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Exploring crop (re)insurance risk in India

RMS

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Contents

Executive summary

This report provides insurers interested in reinsuring crop business schemes in India with an overview of the (re)insurance market, a detailed description of the impact of weather (monsoon and extreme events) on crop yields and losses, and a description of the benefits of using probabilistic crop models to quantify India's crop risks. The report also provides an assessment of the correlation between crop and property insurance in the country.

By understanding Indian (re)insurance crop risks better, insurers can improve their portfolio exposure management, set appropriate limits and gain the confidence to expand into this fast-growing market.

This report is aimed at underwriters and exposure managers who are or will be exposed to crop risks in India.

Key facts

- India is the world's second largest agricultural economy after China with an Agriculture Gross Domestic Product of USD 392 billion (about 17% of the country's GDP).
- Crop insurance is now the third largest non-life market segment in India behind motor and health, with premiums around USD 3.3 billion.
- India has two main cropping seasons: Kharif (July-October) and Rabi (October-March).
- More than 60% of crops in India remain uninsured.
- No crops in India are safe from crop damage given the wide-range of weather events India is exposed to.
- Droughts cause most the widespread damage to crops, particularly as less than 50% of crops in India are irrigated.

Key facts

- During Kharif 2016, an average monsoon year, crop claims were just under USD 1 billion (Bushan & Kumar 2017).
- The Government aims to reduce the protection gap via the latest crop insurance scheme PMFBY. This will require the capacity and resources of the international (re)insurance market.
- Crop treaties cover an annual period, with renewal typically on 1 April, covering both PMFBY and RWBCIS schemes for both seasons. Due to PMFBY's timelines and that insurance companies prefer reinsurance to be in place prior to the tendering process, exposures and rates at the time of treaty underwriting are relatively unknown.
- Quota share proportional treaties are most commonly used for Indian crop. Stop loss treaties are purchased in addition to the quota share treaties to protect companies from very high claim ratios.
- Crop models provide greater insight into next-year possible outcomes by simulating realistic adverse weather events that have not occurred in the past based on the true frequency of recent historical events.
- Property business contributes to around 9%of Indian non-life premiums (USD 1.9 bn), compared to 16% for crop. The correlation between large crop and property losses is likely to be at regional scale and event dependent. As the non-life insurance market grows in India to reduce the protection gap, the risk of large correlated losses is likely to increase. It is vital that this risk is supported by the reinsurance market to better protect India against natural disasters.

Crop (re)insurance – a growing market

India is the world's second largest agricultural economy after China with an Agriculture Gross Domestic Product of USD 392 billion (CIA World Fact book, 2016) - about 17% of the country's GDP. Around 50% of the population is employed in agriculture. Farming in India is generally localised in scale (subsistence agriculture), with more than 100 million farmers[a], and an average farm size of only 1.3 hectares (Department of Agriculture, Cooperation and Farmers Welfare). India's crop production has increased in terms of both land area devoted to crop production and yield. The latter has been largely achieved thanks to crop management and technology improvements such as fertilisers use, seeds genetics and widespread irrigation schemes (known as the Green Revolution[b]).

With agricultural risk increasing from a growing population coupled with the related impacts of land use changes, water scarcity and climate change, governments around the world are increasingly interested in building more resilient agroecosystems. (Re)insurance can play a key role in this by transferring risk. In 2015, the crop insurance take-up rate across all farmers in India was around 22% (Press Information Bureau, PIB, Dec 2016 press release). In 2016, a new crop insurance scheme was introduced by the Government known as Pradhan Mantri Fasal Bima Yojana (PMFBY) with the intention to expand crop insurance coverage to 50% of farmers by 2018 (Business Today, 2016). It is designed to close the agricultural protection gap for Indian farmers who suffer potentially dramatic consequences in years when monsoon rains are delayed or other adverse weather impact crops.

As part of this new scheme, the sums insured have significantly increased, which has resulted in a huge increase in market insurance premiums by nearly 300% (General Insurance Council, GIC Industry Data Statistics, March 2017) from about USD 850 million in 2015/16 to more than USD 3 billion in 2016/17. As a result of this growth, General Insurance Corporation of India (GIC) Re, which has first rights on Indian reinsurance business, has become the world's largest agricultural reinsurer, with crop premiums of USD 1.6 billion, recording an 80% growth in total premiums in the first year of the PMFBY scheme. Crop insurance is now the third largest non-life market segment in India behind motor and health, with premiums around USD 3.3 billion (INR 206 bn) in 2016-17 (GIC Industry Data Statistics, March 2017), placing it third in terms of global agricultural insurance premiums behind the US and China. Industry statistics from the General Insurance Council suggest an increase in crop premiums in 2017-18, although this is in contrast to a recently reported drop in the insured crop area, number of farmers and sums insured in 2017-18 to below 2016-17 levels (Financial Express, 2018).

Crop insurance is administered at state level. For states opting to implement crop insurance schemes, coverage has been compulsory for farmers with seasonal agricultural operations loans from banks (loanee farmers) since 1999. For the farmers without loans (non-loanee farmers[c]), crop insurance is voluntary and despite Government subsidies, take up is currently less than 5% (Bushan & Kumar, 2017). Crop insurance is typically issued separately per crop per growing season. Districts within each state are grouped into clusters with the intention to diversify risk and insurance companies bid per cluster, via the state governments. Crops are at risk from damage throughout the entire growing season from the planting time through to post-harvest when crops are cut and spread out to dry in the fields. Today's crop insurance policies in India provide protection for the entire period. Currently, in India, around 25-30% of food crops and around 44% of oilseed crops are insured (Pocket Book of Agricultural Statistics 2016, DAC-FW). To date, insurance is predominantly purchased for Kharif crops (cultivated July – October) (DAC-FW May 2014 report), which is more dependent on the monsoon compared to Rabi crops (cultivated October – March) (see Section 2 for more detail).

Crop treaties cover an annual period, with renewal typically on 1 April, covering both Pradhan Mantri Fasal Bima Yojana (PMFBY) and Restructured Weather Based Crop Insurance Scheme (RWBCIS) schemes for both Rabi and Kharif seasons. Due to PMFBY's timelines and that insurance companies prefer reinsurance to be in place prior to the tendering process, exposures and rates at the time of treaty underwriting are relatively unknown. Buffers that account for uncertainty in the final tendering outcome and farmer enrolment are built into the reinsurance contracts. Because of this uncertainty, quota share proportional treaties are most commonly used for Indian crop business as it is an effective way to cede "unknown" risk, usually with low retentions. They are also attractive to insurance companies who do not have

[a] Note: the reported number of farmers varies between 100-138 million, depending on the source and census method.

[b] The Green revolution was a period that started in early 1960s and saw agriculture in India increasing due to improvement in method and technology.

[c] The total number or percentage of non-loanee versus loanee farmers is a grey area and not clearly reported. Non-loanee farmers might be loanee but via different channels i.e. loaning for local lenders. In West Bengal, the state waived off the farmer's premium contribution so insurance is not truly voluntary (non-loanee). In Maharashtra, the scheme is voluntary for all farmers and thus loanee farmers have been mis-classed as non-loanee (Bhushan & Kumar 2017).

sufficient capital to retain their entire crop portfolio. Stop loss treaties are purchased in addition to the quota share treaties to protect companies from very high claim ratios. Traditionally, many Indian crop stop loss treaties have similar attachment and limits regardless of the exposure mix (states, crops, season, scheme) and company (underwriting practices, reserve strength, risk appetite), suggesting that treaty conditions are not technically-based. However this is starting to change with smaller portfolios typically having higher limits. Stop loss treaties usually start around 110-140% and many cap at around 200-250% loss ratio, depending on the state.

The market needs confidence that crop insurance schemes in India are transparent, fair and properly implemented. The Government has recently prioritised gathering and maintaining a centralised data portal including historical yield and loss data, sums insured and premiums, that is available to all interested parties to better assess and price risks. Improvements are required to the claims settlement process to ensure claims are reliable and payments can be settled quickly. The government has stepped up the drive to implement technology (digital insurance platforms, smart phones, drones, satellite imagery) to identify areas of damaged crops and support a more efficient and audited assessment of crop yields and claims (traditionally done by crop cutting experiments requiring a large pool of human resources that are not always available or adequately trained).

As the Indian crop market stabilises and matures, innovative products may become available to better suit the farmers. In some countries, such as the US, crop revenue based schemes have been available for several years to protect farmers against revenue shortfalls when commodity prices decrease, for example, as a result of surplus supply in years with above-average yields. Crop revenue protection in India is beginning to appear, and may increase in the future given the recent difficulties faced by some farmers following the bumper harvest in 2016 and the subsequent crop price drop.

The importance of weather

Crop yields are dependent on weather-related conditions, soil type, pest and disease occurrence and management practices such as crop selection, use of pesticides and fertilisers, labour schemes and agricultural technology adoption like irrigation. Weather-related variables include rainfall, maximum and minimum temperatures, solar radiation, relative humidity and wind (Hoogenboom, 2000). Many of these drivers also interact with each other through complex feedback processes. While long-term yield trends are driven by enhanced managerial practices including the use of new genetics and fertilisers, researchers have shown that weather (attritional and/or extreme events) can explain up to 80% of year-to-year crop yield variability (Petr, 1991; Fageria, 1992; Kumar et al., 2006), especially for rain-fed production systems.

Historically India's economy and society has been bound to the monsoon, sometimes referred to as the "real finance minister of India", which delivers 75-80% of India's annual precipitation between June and September. Fundamentally the monsoon occurs regularly and the agriculture sector relies heavily on the timely onset and spatial distribution of monsoon rainfall for successful cultivation of rainfed systems and for the replenishment of water levels for irrigated systems. The agricultural growing period is split into two major seasons defined by monsoon seasonality: Kharif crops are cultivated at the arrival of the monsoon, between July and October and Rabi crops are cultivated after the monsoon rains, between October and March.

A deficit summer monsoon (drought) generally leads to a reduction in crop yields, especially for rainfed systems. Excess monsoons often result in higher crop yields nation-wide, although spells of very heavy rainfall can damage crops locally. States in the North-West are most prone to drought, followed by the central states of India running from north to south. Flooding is a common phenomenon across India, with the most frequent flooding occurring in the north. Kharif crops are at greater risk from droughts and monsoon flooding since their growing season coincides with the monsoon. Rabi crops can also be damaged by monsoon flooding (water-logged ground) or drought (reduced water supply for irrigation). At a nation-wide level, drought years have a more significant negative impact on crops than years of excess rainfall.

