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Research Article

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Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11240277/v1>

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Additional Declarations: No competing interests reported.

Drought risk conditions determine the recent evolution in crop insurance claims in France

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Abstract

Agro-climatic risk management is a key practice in agriculture, as climate particularly affects crop production with the occurrence of extreme weather events. Crop weather insurance is one of the main tools available to farmers to protect themselves against weather-related risks. However, in France, since its creation in 2005, the multi-risk climate (MRC) insurance contract is mostly underperforming. Drought is identified as one of the major agro-climatic risk affecting crop production and, by extension, insurance loss ratio. Maize cultivation, in addition to being one of the most widely grown crops in France, is severely affected by water deficit. Resulting from a collaboration between a research laboratory and an insurance company, this study aims to assess the impact of evolving drought risk due to climate change on crop insurance losses in France. Using an innovative modeling chain

combining crop phenology and water balance modeling, we developed a crop specific annual drought index (*DI*) computed over the entire French territory. Original economic data provided by the insurer enables to correlate this drought index with the destruction rate (*DR*) of crop insurance contracts. Results show that the drought index *DI* provides a good proxy for crop insurance claims, at production basin and departmental scales. The parametrization of the modeling chain, the quality of the economic database and the spatial scale considered affect the quality of the correlation between the two studied indices. Those promising results support further investigations: future research could lead to extend this methodology for other crops and other agro-climatic risks.

Keywords

Agro-climatic risk, drought, maize, crop weather insurance, loss ratio

Length of the manuscript:

Number of words: 5768

Number of figures and tables: 6 (x300)

Total number of words: 7568

1. Introduction

Risk management is a key practice in agriculture, as agricultural production is subject to numerous market or natural hazard risks. Among these, climate particularly affects crop production, with the occurrence of extreme weather events such as frost, hail and drought for example (Challinor et al., 2014; Ortiz-Bobea et al., 2021; Petit et al., 2023). In France, agro-climatic risk management has

historically been a public policy issue. The agricultural disaster relief program created in the 1960s was the first form of government support for farms (Boucher et al., 2019). In the early 2000s, this system was modernized through a gradual shift toward individual insurance policies and greater accountability on the part of farmers. The multi-risks climate (MRC) crop insurance was created in 2005 and defined at the European level in 2016, resulting in a highly regulated insurance contract. However, since its creation, crop insurance has recorded a high loss ratio. MRC insurance contracts have been underperforming for 15 out of 18 years between 2005 and 2022, and the loss ratio is intensifying over the last decade (Fédération Française de l'Assurance, 2023). Specific extreme weather events are identified as the main causes of these losses: water excess, drought and frost.

Climate change modifies the occurrence and intensity of extreme events in all regions of the world (IPCC, 2021). Increasing climate extremes are expected to cause crop production losses, in major food-producing regions of the world (Daryanto et al., 2016; Deryng et al., 2014; Gaupp et al., 2020). Over Europe, extremes in temperature and precipitation are associated with negative yield anomalies (Beillouin et al., 2020; Siebert and Ewert, 2014). For Europe, adverse weather events are expected to become more frequent with climate change, leading to severe yields declines (Brás et al., 2021; Trnka et al., 2014). In France, in the coming decades, the emergence of heat stress and increasing water deficit exacerbates agro-climatic risk (Le Roux et al., 2024). This might have a direct impact on the insurance sector by affecting the performance of crop insurance contracts. In this context, collaboration between research and the insurance sector seems necessary in order to better assess i) changes in the structure of agro-climatic risk and ii) the impact of climate change on crop weather insurance (Bucheli et al., 2023; Santeramo et al., 2024).

Agricultural and ecological droughts in particular are expected to become more frequent and intense with climate change over Western Europe (IPCC, 2021). France could experience a steady worsening of soil drought in summer, with drought conditions occurring 3 to 6 times more frequently by 2100 under the RCP8.5 scenario compared to the historical period (Tramblay et al., 2024). This increase in drought risk in the future results from either decreased precipitation and/or increased

70 evapotranspiration (Dai, 2013). Over France, since the end of 1980s, water constraint rises sharply,
71 driven by an abrupt increase in evapotranspiration (Laurent et al., 2024). Drought stress intensification
72 is expected to affect the growth and yields of major crops (Senapati et al., 2021; Vadez et al., 2024;
73 Zampieri et al., 2017). Maize cultivation has high water requirements, making it one of the most
74 drought-sensitive crops (Bolaños and Edmeades, 1996; Lobell et al., 2013). Its yields could be
75 particularly affected by the drought risk increase (IPCC, 2023; Lobell et al., 2014), especially over
76 Europe (Barna and Manescu, 2025; Webber et al., 2018). As maize is one of the main crops in French
77 cereal crop rotation, the increased agro-climatic risk associated with drought constitutes a major
78 challenge for the agricultural sector (Battude et al., 2017; Ceglar et al., 2020).

79 Resulting from a collaboration between a research laboratory and an insurance company covering the
80 agricultural sector, this study aims to assess the impact of evolving drought risk due to climate change
81 on crop insurance losses in France. The work focuses on maize cultivation, as it is one of the main crops
82 in the insurer's portfolio and is highly sensitive to drought. Using reanalyzed climate data, fitted
83 phenology and soil characteristics of the crop, daily water balance is computed based on a two-
84 reservoirs water balance model (Jacquart and Choisnel, 1995). The application of a hydric stress
85 threshold leads to the development of a crop specific annual drought index (*DI*) computed from 1960
86 to 2024 on each 8km grid point of the climate dataset covering the entire French territory (Laurent et
87 al., 2025). This allows to study the evolution in space and time of maize *DI* on the main French
88 production basins. Economic data provided at the departmental scale by the insurer enables to
89 correlate this drought index with the destruction rate of crop insurance contracts. The latter is an
90 integrated measure of the performance of insurance contracts and implicitly address natural hazards.
91 In this paper we explore first the correlation at the level of the main maize-producing regions of the
92 country. Then, the impact of the parametrization of our modeling chain (sowing date, crop cycle
93 length, hydric stress threshold) and of the spatial scale considered on the robustness of the correlation
94 is assessed. This work aims to determine if our drought index *DI* developed through a modeling chain

is able to assess the drought risk level that significantly explains the loss ratio evolution of crop weather insurance contracts.

