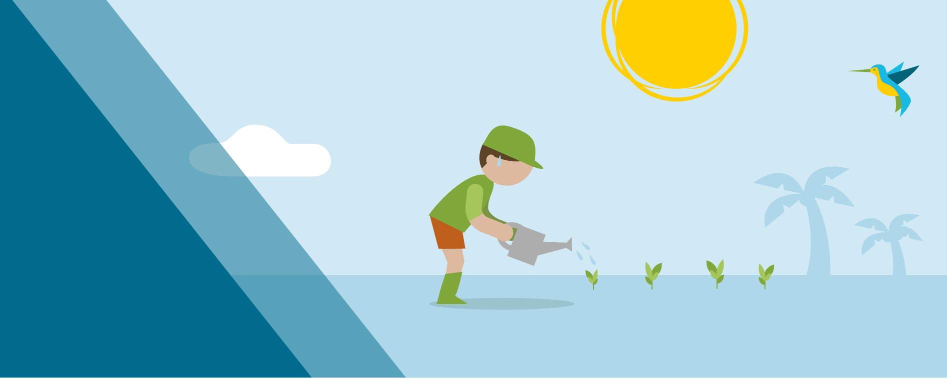
TECHNICAL NEWSLETTER
#59 - March 2022



CROP INSURANCE IN INDIA AND BRAZIL: KEEPING ABREAST OF A CHANGING CLIMATE

Part Two of a Five-Part Knowledge Series

SIGNIFICANCE OF CLIMATE CHANGE FOR AGRICULTURAL (RE)INSURANCE

Anthropogenic climate change is associated with changes in severe weather affecting agriculture such as heat waves, heavy precipitation, and drought (IPCC, 2021)[1]. The impact of climate change on agriculture is relevant in both economic terms and in terms of food security. This Technical Newsletter focuses on agriculture insurance in India and Brazil. Both countries have a significant agricultural sector and a large and expanding agriculture insurance market, so, assessing the risk associated with climate change and agriculture is important from an insurance point of view. Increasing scrutiny from regulators, rating agencies and investors provides further reason to act.

The impact of climate change risk is not yet sufficiently investigated and quantified in the insurance industry. SCOR has developed a framework to assess the impact of climate change on key natural perils that affect insurers and reinsurers. This Technical Newsletter is the second part in a series, where we set out to quantify potential (re)insurance loss impacts on the property and agriculture lines over a 5 to 10-year time horizon. The first part of this Knowledge Series (Seria and Herboch, 2021)[2] gives further background. This second part is focused on the agriculture line of business and presents an assessment of the impact of climate change on gross modelled attritional and large losses for the major agriculture insurance markets of India and Brazil.

IMPACT OF CLIMATE CHANGE ON KEY CROPS

There is compelling evidence that temperatures in India have been increasing (e.g., Ross et al. 2018), that they will continue to do so in the future and that the observed and projected temperature increases can be largely attributed to anthropogenic forcing such as elevated CO_2 concentrations (Basha et al., 2017)[3]. Figure 1 shows temperature projections for India based on different CO_2 emission scenarios. These temperature increases have an impact on crop yield as described below. Climate change is not only associated with changes in temperature but also with changes in other atmospheric variables and atmospheric events that affect agriculture, such as drought, flood, and hail. Such events can have a greater impact on agriculture than temperature increases but confidence regarding the past and future trends of these events is lower than confidence in temperature changes.

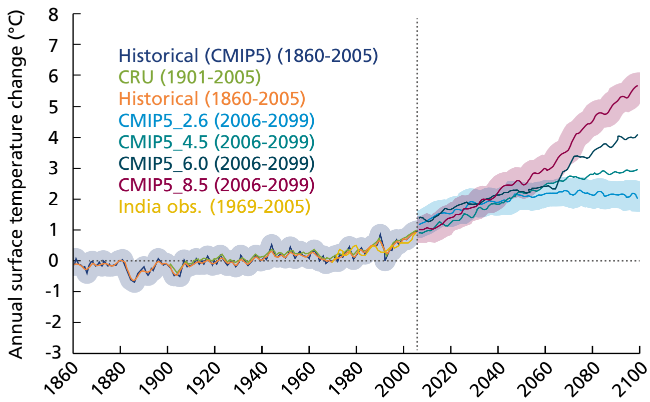


FIGURE 1: PROJECTED CMIP5 AND CRU ANNUAL TEMP. CHANGES OVER INDIA RELATIVE TO THE 1901-1960 REFERENCE PERIOD

Projected annual mean surface temperature in India from model ensemble (Coupled Model Intercomparison Project, CMIP5) average data for the period between 1860 and 2100 relative to the reference period 1901–1960. The period 2006–2099 represents future projections for various CO_2 emission scenarios (Representative Concentration Pathways, RCP). The shaded region represents one standard deviation around the average of the model ensemble.

Source: Basha et al., 2017

1. IPCC *Climate Change 2021: The Physical Science Basis. Summary for Policymakers* [Report]. - [s.l.] : Cambridge University Press. In Press., 2021. - p. 1535
2. Seria Junaid and Herboch Ivan *Modelling Climate Change for the (Re)insurance Industry. A Practitioner's Guide to Extreme Event Scenario Analysis* [Report]. - Paris : SCOR P&C Strategy and Development, 2021
3. Basha G. [et al.] *Historical and Projected Surface Temperature over India during the 20th and 21st century* [Journal] // Nature Scientific Reports. - 2017

The Art & Science of Risk

Increased temperatures accelerate the development of many major crops such as rice (Guo et al., 2019)[4], wheat (Asseng, 2014)[5], maize (Zhu et al., 2019)[6] and soy (Tan et al., 2021)[7]. This accelerated development results in a shortening of key growth periods, which in turn results in less photosynthesis, lower biomass, and eventually lower yield. Various additional effects of heat stress, depending on crop and development stage, have been documented in the scientific literature. Each crop type has a different sensitivity to temperature changes. For rice, a 1.0°C temperature increase could reduce yields by 3 to 10% (Guo et al., 2019)[8]. Temperature impact on maize and wheat is larger than on rice and soy (Zhao et al., 2017;[9] Sun et al., 2019)[10]. Possible strategies to adapt crop cultivation to increasing heat stress include the use of heat-tolerant cultivars, adjusting sowing time, and irrigation (Khan et al., 2019;[11] Akter et al., 2017)[12]. Although earlier sowing lengthens growth periods and decreases wheat exposure to heat stress, this is often not done for various reasons, such as rice cultivation in the preceding season (Newport et al., 2020)[13].