Despite fluctuations in the annually recurring monsoon pattern, monsoon variability is not the only weather event driving large variations in year-to-year crop yields. Tropical cyclones, periods of freeze, heat waves, hail storms and unseasonal rain can also cause significant localised damage to crops. The impact on crop yields depends on both the intensity and timing of adverse weather in relation to a crop's development stage at the time of each event. Weather perils impacting crops tend to have distinct seasonal behaviour which overlap with different stages of the two main crop growing seasons. Kharif crops are mainly impacted by monsoon variability and tropical cyclones, while Rabi crops are most impacted by extreme temperatures, hail and unseasonal weather. Drought typically causes most wide-spread crop damage and has the potential to impact market-wide crop insurance portfolios.

Uttar Pradesh, the top wheat (Rabi) producing state and the second largest rice (Kharif) producing state, is one of the states most at risk from flooding. Other Kharif rice growing regions such as West Bengal and Andhra-Pradesh in the East and the cotton growing region of

Gujarat in the West also have frequent floods. Along the eastern coastline, flooding can occur during the north-east monsoon as well as the summer monsoon.

In many of these regions, rice production extends into the winter to make the most of the additional rainfall.

In the past 60 years, at a national level, there have been more deficit/drought years than excess monsoon years. Studies investigating observed trends in the Indian summer monsoon reveal a patchwork of increasing and decreasing trends with significant regional differences. Historically most severe droughts are associated with the impacts of El Niño. The impact of El Niño Southern Oscillation on crop yields via its influence on the Indian climate is explored in Section 4. The strong signal for El Niño suggests that crop insurance could make increasing use of quality ENSO forecasting.

Climate change impacts are not expected to result in significantly different climate and crop yields over the next few years beyond what has been observed in the more recent past. It is generally agreed that the warming climate has intensified the hydrological cycle in the tropics and is contributing to more severe extreme rainfall events over India. There is uncertainty on the overall effects of future climate change, such as negative impacts of rising temperature versus positive impacts of increased carbon dioxide fertilisation. The impacts of climate change must be considered by the (re)insurance industry, across all sectors, including agriculture, to avoid unexpected losses.

Modelling India crop risks

The challenge of insuring Indian crop risk is the lack of data, particularly on exposure, historical crop yields and insured losses. What loss data there is gives only limited insight into how to price current crop schemes because of the changes to the market caused by PMFBY's introduction. Furthermore historical data must be interpreted, considering all possible trends, and be used with caution to ensure a consistent robust data record is used for insurance pricing. Crop models can be used to extend the historical view by applying historical climate data and/or probabilistic simulations of climate scenarios to crop yield models. These models also provide greater insight into next-year possible outcomes by simulating realistic adverse weather events that have not occurred in the past based on the true frequency of recent historical events. An example, shown in Section 3, reveals that modelled PMFBY annual average loss cost based on 45 years of de-trended past weather data is more than 60% higher than PMFBY annual average loss cost based on 13 years of de-trended observed yield data. Crop models can also provide a view on future crop yield impacts when fed with projections of climate change related scenarios, or be used in forecasting application when driven by current weather data.

A probabilistic crop risk model for the Indian crop insurance market must reflect the way crop insurance is administered and written in India. Models must therefore include the following:

- Major drivers of crop yield variability
- Nation-wide coverage for most perils
- Account for insurance clusters
- Attritional and catastrophe losses
- The impact of irrigation
- Separate models of different crops for Kharif and Rabi seasons
- Model both PMFBY and WBCIS schemes
- Historical and probabilistic simulated loss models
- Exposure management functionality

In the current Indian crop (re)insurance market, where risk is not known at the time of reinsurance renewals, and there is limited historical data, crop risk models can provide a valuable tool to better understand and account for exposure uncertainty, as well as portfolio management decisions once exposures are confirmed.

A nation-wide initiative backed by the Government and insurers, to collect, digitise and disseminate, exposure, weather, yield and loss data at the finest spatial resolution, in a consistent format within a centralised database, would create a historical dataset that would help insurers develop premiums that more closely reflect the potential risk.

The Government has set up a national crop insurance data portal (www.agri-insurance.gov) to collect data related to crop insurance, but a greater wealth of information is required to fully meet (re)insurers' needs. Digitising data will reduce the time lag between gathering, processing and analysing information for all stakeholders.

Model results

Probabilistic crop risk models produce simulated loss distributions based on thousands of simulated years of weather scenarios, the impact of attritional as well as extreme events over each crop season. Metrics such as annual average losses and losses at different return periods can be output at different scales (e.g. district, state or a particular portfolio).

To explore the benefits of crop risk modelling, the report includes results from the RMS® India Agriculture Model. The model applies two sets of weather data, (i) 10,000 years of simulated weather and (ii) 47 years of historical de-trended weather data, to crop yield models, to generate modelled yields from which insured losses are calculated. The model output represents the pure technical loss based on applying the PMFBY index calculation (performed at 25km resolution) to dis-aggregated exposure information. It does not include uncertainty loadings or any additional loadings that are applied by insurance companies when determining their overall rate. It is very important to realise that the results presented here are for a hypothetical nationwide portfolio for 6 major crops (rice, wheat, sugar cane, soybean, cotton & potato), assuming 100% insurance within the districts included in the 2016/17 Kharif and Rabi clusters. As such, the results do not represent any specific insurance portfolio which could experience different results. Also, actual losses from events may differ from the results of simulation analyses[d].

Based on the hypothetical nation-wide portfolio for 6 crop types (rice, wheat, sugar cane, soybean, cotton & potato), analysed in this report:

- PMFBY losses are highly sensitive to the exact mix of crop types, their exposure distributions, levels of irrigation and indemnity values. At district-level, loss costs (as a percentage of sums insured without loadings), for individual years can range between <1% to over 80% for certain crops.
- Districts with high annual average lost costs are distributed throughout India, although many are concentrated in the central, north-eastern and north-western states, often driven by specific crops. For example, high annual average loss costs in the north-east are driven by Kharif rice whereas high loss costs in the north-west are driven by cotton.
- The states with highest PMFBY loss costs per crop type are: (i) Kharif rice: Bihar, (ii) Kharif sugarcane: Andhra-Pradesh, (iii) Kharif soybean: Maharashtra, (iv): Kharif cotton: Rajathsan, (v) Rabi rice: Maharashtra, (vi) Rabi wheat: Himachal-Pradesh and (vii) Rabi potato: Chhattisgarh.
- At a national level, PMFBY annual average loss costs are highest for Kharif soybean, followed by Kharif cotton, Kharif rice, Rabi potato and lower for Rabi wheat, Rabi rice and Kharif sugarcane.
- Madhya-Pradesh, Maharashtra, Odisha, Bihar and Uttar-Pradesh contribute to around two thirds of the national PMFBY annual average loss (AAL).
- Probabilistic modelled loss costs increase with larger return periods, exceeding maximum historical values and demonstrating simulated losses can provide a better view of uncertainty by capturing inter-annual and inter-decadal climate variability via thousands of years of simulation. For example, at a nation-wide level, based on the hypothetical portfolio, the largest historical modelled loss cost over the past 47 years for potato is 14%, compared to 26% in the simulated results (10,000 years). Similarly the largest historical modelled loss cost for soybean is 25% compared to 49% in the simulated results. At state-level, 200 year return period loss costs can be as large as 40-70% for crops such as rice (Kharif & Rabi), wheat and soybean and even higher for more vulnerable crops such as cotton and potato.
- El Nino years often, although not always, result in higher crop losses. Model results demonstrate that at a national level, annual average loss costs are more than 50% higher for Kharif rice during El Nino years compared to the long-term average over 47 years.

The model results demonstrate how crop risk models can be a valuable tool to better understand and account for the sensitivity of crop losses to exposure uncertainty in India.

The correlation between crop and property insurance

Non-life insurance penetration in India is around 0.8% (IRDAI, Annual Report 2016-17) compared to 4.3% in the US, 2.6% in the UK and 1.8% in China (Swiss Re Sigma Explorer Database, 2018). Property business contributes to around 9% of Indian non-life premiums (USD 1.9 bn) while agriculture accounts for 16% (USD 3.3 bn) (GIC Industry Data Statistics, March 2017). Property insurance take up is higher for commercial and industrial lines compared to residential, where there is a lack of awareness of the benefit of insurance amidst concerns homeowners will not be adequately covered nor receive prompt and full claims settlement (The Tribune, 2014).

No state in India is safe from floods but the north/north-east has greatest flood risk. These regions contribute a smaller amount to crop and property premiums, meaning the risk of a large correlated crop and property loss is less likely in these regions.

[d] In view of the hypothetical nature of the modelled portfolio Lloyd’s and RMS disclaims any and all liability.

However as insurance penetration increases, these insured losses could become larger.

Floods caused by the monsoon and their impact on crops are discussed in Section 2 where the report shows that Kharif crops are most at risk from flood damage. Property flood damage has increased over the past few decades as a result of population growth. As people look for more space to live, floodplains are becoming populated and natural drainage systems are covered up reducing the land's capacity to handle heavy rainfall. Recent flooding events have been aggravated by increased urbanisation and unplanned growth (e.g. Mumbai 2005 & 2017 and Chennai 2015). Industrial sites are particularly susceptible to flooding as they are usually located close to rivers.

Property and crops are not always vulnerable to the same perils. Analysis based on based on data from Cambridge Centre for Risk Studies identifies flood as the top natural threat to GDP in India's large cities. The impact of cyclone is low for most of the cities included in the analysis, with the exception of Kolkata. However, while cyclones are less likely to occur they can cause greater losses. Since flood and tropical cyclones are important perils for property and crop risk, the correlation of crop and property risk for these two perils is explored in this report. Hail and extreme temperatures are not considered for this investigation as they have a more localised impact and will not drive major correlated losses. Drought and earthquake, with less correlation between crops and property (with the exception of tsunami), are considered later when discussing the relative impact of natural catastrophes perils on crop and property losses.

Due to the geographical scale of cyclone damage, and considering the distribution of crop and property exposures, there is a risk of coincident large crop and property losses if cyclones impact Chennai, Kolkata or Mumbai. Based on the current distributions of crop and property premiums, a cyclone making landfall in Mumbai and moving inland over Maharashtra could create the greatest correlated cyclone loss.

Given the size of India, any natural catastrophe event will impact only a portion of the whole country meaning nation-wide portfolios will be less impacted by an event than regionally focused portfolios. In summary, the correlation between large crop and property losses is likely to be at regional scale and event dependent. As the non-life insurance market grows in India to reduce the protection gap, the risk of large correlated losses is likely to increase. It is vital that this risk is supported by the reinsurance market to better protect India against natural disasters. Due to the large number of different types of natural disasters that impact India, a more holistic risk modelling approach might be required for major lines of business such as crop, motor and property, covering key perils such as flood, cyclone, and earthquake and specifically for crops, the impact of droughts and attritional weather events.

