and Drought Combined

Heat and drought stresses tend to reinforce each other even in non-linear ways, many studies claim (Lobell et al. (2011), Webber et al. (2018)). Certainly, the importance of moisture in the ability to cope with heat cannot be overstated: higher temperatures raise crop water demand as saturation vapour pressure increases (Rezaei et al. (2023)). But dynamics operate in the opposite way as well: under drought conditions, for example, roots become very susceptible to heat, and with higher soil temperatures nutrients and water uptake get hindered (ibid.). Awareness of this compounded risk is pivotal for adaptation strategies. In this regard, empirical results have shown that maize varieties tolerant to individual stresses are genetically distinct from inbred lines tolerant to combined heat and drought stress (Cairns et al. (2013)).

2.4 Waterlogging (WL)

Increased variability of precipitations, while generally prolonging drought seasons, means that rain comes often in huge downpours which can lead to supersaturation of soil water capacity. WL stress originates mainly from decline of oxygen in the rhyzosphere (as diffusion rates of gases in flooded soils are extremely

[1] Maize is a monoecious plant with spatially separate male (tassel) and female (ear) organs; tassels emerge first and begin shedding pollen before the silks (stigmas) from the ear appear Steduto et al. (2012)

[2] Cardinal temperatures are thresholds that define the temperature range for crop growth. They comprise the minimum, maximum and optimal temperature for the specific plant Sánchez et al. (2014)

[3] Silking refers to female flower emerging

low). As a result, plant roots suffer hypoxia (low oxygen), and during extended WL (more than 3 days), anoxia (no oxygen), these conditions inhibiting root respiration (Zaidi et al. (2004)). Further, decreased plant root uptake favours the accumulation of several toxic nutrients (iron and magnesium) which enter the plant system (Thapa et al. (2025)). Naturally, genotypes capable of forming adventitious roots with high porosity are likely to withstand WL stress effectively (Zaidi et al. (2004)).
This main mechanism through which WL impinges upon yields is displayed with delayed growth and reduced dry matter accumulation, and there is a consensus that susceptibility is highest in the early vegetative stage up until tasseling (ibid., Ren et al. (2014)). This does not mean that WL has no effect during and after reproduction: Ren et al. (2014) highlights how maize growth is restricted by lack of enough sinks for assimilates (as ear volume is decreased in these stages). Finally, WL stress depends also on the stress severity. Different WL duration have been applied in experimental studies, emphasising the uncertainty in the exact tolerance parameters for maize.

3 Exploration of Model Behaviour and Limitations

The DPSIR model prototype represents a watershed agroecosystem in which water comes from precipitation, is then used for agriculture and by riparian zones while some gets lost due to deep perculation, and it finally gets discharged as freshwater. Even though the watershed is an entire area of 10.000 ha, the driving force constituted by agriculture is modelled as an individual maize crop field of 1 ha, which accumulates growing degree days (variable *GDD*) solely based on temperature. The irrigated crop demands water during the one-year time bound, thereby forcing an irrigation outflow from the watershed. There is thus a trade-off between maximisation of agricultural output, represented by the *Yield* variable, and the downstream sustainability of the river, represented by *Freshwater Discharge*.

In light of what discussed in the literature review and keeping in mind the goal of trying to see the effect of climate-induced abiotic stresses, the following model inconsistencies were identified in the behaviour of the crop:

- Growing degree days, expressed in thermal units (°C) and calculated as the difference between *Scenario Temperature* and a *base T* dependent on crop development, are not bounded by an upper threshold. Standard GDD formulas, instead, normally and rightfully cap GDD incorporating in the formula an upper *Tmax* (see, for example, Anandhi (2016)). In any case, heat stress is in not taken into account;

- The water stress coefficient *Ks*, calculated as the ratio between available water (*AWC*) and total available water in the root zone (*TAW*), is allowed to float above 1, as shown below in Figure 1. Being a factor of the biomass accumulation, the high values of Ks at the start and end of the year disproportionally increase the yield in those periods[4]. Ks, nonetheless, still remains a good estimator of drought stress;