Precipitation in India (especially during monsoon) has a major influence on crop yields and agriculture insurance losses. However, there is low confidence in past drought trends and precipitation trends are less significant than they are for temperature (Birthal et al., 2014;[14] Hoegh-Guldberg et al., 2018)[15]. Higher precipitation is projected in a warming environment in India (Hoegh-Guldberg et al., 2018)[15]. There are scientific publications indicating both a recent increase in drought events (Mallya et al., 2016)[16] and a recent decrease (Jin et al., 2017)[17]. During monsoons, there is emerging evidence that even though total precipitation is not decreasing, it is becoming more erratic (more dry days, more days with intense precipitation), thus having a negative impact on crop yields (Mishra et al., 2014;[18] Fishman, 2016)[19]. A study that investigated each season separately showed that winter and autumn extreme rainfall displayed an increasing trend, while the spring seasonal extreme rainfall showed a decreasing trend (Pal et al., 2009)[20].

Elevated CO_2 concentrations are important for crops not only as a driver of climate change, but also as a factor directly affecting plant development. Experimental studies show that yields of C_3 plants (e.g. wheat, rice, soy) increase under elevated CO_2 concentrations, provided there is ample availability of water and nutrients (Toreti et al., 2020)[21]. This is usually not the case with C_4 crops, such as maize and sorghum. Yield gains due to elevated CO_2 concentrations are low or insignificant for crops in conditions where water and nutrients are limited.

Increased temperature
Increased temperatures accelerate crop development. As a result, growth period shortens and yield decreases.

Erratic precipitation
Scientific literature suggests there are more dry days and more days with intense precipitation in India. This has a negative impact on crop yield.

CO_2 concentrations
The impact of elevated CO_2 concentrations is one of the largest sources of uncertainty in crop yield estimates for future scenarios.

FIGURE 2: FACTORS RELATED TO CLIMATE CHANGE THAT AFFECT CROP YIELD LEVELS

Source: SCOR

4. Guo Yahui [et al.] *Modeling Climate Change Impacts on Rice Growth and Yield under Global Warming of 1.5 and 2.0°C in the Pearl River Delta, China* [Journal]. - [s.l.] : atmosphere, 2019
5. Asseng S [et al.] *Rising temperatures reduce global wheat production* [Journal]. - [s.l.] : nature climate change, 2014
6. Zhu Peng [et al.] *Dissecting the nonlinear response of maize yield to high temperature stress with model-data integration* [Journal]. - [s.l.] : Global Change Biology, 2019
7. Tan Qinghua [et al.] *Shortened key growth periods of soybean observed in China under climate change* [Journal]. - [s.l.] : scientific reports, 2021
8. Guo Yahui, Wu Wenxiang and Bryant Christopher Robin *Quantifying Spatio-Temporal Patterns of Rice Yield Gaps in Double-Cropping Systems: A Case Study in Pearl River Delta, China* [Journal]. - [s.l.] : sustainability, 2019
9. Zhao C. [et al.] *Temperature increase reduces global yields of major crops in four independent estimates* [Journal] // Proceedings of the National Academy of Sciences. - 2017. - pp. 114(35), 9326-9331
10. Sun Qiaohong [et al.] *Global heat stress on health, wildfires, and agricultural crops under different levels of climate warming* [Journal] // Environment International. - 2019. - pp. 125-136
11. Khan Shahbaz [et al.] *Mechanisms and Adaptation Strategies to Improve Heat Tolerance in Rice. A Review* [Journal] // Plants. - 2019
12. Akter N. and Islam M. R. *Heat stress effects and management in wheat. A review* [Journal] // Agronomy for Sustainable Development. - 2017
13. Newport Danielle [et al.] *Factors Constraining Timely Sowing of Wheat as an Adaptation to Climate Change in Eastern India* [Journal] // Weather, Climate and Society. - 2020. - pp. 515-528
14. Birthal P. S. [et al.] *Impact of Climate Change on Yields of Major Food Crops in India: Implications for Food Security* [Journal] // Agricultural Economics Research Review. - 2014
15. Hoegh-Guldberg O. [et al.] *Impacts of 1.5ºC Global Warming on Natural and Human Systems. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways* [Journal]. - 2018
16. Mallya G. [et al.] *Trends and variability of droughts over the Indian monsoon region* [Journal] // Weather and Climate Extremes. - 2016
17. Jin Q. and Wang C. *A revival of Indian summer monsoon rainfall since 2002* [Journal] // Nature Climate Change. - 2017
18. Mishra A. and Liu S. C. *Changes in precipitation pattern and risk of drought over India in the context of global warming* [Journal] // Journal of Geophysical Research: Atmospheres. - 2014
19. Fishman R. *More uneven distributions overturn benefits of higher precipitation for crop yields* [Journal] // Environmental Research Letters. - 2016
20. Pal I. and Al-Tabbaa A. *Trends in seasonal precipitation extremes – An indicator of 'climate change' in Kerala, India* [Journal] // Journal of Hydrology. - 2009. - pp. 367(1-2), 62-69
21. Toreti Andrea, Deryng Delphine and Tubiello Francesco N. *Narrowing the uncertainties in the effects of elevated CO2 on crops* [Journal]. - [s.l.] : Nature, 2020

In addition, elevated CO_2 concentrations can have a negative impact on crop quality and nutritional value (Toreti et al., 2020)[21]. Overall, the impact of elevated CO_2 concentrations is one of the largest sources of uncertainty in crop yield estimates for future scenarios (Jägermeyr et al., 2021)[22].