Areas of improvement

Lloyd's obtained its reinsurance licence in India on 17 January 2017. The licence allows Lloyd's underwriters to underwrite reinsurance business in India, through a service company in India. Following the implementation of PMFBY scheme, Lloyd's sees crop reinsurance in India as a significant opportunity, but would recommend the following to ensure business sustainability:

1. Provide uniform consistent data. Standardised uniform data templates, including high data resolution (per district and crop, for loss costs and yields), provided and used by all involved stakeholders to make the (re)insurance process much simpler and transparent. There should be consistent data formats used at time of treaty underwriting and when exposures are confirmed when Kharif and Rabi tenders and enrolment are completed later in the year. Furthermore, there is a need for continued effort to gather and maintain a centralised database of exposure information and high quality historical yield, loss and weather measurements at local level, available to all interested parties that can be used to better assess and price risks. As crop insurance schemes improve, the insured unit area decreases. However, crop yield data at this geographical scale is limited and is typically available only at district resolution. Thus, to accurately assess and price crop risk at this level, finer resolution data is required, which presently does not exist across all of India. While longer records of historical weather data exist, they may not always be co-located within an insured unit area. Some weather stations may have been recently set up within an insured unit and thus long historical records may not always exist and a station further away may be used for historical weather information.

2. Ensure greater transparency and underwriting discipline. It is critical for business written to high loss ratios, that insurance and reinsurance rates are based on actuarial rates with a catastrophe load, and the temptation to bid below this rate to win business is avoided. Crop risk is more complex than other lines of business and it is vital that those involved in the market have a good understanding of these complexities. There should be concerted effort between all stakeholders to maintain underwriting discipline so that the market can absorb losses from a

major drought year. With many insurance companies now approved to provide crop insurance and competing with each other to win bids for each crop cluster, the tender process may lead to winning bids below actuarial rates. Rates are priced around a 75-85% loss ratio.

3. Minimise exposure certainty. The timelines of the bidding process (establishing direct rates between insurers) and scheme enrolment, as well as the bidding process itself in which an insurer can opt to bid for only one season and that insurance companies prefer reinsurance to be in place prior to the tendering process, results in a degree of uncertainty over underlying rating, premium levels and risk exposures at the time of inception of reinsurance contracts (1st April) which cover both Kharif and Rabi seasons. Potential solutions to minimise this uncertainty include shifting the timing of the bidding process forwards, performing Rabi tenders at the same time as Kharif tenders (becoming more popular), or, if feasible, splitting treaties into separate Kharif and Rabi six month contracts. This latter option would incur extra effort and increased volatility and reinsurance rates. Alternative solutions could include providing incentives to the insurers to bid over several years, thus spreading their risk, as well as the risk for governments and reinsurers over longer time periods. Multi-year contracts are currently not common due to concerns around scheme stability and locking in rates. Changing cluster definitions each year also adds to further exposure uncertainty.

4. Improve claims handling process and assessment. To date the PMFBY scheme has suffered from the very large number of crop cutting experiments required to assess yields and determine insured crop losses. Resources and infrastructure are not yet in place to support the large number of time-consuming crop cutting experiments required by the scheme. The human resources, technology and expertise within both the Government and insurance companies are not sufficient to provide confidence in market-wide claims reliability. As a result, there can be a long delay in claims settlements due to the time it takes to conduct the crop cutting experiments, pass back the yield data, and then verify and agree claims. Reinsurers need confidence that robust loss adjusting processes are in place. Incorporating technology into the claims handling process, as demonstrated in Tamil-Nadu (Box 4) and Karnataka, can make a significant difference. There are also concerns that novice insurers may not have robust exposure management practices and claims handling teams. Insurers are meant to monitor crop cutting experiments, but often the resources are not available to do this or there is a lack of expertise to evaluate the crop cutting experiments process. In some cases, external agencies are used for third party independent evaluation of claims.

5. Ensure timely premiums. The state and central governments are encouraged to pay their premium subsidy in a more timely fashion than has happened to date in the PMFBY scheme. This has many consequences including delayed payment of claims to the farmers and premium to reinsurers. Streamlining the state governments process to verify crop insurance policies would help to speed up the delivery of subsidised premiums.

6. Strengthen regulations. The insurance industry is highly encouraged that the Government is committed to adequately funding the crop insurance schemes and supporting them via appropriate tax concessions. As the Indian reinsurance market grows, it is expected that (re)insurance regulations may be reviewed and updated to consider stakeholder feedback. At the moment GIC Re has the first right of refusal on any reinsurance treaty in the country. The current Order of Preference Regulations could pose administrative burden on cedants trying to obtain the best possible reinsurance protection for their crop portfolio. The IRDAI is currently drafting revisions to the 2016 General Insurance-Reinsurance Regulations, including updates to the Order of Preference Regulations (PWC, 2018). The crop (re)insurance market needs to ensure business can be financially viable in the long term and that the market takes advantage of the influx of foreign expertise currently entering the Indian insurance sector.

Introduction

Introduction

Agriculture is a core part of India's economic and social framework. India is the world's second largest agricultural economy after China with agriculture accounting for 17% of gross domestic product (GDP) and 10% of export earnings (Central Intelligence Agency (CIA) World Fact Book, India Brand Equity Foundation, 2017). Approximately half of the population (around 650 million people in 2016) relies on agriculture as its principal source of income, and it is a source of raw material for many industries.

Thanks to its large range of agro-climatic regions, India can grow a variety of different crops throughout the year. The diversity in climatic regions also exposes crops to a wide range of different weather events, many of which can have devastating impacts for crops. Crop yields can be impacted by both significant individual weather events or by the accumulation of adverse weather events over a crop's growing season. The impact on crop yields depends on both the intensity and timing of adverse weather in relation to each crop's development cycle. Crop yields are also influenced by agricultural management practices such as irrigation, choice of seed, use of pesticides and fertilisers. However, the main driver of regional and nation-wide year to year crop yield variability is the weather (Petr, 1991; Fageria, 1992; Kumar et al., 2006).

To protect over 100 million farmers, who largely rely on rainfall to water their fields, from the vagaries of weather, a succession of nation-wide crop yield and weather based index insurance schemes, subsidised by the central and state governments, has been tested over the past 30 years, but with limited take-up. Agricultural insurance penetration (defined as agri-insurance premium as a percentage of agri-GDP) is much less than 1%, compared to 6% for the US (based on GDP data from CIA World Fact book and premiums from AXCO Insurance Information Services[1]).

In 2016, a new yield based crop index insurance scheme was introduced by the Modi government known as Pradhan Mantri Fasal Bima Yojana (PMFBY) with the intention to expand crop insurance coverage to 50% of the farmers by 2018 and to close the agricultural protection gap for Indian farmers who suffer potentially dramatic consequences in years when monsoon rains are delayed or other adverse weather impact crops. As part of this new scheme, sums insured have significantly increased, which has resulted in a huge jump in insurance premiums with market-wide premiums increasing by nearly 300% (General Insurance Council, GIC Industry Data Statistics, March 2017) from about USD 850 million in 2015/16 to around USD 3.3 billion in 2016/17. As a result of this growth, General Insurance Corporation of India (GIC) Re, who has first rights on Indian reinsurance business, has become the world's largest agricultural reinsurer recording an 80% growth in total premiums (USD 1.6 bn crop premiums) since the introduction of PMFBY in 2016.

The Indian Government is committed to transfer and spread risk, including agricultural risk, both nationally and internationally through insurance mechanisms. The Government and insurance regulators have implemented changes to encourage growth and bring foreign expertise into the local market, such as product design, ratemaking, underwriting and loss adjustment, and to bring Indian re/insurance practices in line with well-established insurance markets. As part of this effort, reinsurance market regulations now permit Lloyd's and other approved foreign reinsurers to operate through branches in India.

Over the past decades probabilistic Cat risk models have grown in sophistication and are now an integral part of pricing risk and managing solvency across many sectors of the insurance market. The concepts of probabilistic modelling have been applied to the agricultural sector on weather derived indices and multi-peril crop insurance to develop innovative solutions and to deliver more comprehensive and scientific underwriting approaches.

This report summarises the history and current status of crop (re)insurance in India and goes on to discuss the challenges of modelling crop risk in India and how this can be improved in the future. The report illustrates how probabilistic crop loss modelling can provide insight into understanding crop loss distributions using results from the RMS India Agriculture Model.

Crop risk models are based on coupling crop yield models and probabilistic weather models, thus extending the view in tail risk. Crop yield models must consider both attritional as well as significant events, the impact of which depends on the severity of the event(s) and their timing depending on each crop's specific development cycle. Finally, the report explores the potential correlation between property and crop risk in India. Rapid urbanisation is exposing increasing concentrated portions of population and economic value to climatic hazards such as floods, storms, droughts as well as earthquakes. While non-life insurance penetration is currently around 0.8% (IRDAI, Annual Report 2016-17) this is expected to change significantly over the next decade with a much greater proportion of property and crops protected by insurance structures. Thus (re)insurance companies should consider the possibility of correlated losses in their risk management approach.

Research approach

This report was developed through a structured research process, across three key stages:

Literature review

A comprehensive desktop review was undertaken to identify:

- the implementation, success and lessons learnt from the succession of Indian crop insurance schemes over the past 20 years, including the most recent PMFBY and RWBCIS,
- the drivers of crop yield variability which translate to insured crop losses,
- latest research and understanding around the drivers of Indian monsoon variability (at multiple different timescales, including the impact of El Niño Southern Oscillation, the Indian Ocean Dipole and climate change) and
- examples of key historical events, where there was potential for correlated crop and property losses at a regional level: Tropical cyclone Orissa 1999 and Tropical cyclone HudHud 2014 (see Box 5, p105); Chennai 2015 floods and Mumbai/ Maharashtra 2005 floods (see Box 6, p106).

Crop risk modelling study

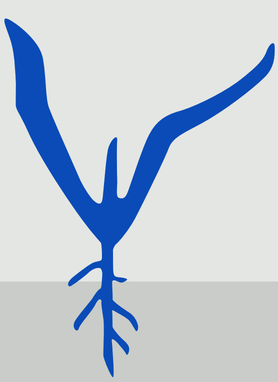
To explore the potential to drive innovative solutions in the crop risk space, the RMS India Agriculture Model was used to investigate the complexity and variability of modelling crop loss distributions, and demonstrate the benefits incorporating coupled crop-weather probabilistic modelling into (re)insurance risk models to deliver assessment of the severity and frequency of potential future crop risk, especially for the tail of the risk.

Insurance sector consultations

A collaborative workshop involving agricultural sector experts and insurance practitioners was organised by Lloyd's to share initial research findings of this report and gather feedback about the latest PMFBY scheme. Following the workshop, Lloyd's organised a series of interviews between RMS and Lloyd's underwriters and brokers to identify how the latest crop insurance schemes are implemented and underwritten. This joint approach resulted in identifying challenges that currently exist in writing Indian crop business and how this can be improved in the future.