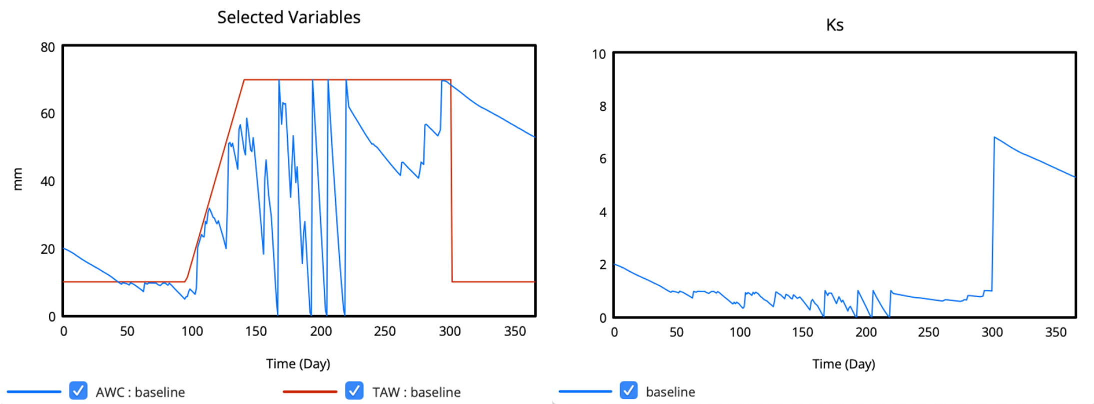

Figure 1: Values for Ks (right) and terms of its ratio (left). Source: own elaboration

[4]A related inconsistency is the fact that the crop is allowed to grow during the whole year, when instead the growing season for maize is centred in summer and lasts between 120-135 days (Steduto et al. (2012))

- As the inflow of water (*Inflow AWC*) is not allowed to increase above TAW, there is no room for the model to account for excess water stress, as if there was a perfect drainage system.

4 Methods

4.1 Input Data and SPI Index

As climate change ushers in more extreme-weather seasons, the scenario drivers of the model (temperature and precipitation) were changed to test the model against more realistic future scenarios. The location chosen was Mont-de-Marsan in the south-west of France[5] in 2022, a severe drought year (Baruth et al. (2022)).
Data was retrieved from the *E-OBS daily gridded meteorological data for Europe from 1950 to present derived from in-situ observations* Copernicus database (Copernicus Climate Change Service, Climate Data Store (2020)). Using Python, a function was built to plot the top 10 ranked temperature and precipitation values for every year from 2011 of a given location[6]. Results shown in Figure 2 helped in the selection of 2022 as the preferred "forcing" year. Finally, to cross-check model results, data for maize production yearly percentage changes in France was calculated from Eurostat (2025).

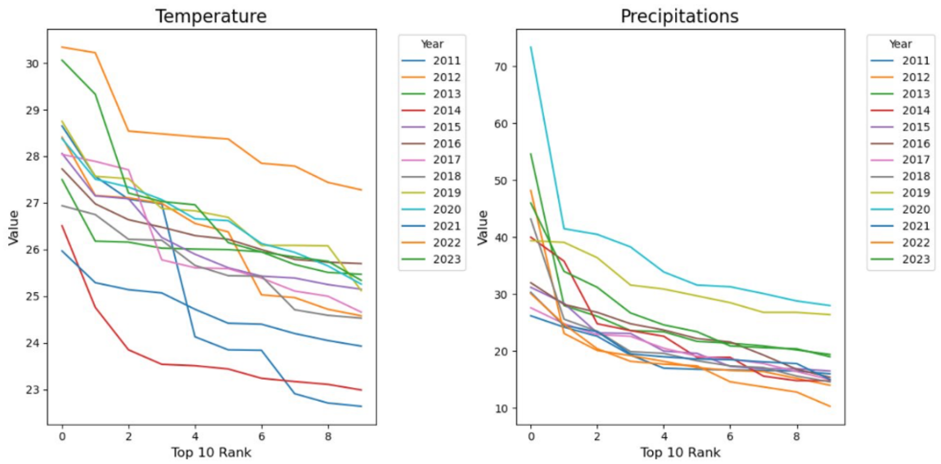

Figure 2: Top 10 values for temp and prec for Mont-de-Marsan from 2011. Source: own elaboration

Even though drought stress was already accounted for in the prototype with the inclusion of *Ks* in the *biomass accumulation* formula, proposed changes (see below) needed the model to know when drought conditions were present. There is not a unique definition of drought (Organization (2012)). After a review of different drought indices (see Keyantash and Dracup (2002)), it was opted for the 1-month **SPI** (Standardized Precipitation Index), as it is computable exogenously without modifying the model just with historical precipitation data as input. The methodology, fully explained in Edwards (1997), consisted of fitting the long-term record to a gamma distibution, normalising it so that the mean SPI is zero, and then comparing it to the monthly precipitation values in 2022[7]. An SPI value of -1.5 was chosen as threshold for drought, as justified by Organization (2012).