WILL FARMERS BE ABLE TO ADAPT TO CLIMATE CHANGE IN THE FUTURE?

Future crop yields will not only depend on climate change, but also on the ability of global agriculture to adapt. Climate adaptation for agriculture includes several elements: the availability of new technology, the application of improved farming methods, shifting cropping patterns and improvements in public infrastructure. In Brazil for example, soybean yield increased significantly in the 2010s (Figure 3). A reasonable hypothesis is that this increase can be largely attributed to the introduction of glyphosate-based herbicides, which occurred at the same time. In India, rice and wheat production have seen very strong increases – rising by a factor of 4 and 11 respectively in the 2000-2017 period compared to the 1950-1959 period (Nelson et al., 2019)[23].

The past benefits gained from agriculture technology and infrastructure do not guarantee that crop yields will continue to increase in the future. In India for instance, as yield gains from additional irrigation are slowing down and temperature increase due to climate change is accelerating, it will be a challenge for wheat yields to continue to increase in the future (Zaveri et al., 2019)[24]. Moreover, adaptation usually entails additional costs for both producers and governments, which means that adaptation is limited by the availability of funds. Global warming of 1.5°C compared to pre-industrial levels would cost global agriculture an estimated USD 63 billion per year (Iizumi et al., 2020)[25]. Of this 63 billion, 53 billion represents the cost of adaptation and the rest is linked to residual damage caused by climate change. Some of the residual damage can be covered by insurance. This damage is projected to increase with increasing warming.

A further challenge to farmers in terms of adaptation is the increasing trend in air pollution, for example due to ozone and aerosols, which has a negative impact on yield (Gupta et al., 2016;[26] Burney et al., 2014;[27] Fischer, 2019)[28]. Moreover, in countries where agriculture is not sufficiently supported by machinery, future production can be negatively affected by the fact that manual labour becomes more difficult in a hotter environment.

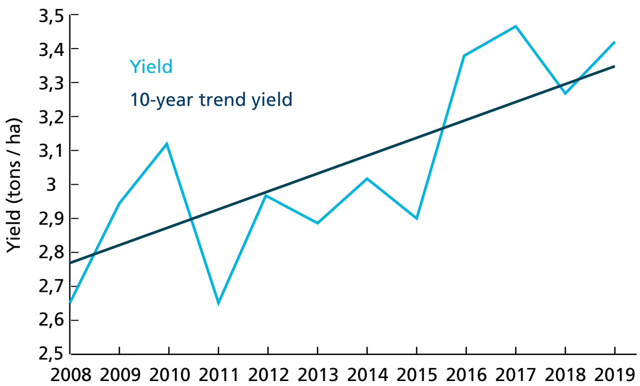


FIGURE 3: BRAZIL SOYBEAN YIELDS TIME-SERIES (USDA, 2020)[28]
Source: USDA PS&D online

22. Jägermeyr Jonas [et al.] *Climate impacts on global agriculture emerge earlier in new generation of climate and crop models* [Journal]. - [s.l.] : Nature Food, 2021
23. Nelson A. R. L. E., Ravichandran K. and Usha A. *The impact of the Green Revolution on indigenous crops of India* [Journal] // Journal of Ethnic Foods. - 2019
24. Zaveri E. and Lobel D. B. The role of irrigation in changing wheat yields and heat sensitivity in India [Journal] // Nature Communications. - 2019
25. Iizumi Toshichika [et al.] *Climate change adaptation cost and residual damage to global crop production* [Journal] // Climate Research. - 2020. - pp. 203-218
26. Gupta R., Somanathan E. and Dey S. *Global warming and local air pollution have reduced wheat yields in India* [Journal] // Climatic Change. - 2016
27. Burney J. and Ramanathan V. *Recent climate and air pollution impacts on Indian agriculture* [Journal] // Proceedings of the National Academy of Sciences. - 2014
28. Fischer T. *Wheat yield losses in India due to ozone and aerosol pollution and their alleviation: a critical review* [Journal] // Outlook on Agriculture. - 2019
29. *USDA World Agriculture Production* [Report] : Circular series WAP 3-20. - [s.l.] : USDA, 2020

CLIMATE CHANGE-DRIVEN TRENDS OF MAJOR CROP YIELDS

The starting point in terms of quantitatively estimating the impact of climate change on crop insurance losses for India was the SCOR pricing for the 2020-2021 renewals. This pricing approach is based on recent history (10 years) of yield data, which is available for hundreds of thousands of location-crop combinations. The Indian government sponsored crop insurance scheme ("Pradhan Mantri Fasal Bima Yojana", hereinafter "PMFBY") guidelines are applied to the yield data to estimate loss costs on an annual basis. Before applying PMFBY guidelines to calculate annual loss costs, a detrending procedure is carried out (Hoffmann et al., 2017).[30] The climate trends for various major crops in India are sourced from two peer-reviewed articles: (Birthal et al., 2014)[31] and (Mall et al., 2004)[32].

The trend estimates found in the original articles have been scaled accordingly, so that they correspond to three temperature scenarios developed by SCOR (Seria and Herboch, 2021)[33]. These scenarios include a lower (0.95°C), a mid (1.075°C) and an upper (1.2°C) temperature increase for 2020-2030 compared to 1850-1900. The trends for each scenario are summarized in Figure 4. These trends refer to near-term yield projections and they relate to major producing areas in India for the respective crops. These trends are comparable with results from other publications (Figure 5) and are deemed to be representative of the overall trends.

