A climate empirical temperature simulator

An application in Provence (France) : 2025-2050

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Abstract *: The importance of being able to make climate projections at the local level is fundamental because they are the ones that will serve as an input for any vulnerability study as part of a climate change adaptation plan.*
The techniques exist and, in France, the DRIAS[1] portal allows you to download these projections with several models and with an 8 km x 8 km grid (called Safran grid).
However, a challenge remains that the local values of these projections do not always correspond well to the data from weather stations.
Corrections must be made to reduce this discrepancy. The operation is tedious, and its quality depends on choices made over the historical reference period.
We have developed an empirical projection tool, based almost exclusively on historical data from weather stations.
This tool is developed in this article with a comparison between the two methods.

1. Introduction

In our previous publications on the climate of southern France (Blanchart, 2024), we used climate models to project the future at the local level. In most of the cases studied, there is a significant gap between the results obtained for the future and the historical data from the weather stations. We applied a procedure consisting of reducing these deviations by translation, rotation, and adjustment of the amplitude of the fluctuations (Blanchart, 2024).
We carried out a complete analysis of these histories, compared several stations with each other and concluded that we could characterize each year by 6 parameters (3 for the daily minimum temperature **TN** and 3 for the daily maximum temperature **TX).**
The study of the historical evolution of these 6 parameters makes it possible to project the consequences of climate change (frost days, tropical nights, days of intense heat, etc.) over a limited period (in this case 2025-2050 for this study). We will therefore recall the method used so far, compare the results with those of an empirical model as well as with projections from other sources (such as Climadiag[2], France).
As a direct thermal consequence, we will use as the main example the number of "hot" days **JTX25** (days when the maximum temperature **TX** is greater than or equal to 25°C).
We have already published a first study in 2024 (Blanchart, 2024) based on the use of climate models. But this first study was based only on the available print run of existing climate models.
We introduce here an empirical model based on an extrapolation of historical data from annual parameters and correlated with climate models. This model has three advantages:

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[1] DRIAS : Donner accès aux scenarios climatiques Régionalisés français pour l'Impact et l'Adaptation de nos Sociétés et environnements (Providing access to French regionalized climate scenarios for the impact and adaptation of our societies and environments)
[2] Climadiag is a website from Météo France where the climate consequences of each municipality are given for 2030, 2050 and 2100 (https://meteofrance.com/climadiag-commune)

- ✓ It only requires a weather history (from weather stations)
- ✓ It allows many random samples to be carried out and therefore confidence limits to be calculated
- ✓ It makes it possible to multiply climate scenarios based on historical values.

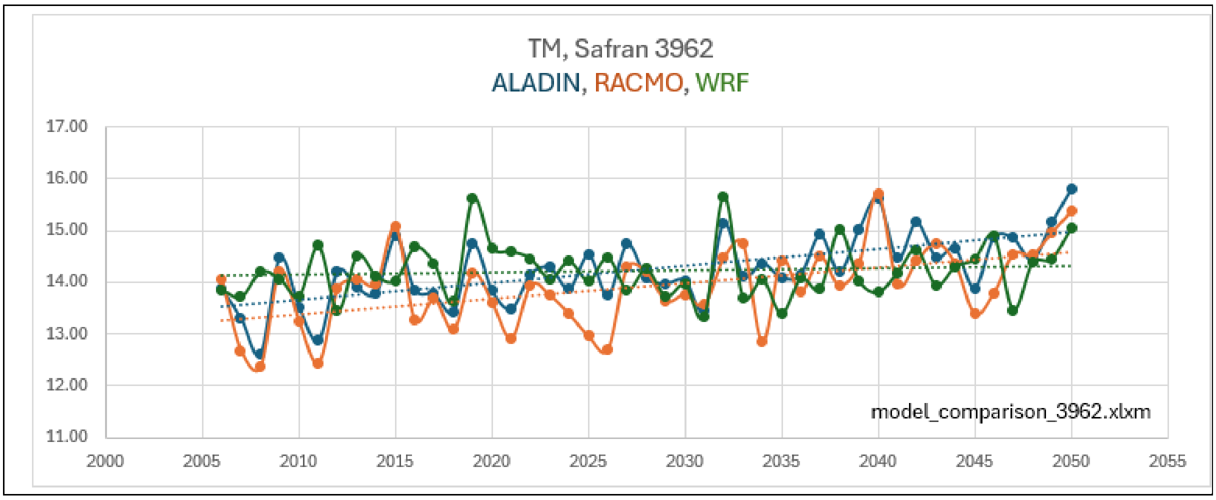
For information, this study is part of a climatic analysis of the Arc Valley in Provence (France).
To illustrate the whole process, we will use data from the meteorological station of Mimet (France, department of Bouches-du-Rhône, see coordinates in chapter 2).

2. Use of physical climate models

2.1.- Model selection

As indicated in (Blanchart, 2024) the most likely climate scenario is RCP8.5.
We had already observed that the warming rates (by the mean temperature TM) measured by the Mimet weather station (and about ten stations in the South of France) were historically higher than the median RCP8.5.
We first made a choice between the available models.
We tested three of them applied to the Safran grid: ALADIN63_CNRM-CM, WRF381P_IPSL-CM5A and RACMO22E_EC-EARTH (DRIAS, 2020) in order to verify several hypotheses and to see if any of them gave results more in line with local warming.

Here is the result on the Safran 3962 point that has been the subject of another study (to be published).



For the three models, we have respectively a warming of 0.33°C/decade (ALADIN), 0.30°C/decade (RACMO) and 0.04°C/decade (WRF)
We already know that the warming calculated from historical data is greater than that modelled, so we will adopt, for the continuation of this document, the ALADIN model that we used in the first exploratory approaches.

2.2.- Choice of the Safran point for Mimet

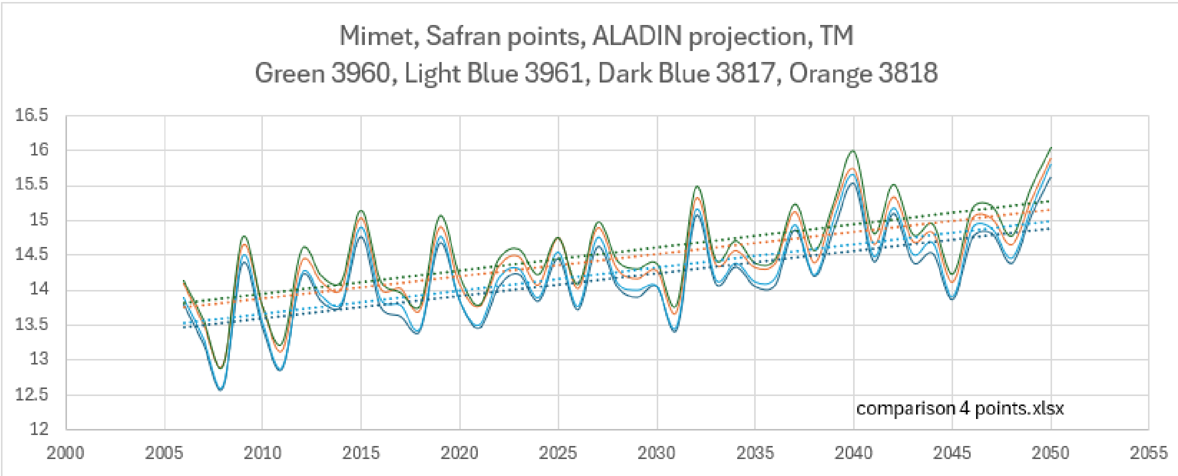
When positioning a weather station on the Safran grid (a grid of points of about 8x8 km), the station rarely coincides with one of these points.
For example, the Mimet weather station (station 13062002) is practically in the centre of the 4 Safran points that surround it (3960, 3961, 3817, 3818).
Here is the geographical distribution of the 4 points and the weather station of Mimet.