2. Material and methods

2.1. Study area and datasets

2.1.1. Study area

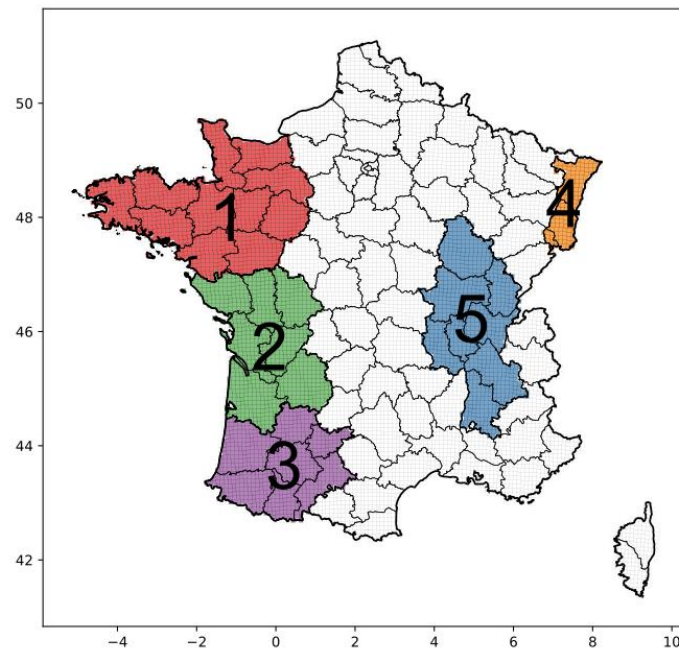
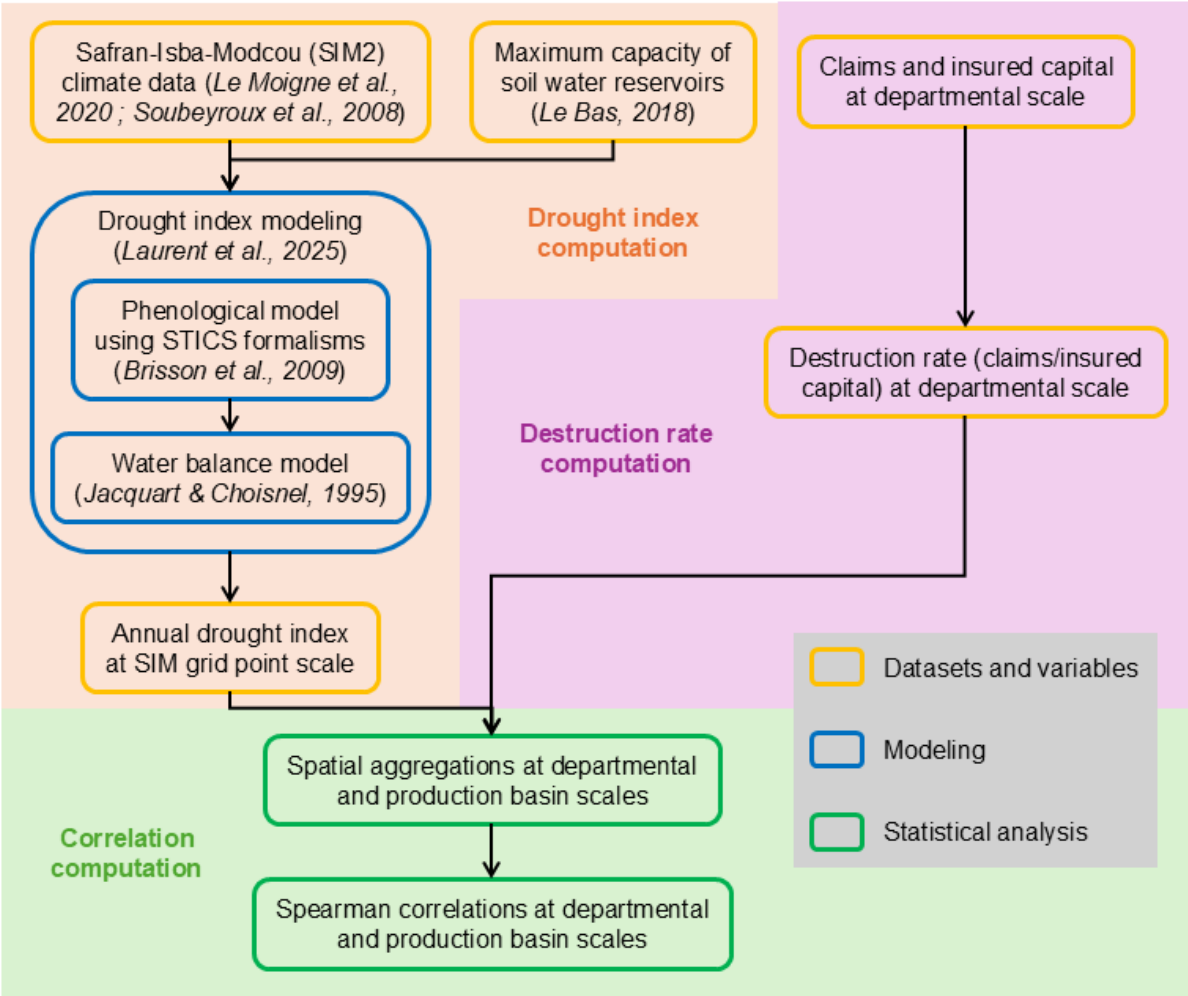