As discussed on page 3 ("Will farmers be able to adapt to climate change in the future?"), the overall crop yield trends are not only driven by changes in climate but also by non-climate factors, such as air pollution, improvements in farming practices, available technology and public infrastructure. These trends (hereinafter "non-climate trends") are also estimated and considered in our loss cost projections, based on the following simple additive rule: overall trend = non-climate trend + climate trend (Equation 1). The overall trend is calculated from the available yield data. We assume that the recent past overall trends will persist in the near term (2025). The climate trends are the near-term projections summarized in Figure 4 and Table 1. Given these estimates for the overall trend and the climate trend, the non-climate trend is calculated from Equation 1.

Loss cost projections for 2025 are produced in two stages. First, the yield data is shifted five years into the future

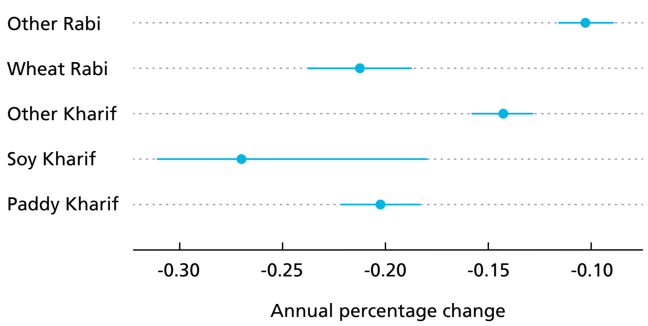


FIGURE 4: COUNTRY-WIDE PERCENTAGE YIELD TRENDS USED FOR THE CLIMATE CHANGE SCENARIOS FOR INDIA

Sources: they are based on Birthal et al. (2014) for wheat and rice and on Mall et al. (2004) for soy. The trends have been adjusted for the SCOR temperature scenarios (Seria and Herboch, 2021). Kharif and Rabi represent the main summer and winter growing seasons respectively

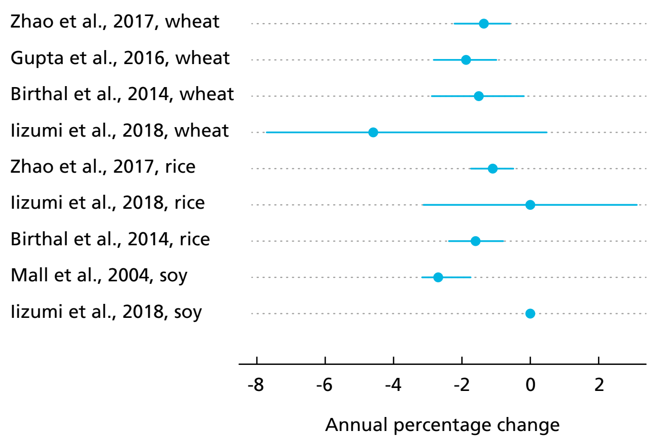


FIGURE 5: COMPARISON OF PERCENTAGE YIELD TRENDS AMONG VARIOUS PUBLICATIONS

Original trends have been converted to annual trends to facilitate comparison. The estimates include an uncertainty range, where available.

Source: they are based on Iizumi et al., 2018, Mall et al., 2004 for soy; Birthal et al., 2014, Iizumi et al., 2018, Zhao et al., 2017 for rice; Iizumi et al., 2018, Birthal et al., 2014, Gupta et al., 2016, Zhao et al., 2017 for wheat

30. Hoffmann T. [et al.] *Guide to Agriculture Insurance Part III: Risk modelling aspects* [Report] : SCOR Technical Newsletter. - [s.l.] : SCOR P&C Strategy and Development, 2017
31. Birthal P. S. [et al.] *Impact of Climate Change on Yields of Major Food Crops in India: Implications for Food Security* [Journal] // Agricultural Economics Research Review. - 2014
32. Mall R. K. [et al.] *Mitigating climate change impact on soybean productivity in India: a simulation study* [Journal] // Agricultural and Forest Meteorology. - 2004
33. Seria Junaid and Herboch Ivan *Modelling Climate Change for the (Re)insurance Industry. A Practitioner's Guide to Extreme Event Scenario Analysis* [Report]. - Paris : SCOR P&C Strategy and Development, 2021

(2023), assuming linear trends. The threshold yield for 2025 is calculated from this projected data. Second, each data point is detrended, following the detrending method described in Hoffmann et al., 2017. Figure 6 shows an example of detrending projected yields. After detrending for each location-crop combination, loss costs are calculated applying the PMFBY guidelines. These losses are then aggregated to obtain loss costs at market level. This procedure can be repeated considering the climate-only and technology-only trends. In this way, separate contributions to the overall 2025 loss estimates can be obtained.

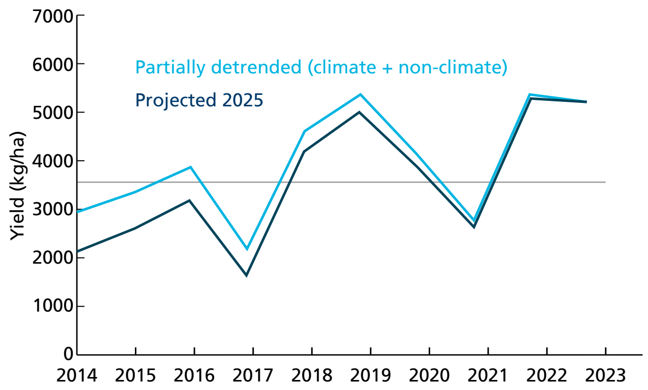


FIGURE 6: DETRENDING OF PROJECTED PADDY YIELDS FOR AN EXAMPLE LOCATION IN INDIA

Source: SCOR

Pricing for Brazil business is mainly carried out through an experience-based approach. One very important step in the modelling of agriculture risk is the restating of data to calculate as-if losses based on today's portfolio or the portfolio projection for the coming underwriting year. Historic losses and exposures should be restated in terms of geographical distribution, type of products (or other features) and premium rates before curve fitting, an analysis method which assumes stationarity.