4.2 Heat stress integration

Model additions for integrating heat stress are based on the econometric work of Lobell et al. (2011), who estimated that each degree day above 30°C reduces the final yield of 1% under normal conditions and of 1.7% in case of drought. First, the formula for *GDD* was capped at $T_{\text{opt}} = 30°\text{C}$ in the following

[5]France is the biggest maize producer in the EU, right above Romania (Eurostat (2025). Within France, the department of Landes is known for significant maize cultivation. The town of Mont-de-Marsan, located in Landes, serves as a representative location

[6]See Appendix 1

[7]The replicable Python function for computing the 1-month SPI for a given location is included in Appendix 1

way:

$$\text{GDD}_{\text{base,opt}} = \sum_{t=1}^{N} \text{DD}_t, \quad \text{DD} = \begin{cases} 0 & \text{if } T_t < T_{\text{base}} \\ T_t - T_{\text{base}} & \text{if } T_{\text{base}} \le T_t \le T_{\text{opt}} \\ T_{\text{opt}} - T_{\text{base}} & \text{if } T_t > T_{\text{opt}} \end{cases}$$

Secondly, a counter (stock: *YieldRed*, flow: *GDD>30*) was added to track the sum of yield losses (in percentage) to deduct at the end of the year from the final yield. The counter activates if daily temperature is above T_{opt} and adds 1 (*YRF*) or 1.7 (*YRFDrought*) if is a drought month. The cumulated percentage impinges upon the final total yield only, so in the model yield losses from extreme heat are calculated only at the final timestep, like a "counterfactual". The Yield Reduction Factors parameters are potentially modifiable.

Further, shorter phenological phases were taken into account reducing the growing season based on degrees of warming, as per Abbas et al. (2017). With *DeltaT*= 5 and setting the *advancement rate* parameter at 10, crop season is reduced by 30 days.

4.3 Waterlogging integration

Firstly, WL conditions were defined as $\frac{AWC}{TAW} > 1$. To allow this, *inflow AWC* was allowed to increase more than *TAW*, thereby eliminating the implicit drainage system included in the prototype. Secondly, using a counter for days of accumulated WL (*WLdays*) and a trigger for WL stress (*WLtrigger*), a *WLimpact* variable set at a default value of 1 gets multiplied by the *WTC* (WL Tolerance Coefficient) to directly reduce the daily yield during periods of WL stress. The use of a *Timer* extends the WL stress for a number of days after the stress is triggered, like a "pulse" reducing the accumulation of biomass for long after WL damages the plant (Ren et al. (2014)). *WLtrigger* (5 days), *Timer* (30 days) and especially the *WTC* (0.5) can be calibrated further if needed.

4.4 Strengths and Limitations

While one strength of the modified model is that it can be easily recalibrated with new parameter values coming from empirical and econmetric analyses, there are many limitations worth mentioning:

- The negative effect of extreme heat does not increase proportionally with increasing temperatures. Moreover, heat susceptibility is not differentiated for crop development stage - something confirmed by the literature, especially during anthesis. Both limits could be obviated in the model by multiplying GDD values by an exponentially decreasing lookup function for every phenological phase, an approach attempted during research. However, values for these curves remain very difficult to justify empirically;

- Another limitation is the use of an exogenously imported drought condition on top of the use of *Ks*. Although methodologically robust, the SPI measures "meteorological" droughts, so it does not compare actual evapotranspiration and potential evapotranspiration and it is not dependent on temperature (Mohammed et al. (2022)). Integrating drought stress "endogenously" would be step forward;

- Including both a *YRF* and a *YRFDrought* enables indirectly to account for heat and drought stresses combined, as the negative effect of a temperature day above 30°C increases in drought conditions. Yet, as the literature suggests, in reality heat and drought stresses occurring together tend to manifest in complex, nonlinear ways.

5 Results

With the growing season restricted to 120 days from May to September[8], results for Mon-de-Marsane for 2021 and 2022 show substantial differences in the main indicators, as shown in Figure 3, depicting huge losses in production and draining of freshwater discharge in 2022.