Station	Lat	Long	AltNASA	AltSafran
3817	43.382401	5.44268	414	391
3818	43.379501	5.54116	342	365
3960	43.4543	5.44658	284	246
3961	43.451401	5.54518	321	266
Mimet	43.4185	5.499667	422	416

Alt NASA : altitudes are measured from NASA satellites (source dCode)

AltFR : altitudes are measured from SAFRAN grid or weather station (Mimet) altitude.

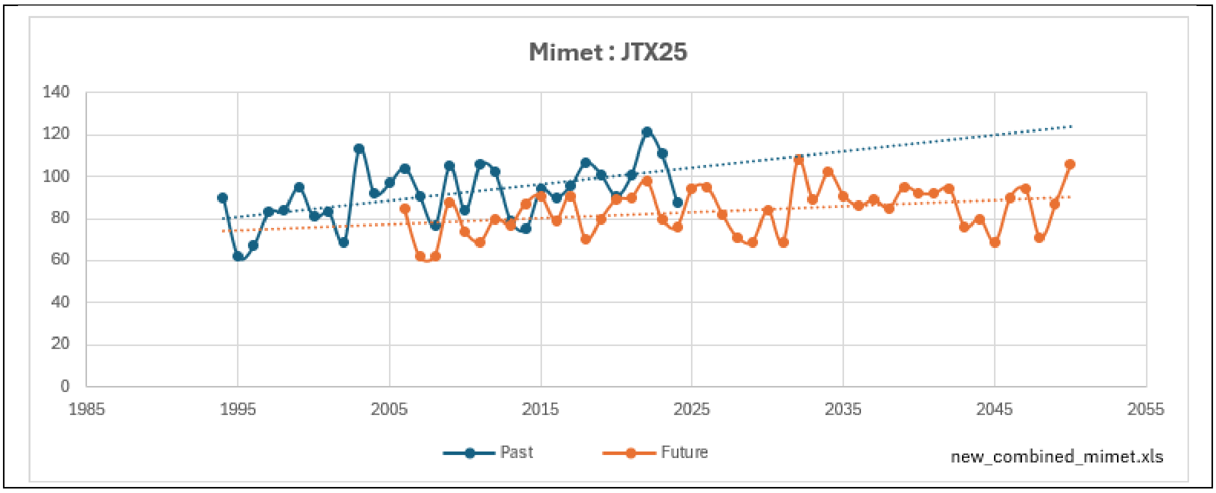
The question therefore arose of bringing the values of the 4 points back to the coordinates of the Mimet weather station.
Calculations were thus carried out combining the results for the 4 points, but because of non-synchronized values, this introduced "smoothing" effects.
We therefore opted for the use of a single point, the results being otherwise very similar between the points as we see hereunder.



First of all, there is a great similarity between the results.
Initially, following an earlier study of neighboring stations, but at different altitudes, it was estimated that there was a correlation between the average temperatures of these stations, with, very roughly, a difference of 0.5°C per 100 m of difference in altitude.
We therefore used the ALADIN model projections for the 4 points and were able to observe a difference of around 0.3 °C per 100 m of difference in altitude. This is obviously a very approximate observation (relating only to the mean temperature TM).
Altitude being a first qualitative criterion, it seems wise to choose one of the two "altitude" stations, i.e. 3817 or 3818. As the present study is part of a study on a larger geographical area, in this case the Arc Valley (rather towards the North-East), we used the **Safran3818/ALADIN** pair as a climatic reference because its location is in the territory of the valley.

__2.3.- Comparison of climate consequences between the past and the future__

Rather than comparing thermal parameters (TN, TX, TM), we have chosen to make the comparison directly on the number of "hot" days JTX25:



We immediately observe that there is a very clear discrepancy between these curves.
As an indication, there are:

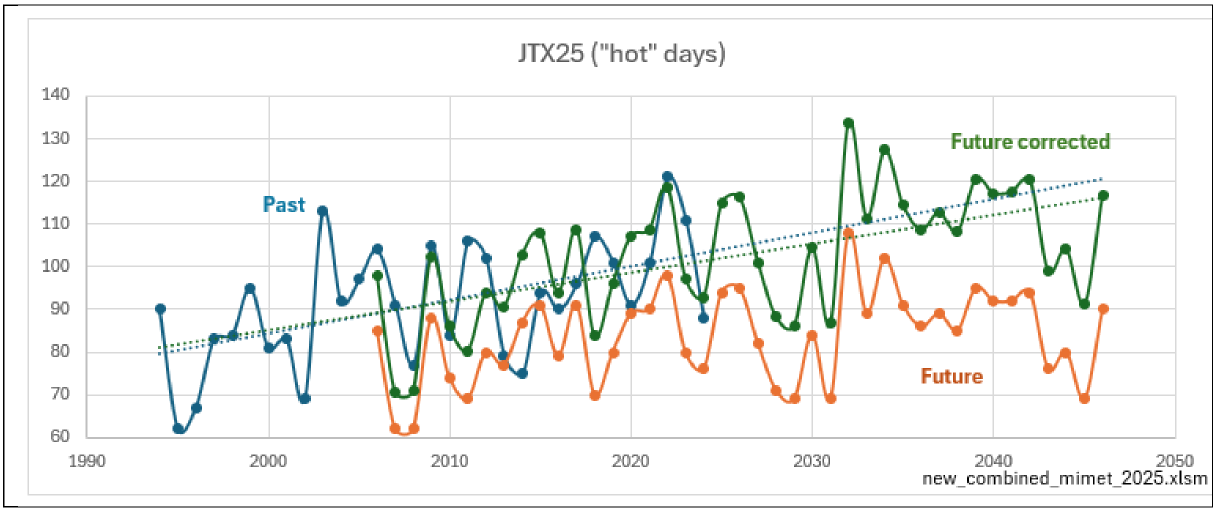
- ✓ a real increase of about 8 days per decade in the past (1994-2024)
- ✓ a projected increase of about 3 days per decade for the future (until 2050).