Fig. 1 Map of the study area. Thin black contours represent French departments, colored areas represent main maize production basins identified using the French Registre Parcellaire Graphique of 2019 (Institut National de l'information Géographique et Forestière, 2019). Production basin 1: Brittany (red area); production basin 2: central west (green area); production basin 3: southwest (purple area); production basin 4: extreme northeast (orange area); production basin 5: central east (blue area)

This work focuses on French territory, considering two different spatial scales. First, the departmental level (continuous thin black contours in Fig. 1), the scale at which economic data are made available (Fig. 1). Secondly, the work is also carried out at the level of the agricultural production basin corresponding to the colored area that spread across several department (Fig. 1). For maize crop, the latter are defined by selecting all the Safran-Isba-Modcou (SIM2) grid points where at least 10% of the surface is covered by maize fields according to the 2019 French agricultural survey called Registre Parcellaire Graphique (Institut National de l'information Géographique et Forestière, 2019). The SIM2 dataset is a gridded climate reanalysis described in the 2.1.2. section, covering the entire metropolitan French territory with an 8km resolution grid. The main production basins are then designed by selecting groups of departments containing previously selected grid points (Fig. 1). Those maize production basins are validated by field insurance experts from the partner company. The analysis of the impact of changes in drought risk on crop insurance performance is conducted at the departmental scale and on the main maize-producing areas of France.



124
125 **Fig. 2** Flowchart of the methodology

126
127 Climate data come from the Safran-Isba-Modcou (SIM2) model, developed and refined by Météo
128 France (Le Moigne et al., 2020; Soubeyroux et al., 2008). SIM2 chain combines the Safran
129 meteorological reanalysis system (Durand et al., 1993), the Isba land-surface model (Noilhan and
130 Planton, 1989) and the Modcou hydrogeological model (Ledoux et al., 1989). All the climatic variables
131 used in this study come from the Safran module, which consists in an 8km spatial resolution reanalysis
132 of observed climate data (Quintana-Seguí et al., 2008; Vidal et al., 2010). Liquid precipitation is one of
133 the 8 meteorological parameters that are analyzed at an hourly time step on more than 9000 grid

points covering the entire French territory. Potential EvapoTranspiration (PET) is also computed is the Safran module using the Penman-Monteith equation (Allen et al., 1998; Vannier and Braud, 2012):

$$PET = \frac{\Delta \cdot (R_n - G) + \frac{\rho \cdot C_p \cdot \delta e}{r_a}}{\lambda \left[\Delta + \gamma \left(1 + \frac{r_s}{r_a} \right) \right]} \quad (1)$$

where Δ the slope of the vapor pressure curve at the average air temperature (kPa.K^{-1}), R_n the net radiation (W.m^{-2}), G the ground heat flow (W.m^{-2}), ρ the air density at constant pressure (kg.m^{-3}), C_p the heat capacity of moist air at constant pressure ($\text{J.kg}^{-1}.\text{K}^{-1}$), δe the difference between the saturated vapor pressure e_s and the effective vapor pressure e_e (kPa), r_a the aerodynamic resistance (s.m^{-1}), λ the latent heat of water vaporization (J.kg^{-1}), γ the psychrometric constant (kPa.K^{-1}), r_s the resistance offered by the stomata to the flow of water vapor (s.m^{-1}).

Those two climate variables are needed as inputs for the drought index modeling chain, and are therefore collected at a daily time step over the 1959-2024 period (Fig. 2). This offers the opportunity to compute the crop-specific annual drought index over a period of more than 60 years, allowing to evaluate the drought risk evolution with climate change.

Along with climate variables, maximum capacity of soil water reservoirs is required to model crop water balance (Fig. 2). This variable is computed at SIM grid point scale using classes of useful water reserve (RU) coming from GISSol database (GISSol, 2011; Le Bas, 2018).

2.1.3. Economic data

The partnership with an insurer in this work provides access to original data concerning the economic performance of crop weather insurance contracts. The insured capital and the cost of claims (or compensation) for insured maize plots are provided at the departmental scale, over the 2011-2022 period (Fig. 2). The insured capital provided is based on all insured plots, not just those affected by a disaster. The cost of claims provided is the cost of claims due to all risks insured by the multi-risks climate (MRC) contract other than hail: drought, water excess, frost, storm, etc. Since the cost of claims

is closely linked to the value of the destroyed property (in our case, the value of the agricultural production), this variable cannot be considered on its own to measure the performance of an insurance contract. To study the cost of claims independently of the insured value, the destruction rate (DR) is computed according to the following equation:

$$destruction\ rate\ (DR) = \frac{cost\ of\ claims\ (\text{€})}{insured\ capital\ (\text{€})} \quad (2)$$

Maize DR is computed at departmental and production basin scales for reasons of confidentiality, by summing the cost of claims and insured capital of each department (Fig. 2). This variable will be correlated at annual time step with the maize drought index at the different spatial scales of the study, over the available time period.

2.2. Drought index modeling chain

To assess the evolution of drought risk for a particular crop, we have developed a modeling chain combining a phenological model and a water balance model (Laurent et al., 2025) (Fig. 2). The modeling of crop growth is based on a growing degree-day model using STICS formalisms (Brisson et al., 2009) applied in R language, available in the *peinnar* package (Le Roux, 2025). Here, we model the maize crop growth on each SIM grid point for 3 different varieties corresponding to three crop cycle lengths: short crop cycle (meribel), medium crop cycle (furio), long crop cycle (cecilia). We also run the phenological model for 3 different sowing dates: 85th, 100th and 115th day of the year (respectively around the 26th of March, the 10th of April and the 25th of April). This module assigns a crop coefficient (Kc) value to each day of the studied time serie (1959-2024) based on the phenological stage reached, then computes the Maximal EvapoTranspiration (MET) from the PET as follows:

$$MET(t) = Kc \times PET(t) \quad (3)$$

MET and liquid precipitation at SIM grid point scale serve as inputs for the water balance model, along with soil useful water reserve data.