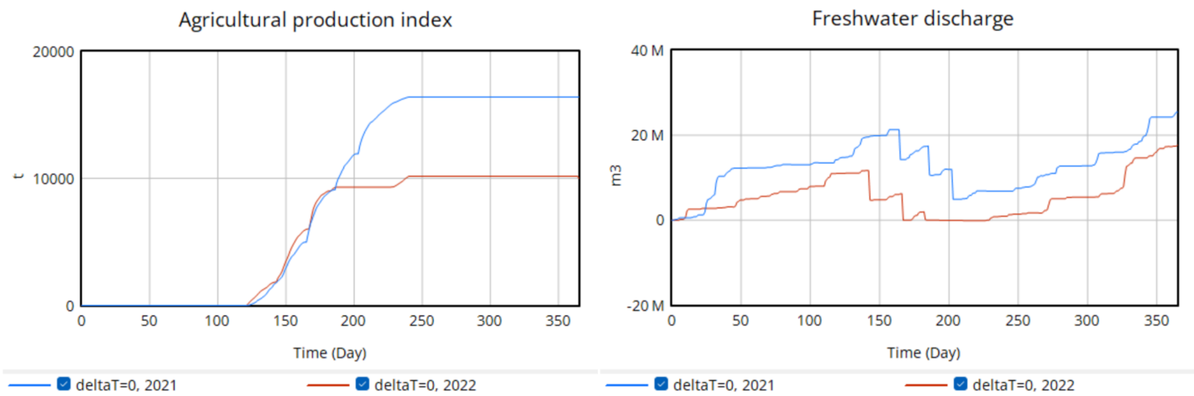

Figure 3: Yield and Freshwater Discharge in 2021 against 2022. Source: own elaboration

The main cause for the catastrophe is lack of rainfall in 2022, which fails to sufficiently fill up the catchment early in the year and to then sustain large irrigation demands during a dry summer. These results would lend credibility to Webber et al. (2018)'s claim that drought stress is dominant in low-yielding years. Interestingly, the percentage reduction in yields from 2021 to 2022 is somewhat similar to the observed one (*29%*) for grain maize in France, provided by Eurostat (2025).

Heat stress contributes to a mere *1.7%*[9]. Yet, if the *deltaT* parameter is artificially increased, the effect of heat stress on yields starts taking place, as shown in Figure 4, reaching a stark *12.8%* loss if temperatures were 3°C higher. Results therefore suggest that in a warming world the heat channel would be more prominent.

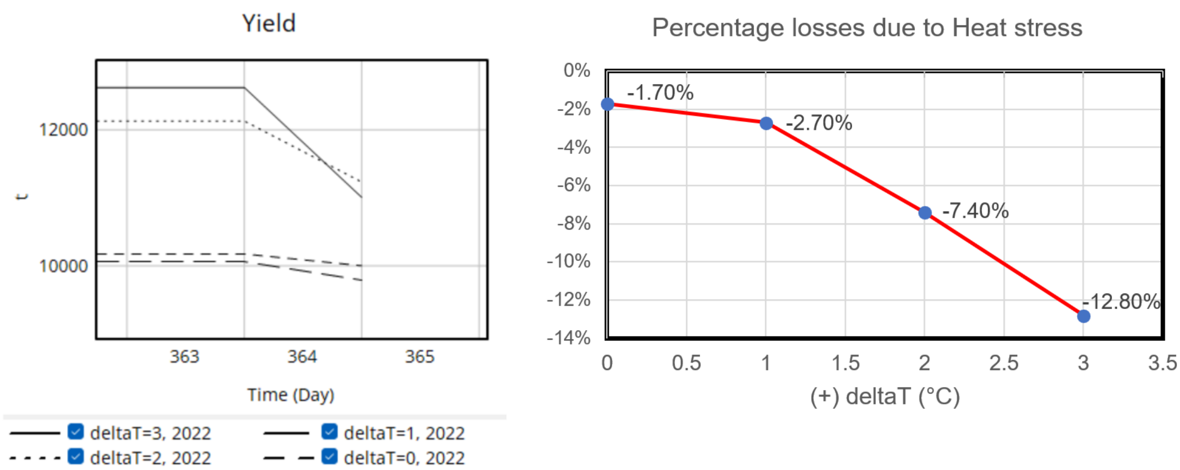

Figure 4: Yield loss due to heat stress, absolute and percentages for different deltaTs. Source: own elaboration