We would therefore find ourselves in 2050:

- ✓ by linear projection of the past, to 124 "hot" days
- ✓ by climate modelling, to 91 "hot" days

Considering that the past was indisputable, we proposed (Blanchart, 2024) to proceed with a "reconciliation" between the past and the future calculated using 3 corrections: a rotation to bring the slope of the projection back to that of the future, a translation and an amplification or reduction of interannual variations.

Here is the result of the protocol used:



It will be noted that the "corrected future" does not have exactly the same slope as the "past". This is the result of a choice we have to make about the time windows used to calculate the slopes. We preferentially use the common part of the data series (2006-2024 in this case).
In this method, we apply three corrections and a choice of reference time window.
The major disadvantage of this method is that we have only one random sample for the future and therefore do not have an estimate of the uncertainty concerning the magnitude of the consequence (JTX25) or the position of the peaks.

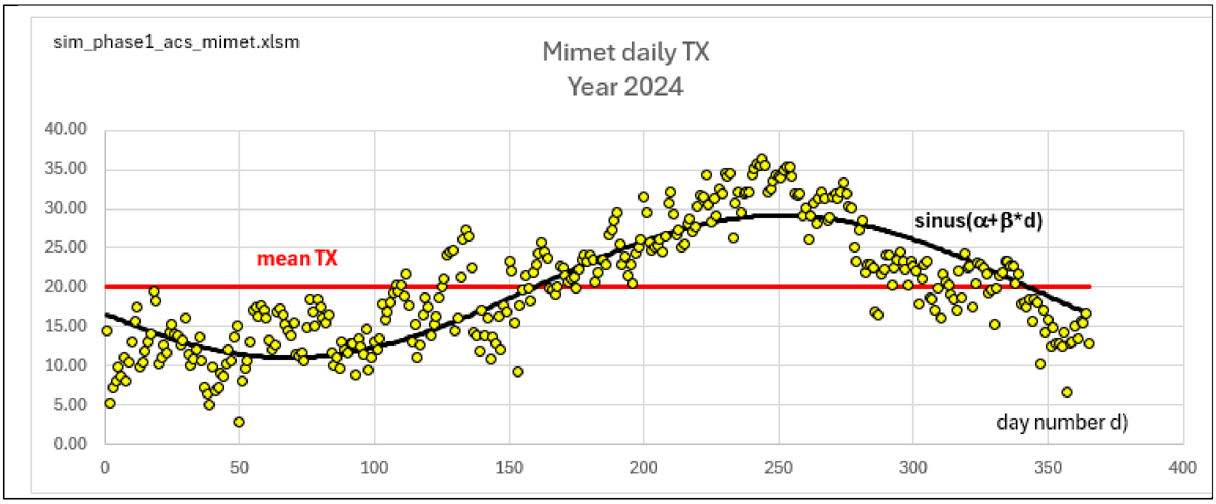
3. The Empirical Model

3.1.- Meteorological year

The idea behind this method is to use only the historical values of a weather station and to return to the two basic thermal parameters: the daily maximum TX and minimum TN temperatures. As a reminder, these are the two parameters that influence the desired consequences: JTN0, JTN20, **JTX25** and JTX35.
When we talk about "year", we usually think of the calendar year, which is easier to use.
But we know that the calendar year does not correspond to the meteorological year that starts in December. We also know that the coldest day is statistically positioned in January.
In order to keep the data consistent, in particular the fact that the frost days must be taken in the same winter sequence, we chose the meteorological year for our calculations: December 1st(year-1) to November 30th(year), the number of the year being that of the summer.
This is also consistent with the conventional definition of seasons.

3.2.- The three parameters

When you look at a TX or TN graph of the 365(366) days of a year, you can easily identify the seasons. Intra-annual variation can obviously be modelled by a sinusoidal function.
Here is the illustration on the daily TX of the weather year 2024 in Mimet, (day "1" = December 1st, 2023):



3.3.- Calculation procedure

We will perform a sinusoidal regression over all the 365(366) days of the year.
One of the most common formulas for a general sinusoid equation is:

$$f(x) = A * \sin\big(W * (x - P)\big) + C$$

If we use the number of the day (d) as the variable (x), and the complete cycle is 365(366) days, this gives:

$$TSIN(X, N\ or\ M) = A * \sin\left(\frac{\pi}{4} + \frac{2 * \pi * d}{365}\right) + C$$

$$TSIN(X, N\ or\ M) = A * \tau + C \Leftarrow \text{regression equation}$$

In these equations, the phase shift $\pi/4$ is there to consider that the meteorological year begins on December 1st and that the coldest day is usually recognized to be January 15th.
This is in fact only an approximation and we can improve the regression by introducing an offset parameter (Lag L(y), y=year) with respect to January 15th.

$$TSIN(X, N\ or\ M) = A * \sin\left(L(y) + \frac{\pi}{4} + \frac{2\pi d}{365}\right) + C$$

where L(y) is the phase shift of the function with respect to January 15 and this by year (y).
In our preliminary analysis, we will not use the values of this offset.
Finally, we calculate the delta between the observed daily value and the value of this regression: this will give us the daily residuals R(d)

$$T(X, N\ or\ M, d) = TSIN(X, N\ or\ M, d) + R(d)$$

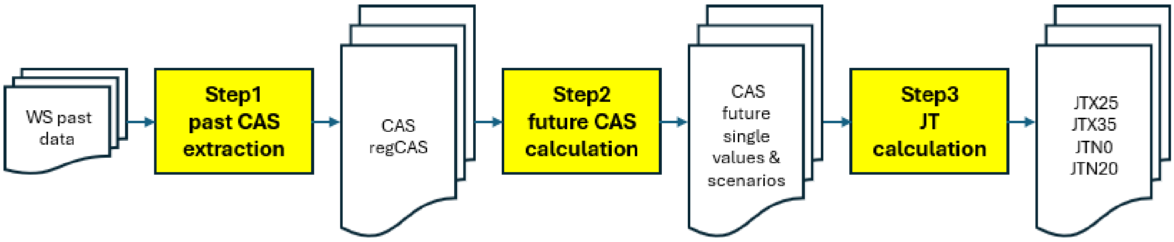
of which we will calculate the yearly standard deviation S(y).

At the end, we will then have, for each year, three parameters : **mean (C), amplitude (A) of the sinus function and (S) the standard deviation** of the residuals.

4. The simulator

The simulator goes through three steps that execute:

- ✓ the extraction of past CAS parameters from weather station data
- ✓ the calculation of future CAS values (2025-2050)
- ✓ the calculation of selected consequences: JTX25, ...