In this study, we choose to use a two-reservoirs water balance model to compute water balance for a given crop (Jacquart and Choisnel, 1995). From 1959 to 2024, considering a one year spin up, the model computes the daily available soil water content $R(t)$, expressed in mm. In order to account for the variability in soil water storage, the Relative Extractible Water ($REW(t)$) index is derived as follows:

$$REW(t) = \frac{R(t)}{RU} \quad (4)$$

with RU being the useful water reserve of the SIM grid point considered and $R(t)$ the level of water reserve at day t .

A crop is considered being under hydric stress when the soil water content falls below a stress threshold (Granier et al., 1999). This threshold represents the moment when crop growth and development start to diverge from a reference value, and depends on several factors such as evaporative demand root distribution and soil texture (Sadras and Milroy, 1996). In our study, this threshold is called critical REW (REW_c) and is initially set at 40% for maize (Das et al., 2024; Steele et al., 1994). Soil Water Deficit ($SWD(t)$), is then computed using the following equation (Laurent et al., 2025):

$$SWD(t) = \begin{cases} 0 & \text{if } REW(t) \geq REW_c \\ 0.4 * RU - R(t) & \text{if } REW(t) < REW_c \end{cases} \quad (5)$$

with $SWD(t)$ expressed in mm. Other REW_c values are also being tested in this study in order to refine the level of agreement between our drought index and crop insurance loss ratio: 30%, 20%, 10%, 5%, 1%.

Our annual drought index DI , is computed using the $SWD(t)$ following this equation:

$$DI = \sum_{t=January1}^{t=December31} SWD(t) \quad (6)$$

with DI expressed in mm. DI is computed for each SIM grid point covering the French territory and for each year between 1960 and 2024. Then DI is spatially aggregated at departmental and production

basin scales by averaging DI of all the grid points that are within the department or production basin respectively (Fig. 2).

For more details concerning the drought index computation, please refer to Laurent et al. (2025). This paper describes more specifically the whole modeling chain used in our study.

Temporal evolution of maize DI on the period of interest (1960-2024) is studied by computing density plots for 3 sub-periods. The 2 first sub-periods are delimited by the abrupt increase in temperature highlighted over France on the 1960-2020 period: 1960-1987 and 1988-2010 (Brulebois et al., 2015; Laurent et al., 2024). The last period covers all years for which economic data are available: 2011-2024. This allows to evaluate changes in maize DI evolution since the creation of the insurance contract compared to its past evolution.

2.3. Correlation between the crop specific drought index and the insurance loss ratio

To assess the impact of drought risk evolution impact on crop weather insurance loss ratio, the correlation between our crop specific drought index DI and the MRC contracts destruction rate DR is studied for maize, at departmental and production basin scales. A rank correlation is used, the Spearman's correlation, available in the *stats* R package (Best and Roberts, 1975; Hollander et al., 1973). The test is run over the whole period for which economic data are available, i.e. 2011-2022, and for each French department and each French maize production basin.

The correlation with DR is also tested with DI computed using several parametrizations of the drought index modeling chain: several crop cycle length, sowing dates and stress thresholds. The aim is to find the best possible parametrization of the modeling chain to maximize correlation. The methodology developed in this work could then be used for actuarial studies within the company.