Being a drought year, 2022 does not meet the conditions for waterlogging. Therefore, data for the year 2019 is employed to test WL stress[10]. Adding artificially just a pulse of 3 consecutive days of *40mm* of rainfall triggers WL in this case. As shown in Figure 5, WL is more significant if the pulse comes in

[8]Results changing significantly if the crop is let growing the whole year. More specifically, agricultural production in 2022 recovers from October thanks to long-awaited rains and high temperatures (higher than in 2021)

[9]The effect can be disentangled because, as explained in the Methods section, the cumulated yield loss is substracted only at the end of the year, providing a sort of a counterfactual

[10]Plots drawn with the function of Figure 2 helped in the selection of 2019, the second wettest year of the decade. 2020 was even wetter, but since it was a leap year, there was an additional data point that complicated matters

early spring, during the "rainy" months[11]. Depending on the magnitude of the *WTC* coefficient, which directly enters the *biomass accumulation* formula, the effect on yields vary widely.

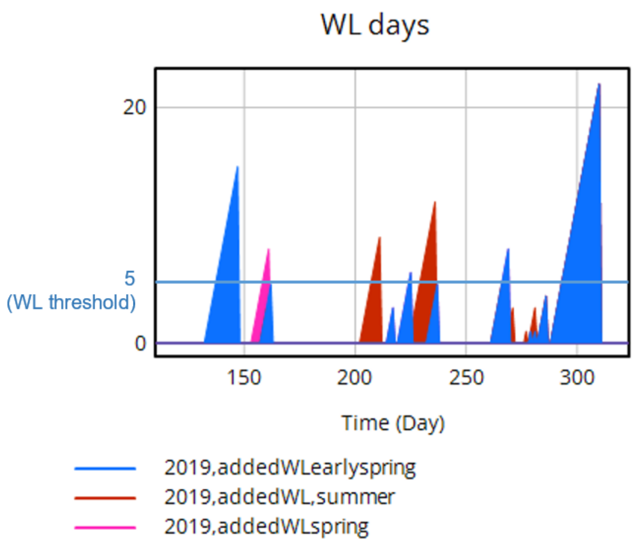

Figure 5: WL (*AWC/TAW*>1) days with an extreme rainfall episode applied in different months in 2019. Source: own elaboration

6 Adaptation options

Different adaptation options, suggested from Cairns et al. (2012), are described in Table 1 and implemented in the model with a twofold objective: maximise yields and trying to avoid complete draining of the catchment. Below, in Figure 6, are also presented the results from the model.

Name	Description	Model implementation
2022,WaterEffVariety	Cultivars with improved WUE (water use efficiency)	*WaterEff Variety = 0.8*
2022,increasedIrrEff	Improved irrigation efficiency through drip irrigation	*Irrigation Efficiency = 0.8*
2022,EarlySowing	Adjusted planting date to start of March	*GDD start/end = 60-180*

Table 1: Description of adaptation options

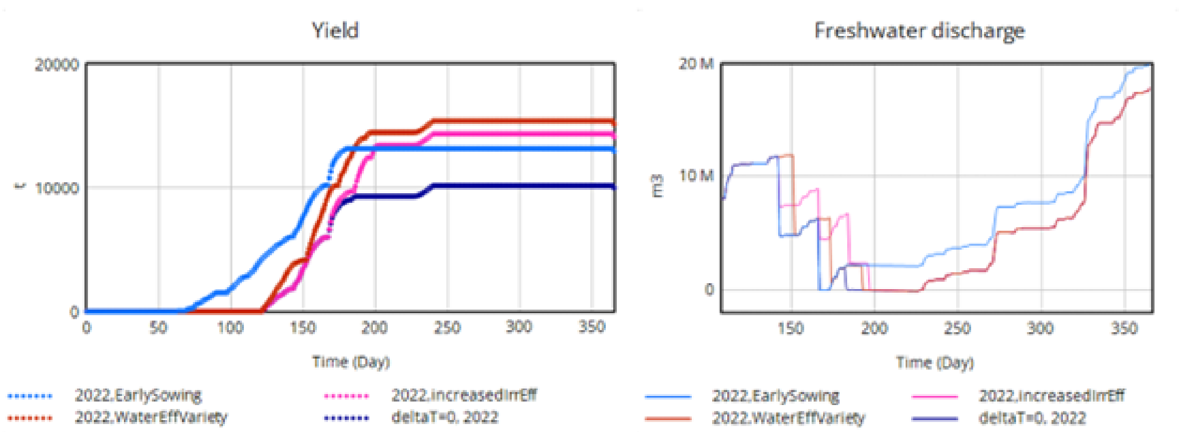

Figure 6: Results with different adaptation options. Source: own elaboration

[11]The large spike in October/November is not relevant for the crop, as harvest has been anticipated to the last day of August