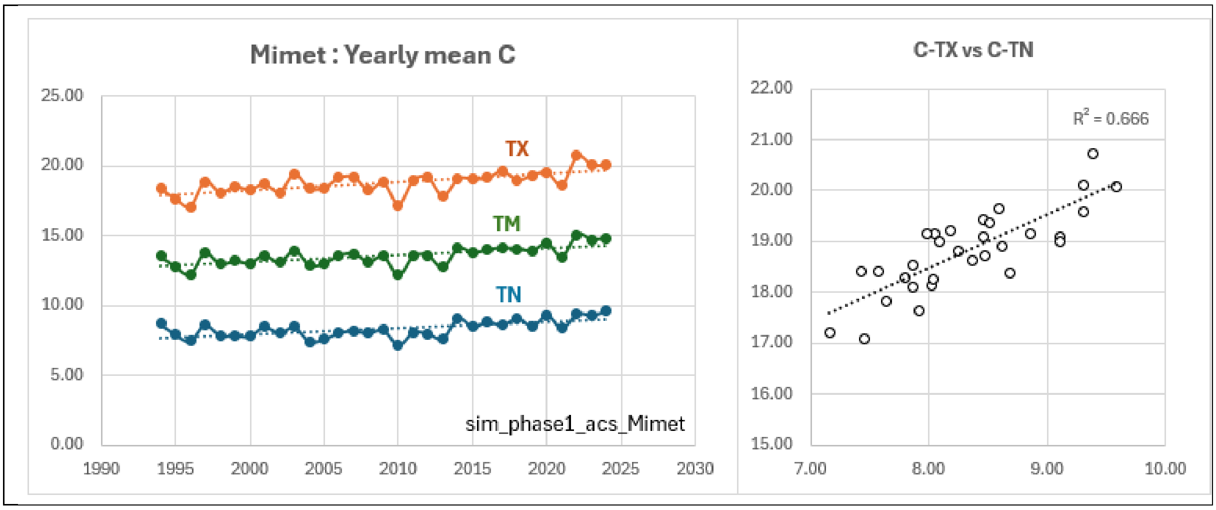


4.1.- Step 1: extraction of the C, A and S parameters from the past (weather station)

The following is the result of extracting the C, A and S parameters from the data of the Mimet station, in accordance with the procedure described in paragraph 3.3:

<u>(i) Mean value C : TX (CTX) and TN (CTN)</u>

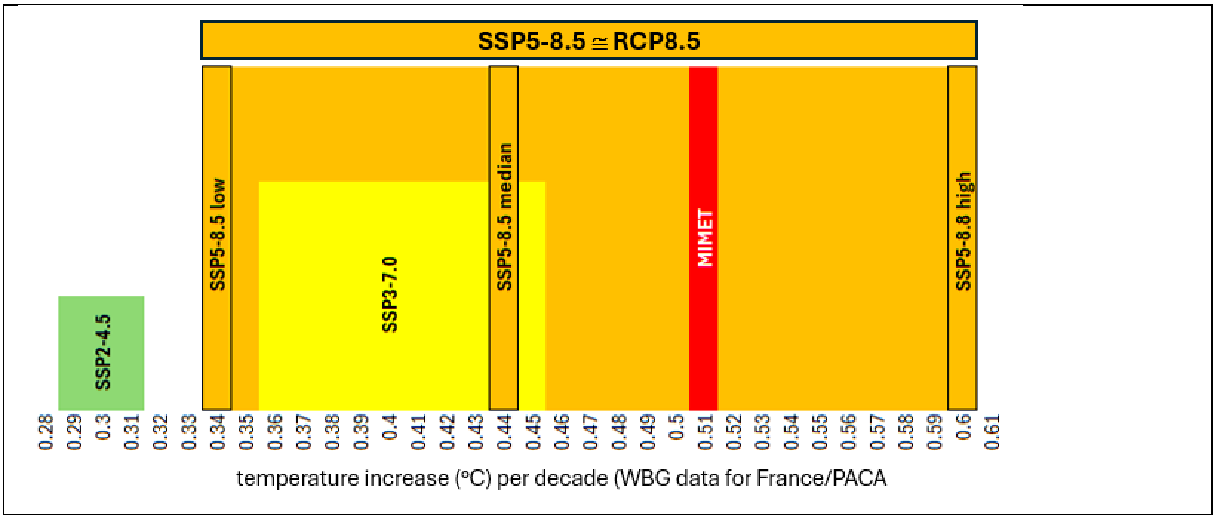
We have added the evolution of the average value of the year (TM) to compare it later with the evolution of the average temperature of the region to which Mimet belongs (PACA, Provence Alpes Côte d'Azur, South East of France).



We can see that beyond the general trend, these temperatures vary from one year to the next. When a simulation is carried out, interannual variations and temperature correlations will have to be considered.

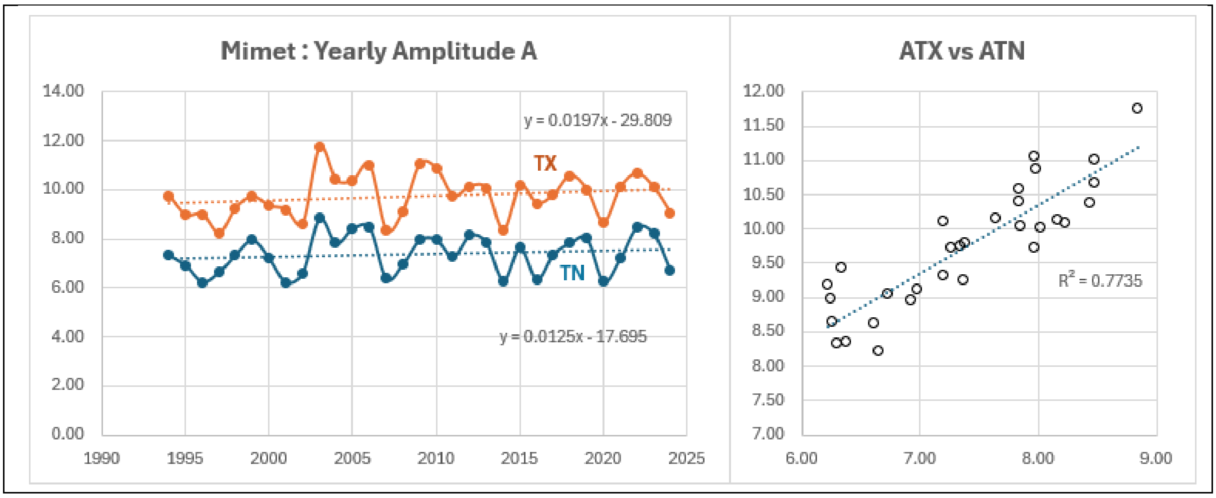
We are obviously seeing the phenomenon of global warming. It is different for the 3 temperature values: TX (0.595°C/decade), TM (0.507°C/decade) and TN (0.418°C/decade).

It is interesting at this level to compare the past evolution of the average temperature of Mimet (which we report in our model to the future for the period 2025-2050) with the evolution predicted for the PACA region in the different climate scenarios (source WBG).
Here is the diagram in question:



We confirm the observation already made for the PACA region and the Occitanie/Languedoc-Roussillon region, that global warming in these regions was higher than the median of the SSP5-8.5/RCP8.5 scenarios.