228 **3. Results**

229 3.1. Maize drought index temporal evolution

230

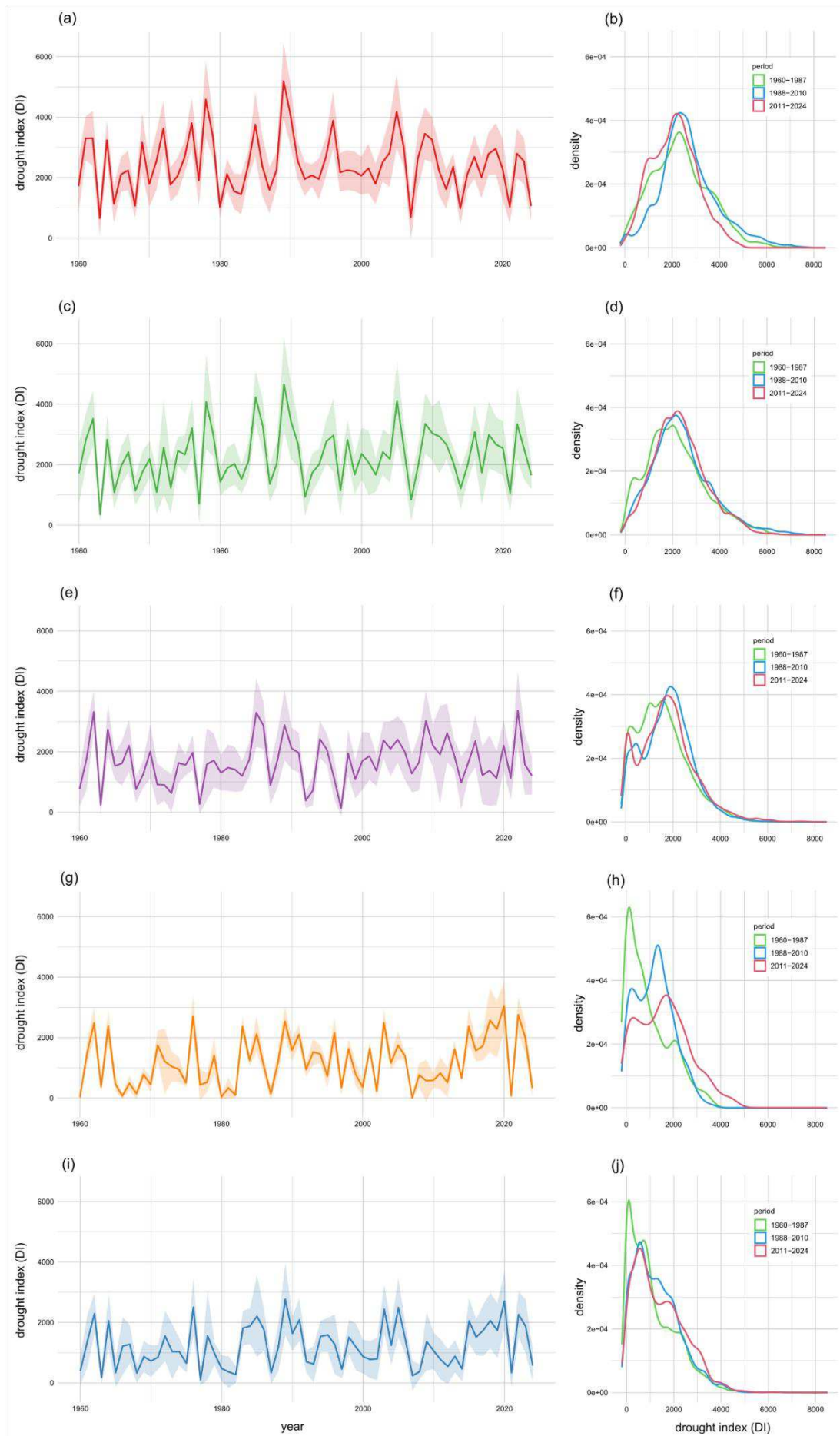


Fig. 3 Drought index (*DI*) temporal evolution between 1960 and 2024 (a, c, e, g, i) and *DI* density for each studied sub-period (1960-1987, 1988-2010, 2011-2024) (b, d, f, h, j) on each French main maize production basin: (a, b) production basin 1, (c, d) production basin 2, (e, f) production basin 3, (g, h) production basin 4, (i, j) production basin 5

Maize drought index (*DI*) displays various changes depending on the production basin considered (Fig. 3). Production basins 1 and 2, corresponding to Brittany and central western France, show no clear trend in *DI* evolution between 1960 and 2024 (Fig. 3a and c). For all the studied sub-periods (1960-1987, 1988-2010, 2011-2024), the main mode of the density plot is around 2000mm on both production basins (Fig. 3b and d).

Production basin 3 in the southwest of France expose a slight increasing trend in maize *DI* over the 1960-2024 period (Fig. 3e). The main mode of the density plot for the 1960-1987 sub-period is around 1700mm while the main modes of the density plots for the 1988-2010 and 2011-2024 sub-periods shift to the right to a value of around 1900mm (Fig. 3f). Same pattern is observed for the production basin 5, in the central eastern France, with a slight increasing trend in *DI* evolution (Fig. 3i). On this region, the main mode of the density plot is moving from around 200mm on the 1960-1987 sub-period to 600mm on the 1988-2010 and 2011-2024 sub-periods (Fig. 3j).

Production basin 4, corresponding to the extreme northeast of France, displays the most important increasing trend in maize *DI* between 1960 and 2024 (Fig. 3g). The main modes of the density plots increase with time, going from around 200mm to 1200mm and then 1600mm for respectively the 1960-1987, 1988-2010 and 2011-2024 sub-periods (Fig. 3h).

Maize drought index *DI* is increasing on nearly every French main production basin over the 1960-2024 period. The 1987-1988 abrupt temperature and evapotranspiration rise seems to particularly affect the evolution of drought risk for maize crop. On the last sub-period, from 2011, *DI* is comparable

to that of 1988-2010 sub-period, and is even increasing on production basin 4. This raises the question of the impact of late drought risk evolution on multi-risks climate (MRC) insurance contracts loss ratio.