All numbers in this report are reported in USD (2017 values) using the exchange rate 1 Indian Rupee (INR)=0.016 USD, unless directly reported in USD by EM-DAT, Swiss Re or Munich Re. All maps presented in this report are based on 2014 district administration boundaries and 2016 state administration boundaries.

Overview of crop (re)insurance in India



Emerging Risk Report 2018

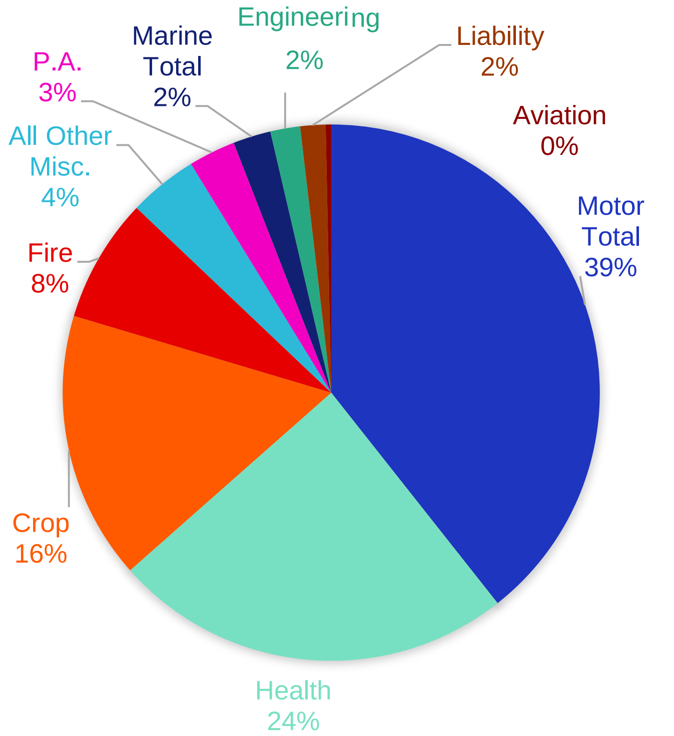
Society & Security

1. Overview of crop (re)insurance in India

1.1 Insurance market overview

India is thought to be the world's fastest growing economy (Business Line, 2018). It was forecasted in 2016 to be the world's seventh largest economy by the IMF in terms of nominal GDP, and third in terms of GDP by purchasing power parity (PPP) (CIA World Fact Book, 2016). According to the World Bank, by 2030, India will likely be the world's largest middle-class consumer market, accounting for 23%of global middle-class consumption, surpassing both China and the United States. Despite this, insurance take up is far below international standards with insurance penetration at 2.72% for life insurance and 0.77% for non-life (Insurance Regulatory and Development Authority of India, IRDAI, Annual Report 2016-17). However, this is starting to change as (re)insurance laws have been updated in 2015 and 2016, in part to allow greater access to foreign capital and there are talks of further changes to support the growing non-life insurance market (AXCO, 2017). There is now large growth potential for the (re)insurance sector in India, as witnessed by the large growth in insurance premiums, particularly for the non-life sector. Non-life premiums have increased over 30% between 2015-16 and 2016-17 to USD 20.5 billion (INR 1.281 bn) compared to a 13% growth the year before (GIC 2016-17 Yearbook). A large part of this growth is due to a significant rise in crop insurance premiums in 2016 from schemes designed to offer protection to farmers against crop damage and poor yields. Crop insurance is now the third largest non-life market segment in India behind motor and health (Figure 1), with premiums around USD 3.3 billion USD (INR 206 bn) in 2016-17 (GIC Industry Data Statistics, March 2017), placing it third in terms of global agricultural insurance premiums behind USA and China. Property (fire+engineering) premiums in 2016-17 were around USD 2 billion (INR 127 bn) (GIC 2016-17 Yearbook). This report provides an overview of crop risk and insurance in India and discusses potential future opportunities in this emerging market for reinsurers.

Figure 1: % of non-life gross direct premiums 2016/17 in India



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from GIC Industry Data Statistics, March 2017

Insurance history

The history of insurance in India dates back to 1818, when *Oriental Life Insurance Company*, the first life insurance company was established in Kolkata (Calcutta) (Siddiqui, 2009). Over the following 140 years, many new insurance companies were formed. In 1956, life insurance was nationalised by the Government of India combining insurance companies under the Life Insurance Corporation of India (LIC). In 1972, the non-life insurance sector was also nationalised under the General Insurance Corporation (GIC) of India.

These state-owned companies monopolised Indian insurance until 1999 when the Insurance Regulatory and Development Authority Act was passed to establish a new regulatory authority, the Insurance Regulatory and Development Authority of India (IRDAI) and the entry of private insurers, with a foreign ownership cap of 26% was approved.

Significant regulatory updates, particularly with regards to foreign (re)insurers, were introduced under the Insurance Laws (Amendment) Act, 2015 (Indian Ministry of Finance), to increase capacity and bring in foreign expertise. The 2015 Act increased the foreign direct investment cap from 26% to 49% and implemented new regulations concerning the registration, approval and operation of foreign reinsurers, resulting in overseas reinsurer branch offices opening in India and entry into the Indian market after approval by the IRDAI. In March 2016, regulations were introduced to establish a Lloyd's office in India.

In May 2016, new IRDAI (General Insurance – Reinsurance) regulations were issued to provide an overarching regulatory framework for the reinsurance of general insurance risks, focused on maximising retention within India and increasing capacity. A priority order for reinsurance purchasing was established where GIC Re has the first right of refusal on any reinsurance treaty in the country. After GIC Re, the local reinsurers, following a prescribed order (see Appendix 1), have the right to the reinsurance (including their foreign partners). There is a possibility of further change as several foreign reinsurers have expressed concerns (Business Insurance, 2017). There is also talk of removing the cap of foreign investment in order to increase market capacity as India's economy and insurance sectors grow (Reinsurance News, 2017). The IRDAI is currently drafting an update to the General Insurance-Reinsurance Regulations following stakeholder feedback (PWC, 2018), including updates to the priority order for reinsurance purchasing. However, at the time of publishing, the revisions were yet to be finalised (Reinsurance News, 2018).

Since 2000, the number of private insurers entering the market has increased each year. Today, the Indian insurance industry consists of 53 insurance companies of which 24 are in life insurance business and 29 are non-life insurers (IRDAI annual report 2016-17). As of October 2017, Lloyd's, Axa Re, RGA, Munich Re, Swiss Re, Hannover Re, SCOR, ITI Reinsurance Ltd, XL Catlin, MS Amlin and Gen Re have been approved R3 registration licences by the IRDAI, to operate locally in India rather than cross-border (IRDAI annual report 2016-17).

1.2 Indian crop overview

India is the world's second largest agricultural economy after China with an Agriculture Gross Domestic Product of USD 392 billion (2016, CIA World Fact book) and accounts for around 17% of the country's GDP. Around 50% of the population is employed in agriculture. Farming in India is generally on a very localised scale (subsistence agriculture), with over 100 million farmers[e], and an average farm size of only 1.3 hectares (Department of Agriculture, Cooperation and Farmers Welfare). India's crop production has increased in terms of both land area devoted to crop production and yield. The latter has been achieved largely thanks to three factors:

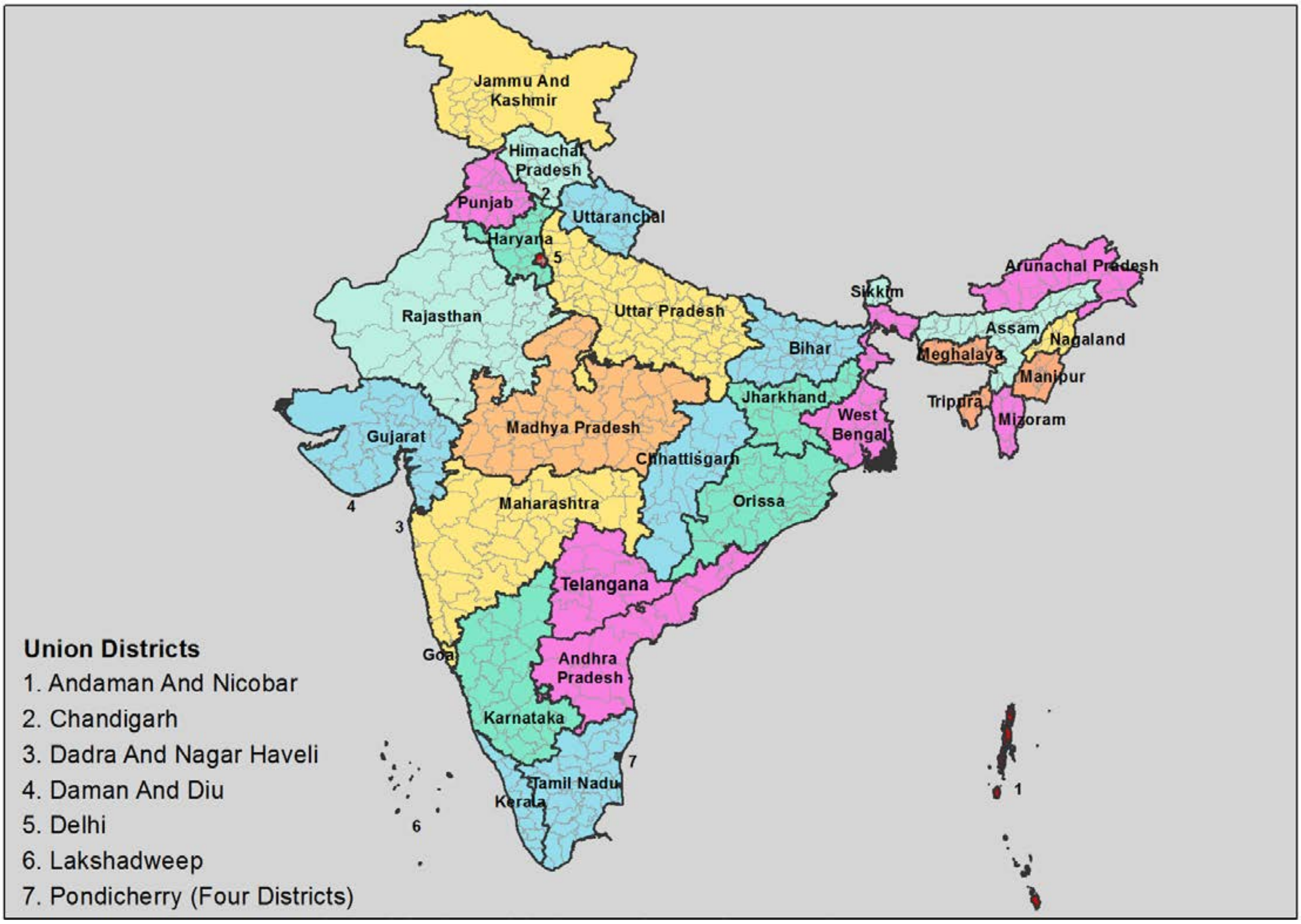
- development and use of high-yielding and resistant varieties,
- increased use of fertilisers and other agro-chemicals and
- changes in agricultural practices such as irrigation (Tripathi, 2009) (both before and during the Green Revolution[f]).