While all options improve significantly agricultural production, the strategy that performs best is **using the drought-tolerant water-efficient variety**. In the model, a lower *ETc* (potential evapotranspiration) improved the *Ks* (Water stress Coefficient) of the plant. One caveat for drought-tolerant varieties evidenced in the literature (Cairns et al. (2013)) is that they are not necessarily also heat-resistant. In warming drought-prone areas, maize varieties will need to be heat-proofed as well, something that genomic selection and CRISP will help in the future (ibid.).

Albeit the lowest in terms of yields, **early sowing** is the only strategy that achieves preserving a flowing freshwater discharge throughout all year. Planting early in March prevents irrigation pressures on the watershed during the driest summer months. Less production compared to the alternatives, eventually, should not worry farmers too much: temperatures will increase also in spring and early sowing potentially avoids heat stress during the sensible flowering phase (Sabagh et al. (2021)).

Improving **irrigation efficiency** with innovative drip irrigation systems (which maximise the "crop-per-drop") comes with yield advantages in drought and extreme heat contexts (WU et al. (2021)) but also with potential drawbacks. Even if promoted as a solution to water stress, intensified irrigation can end up increasing water withdrawals and reducing water availability. Indeed, nonconsumed water "losses" (like runoff) are frequently recovered and reused at watershed scale[12]. Moreover, irrigation demand often tends to increase, as farmers change behaviour and decide to grow thirstier crops. This has been dubbed the irrigation paradox (Grafton et al. (2018)).

Finally, one insight that the model provided on WL stress is that for crops without covers or efficient drainage systems, irrigating the crops *until saturation* significantly increases the risk of WL, simply because the next day could rain heavily. With extreme precipitations coming more and more often, this risk cannot be ignored by farmers with irrigation crops. Needless to say, WL risk will be substantially more pronounced for rainfed crops in countries like India or SouthEast Asia (Zaidi et al. (2004)).

7 Conclusions

After a comprehensive literature review, the DPSIR watershed model has been enriched, now embryonically accounting for heat, drought and waterlogging stresses. While the effect of drought has been found already impinging upon yields through the *water stress coefficient*, heat and WL stresses were not present and have so been integrated. Even if not representing real "mechanistic" crop behaviour, the additions are advantageous because they are provided with readily modifiable coefficients that can be recalibrated based on empirical analyses.

Forcing the model with data representative of a more extreme weather, results show severe losses of output and a waning natural flow, differently from the model original runs. Identifying the key drivers of yield alterations in the catastrophic main scenario (Mon-de-Marsane, 2022) sheds light on the need to adopt targeted adaptation measures, such as: stress-resistant varieties; investments in irrigation infrastructure; or advancing plant sowing dates. Implementing these different adaptation strategies in the model confirms the trade-off between maximising agricultural output and preserving the watershed. Notwithstanding, as suggested by much of the literature, the choice of the best adaptation option to pursue must then be evaluated case-by-case based on local circumstances.

[12]Having a 100% irrigation efficiency would thus be impossible in reality. This is why in the model the *Irrigation Efficiency* parameter is increased only to *0.8*