3.2. Weather crop insurance loss ratio vs. drought index

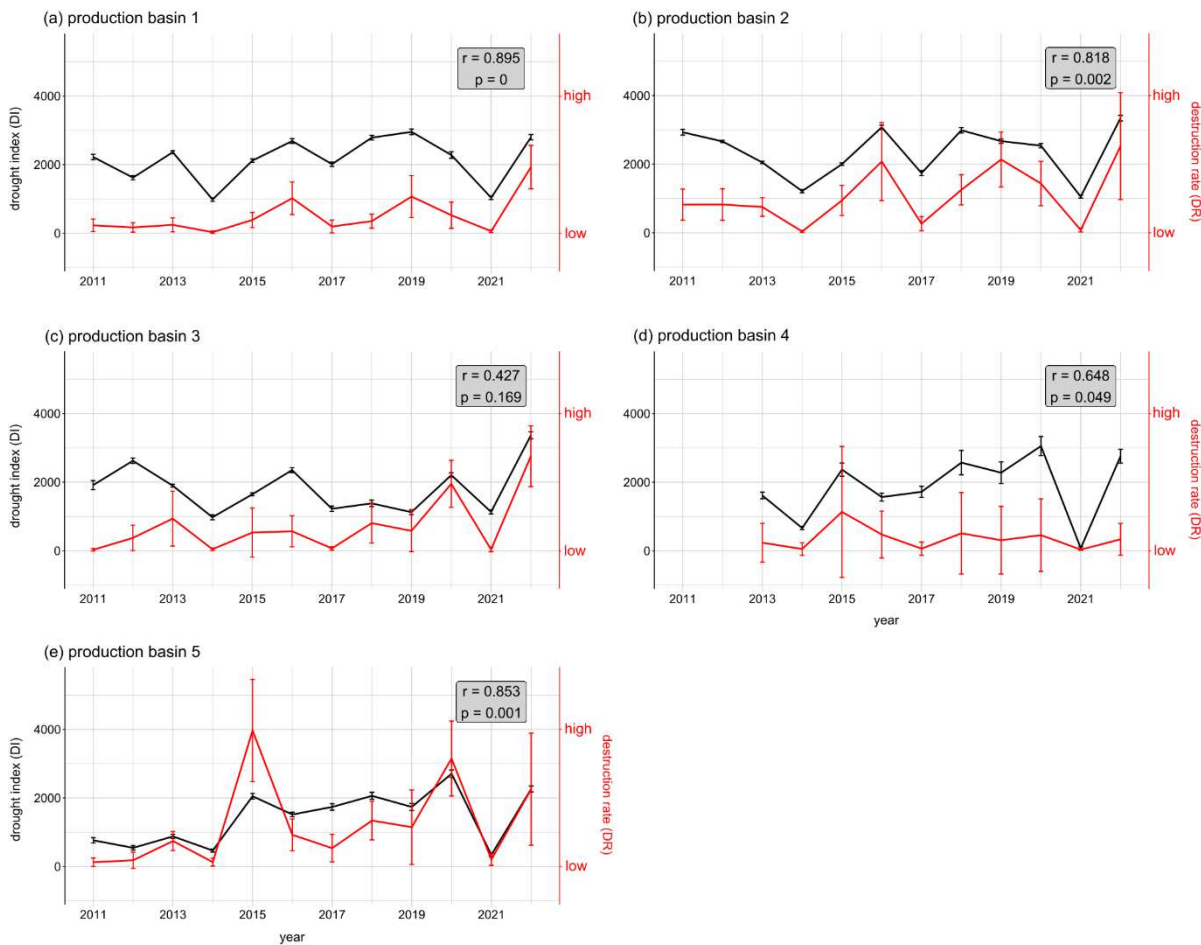
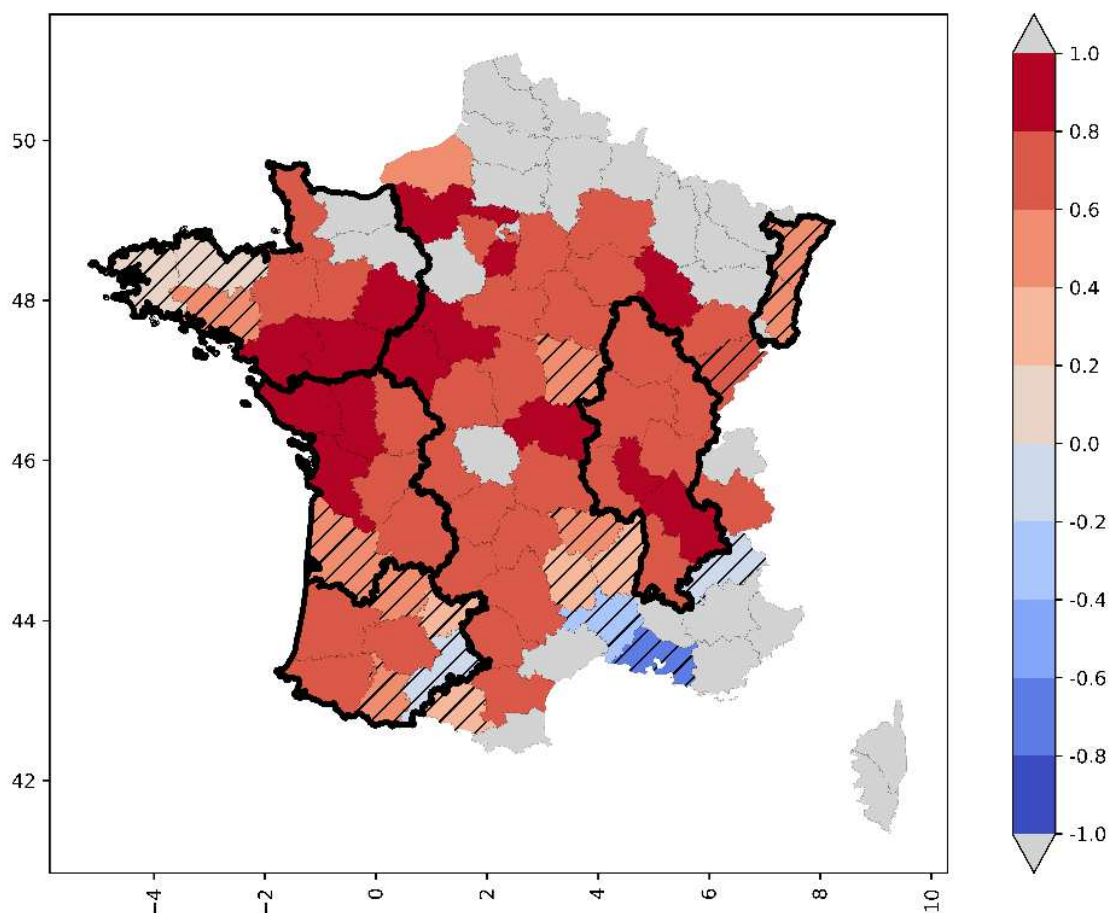


Fig. 4 Temporal evolutions of drought index (DI, black line) and destruction rate (DR, red line) between 2011 and 2022 for each French main maize production basin. Error bars represent spatial 95% confidence intervals. Grey boxes show the Spearman's correlation coefficient and p-value between the two variables. DR values have been modified for confidentiality reasons

267 At production basin scale, maize drought index *DI* shows good correlation with destruction rate *DR*
268 on almost all production basins (Fig. 4). Production basins 1, 2 and 5 (Brittany, central western France
269 and central eastern France) display strong significant correlations between maize *DI* and *DR*, with a
270 Spearman's correlation coefficient between 0.8 and 0.9. Production basin 4, in the extreme northeast
271 of France, also shows a significant correlation, but less important than that of the above-mentioned
272 production basins, around 0.65. For this production basin, *DR* data are only available from 2013, which
273 allows to compute Spearman's correlation only on the 2013-2022 period. Only production basin 3, in
274 the southwest of France, displays non-significant Spearman's correlation. Overall, crop specific *DI*
275 appears to be a good proxy for MRC insurance contracts *DR* at the production basin scale. An analysis
276 at a finer spatial scale, i.e., the department, can provide a better understanding of the spatial
277 disparities highlighted above.