(ii) Magnitude of the annual change A : TN (ATN) and TX (ATX)



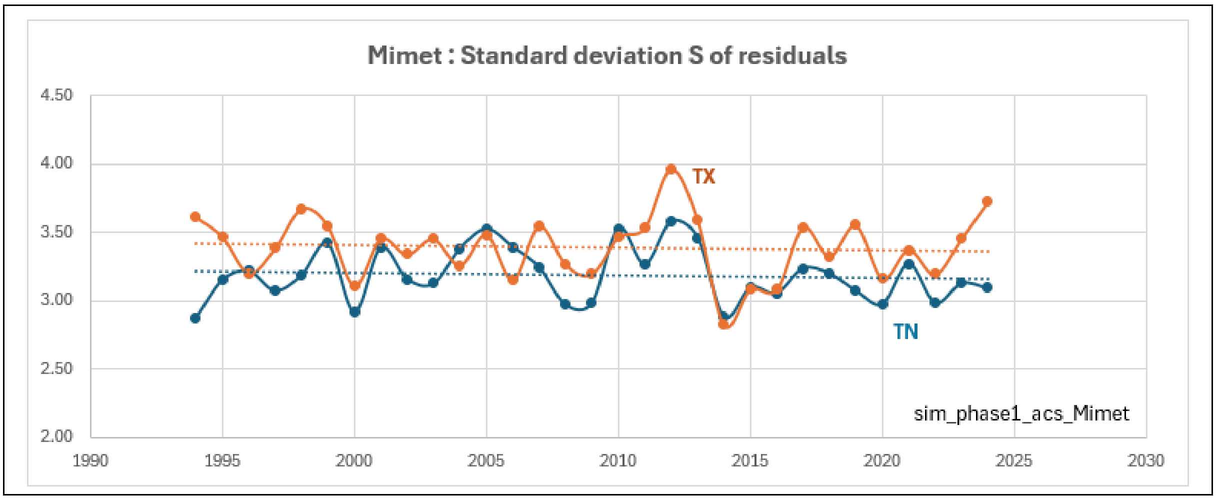
It can be seen that:

- ✓ ATX and ATN amplitudes vary significantly from year to year
- ✓ this amplitude is much greater in value for TX than for TN
- ✓ that these amplitudes are relatively correlated, the difference being of the order of 2°C.

As an indication, it should be noted that there is no correlation between the mean C and the amplitude A for either TX or TN.

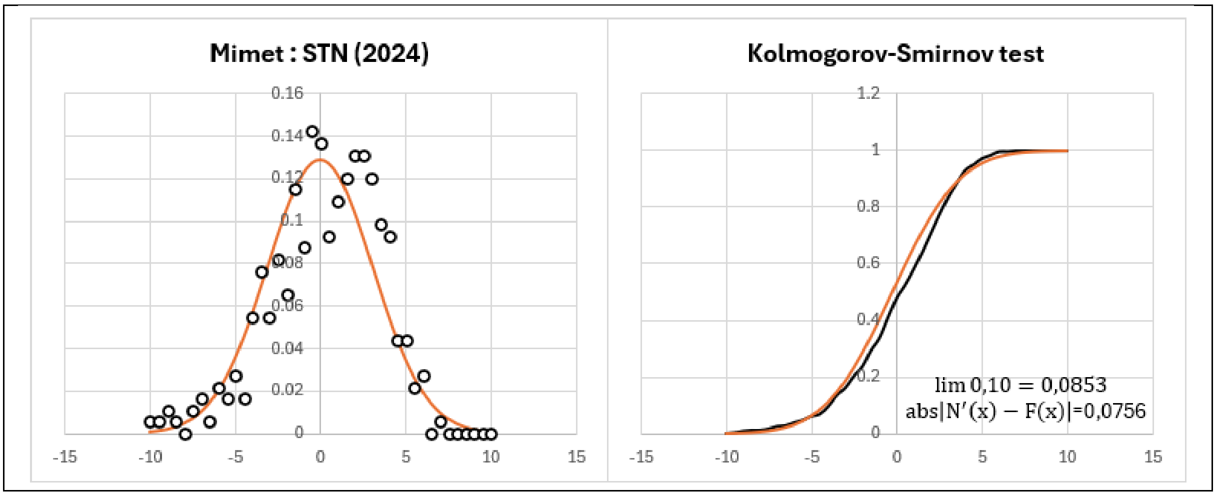
(iii) Standard deviation of residuals R(d) : S(y)

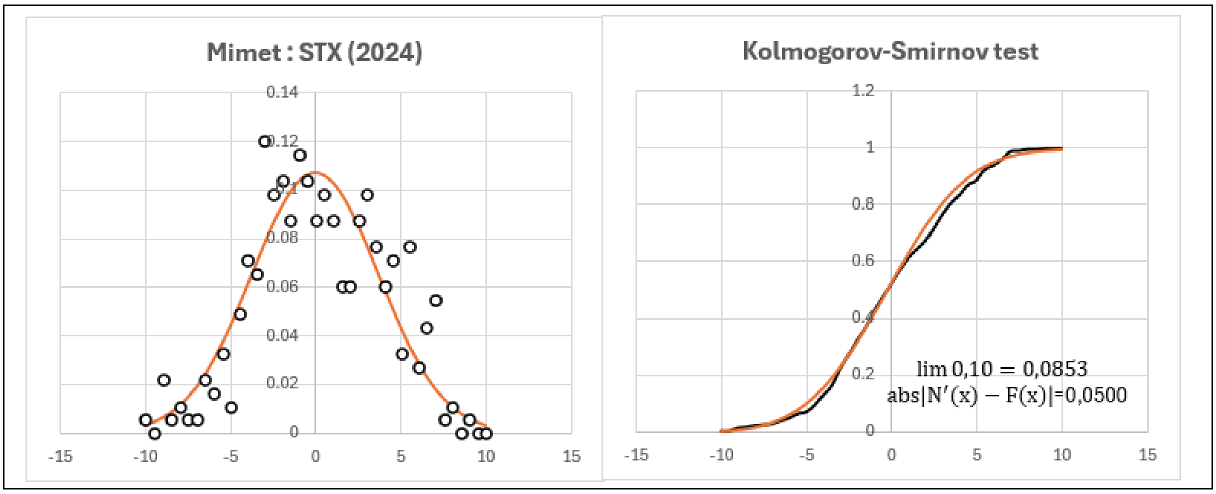
Once the values of A and C have been calculated, the daily residuals R(d) can be determined for each year. And thus calculate the standard deviation S(y) of these residuals for year (y).
Here is the evolution for the Mimet station:



The main remark that can be made is that these differences between the A-C sinusoid and the daily values are slowly decreasing, in this case less than 1% per decade.
We will come back to this observation when the simulator is built.