The Indian climate and soil comprise a wide range of conditions across a vast geographic scale, ranging from arid desert in the west and alpine tundra and glaciers in the north, to humid tropical regions in the southwest. As a result, India can grow a wide variety of crops in its different agro-climatic zones. Plant growth and development depends on water availability, the majority of which is provided by the monsoons in India. Around 75-80% of India's rainfall comes from the monsoon (Walker Institute for Climate System Research, 2013).

[e] Note: the reported number of farmers varies between 100-138 million, depending on the source and census method.

[f] The Green revolution was a period that started in early 1960s and saw agriculture in India increasing due to improvement in method and technology. Irrigation systems developed before the Green Revolution, particularly the canal systems in the western Indo-Gangetic Plains have increased crop productivity.

Figure 2: Indian State, Union Territory and District boundaries[g]



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from DIVA-GIS, 2014 and 2016

[g] India is ruled both by central and state governments. There are currently 29 states and 7 union territories (purely run by central government).

Crop seasons in India

Although there has been considerable effort to improve irrigation, agriculture in India is still mainly dependent upon the monsoon, which generally arrives in India with great reliability year on year, but with irregularity in the exact arrival time and the regional distribution and intensity of precipitation over India. The monsoon brings most of the country's annual rainfall over the summer period arriving in the south around May/June and progressing northwards before departing from the north around early-mid September. These features of the monsoon seasonality define the agricultural growing season in two major growing periods in India: Kharif (meaning summer in Arabic) and Rabi (meaning winter) seasons. Kharif crops are cultivated at arrival of first rains, between July and October. Rabi crops are cultivated after the monsoon rains, between October and March. There are also some crops that grow on irrigated lands between the Rabi and Kharif seasons, between March and June, known as Zaid (Zaya) crops. The timing of the Kharif and Rabi seasons varies regionally depending on the arrival and departure of the monsoon as it progresses northwards (greater detail about the monsoon and its impact on crops is described in Section 2).

Key crops in India

India's primary agricultural products are rice and wheat being the second-largest producer of both crops behind China (United States Department of Agriculture, USDA). Other important crops include oilseed, pulses, sugarcane, cotton, potatoes, tea, coffee, rubber and jute (natural fibre) (Figure 3). Indian crops are typically classed into the following categories by the Indian Government's Department of Agriculture, Cooperation & Farmers welfare (DAC-FW):

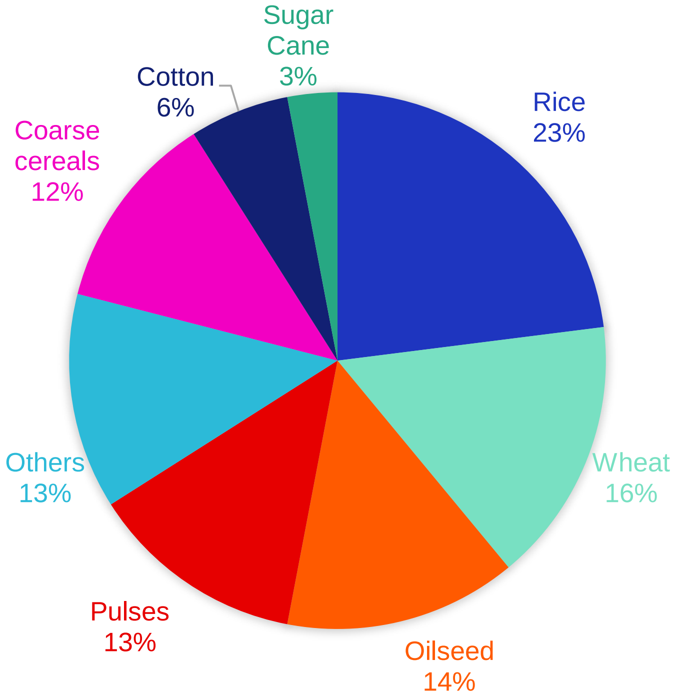
Food Crops:

- Cereals: rice, wheat, coarse grains (including millet (bajra, ragi), sorghum (jowar), maize)
- Pulses (including gram)

Non-food crops:

- Oilseeds (including soybean, ground nut, rape seed, mustard)
- Commercial crops (including sugar cane, cotton, jute, tea, coffee, rubber, tobacco)
- Horticultural crops (including fruit and vegetables)

Figure 3: Percentage (%) contribution per crop type to the total crop planted area in India



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from the 2016 India pocket book of Agricultural Statistics, Department of Agriculture, Cooperation & Farmers Welfare (DAC-FW)

Many crops are grown in either the Kharif or Rabi season:

- **Kharif crops**: India's major Kharif crop is rice which is grown along the eastern and western coasts of India as well as in the north (Figure 4a). Other important Kharif crops include coarse cereals, ground-nut, soybean, cotton and sugarcane.
- **Rabi crops**: Wheat is the key Rabi crop, grown predominantly in the north-west of India (Figure 4b), known as the bread basket of India. Other important Rabi crops include gram pulse, mustard, oilseed rape and potato.

Some crops, such as rice, can be grown during both seasons. Around 15% of India's rice is grown outside of the Kharif season, particularly in eastern parts of India, thanks to rain from the north-east monsoon which reaches this region during October to December. There can be regional variations in the distribution of different crop types depending on the agro-climatic zones that best suit each crop.

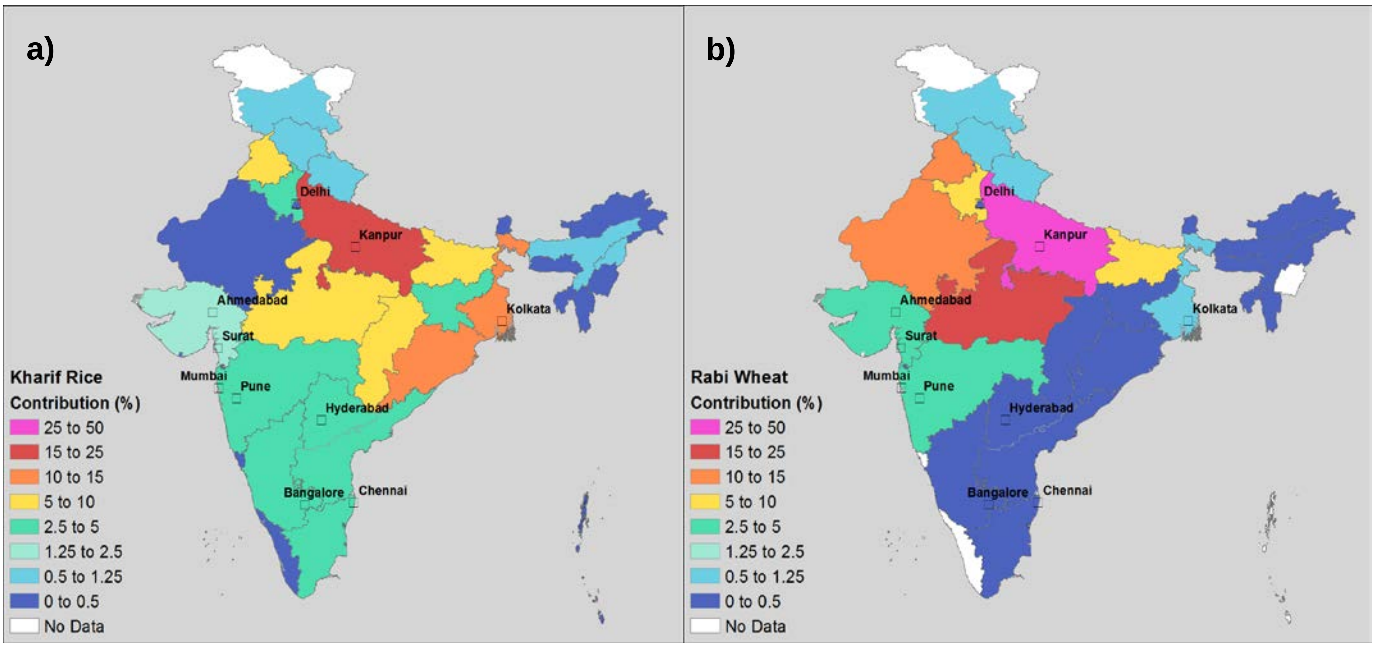
Some crops are grown across many states such as rice. Others are more localised such as wheat (North-West India, Figure 4b) and cotton (Western India). Table 1 summarises the top 3 producing states for the main crop types.

Table 1: Top 3 producing states for key crops

	Rice	Wheat	Coarse Cereals	Total Pulses	Total Oilseeds	Sugarcane	Cotton
1	West Bengal (15%)	Uttar-Pradesh (29%)	Rajasthan (16%)	Madhya-Pradesh (31%)	Madhya-Pradesh (25%)	Uttar Pradesh (41%)	Gujarat (32%)
2	Uttar Pradesh (12%)	Madhya-Pradesh (19%	Karnataka (15%)	Rajasthan (12%)	Rajasthan (23%)	Maharashtra (21%)	Maharashtra (22%)
3	Punjab (11%)	Punjab (17%)	Madhya-Pradesh (10%)	Maharashtra (9%)	Gujarat (16%)	Karnataka (11%)	Telengana (13%)

Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from the 2016 India book of Agriculture Statistics, Department of Agriculture, Cooperation & Farmers Welfare (DAC-FW)

Figure 4: % contribution of planted (a) Kharif rice and (b) Rabi wheat per state to India-wide planted area

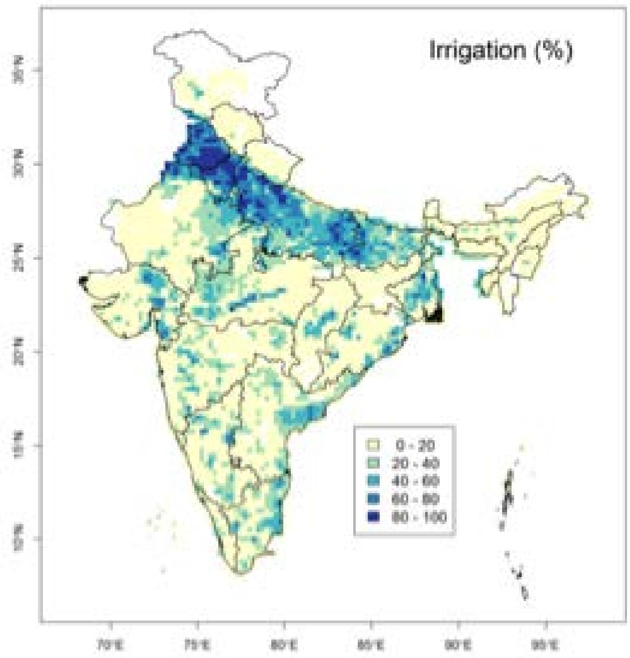


Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from Directorate of Economics & Statistics - DAC-FW, Open Data Government Platform India

Drivers of crop yield variability

Just over 50% of agricultural land in India is rain-fed and relies on the timely onset and spatial distribution of monsoon rainfall for successful cultivation of mainly Kharif crops (Department of Agriculture, Cooperation and Farmers Welfare, DAC-FW, 2017 annual report). The remaining agricultural land is irrigated, predominantly along the northern part of India and along the eastern coastal regions (Figure 5). Irrigated crops also rely on the monsoon for the supply of water for irrigation.