278



279

Fig. 5 Spearman's correlation coefficient between drought index (*DI*) and destruction rate (*DR*) over the 2011-2022 period at departmental scale over France. Grey colors means that no *DR* data are available for the correlation computation. Dashed departments mean the correlation is non significant on that department. Thick black contours delimit French main maize production basins

Fig. 5 displays Spearman's correlation coefficients and their significance at departmental scale. Most departments for which destruction rate *DR* data are available show a significant Spearman's correlation. But some departments inside main maize production basins still display non-significant correlations. That is the case for the departments of the production basin 4, in the extreme northeast of France, which could explain the weak significant correlation at production basin scale (Fig. 4d). In the same way, four departments out of seven in the production basin 3 present non-significant correlations, which could explain the non-significant correlation at production basin scale (Fig. 4c). For production basins 1 and 2, the proportion of departments showing a significant correlation is greater than those showing a non-significant correlation (Fig. 5). In addition, several departments show a very strong correlation coefficient in those 2 production basins, above 0.8. This confirms the significant and strong correlation at production basin scale (Fig. 4a and b). Production basin 5 comprises only departments with a significant correlation and 2 departments with a correlation coefficient above 0.8, supporting the significance and strong correlation at production basin scale (Fig. 4e).

The results reveal that for maize crop in France drought index and crop insurance loss ratio are related. The correlations vary by location, which is likely due to differences in soil and climate conditions, farming practices, and crop varieties. These may affect the drought index *DI* computation through for instance the length of the growing cycle, the sowing date and the hydric stress threshold. The impact of changes in these different parameters on the correlation at the departmental scale needs further investigations.

3.3. Impact of modeling chain parametrization on the correlation between the drought index and insurance loss ratio

Table 1 Percentage of French departments recording a significant Spearman's correlation between drought index (*DI*) and destruction rate (*DR*) at departmental scale as a function of: crop cycle length, sowing date, hydric stress threshold. The color gradient from blue to red represents the proportions from lowest to highest, respectively

crop cycle length	sowing date	hydric stress threshold					
		1	5	10	20	30	40
short	85	71,08	73,49	77,11	74,7	73,49	73,49
	100	71,08	73,49	77,11	74,7	73,49	72,29
	115	68,67	73,49	75,9	74,7	72,29	72,29
medium	85	68,57	72,86	74,29	77,14	74,29	70
	100	68,57	72,86	74,29	77,14	74,29	71,43
	115	67,14	74,29	72,86	75,71	74,29	70
long	85	70,91	70,91	72,73	70,91	69,09	65,45
	100	69,09	70,91	74,55	70,91	69,09	67,27
	115	69,09	70,91	74,55	67,27	67,27	63,64

Table 1 presents the percentage of departments recording a significant correlation between the drought index *DI* and the destruction rate *DR* based on different parameters of the *DI* modeling chain. Various crop cycle lengths are determined based on the degree-day needs in the phenological model used, and different sowing dates are also tested. In addition, diverse values for the hydric stress

317 threshold, also called in our study the critical Relative Extractible Water (REW_c), are used to compute
318 DI .

319 Results show that crop cycle length and sowing date only have a minor effect on the percentage of
320 departments registering a significant correlation (Table 1). Overall, the longest crop cycle gives in
321 average the poorest results, with the majority of crop cycle length * sowing date * hydric stress
322 threshold combinations using the long crop cycle showing a proportion of departments recording a
323 significant correlation inferior to 70%. A change in the sowing date for a given combination of crop
324 cycle length and hydric stress threshold results in little or no change in the proportion of departments
325 recording a significant correlation.

326 However, the hydric stress threshold (critical Relative Extractible Water REW_c) appears to play an
327 important role in the correlation level between DI and DR . The analysis demonstrates that using a
328 REW_c below 40% increases the percentage of departments recording a significant correlation (Table
329 1). More specifically, hydric stress thresholds of 10% or 20% result in the highest levels of correlation.
330 The best results are obtained using a medium crop cycle, an early (85) or median (100) sowing date
331 and a REW_c of 20%. This could be explained by the shape of the distributions of the two correlated
332 indices. The distribution of DR at departmental scale shows an inflation of zeros, corresponding to the
333 years and departments for which there were no claims for climate-related damage to maize plots, or
334 where such claims did not result in compensation from the insurer (Supplementary Fig. 1). The shapes
335 of DI distributions vary depending on the hydric stress threshold used: the lower the REW_c , the higher
336 the frequency of zeros in the DI distributions (Supplementary Fig. 2). This increase in the frequency of
337 zeros is due to the structure of the DI : the lower the REW_c , the lower the DI , because daily REW is
338 less likely to fall below REW_c . Supplementary Fig. 1 and 2 suggest that using a REW_c of 10% or 20%
339 to compute DI allows its distribution to better approximate that of the DR thereby improving the
340 quality of the correlation between the two indices (Table 1).

To summarize, the quality of the correlation between the drought index *DI* and the destruction rate *DR* depends on the parametrization of the *DI* modeling chain. The choice of the hydric stress threshold *REW_c* is a key factor in the strength of the correlation. At the departmental scale, a *REW_c* of 10% or 20% seems to give the best correlation results. However, this may vary depending on the spatial scale considered, as spatial aggregation modifies the *DI* and *DR* distributions by reducing the frequency of zeros.

4. Discussion

4.1. Maize drought risk evolution

Resulting from a public-private partnership, this work aims to assess the impact of evolving drought risk due to climate change on crop insurance losses in France. Since maize is a highly drought-sensitive crop, it has been chosen as the crop of interest for our study. A modeling chain combining phenological and water balance models has been developed, enabling the computation of a crop-specific drought index, called *DI*.