On this large amount of data (365 per year), we tested normality (year 2024):

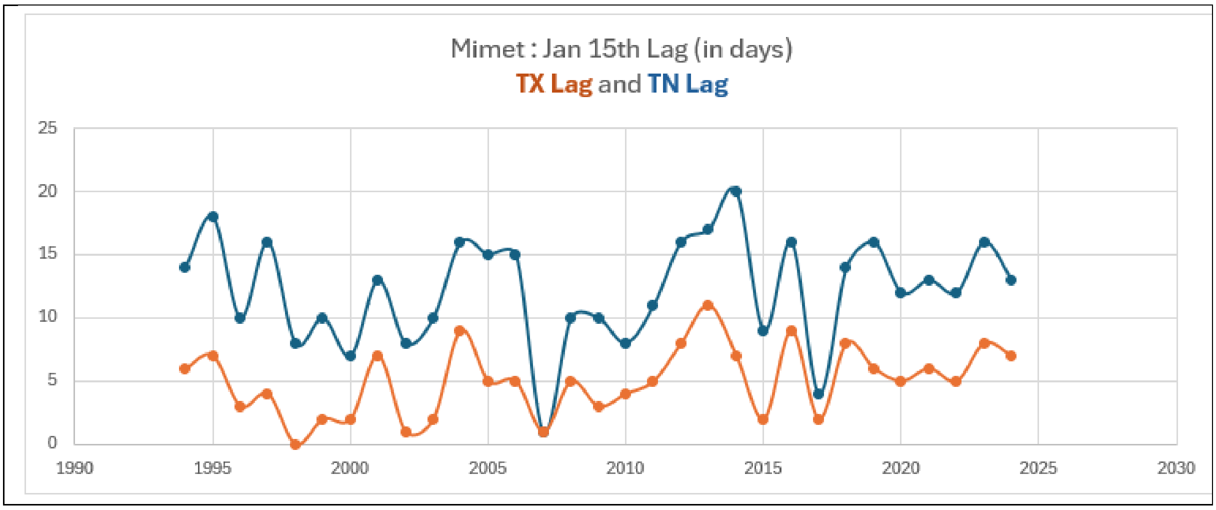




Despite the very noisy aspect of the results, at least one may not reject the hypothesis of normality at the confidence level 0.10.
Unfortunately, we don't have enough data to do a meaningful test with C and A.

(iv) Lag L

For information, here is the evolution of Lag:



It is around 5 days for TX (TX minimum shifted to January 20th) and 10 days for the TN minimum (coldest day) around January 25th.
A subsequent study will be devoted to this last parameter.

4.2.- Step 2: 2025-2050 projection of TX and TN (C,A,S scenarios)

We will now project the values of C, A and S from the past to the future period envisaged (2025-2050) considering not only their trends but also their fluctuations.
For each TX and TN (annual values), we will construct annual C,A,S scenarios.
These scenarios are built one by one. We'll see later how to use several different scenarios.

For parameters C and A :

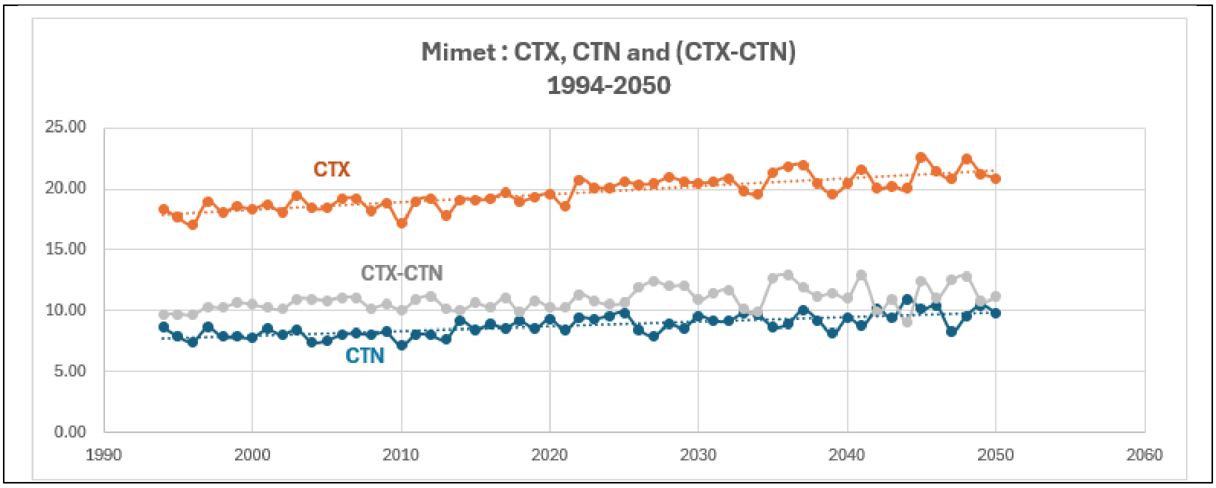
The procedure is as follows:

- ✓ we perform the linear regression of the values of the past of CTN(y), CTX(y), ATN(y), ATX(y)
- ✓ for each year of the entire period (1994..2050), we therefore have a linear regression value rCTN(y), rCTX(y)...
- ✓ from these regressions, we calculate the standard deviations of the variations in these parameters: sCTN,...
- ✓ These standard deviations of the annual parameters are valid for the entire calculation period (i.e. until 2050)
- ✓ for each year of the future and for each parameter, we run a random sample in a normal distribution N(-1,1), giving a BM value[3] and we obtain the new parameters:

$$CTN(y) = rCTN(y) + k * BM * sCTN$$

with y=2025..2050

In principle, we systematically use k=2 to define the uncertainty domain.
But the existing correlations will lead us to reduce this value empirically to k=1.0-1.5 in order to maintain a coherence between TN and TX.
Here's an example of what this looks like for the CTX parameter (from 1994 to 2050):

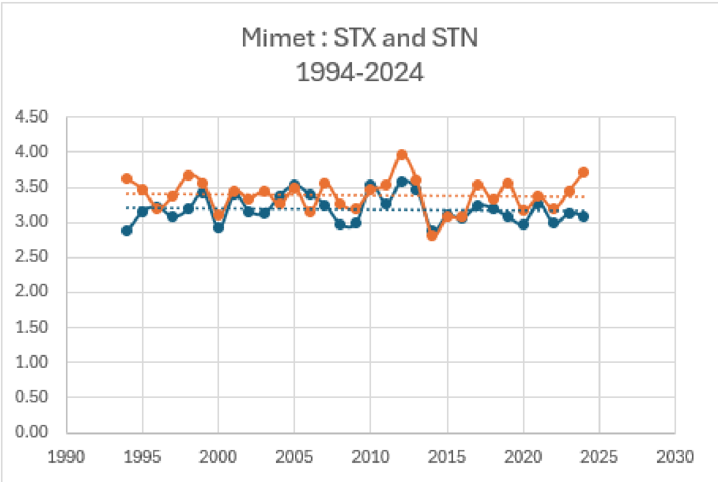


The same procedure will be performed for the amplitude A.

[3] with the Box-Muller algorithm

For the calculation of the deviation S

We observed that for the Mimet station, the annual values fluctuated in a relatively narrow range (3.0-3.5) and that they did not change much over the years.
We also know from preliminary tests that the S parameter is not the most influential for determining the consequences of climate change. This will be confirmed later.