Figure 5: Geographic distribution of level of irrigation in India (% irrigation per 25km grid cell)



Source: Lloyd's- Risk Management Solutions, Inc., 2017 based on data from the Global Map of Irrigation Areas (GMIA), Food and Agricultural Organisation of the United Nations (FAO), 2013

Crop yields are dependent on rainfall and other weather variables (such as maximum and minimum temperatures and solar radiation; Hoogenboom, 2000) as well as land management practices (such as choice of seed, use of pesticides and fertiliser). Figure 6 shows the different factors that impact crop production. Many of these drivers also interact with each other through complex feedback processes. Research has shown that weather drives year-to-year variability in crop yields. Some studies suggest that as much as 80% of the variability of agricultural production is due to the variability in weather conditions, especially for rain-fed production systems (Petr, 1991; Fageria, 1992). Weather also has a major impact on pests and disease outburst which can in turn cause damage to crops.

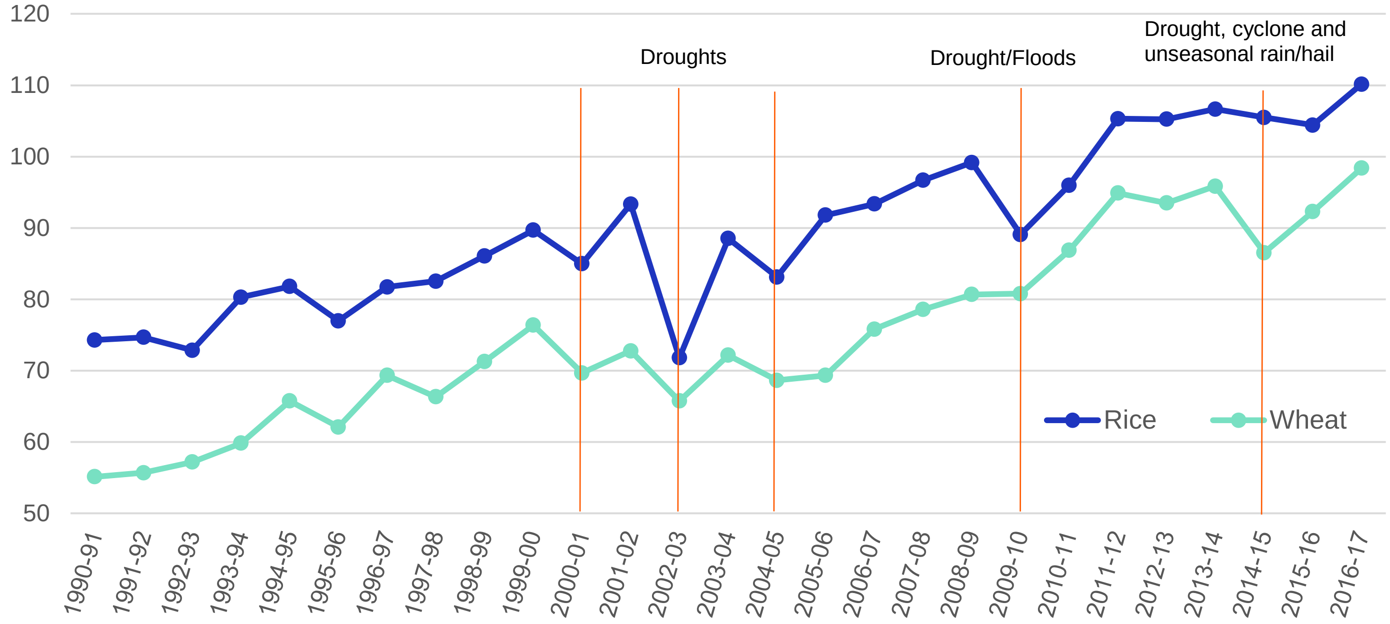
Figure 6: Drivers of crop yield variability

Source: Lloyd's - Risk Management Solutions, Inc., 2017

The impact of weather on year-to-year crop yield variability is evident in historical rice and wheat production (Figure 7). Despite the overall positive trend in production (thanks to changes in agricultural management practices), there is clear variability in the year-to-year production levels. Years with notable drops in rice and wheat production coincide with drought years demonstrating the impact of weather on year-to-year crop yield variability.

In some cases, farmers are adapting to long-run climate trends by adopting technology before the season begins, as shown by increased demand of water-conserving technologies in areas with depleting water tables (Lybbert et al 2018).

Figure 7: India rice and wheat production (millions of tons) from 1990



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from the Reserve Bank of India (RBI)

The critical weather variables required for crop growth are:

- **Precipitation** is critical as all crops need water to grow. The amount of soil water required for growth is crop-dependent, some species are more drought-tolerant than others. Too little rain will impact crop development. Too much rain can also have a negative impact, lowering the ability of plants to absorb nutrients and water.

- **Air temperature** is the main weather variable that regulates the rate of growth and grain development (Hodges, 1991). An increase in temperature typically increases developmental rates, up to a certain threshold, beyond which development slows down.

- **Solar radiation** provides the energy required for the photosynthesis and thus for the growth of the individual plant components (Boote and Loomis, 1991).

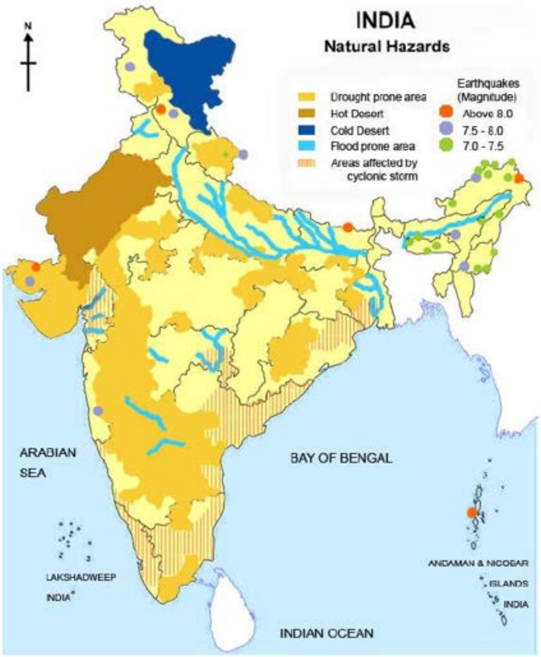
Other weather factors that can affect crop production include soil temperature, wind, and relative humidity or dew point temperature. In many regions, soil temperature is important during the early part of the growing season, as it affects planting and germination.

Due to India's multiple climate zones, the country is exposed to a wide range of different weather events, often with different temporal and spatial variability (Figure 8). Crop yields can be impacted by both:

- significant individual weather events (extreme events) or
- by the accumulation of smaller weather events over a crop's growing season (attritional events).

The impact on crop yields depends on both the intensity and timing of adverse weather in relation to each crop's development (phenological) stage.

Figure 8: Indian areas affected by one or more natural hazards



Source: Poorest Areas Civil Society (PACS) Programme, 2008

The monsoon plays a critical role in crop productivity. Late arrival of monsoons can delay the planting period reducing the overall growing period and thus reducing potential yields. It can also prevent planting in worst case scenarios.

Under extreme conditions, too little (drought) or too much rain (flood) will negatively impact crop growth and development. The optimum range of soil water content depends on the crop type and development stage, as well as the antecedent weather conditions. As a result, periods of heavy rainfall during the monsoon can spoil Kharif crops as well as Rabi crops grown post-monsoon, depending on the level of soil saturation. Also, excess rainfall can also result in mudslides and generation of pests and disease that can thrive in these conditions and cause further damage to crops. Droughts have greatest impact on Kharif crops, but can also impact Rabi crops by reducing the supply of water available for irrigation. Kumar et al (2004) investigated the India crop production of various crops and the impact of rainfall during the summer monsoon season, revealing that the correlations between crop yields and rainfall can vary by crop type.

Other weather phenomena such as extreme temperatures (heat wave/frost), extreme winds, tropical cyclones, and unseasonal rain and hailstorms can also impact crop yields. These are typically more local phenomena that can be linked to a specific potentially "named" event. Earthquakes and resulting landslides and tsunamis can also result in significant crop damage (e.g. 2004 tsunami). Crops are also susceptible to damage from pests from wild animals in certain regions.

Weather perils impacting crops tend to have distinct seasonal behaviour which overlap with different stages of the two main crop growing seasons. Kharif crops are mainly impacted by monsoon variability and tropical cyclones, while Rabi crops are most impacted by extreme temperatures and unseasonal weather (heavy rain and/or hail outside of the monsoon) (RMS research). Summer droughts can also impact the amount of water available to irrigate Rabi crops. In the past few years farmers have faced crop damage from widespread droughts during Kharif 2014 and 2015, flooding during Kharif 2017 and from unseasonal rain, hailstorms and flooding during Rabi 2015/16 and 2014/15. Recent significant crop damage years are summarised in Table 2. Further details of the impact of the monsoon and other weather on crop yield variability are discussed in Section 2.