Climate trends for various major crops in Brazil are also sourced from scientific publications (Follador, 2016;[34] Assunção et al., 2016)[35]. These trends refer to near-term yield projections and they are assumed to be constant across Brazil (Table 1). This assumption is made for modelling purposes but could be refined to consider variations across the country. Table 2 provides an overview of these variations.

To convert the above yield reductions into loss costs and capacity, the following modelling steps are taken:

Crop	Scenarios		
	Lower	Mid	Upper
Wheat	-23.4%	-25.3%	-29.2%
Soybean	-13.4%	-14.5%	-16.7%
Corn	-7.4%	-8.1%	-9.3%

TABLE 1: COUNTRY-WIDE YIELD TRENDS USED IN THIS INVESTIGATION FOR BRAZIL

Source: Follador, 2016

Reduction	Wheat	Production	Soybean	Production	Corn	Production
Central West	-	-	-4%	15,516,018	0%	7,880,159
South	-18%	1,853,315	-30%	11,756,357	-4%	3,440,878
South-East	-100%	181,349	-12%	2,482,634	-5%	1,928,009
North-East	-	-	-18%	3,242,058	-40%	2,615,196
North	-	-	-1%	1,834,676	-8%	674,309
Average	-25.3%	2,034,664	-14.5%	34,831,743	-8.1%	16,538,551
Overall Reduction	-13%					

TABLE 2: YIELD CHANGES FOR THE 2020-2030 DECADE COMPARED TO 2009 FOR VARIOUS CROPS AND AREAS IN BRAZIL FOR THE MID SCENARIO

Source: Follador, 2016

a) Use IBGE (official yield data provided by the Brazilian government) data for wheat, soybean and corn.

b) Estimate the relation between IBGE yields and losses using a Generalized Linear Model.

c) Use the above scenarios to estimate the impact of reduced yields on losses.

d) Review the loss ratio distribution based on the above loss changes and reprice the major insurance portfolio.

34. Follador Marco *Potential impacts of climate change on Brazilian agriculture and economy* [Report]. - 2016

35. Assunção J., Pietracci, B. and Souza P. *Fueling development: sugarcane expansion impacts in Brazil* [Journal] // Climate Policy Initiative, Iniciativa para o Uso da Terra. - 2016

CHANGES IN SEVERE DROUGHT EVENTS

The detrending approach described so far for India is based on only 10 years of data. A different method is used to estimate possible changes in the frequency of severe events. This method is based on a 117-year-long (1901-2017) country-wide precipitation record for India, compiled by the Indian Meteorological Department (Figure 7). The reason we use precipitation is that it has a large influence on crop yields, and we consider drought to be the major driver of large losses in India. Although precipitation data can only be considered as a rough proxy for large insurance losses, the length of this dataset makes it more suitable for a study of extreme events. The precipitation data includes one monthly precipitation time series for each of the 36 meteorological subdivisions[36] in India. In total, out of the 36 subdivisions we have considered 25 with significant agriculture exposure.

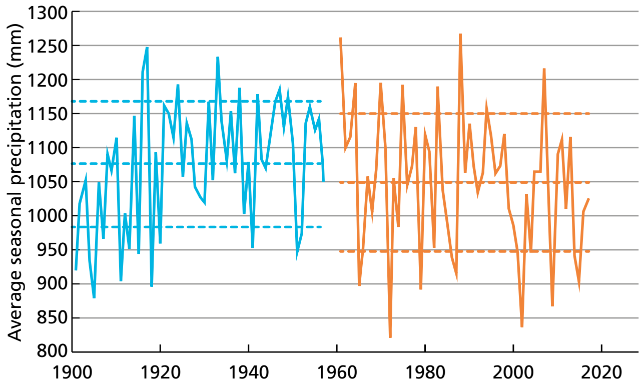


FIGURE 7: INDIA AVERAGE PRECIPITATION FOR THE MONSOON SEASON (JJAS) BASED ON 25 SUBDIVISIONS

The data is split into two parts (blue and orange).
The average of each part along with +/- one standard deviation is plotted with dash lines.

Source: SCOR

Before using precipitation data to derive conclusions about insurance losses, we investigated the relationship between the two. Insurance losses for the period 2008-2017 were aggregated at subdivision level and at market level using the sum insured as weight, and precipitation data was also aggregated in the same way. Then the Standardized Precipitation Index (SPI) was calculated for subdivision level and market level precipitation data. SPI (Lloyd-Hughes et al., 2002)[37] facilitates the comparison of precipitation amounts among regions with different climates.

Figure 8 shows the relationship between losses and drought at a market level. The correlation coefficient between the two quantities is -0.70 when we consider the 2009-2016 period. This correlation is not statistically significant at the 95% level of confidence. The years 2008 and 2017 have many missing data points. If we include them in the calculation of the correlation coefficient, we get a value of -0.66, which is statistically significant at the 95% level of confidence. The correlation coefficient indicates a moderate degree of correlation. In general, small losses occur when SPI is high and large losses occur when SPI is low. 2015 stands out in the sense of having the largest loss but not an extremely low SPI. According to Mishra et al. (2016),[38] the 2015 drought was not extreme in its own right but was exacerbated by the fact that it was preceded by another drought year in 2014.