Maize *DI* is increasing on every main production basin, with varying intensity depending on the region. It has been shown that this increase in drought risk can be explained first by significant changes in potential evapotranspiration which strongly affect the water cycle (Laurent et al., 2024). The 1987/1988 abrupt warming over France, along with rapid modification of surface solar radiation, induces an important increase in evapotranspiration (Vicente-Serrano et al., 2014). The latter is identified as the main driver of climatic water balance over the country, leading to changes in hydric constraints (Teuling et al., 2013). This increase in drought risk, affecting crop water balance, is worsening over the last decade (Laurent et al., 2025). Our work confirms those findings, with the maize drought index *DI* increasing more significantly since 2011. For this crop, drought risk is expected to

become even more severe by 2050 (Webber et al., 2018). This is of major concern for our private partner, whose profits for crop insurance contracts are closely linked to changes in agro-climatic risk.

4.2. Impact of drought risk evolution on crop insurance claims

In order to assess the impact of drought risk evolution on the performance of insurance contracts, the drought index DI is compared to crop insurance claims, measured by the destruction rate DR . The scale of main maize production basin is initially considered. On production basins 1, 2 and 5, the correlation between DI and DR displays very satisfying results, with strong significant Spearman's correlation coefficient. Only production basins 3 and 4 show a non-significant correlation and a weak significant correlation, respectively. This could be explained by the quality of the information provided in the economic database. In this work, only cost of claims and insured capital coming from non-irrigated plots are selected to compute destruction rate DR , as DI modeling chain does not allow irrigation to be taken into account. However, information on the irrigation of the plot must be provided by the farmer when drawing up the insurance contract, and is not necessarily updated regularly. In production basins such as southwest or extreme northeast of France (3 and 4), where irrigation is very widespread, this can lead to numerous errors in the database. The unintentional inclusion of irrigated plots in the DR computation may therefore explain the lower quality of the correlation in production basins 3 and 4.

A second analysis at the departmental scale shows that the quality of the correlation depends on several parameters, such as the hydric stress threshold REW_c (critical Relative Extractible Water) used and the spatial scale considered. The use of lower stress thresholds (or critical Relative Extractible Water REW_c) – for example 10 or 20% – increases the score of the percentage of significant departmental correlations between DI and DR . This is probably due to the shape of the distributions of the two correlated indices, in particular the zero-inflation highlighted in DR distributions.

Even though the original insurance data to which we accessed had been filtered, the results show that the quality and the spatial grain of the economic database plays an important role in studying the link between drought risk and crop insurance claims. The spatial scale considered and the parametrization of the modeling chain also determine the performance level.

4.3. Towards the integration of climate change into insurance risk models

This groundbreaking study presents very encouraging results, demonstrating that the drought index DI developed in this work provides a good proxy for crop insurance claims. The modeling chain established allows to compute a crop-specific drought index DI , which can be correlated with the destruction rate DR of the insurance contracts. The analysis was carried out on maize, a highly drought-sensitive crop. The integration of the modeling chain in the insurer internal actuarial model allows to integrate climate change in drought risk evaluation for this crop. But weather crop insurance also covers other crops, such as wheat, grapevines and rapeseed for example. These crops are also affected by drought risk, whose effects on their yields are expected to intensify with climate change (Aubry et al., 2026; van Leeuwen et al., 2024). But they are also sensitive to other agro-climatic risks, such as frost, water, excess, heat waves, ... (Ben-Ari et al., 2018). The drought index DI used in this work could therefore be less correlated with the destruction rate DR , especially if the latter is computed using the cost of claims due to all risks insured by the multi-risks climate (MRC) contract other than hail. The first challenge for future research is therefore to gain the best possible understanding of the destruction rate DR for other crops than maize. This may lead to better associated DR with agroclimatic index such as DI . This requires insurers to refine for example the reporting of the cost of drought-related claims. The second challenge is to develop new integrated agro-climatic indices that could explain the evolution of MRC loss ratio due to other insured risks. One last challenge concerns perennial crops such as grapevines which represent major economic and socio-cultural activities for various region in France. The phenological behavior of grapevines differs from

that of other insured crops, meaning that grapevines-specific indices are needed. The originality and the high promising results of this study encourage further analysis for other crops and other insured risks.

5. Conclusion

This work first explores the evolution of agro-climatic risk linked to drought on main maize production basins in France over the 1960-2024 period. The drought index *DI* developed in our research is increasing on every studied production basin, with various intensities depending on the region. Being particularly affected by the rise in water demand from the atmosphere, the drought risk is worsening for maize over the last decade. This is a major issue for insurance companies, whose economic results of crop weather insurance contracts depend on agro-climatic risks changes.

The second objective of this study is to assess the impact of drought risk evolution on crop insurance loss ratio for maize crop. At production basin scale, results show that maize *DI* and maize weather insurance destruction rate *DR* are significantly correlated for most of the region studied. The analysis at departmental scale confirms those results. Further investigations highlight that the quality of the correlation depends on the parametrization of the *DI* modeling chain, especially the choice of the hydric stress threshold used. The quality of the economic database also plays an important role in studying the link between drought risk and crop insurance, as well as the spatial scale considered.

This innovative research offers very promising results, presenting a new methodology to compute a crop specific drought index *DI* which constitutes a good proxy for crop weather insurance loss ratio for maize. The first challenge for future research is to extend this analysis for other crops. This implies to gain the best possible understanding of the destruction rate *DR*, particularly by refining for example the reporting of the cost of drought-related claims. The second challenge is to develop new integrated agro-climatic indices that could explain the evolution of MRC loss ratio due to other insured risks. This

would lead to a comprehensive understanding of the impact of agro-climatic risk on crop insurance claims, and could enable insurers to implement adaptation and mitigation measures.

Acknowledgments

This work is part of a research project resulting from a partnership between the Biogéosciences laboratory and Groupama Assurances Mutuelles insurance company. In this context, we would like to acknowledge Charles Méliand, head of the internal actuarial modeling team, for his help and expertise, which were essential to the project's success. We would also like to thank Karen Alameddine for providing the data needed for the analyses and for her help throughout the project.

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