A Appendix 1

The function used in Figure 2 shows the highest values for temperature and precipitation of the year *for the top 10 years.* Using data from the Copernicus database *E-obs daily gridded meteorological data for europe from 1950 to present derived from in-situ observations* (Copernicus Climate Change Service, Climate Data Store (2020)), here is the fully replicable function:

```
def topten(da, your_lat, your_lon, flag, ax):
    if flag == 'temp':
        index = 'tg'
    else:
        index = 'rr'
    #selection of data for required location:
    selected_da = da.sel(latitude = your_lat, longitude = your_lon, method="nearest")
    df = selected_da.to_dataframe().reset_index()
    df["year"] = df["time"].dt.year #addition of "year" column
    new_df = {}
    for i in range(2011, 2024): #range can potentially be widened if longer-term data is provided
        val = df[df['year'] == i][index].values
        if len(val) > 365:
            val = np.delete(val, 59) #correcting the "leap" years (anni bisestili)
        new_df[i] = val
    new_df = pd.DataFrame(new_df)
    for year in range(2011, 2024):
        #plotting the top 10 years (highest value of an year):
        ax.plot(sorted(new_df[year], reverse=True)[:10], label=str(year))
    ax.set_xlabel("Top 10 Rank", fontsize=12)
    ax.set_ylabel("Value", fontsize=12)
    ax.legend(title="Year", bbox_to_anchor=(1.05, 1), loc='upper left')

#To call the function:

fig, ax = plt.subplots(1, 2, figsize=(12, 6))

for j, (df, index) in enumerate(zip([temp, prec], ['temp', 'prec'])):
    ax_idx = ax[j]
    topten(df, mdm_targetcoo[0], mdm_targetcoo[1], index, ax_idx)
    if j == 0:
        ax[j].set_title("Temperature", fontsize=16)
    else:
        ax[j].set_title("Precipitations", fontsize=16)

plt.tight_layout()  # Adjust layout to prevent overlap
```

A Appendix 2

The monthly **SPI (Standardized Precipitation Index** for Mon-de-Marsane was computed from the long-term precipitation record drawn from the Copernicus database *E-obs daily gridded meteorological data for europe from 1950 to present derived from in-situ observations* (Copernicus Climate Change Service, Climate Data Store (2020)).
The computation required fitting the cumulated monthly precipitation values of the long-term record to a **gamma** distribution. Then thresholds values based on a drought threshold set at -2 were computed through a normal transformation of the gamma cdf. The methodology is thoroughly described in Edwards (1997).
Here is reported the fully replicable Python function and its function call for Mon-de-Marsane in 2022 built for the computation:

```
def SPI(prec_da, your_lat, your_lon, year, norm_threshold):
    #selecting the location in the gridded area:
    selected_da = prec_da.sel(latitude = your_lat, longitude = your_lon, method="nearest")
    #summing daily precipitations and aggregating per months:
    monthly_precip = selected_da.resample(time='1ME').sum()
    prec_series = monthly_precip.to_pandas()
    df_series = prec_series.to_frame(name='value')
    df_series['year'] = df_series.index.year
    df_series['month'] = df_series.index.month
    #DataFrame with yearly index and monthly columns, with cumulated monthly precipitations
    wide = df_series.pivot(index='year', columns='month', values='value')
    p_selyear_months= wide.loc[year] #Series of the year of interest
    shape, loc, scale = [], [], []
    for i in range(1,13):
        #Series for every month (along all years in the record):
        month_data = wide[i].dropna().values
        month_dataclipped = np.clip(month_data, 0.2, 500)
        #fit GAMMA distribution with loc fixed at 0:
        fitted = stats.gamma.fit(month_dataclipped, floc=0)
        shape.append(fitted[0])
        loc.append(fitted[1])
        scale.append(fitted[2])
    drought = norm_threshold
    thresholds = []
    for i in range(12):
        #Thresholds for drought condition based on the Gaussian threshold provided, for every month
        thresholds.append(stats.gamma.ppf(stats.norm.cdf(drought), a=shape[i], loc=0, scale=scale[i]))
    display(Markdown(f"**Monthly SPI index** for year **{year}** *(drought threshold = {thre}*):\n"))
    for i in range(12):
        #comparison between year of interest and drought threshold, to see whether it was a drought month
        if (p_selyear_months[i+1] < thresholds[i]) :
            print(f"Month {i+1} : {p_selyear_months[i+1].round(2)} < (thresh){thresholds[i].round(2)} ")
        else:
            print(f"Month {i+1} : {p_selyear_months[i+1].round(2)} > (thresh){thresholds[i].round(2)} ")

# To call function: precipitation record (xarray.DataArray), coordinates,
# year of interest, Gaussian threshold for drought:
SPI(prec_f, mdm_targetcoo[0], mdm_targetcoo[1], 2022, -2)
```

SPI results for Mon-de-Marsane in 2022:

Month	**SPI Index**	**Status**
Month 1	49.5	✓
Month 2	41.4	✓
Month 3	45.6	✓
Month 4	66.3	✓
Month 5	17.2	✗
Month 6	72.2	✓
Month 7	0.7	✗
Month 8	29.6	✓
Month 9	65.7	✓
Month 10	10.0	✗
Month 11	141.3	✓
Month 12	60.4	✓

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