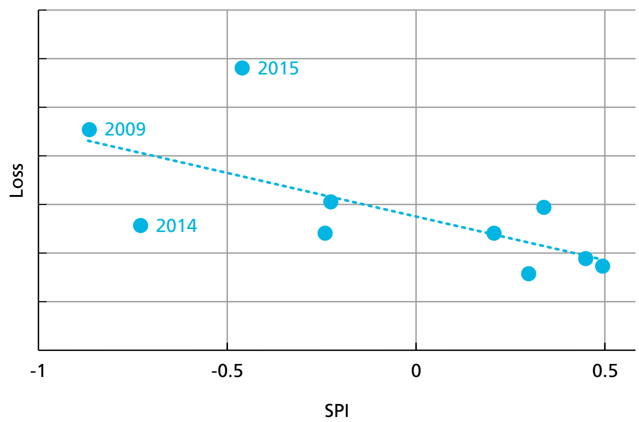


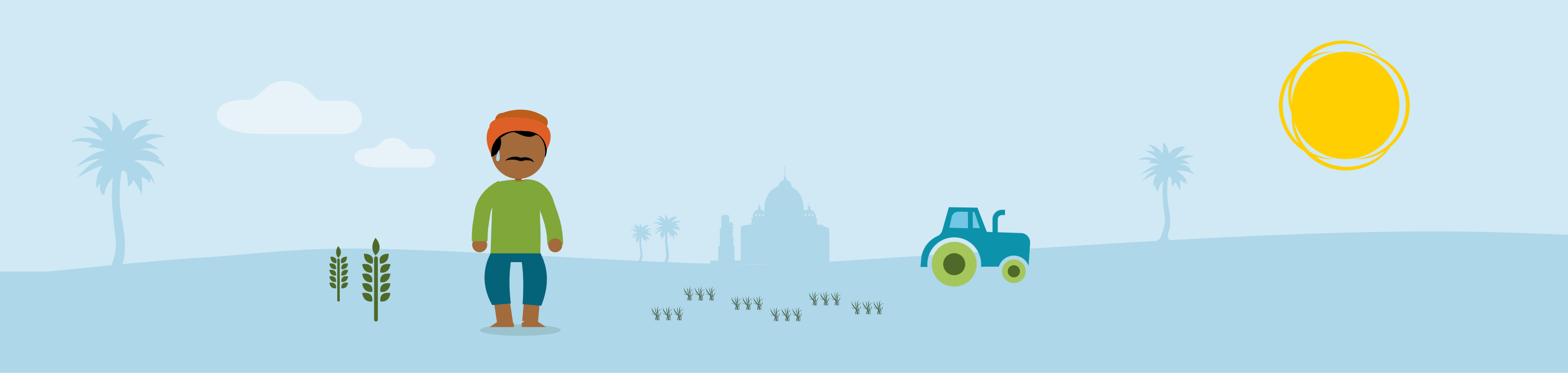
FIGURE 8: SCATTERPLOT OF SPI *VS* LOSS FOR THE INDIA MARKET FOR THE PERIOD 2008-2017

The three driest years are indicated.

Source: SCOR with precipitation data from the Indian Meteorological Department

The relationship between SPI and insurance losses was also examined at subdivision level. Figure 9 shows the linear correlation coefficient between SPI and insurance losses for each subdivision across India. Most correlations are not statistically significant, mainly due to the short loss data record. Linear correlations are in general negative, i.e. for

36. Indian meteorological subdivisions have been defined in such a way, that each one has a relatively homogeneous climate. In addition, these subdivisions partly overlap with State political boundaries.
37. Lloyd-Hughes Benjamin and Saunders Mark *A drought climatology for Europe* [Journal]. - [s.l.] : International Journal of Climatology, 2002
38. Mishra A. and Liu S. C. *Changes in precipitation pattern and risk of drought over India in the context of global warming* [Journal] // Journal of Geophysical Research: Atmospheres. - 2014



low precipitation, there were high losses. However, there are exceptions. East Madhya Pradesh, a subdivision with a high sum insured, has a low correlation with losses. The reason is that in 2013 there was excess rainfall and high losses. In general, although we use a linear correlation coefficient as a measure of dependence, the relationship between precipitation and losses does not have to be linear: one can expect high losses for low precipitation, a decrease in losses as precipitation increases, and another increase in losses as precipitation becomes excessive. Another reason for not seeing negative correlation in some cases is that precipitation can be near average overall during the season but erratic, leading to low yields. Kharif season in Odisha in 2011 is such an example. Moreover, subdivisions with very good irrigation, such as the Gangetic West Bengal, also have low correlation between losses and precipitation.

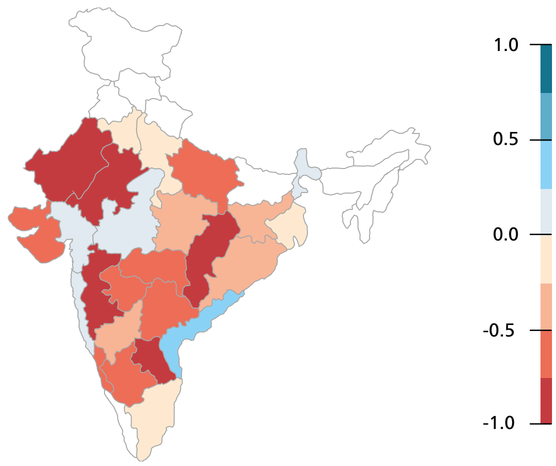


FIGURE 9: LINEAR CORRELATION BETWEEN LOSS COST AND SPI FOR EACH METEOROLOGICAL SUBDIVISION

Source: SCOR with precipitation data from the Indian Meteorological Department

Having established a relationship between precipitation and insurance losses, a method was developed to detect changes in extreme drought events. This method is based on a recent publication on flood events (Myhre et al., 2019)[39].