We have therefore chosen to take a constant value over the period 2025-2050 for both TX and TN, namely STX=3.39 and STN = 3.19 (average values of 1994-2024).
If it turns out that this parameter fluctuates significantly, we will proceed with the same method as for C and A.

4.3.- Step 3: Calculation of the direct consequences for a CAS triplet

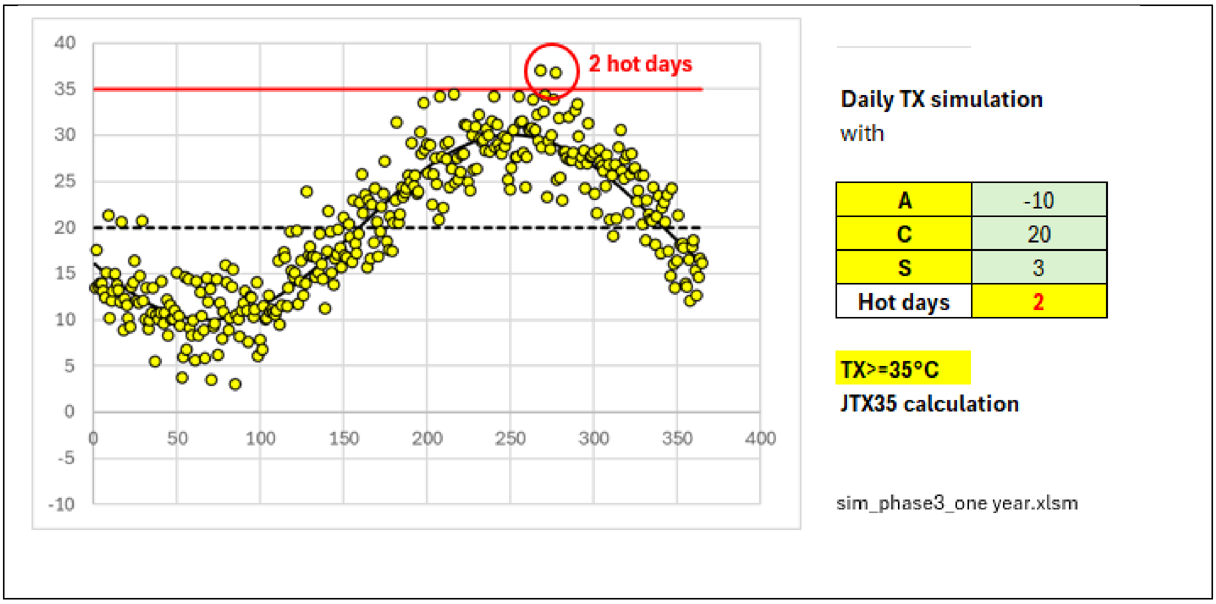
Now that precise values are available for the parameters C, A and S for each year (2025-2050), it is easy to recalculate, for a given CAS triplet, T (TN and TX) for each day of the year in question:

$$T(d) = C + A * \sin\left(L + \frac{\pi}{4} + \frac{2\pi d}{365}\right) + k * BM * S$$

Once the year has been reconstructed, the number of frost days, tropical nights, etc., can be calculated for each type of temperature:

- ✓ for TX: JTX25 and JTX35
- ✓ for TN: JTN0, JTN20.

Here is an example of the resulting graph obtained by this technique:



This third step makes it possible to calculate the thermal consequences of a set of parameters (CAS) (single run) but also to perform 100 repetitions, thus allowing the amplitude of the results to be measured.
Thus, in the case of the figure above, after 100 repetitions we obtain:

JTX35(min) = 0, JTX35(max) =8.

We will now have to decide what we want to look for:

- ✓ a single year with a defined (CAS)
- ✓ a single year with a set of random (CAS)
- ✓ A hot or cold year
- ✓ a complete sequence with random CAS with a search for specific situations, etc.

The simulator lends itself to all these cases.
The choice of scenarios from a random sample is particularly important.
This subject will not be addressed here in an exhaustive manner, but a few additional elements can guide the analysis to be carried out.

5. Scenario development

Remember that the analyzed consequence (JTX25) is the result of a complete sequence that starts from the data of a weather station and results from successive random samples from:

- ✓ fluctuations in each of the parameters (CAS) of the past and carried forward by sampling on the parameters (CAS) of the future (here 2025-2050)
- ✓ daily fluctuations of (S) for each scenario in a year.

If we want to multiply the repetitions for each case to estimate their amplitude, this leads to many results.
Sometimes we look for worst cases or best cases when we establish vulnerability analyses.
It is therefore useful to know the factors influencing the parameters on a particular result.

It is, for example, obvious that high values for each parameter (CAS) of TX will increase the number of hot (JTX25) or very hot (JTX35) days.
It is nevertheless useful to quantify this influence.
There are several solutions to determine which parameters are the most influential.
The simplest method is to proceed with a "design of experiments", virtual experiments of course.
Here is the treatment for JTX25.

We chose a complete design of experiments with 3 factors: C, A and S.
We normalized the values of C, A, and S to cover the full excursion of these parameters over the past.
The plan therefore looks like this.

Mimet TX

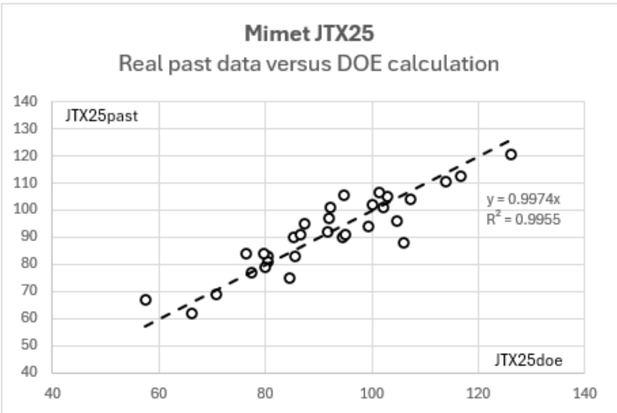
		Past data	A	C	S
		min	8.22	17.08	2.82
		max	11.75	20.73	3.96
a	c	s	A	C	S
-	-	-	8	17	2.8
+	-	-	12	17	2.8
-	+	-	8	21	2.8
+	+	-	12	21	2.8
-	-	+	8	17	4
+	-	+	12	17	4
-	+	+	8	21	4
+	+	+	12	21	4

We performed 4 repetitions for each of the 8 experiments.
The final table of the effects is shown opposite.
After analysis of variances, we reduced the final equation to 4 parameters, giving the very simple equation:

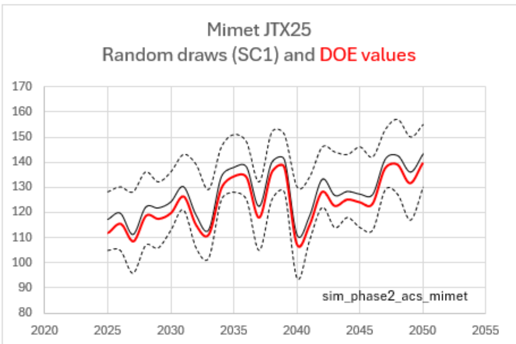
$$JTX25 = 96.6 + 16.6 * a + 29.4 * c - 5.2 * a * c$$

Intercept	96.6
a	16.6
c	29.4
s	0.1
ac	-5.2
as	-1.9
cs	-0.1
acs	-0.5

In order to compare the results between this equation and the actual values, the values of JTX25 from the weather station have been plotted opposite as a function of values calculated with the equation.
We observe that there is a good correlation.