Table 2: Examples of weather events in past 20 years resulting in notable crop damage

Crop Year	Weather Event	Geographic Area	Crop Impact	Economic Impact (time of event, USD)
1999	Cyclone Orissa (Oct)	Odisha	1mn+ hectares of Kharif crops, including rice & sugar cane damaged[1]	0.1bn insured, 2.5bn total[2]
2000	Drought (-8% rain deficit, 27% area[3])	Widespread (168 districts[4])		
	Flood (summer)	West Bengal	38bn INR loss Kharif crops[5]	
2002	Drought (-19% rain deficit, 29% area[3])	Widespread (383 districts[4])	47mn hectares crops damaged[1], 18% drop in food grain production[5], 300bn INR loss Kharif crops[6]	0.9bn total[9]
2003	Floods (summer)	Andhra-Pradesh, Odisha, Uttar-Pradesh	73bn INR loss Kharif crops[6]	
2004	Drought (-13% rain deficit, 19% area[3])	Widespread (223 districts[4])	7% drop in food grain production[5]	
2009	Drought (-17% rain deficit[7])	Widespread (338 districts[4])	7% drop in food grain production[5]	
	Floods (Oct)	Karnataka/ Andhra-Pradesh	0.25mn hectares of Kharif crops damaged[1], 42bn INR crop loss[6]	
	Heat wave (Mar 2010)	N India	wheat production -40% in some states[1]	
2010	Floods	Andhra-Pradesh, Karnataka, Himachal-Pradesh	58bn INR loss[6]	
2013	Floods	Multiple states	32bn INR crop loss[6]	
	Cyclone Phailin (Oct)	Odisha	1.3mn hectares crops	
	Cyclone Helen (Nov)	Andhra-Pradesh	1mn acres of Kharif crops, especially rice.	
2014	Drought (-13% rain deficit[7])	Widespread (104 districts[4])	5% drop in food grain production[5]	
	Flood (Aug)	Assam	Kharif crop damage[1]	
	Cyclone HudHud (Oct)	Andhra-Pradesh	0.25-0.45mn hectares Kharif crop damage[1]	0.35-0.6bn insured, 5.5-7bn total[8]
	Unseasonal rain/hail (Mar 2015)	N/NW India	Rabi wheat & mustard[1]	0.1bn insured, 0.9bn total[2]
2015	Drought (-14% rain deficit[7])	Widespread (270 districts[4])	30% crops damaged (mainly Kharif), 0.037mn km^2.[8]	1.5bn total[8]
	Flood (Aug)	Gujarat (June)	0.2mn hectares Kharif crops damaged[2]	

	Flood (Dec)	Tamil-Nadu/Chennai	0.4mn Kharif crops damage[1]	0.6bn total[2]
	Unseasonal rain/hail (Mar 2016)	N India	Rabi wheat, mustard & pulses, 18mn hectares[1]	
2016	Floods (summer)	Bihar, Madhya-Pradesh	1,000's km^2 Kharif crops damage[8]	
	Drought (NE monsoon, worst since 1876)	E India, especially Tamil-Nadu	Damage to Kharif crops[1]	
	Cyclone Vardah (Dec)	Tamil-Nadu	Damage to Kharif crops including rice, sugar cane, coconut, bananas[1]	

Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from [1]RMS research, [2]Swiss Re, [3]Indian Meteorology Department (IMD) Drought report (Shewale & Kumar, 2005), [4]Department of Agriculture & Cooperation and Farmers Welfare, [5]LiveMint, (http://www.livemint.com/Politics/TkKaRlSes4GxHCbGz30RLP/Indias-rural-distress-set-to-worsen.html), [6]Central Water Commission, [7]Indian Institute of Tropical Meteorology (Kothawale & Rajeevan, 2017), [8]Munich Re, [9]EM-DAT

1.3 Crop insurance overview

To protect farmers from the vagaries of weather and the direct impact on crop yields, a succession of nation-wide crop insurance schemes, subsidised by the central and state governments, has been tested over the past 30 years, but with limited take-up. For many small- and medium-scale farmers, who live and earn season to season, damaged crops can leave them in great debt as they are unable to pay off high-interest loans from local lenders, to buy seed, fertiliser and hire equipment. As a result, farmer suicides account for 11.2% of all suicides in India (National Crime Reports Bureau, 2014) and failure of crops is the reason for 16.81% of national suicides in 2002 (Panagariya, 2008). For example, following the spring floods in Uttar Pradesh in 2015 over 30 farmers took their own live (CBS News, 2015). Crop insurance in India, along with debt relief packages, plays an important social and economic role.

Crop insurance is typically issued separately per crop per growing season. Crops are at risk from damage throughout the entire growing season from the planting time through to post-harvest when crops are cut and spread out to dry in the fields. Today's crop insurance policies provide protection for the entire period. Currently, in India, around 25-30% of food crops and around 44% of oilseed crops are insured (Pocket Book of Agricultural Statistics 2016, DAC-FW). To date, insurance is predominantly purchased for Kharif crops (DAC-FW May 2014 report), which is more dependent on the monsoon compared to Rabi crops (see Section 2 for more details).

Crop insurance is administered at state level. For states opting to implement crop insurance schemes, coverage has been compulsory for farmers with seasonal agricultural operations (SAO) loans from banks (loanee farmers) since 1999.

For the remaining farmers without loans (non-loanee farmers[h]), crop insurance is voluntary and despite government subsidies, take up remained less than 5% during the 2016/17 season (Bushan & Kumar, 2017). One reason for the lack of voluntary enrolment is that most farmers are unaware of crop insurance and its benefits (Bushan & Kumar 2017). Furthermore, factors in crop insurance schemes such as non-loanee registration process, cost, limited coverage of crops, perils, growing season and sums insured, in addition to a complicated method to assess yield, loss and subsequent delayed settlements, have also hindered the take-up rate.

In 2015, crop insurance take-up rate across all farmers was around 22% (Press Information Bureau, PIB, Dec 2016 press release). In 2016, the Modi Government launched a new crop insurance scheme (Pradhan Mantri Fasal Bima Yojana, PMFBY, meaning Prime Minister Crop Insurance Scheme) with the aim to insure 50% of gross cropped area (GCA) within the next 3 years by 2018-19 (Business Today, 2016) and significantly increase the coverage of non-loanee farmers by promoting the scheme more widely. In its first year, the scheme successfully grew to insure 30% of GCA (Government of India Press Release, March 2017) but was less successful in attracting non-loanee farmers, despite initial claims of success which were later demonstrated to be erroneous (Bhushan & Kumar 2017).

[h] The total number or percentage of non-loanee versus loanee farmers is a grey area and not clearly reported. Non-loanee farmers might be loanee but via different channels i.e. loaning for local lenders. In West Bengal, the state waived off the farmer's premium contribution so insurance is not truly voluntary (non-loanee). In Maharashtra, the scheme is voluntary for all farmers and thus loanee farmers have been mis-classed as non-loanee (Bhushan & Kumar 2017).

The new PMFBY scheme addresses many of the shortcomings of the previous schemes (discussed later in this section) which the government hopes will reduce barriers to insurance take-up. The scheme aims not only to provide financial support to farmers suffering crop loss/damage and stabilise their income, but also to encourage farmers to adopt innovative and modern agricultural practices and ensure a flow of credit to the agriculture sector which will contribute to food security, crop diversification and enhancing growth and competitiveness of agriculture sector.

To put this latest crop insurance scheme into context, the following section provides an overview of the history of crop insurance schemes and the challenges that have been addressed through their evolution.

History of crop insurance schemes

Over the past 40-45 years, there has been a succession of crop insurance programmes in India (Figure 9). Some schemes have been implemented as pilot schemes in a selected number of states or districts, while other schemes have either evolved to become fully-nationwide offered schemes or are launched as a nation-wide scheme without a pilot phase. More recently, crop insurance schemes have sat within broader umbrella insurance schemes for farmers (e.g. UPIS, NCIP – described later). To meet the farmers' needs a crop insurance scheme should ideally include the followings:

- Localised insured unit area: ideally insure individual farmers
- Good crop coverage: covering all types of crops
- Total temporal coverage: from planting through to post-harvest
- Multiple peril coverage: cover all types of perils that can damage crops
- Adequate sums insured: sums insured should cover more than basic cost of cultivation
- Affordable for farmers: for financial viability, premiums should be actuarially based including catastrophe load but subsidised, if necessary, by the government so premiums are affordable and attractive to farmers
- Quick and simple settlement

Barriers exist for the development of a comprehensive agriculture insurance scheme (see Box 1).

Box 1: Barriers for the development of a comprehensive agriculture insurance scheme

- Lack of participation from farmers due to limited awareness of insurance schemes, poor understanding of insurance benefits and historical delays in payments of covered insured losses
- Reluctance of some state governments to provide adequate subsidies for crop premiums
- Limited historical data for insurance companies to price risks actuarially. Currently 10 years of yield data should be provided by the state government to insurance companies for pricing. However there are issues around the spatial resolution of the data, completeness of records and data quality (see Section 3).
- Year-to-year volatility in the reported yield and threshold yield used in crop yield based insurance schemes (described in more detail in Box 2). This volatility, a result of the scheme definition of the threshold yield, may impact the stability of insurance pay-outs to farmers and thus their perceived value of the scheme, as well as the stability of the annual insurance rates.
- Risk of moral hazard or soft fraud. Moral hazard occurs when an insured deliberately alters their behaviour to increase the magnitude of potential loss. Some studies report that moral hazard incentive leads insured farmers to use fewer chemical inputs (Smith and Goodwin 1996), poor quality seeds or plant on marginal lands that are not suitable for certain crops (Iturrioz, 2009), thus making their crops less resilient and productive.
- High operational effort and cost due to enormous number of crop cutting experiments used to determine the actual yield for the loss settlement process of crop yield based insurance schemes
- Size of the insured unit area under the area-approach schemes. While in an ideal world, individual farmers would be insured, crop insurance schemes in India to date have been area-based index schemes which offer an efficient way of crop insurance in countries with a lack of developed insurance infrastructure and many small farms (Carter et al., 2007). However farmers are unhappy as an individual farmer with poor yields will not receive compensation if the actual yield of the insured unit they are within is not below the index threshold. Over time, the size of the insured unit area has decreased to be more reflective and consistent so that an insured unit is ideally homogenous from the point of view of crop production and annual variability. The insured unit area currently offered in schemes for major crops at Village/Village Panchayat level (4-5 neighbouring villages) is the minimum level where crops can be considered reasonably homogenous.

Over the past ten years, crop insurance in India has been offered via crop yield and weather index schemes (see Box 2 and Box 3). Crop yield schemes cover against a deficit in the realised crop yield below the threshold level. Weather based schemes provide protection to farmers against “adverse weather incidences” using weather parameters such as deficit or excess rainfall, length of dry spells, high/low temperatures and humidity as proxies for crop yields.

Box 2 Yield based index schemes

Yield based crop insurance schemes provide insurance cover against a deficit in the **realised crop yield** below the **threshold level** for a given "insured unit area".

Insured unit area: is defined per scheme, crop and state.

Threshold yield: is calculated from the historical realised yields records. It is defined annually as the average yield multiplied by the indemnity level assigned by the insurance scheme per region and crop. Over the years there have been concerns over the method used to calculate the threshold yield (number of years, impact of bad years on calculation - especially in areas with consecutive adverse seasonal hits, indemnity levels, impact of year-to-year volatility on insurance rate stability and insurance pay-outs) and the method to determine the threshold yield has evolved through the schemes to be as reasonable as possible. There are also many issues surrounding data quality including the length of historical records available, how representative historical records are if farming techniques have improved over time and the spatial resolution of yield records.