The subdivision level precipitation data for India is averaged for the whole country. The resulting time series is split into two parts: the first 58 years (1901-1958) and the last 58 years (1960-2017). Another three splits have been used as a sensitivity test: a 30-year split (1901-1930, 1988-2017), a 40-year split (1901-1940, 1978-2017) and a 50-year split (1901-1950, 1968-2017). For each part of the data, a probability distribution is fitted using the same approach as for the SPI calculations. Thus, for each data split, one distribution is fitted to the first part and another one to the second part of the precipitation time series. As a second sensitivity test, a further two distribution fits were carried out for each data part.

The two distributions enable us to study possible changes in the probability of extreme events. This is illustrated in Figure 10, where two loss distributions are shown in blue and orange respectively: the blue line corresponds to the first period and the orange line to the second period. Let us assume there was a low precipitation season of 900 mm in the first period. We can see in Figure 10 that having the same precipitation amount in the second period has a higher probability (0.0012) compared to the first period (0.0007).

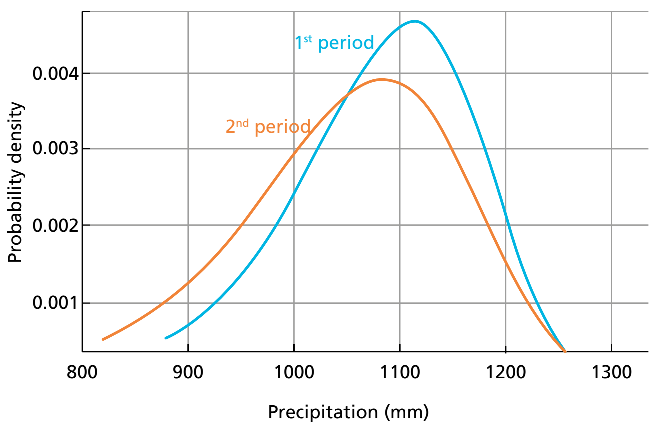


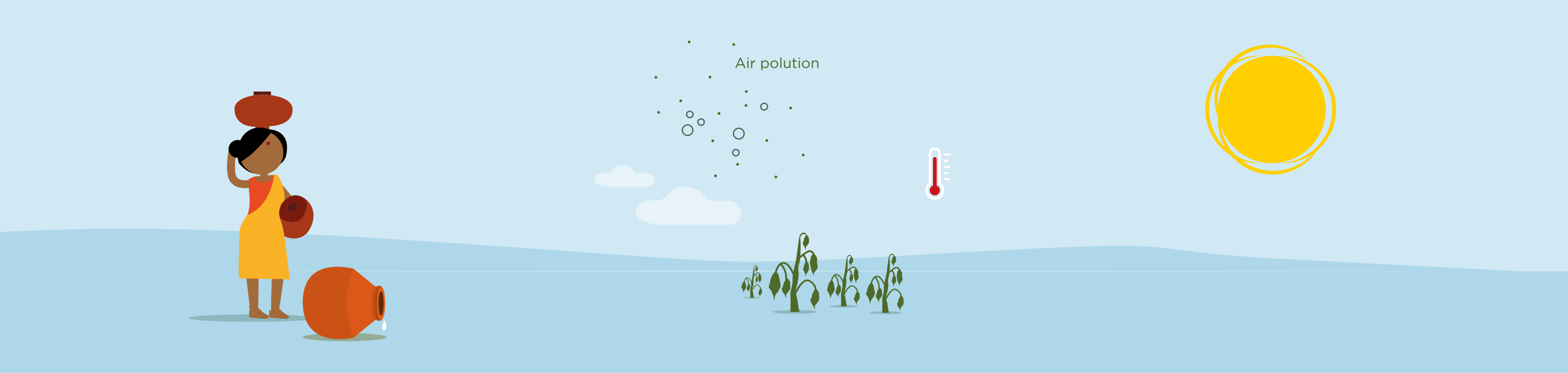
FIGURE 10: USE OF TWO DISTRIBUTION FUNCTIONS TO ESTIMATE CHANGES IN THE FREQUENCY AND SEVERITY OF A GIVEN EVENT

The probability of having 900 mm rainfall is higher in the second period (orange line) compared to the first period (blue line).

Source: SCOR with precipitation data from the Indian Meteorological Department

This method was applied to the precipitation dataset for India for the 2009 drought event. This event was chosen as a recent large event for which there are as-if loss estimates. Another important event is the 2015 drought, which represents the largest market loss in recent history. However, this is probably not a typical drought loss in the sense that it is related to 2014, which was also a drought year (Mishra et al., 2014). Further recent severe droughts occurred in 2002 and in 1987.

39. Myhre G. [et al.] *Frequency of extreme precipitation increases extensively with event rareness under global warming* [Journal] // Scientific Reports. - 2019



NEAR-TERM IMPACT OF CLIMATE CHANGE ON CROP INSURANCE

Based on our estimation using the methods above, climate change will continue to have a considerable impact on agriculture losses if no adaptation takes place. This impact translates to an increase in loss costs depending on the temperature scenario. This is partially offset by the impact of non-climate factors. SCOR monitors relevant changes in the risk and adapts its pricing method so that these changes are reflected in pricing.

The main driver of yield changes is temperature increase due to climate change (e.g. Birthal et al. (2014))[40]. This increase has a negative impact on crop growth in India for most crops. Precipitation is also considered but it is not found to be a major driver of yield changes because near-term average precipitation changes for India are small.

The same conclusion as seen in India applies for Brazil: The climate change and non-climate change impacts partly offset each other in relation to the proposed scenarios and their time horizons (5 to 10 years).