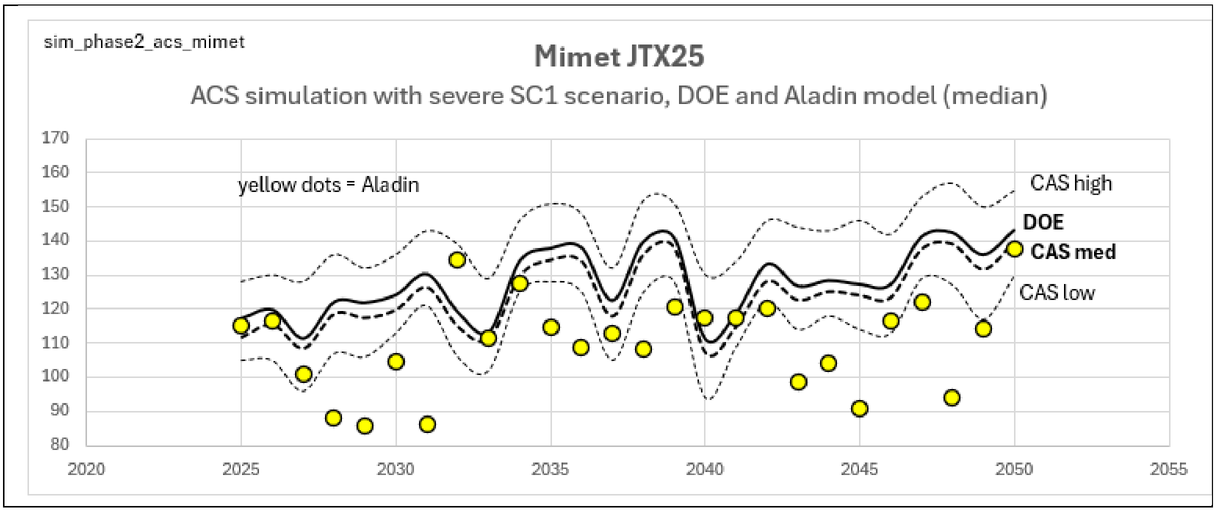


If we calculate JTX25 on the future with the DOE and compare them with the result according to the random samples, here is the result obtained.
It should be noted that the SC1 scenario was chosen for the CAS random sampling and also for the calculation with the parameters of the design of experiments.
As we have done repetitions, we could also compute the resulting limits (max and min of the sampling)



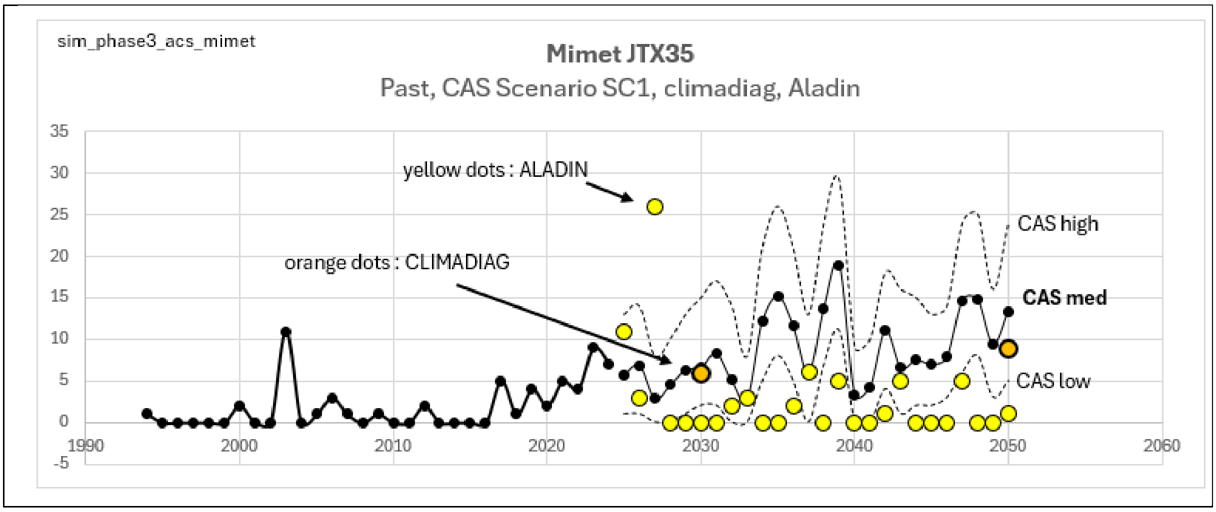
6. Comparison with other data

JTX25 : the next graph shows a comparison between the empirical CAS model and the ALADIN model corrected according to the methodology described in paragraph 2:



It can be seen here that the available data from the ALADIN model give results about ten days below the CAS-SC1 scenario, the most severe of the 10 scenarios randomly selected in the CAS model. This is quite logical since the ALADIN data correspond to a median RCP8.5 general scenario.

JTX35 : another comparison with the same models, plus data from the MétéoFrance Climadiag website (2030 and 2050) and also data from the weather station:



Here too, the results of the Aladin simulation are lower than those of the CAS model. It can be seen that the Aladin results do not seem to reflect a possible beginning of a mathematical tipping point. On the other hand, the 2030 and 2050 data of the Climadiag data for the municipality of Mimet are well aligned in the median CAS model.

7. Conclusion

Using archived data from a weather station, the CAS method developed in this article makes it possible to recalculate, on a daily basis and locally, the thermal consequences of the climate over a near horizon (here, 2025-2050). JTX25 was used to illustrate this procedure and other consequences like JTX35, JTN0, JTN20 can of course be calculated in the same manner.
We did not use this model until 2100 because empirical extrapolations often lead to significant uncertainties.

We believe that this model is applicable within a timeframe of 25 years (a "generation"), which can be part of the establishment of an adapted and operational climate vulnerability study, the centerpiece of a local climate change adaptation plan.

In addition, this method requires only conventional spreadsheet and standard skills, allowing it to be used on a large scale.
Due to its construction, this model can easily be adapted to seasonal or monthly needs that are of more interest to certain activities : frost during the budding period for wine growers, tropical nights in summer for retirement houses,...
However, this model deserves further verification and a lot of improvement, especially in terms of automation of calculations, but the basic principle is established.
Finally, this model must be able to be extended to other parameters, such as precipitation. This will be the subject of another publication.

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References

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Disclaimer : the Author, an independent data scientist and citizen scientist, only works with data and publications made available to the public. As such, not having the most efficient tools, apart from his own calculations and results, his studies are certainly incomplete.

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Conflict of interest
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