Changes in the frequency of severe events in India were quantified by calculating the ratio:

$$r^{2009} = (p_2^{2009} - p_1^{2009}) \;/\; p_1^{2009}$$

where p_1^{2009} is the cumulative probability of the 2009 drought event in past conditions (first part of the split data) and p_2^{2009} is the cumulative probability of the same event in current conditions (second part of split data). Quantities r^{2002} and r^{2015} were calculated in the same way. As a sensitivity test, the calculation for each event was repeated for four different data splits (30, 40, 50 and 58 years) and three different distributions (Lognormal, Weibull and Gamma) leading to 12 different estimates for each of r^{2002}, r^{2009} and r^{2015}. The results are summarized in Figure 11. There is a considerable range of estimates for r^{2009} but almost all of them are positive. This means that the probability of severe events is larger for the first period than for to the second period. Comparing the ranges of outcomes for the 2002, 2009 and 2015 events leads to the conclusion that the probability increase is larger for more extreme events.

An additional analysis of changes in the frequency of severe events was conducted using a different aggregation method for the precipitation data. Namely, subdivision precipitation

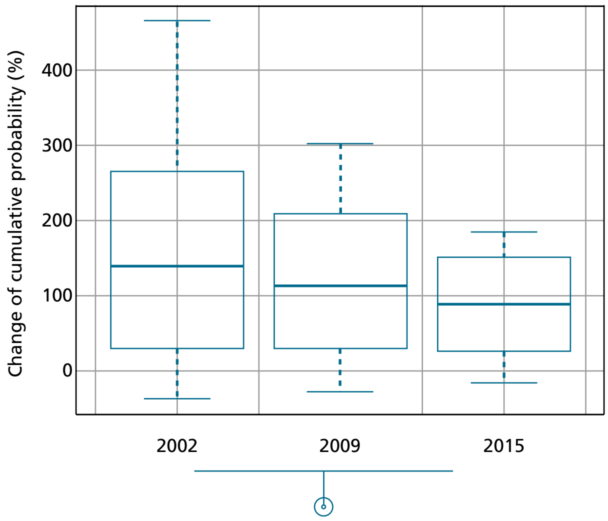


FIGURE 11: PERCENTAGE CHANGE OF CUMULATIVE PROBABILITY OF THE 2002, 2009 AND 2015 DROUGHTS BETWEEN TWO TIME PERIODS. EACH BOXPLOT INCLUDES THE CALCULATIONS FOR 12 COMBINATIONS OF DATA SPLITS (30, 40, 50 AND 58 YEARS) AND DISTRIBUTION CHOICES (LOGNORMAL, GAMMA, WEIBULL)

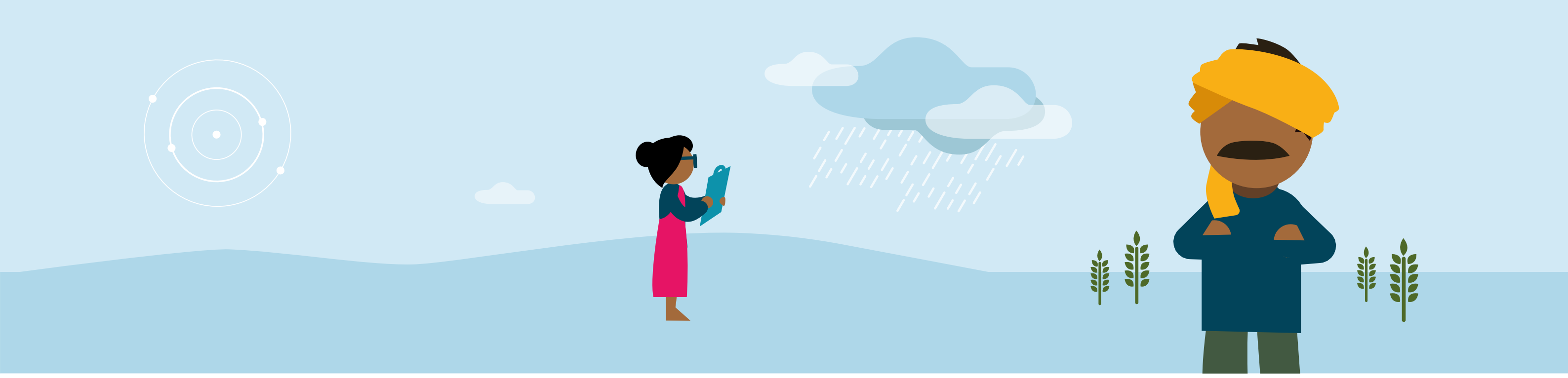
Source: SCOR with precipitation data from the Indian Meteorological Department

data was aggregated at country level using the sum insured as weight. No increase in the frequency of severe events is observed based on these data. In areas with a large sum insured (Rajasthan, Gujarat, Maharashtra, Madhya Pradesh), there is a tendency for less volatility in the recent periods.

The analysis of severe drought events using precipitation data leads to the conclusion that the probability of these events has increased over the past century in India. For the part of the study related to severe events, we have assumed that no adaptation occurs because changes in the probability of severe events are difficult to observe within a human generation and therefore are less likely to be acted upon in a timely manner. In addition, adaptation to severe events is more difficult than adaptation to moderate events.

Climate change has a negative impact on the yields of major crops and on associated insurance losses. At SCOR our pricing approach captures changes in yield trends and the increasing probability of severe drought. These impacts lead to an increase in loss costs mitigated largely by new technology and improved farming practices. We expect this

40. Birthal P. S. [et al.] *Impact of Climate Change on Yields of Major Food Crops in India: Implications for Food Security* [Journal] // Agricultural Economics Research Review. - 2014



will continue over the next five to ten years. However, as temperatures continue to increase, the impact on crop yields may well worsen making adaptation harder. It is imperative that we continue to partner with our clients to understand these trends and develop tailored insurance solutions that help them remain resilient in this evolving risk landscape.

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Editor: SCOR SE
ISSN: 1967-2136