Realised yield: is determined by manual crop cutting experiments (CCE) where the yield is measured at the end of the season within each insured unit area. CCE are a compulsory step in the claim settlement process. Within each insured unit, areas are designated for CCE where the yield is measured post-harvest and used to represent the realized yield for the insured unit area. The number of CCE per unit area is often determined per crop and state. There are two main shortcomings of the approach:

- Firstly that if the "unit area" is large, the CCE is unlikely to be representative of the entire "unit area". Some farmers report that CCE regions are typically in the better farmed locations.
- Secondly, since the CCE only take place post-harvest, there can be a lag of at least 8 months between the time the loss occurred to the actual claims payment. The CCE process has evolved over time to try and speed up the settlement process by reducing the number of CCE required per unit per crop. Also in the latest schemes, the use of technologies such as smart phones and drones has become mandatory to help speed up the process.

The PMFBY scheme is defined by the loss cost (loss/sum insured), as follows:

$$LC_{yr} = \max\left[0, \frac{TY - Yield_{yr}}{TY}\right]$$

where

$$TY = Average\ Yield\ x\ Indemnity$$

A contract loss occurs when the realised yield ($Yield_{yr}$), as determined from crop cutting experiments, is below a threshold yield (TY). The average yield is defined in the PMFBY scheme as the average over the past 7 years excluding a maximum of 2 calamity years. Depending on the region and crop the indemnity levels, assigned annually, can be 70%, 80% or 90%. As a result of this method, there is the potential of large volatility in the year-to-year threshold yield calculated per insured unit area. Previous schemes used different definitions for the average yields and different indemnity levels (see Table 3, p34 for more detail).

For more details see Appendix 2.

Box 3: Weather based index schemes

Government agencies design weather indices based on multiple weather parameters, to act as proxies for crop yields, using historical weather records. The most common indices are listed in Appendix 3. There are over 80 types of term sheets which can include special features such as “rolling limits” and “super covers”.

A key benefit of using a weather index approach is that the claims settlement is quick and more transparent (in contrast to the yield based schemes). Farmers are not required to submit claim forms and prove loss of yield. Furthermore, weather data is more objective than yield data, with reduced risk of fraud and moral hazard, as it is provided by automated weather stations and is readily accessible by both farmers and insurers, and can be tracked in real-time during the progress of the index. Also weather based schemes cover a broader range of crops including many horticultural crops. The main concern surrounding weather indices is the basis risk that weather proxies do not adequately represent crop yield deviations.

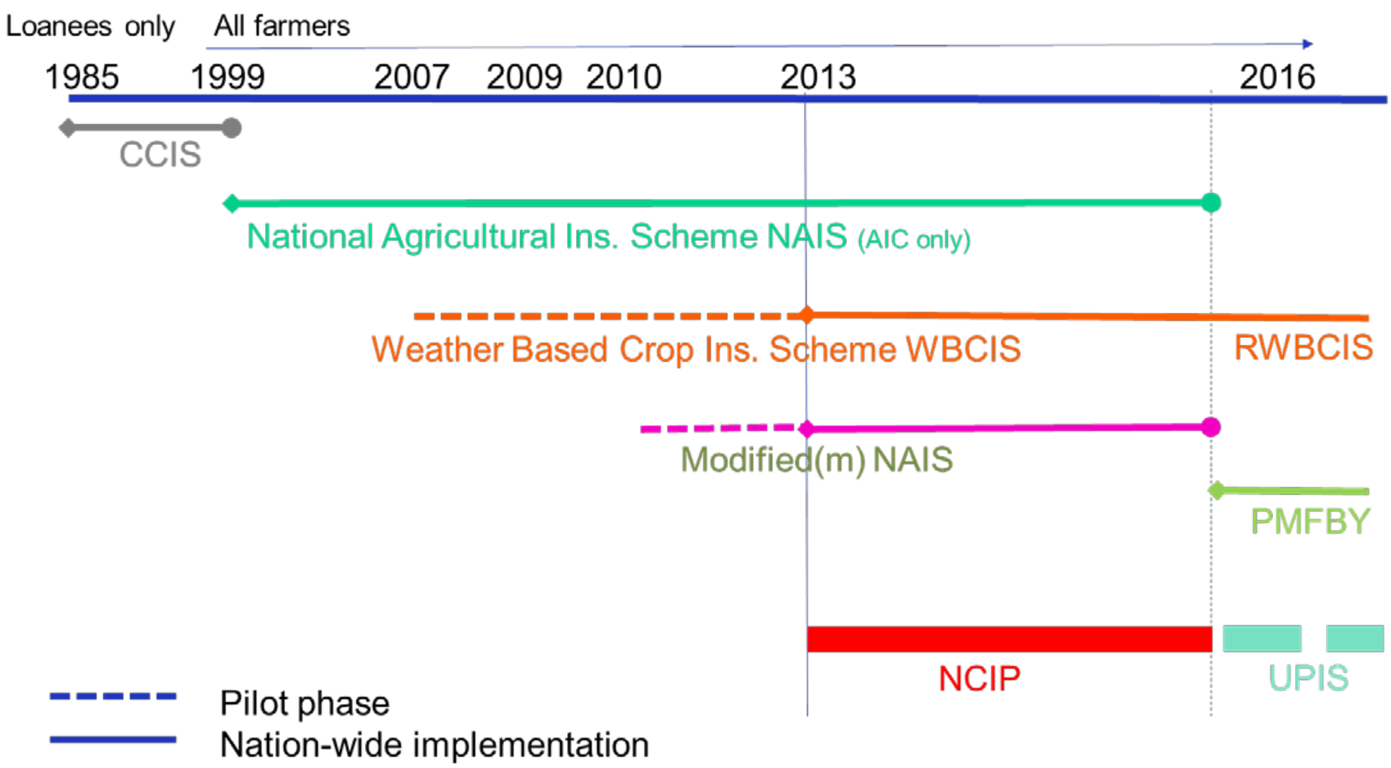
For more details see Appendix 3.

Description of crop insurance schemes

The first crop insurance programme was introduced in 1972 by General Insurance Corporation (GIC) based on an “Individual approach” (insuring each farmer) for cotton in Gujarat. The scheme was later extended to few other crops and implemented in 6 states. This scheme was followed by the Pilot Crop Insurance Scheme (PCIS) during 1979-1984 which was offered on a voluntary basis to loanee farmers and implemented in 12/13 states on a pilot basis. The scheme was based on the “area approach” providing insurance cover against a deficit in the realised crop yield below the threshold level.

The insurance premiums ranged from 5-10% of the sums insured and were subsidised by 50%, shared equally between the state and central governments, for small/marginal farmers. The PCIS was expanded and replaced in 1985 by the first nationwide scheme known as the Comprehensive Crop Insurance Scheme (CCIS). From this time onwards, there has been a succession of different national crop insurance schemes, each trying to address short comings of previous schemes and improve take-up. The schemes (Figure 9) are briefly described below and the key features of the schemes and the evolution to today’s offerings are summarised in Table 3.

Figure 9: Timeline of major nation-wide crop insurance schemes since 1985



Source: Lloyd’s - Risk Management Solutions, Inc., 2017. PMFBY stands for Pradhan Mantri Fasal Bima Yojana and RWBCIS stands for Restructured Weather Based Crop Insurance Scheme

Timeline of major nation-wide crop insurance schemes since 1985:

- Comprehensive Crop Insurance Scheme (CCIS) 1985-1999: first nation-wide scheme, available to loanee farmers only.
- National Agricultural Insurance Scheme (NAIS) 1999-2015: first implemented by GIC and then by the state-based specialised agricultural insurer Agricultural Insurance Company of India (AIC) since 2003. The scheme expanded coverage to all farmers (compulsory for loanee farmers, voluntary for non-loanee farmers) and for a greater number of crops and perils during the growing period. The scheme should have been retired in 2013, when modified NAIS (mNAIS) was introduced, but many states continued to choose NAIS over mNAIS and the scheme remained operational until the introduction of PMFBY.
- Weather Based Crop Insurance Scheme (WBCIS) 2007: a pilot Weather Based Crop Insurance Scheme (WBCIS) was launched in 2007 in 20 states as an alternative to yield based insurance schemes to help further expand the coverage of crop insurance. From Rabi 2013-14, the scheme became a nation-wide component of the National Crop Insurance Programme (NCIP– described later) with premiums in line with NAIS. In 2016, the WBCIS scheme was restructured to ensure that the terms of the scheme were identical to PMFBY crop yield insurance scheme such as sums insured and premiums. Since 2016, the scheme is referred to as RWBCIS (restructured WBCIS).
- Modified NAIS (mNAIS) 2010-2015: to rectify some of the short comings of the NAIS, such as large insured unit area and coverage of standing crop phase only, mNAIS was implemented from Rabi 2010-11 as a pilot scheme in 50 districts covering 10 crops. From Rabi 2013-14, the scheme was launched as a component of the NCIP available nation-wide.
- National Crop Insurance Programme (NCIP) 2013-2015: in 2013, the National Crop Insurance Programme (NCIP) was introduced offering mNAIS and WBCIS. It was withdrawn at the end of 2015 with the introduction of PMFBY scheme and the pilot UPIS schemes described next.
- Pradhan Mantri Fasal Bima Yojana scheme (PMFBY) 2016-: to address many of the shortcomings from NCIP/mNAIS/NAIS, a new crop insurance scheme, the PMFBY was implemented by the government from the Kharif 2016 season. It hopes to expand insurance coverage to 50% of crops within 3 years. This scheme includes both crop yield insurance (PMFBY) and restructured weather yield insurance (RWBCIS) schemes.
- Unified Package Insurance Scheme (UPIS) 2016-: following on from NCIP, the government implemented the Unified Package Insurance Scheme (UPIS) as a pilot scheme in 45 selected districts. In contrast to NCIP, which covered only crop insurance, UPIS contains seven insurance schemes for farming households to provide a comprehensive and holistic set of insurance cover.

As well as the traditional crop schemes listed in Figure 9 there are also crop schemes for other crops such as:

- Coconut Palm Insurance Scheme (CPIS) (2009 -). The Coconut Palm Insurance Scheme (CPIS) was launched as a pilot scheme in 2009-10 in the coconut growing areas on India. The scheme is implemented by AIC. Premiums are subsidised 50% by the central government and 25% by the state government with the remaining 25% payable by the farmer. The scheme was fully implemented into the NCIP and is now part of the PMFBY/UPIS scheme.
- Revenue Insurance Scheme for Plantation Crops (RISPC) (Sept 2016 -). The RISPC has been launched as a pilot project for 8 districts over the next 2 years. The scheme covers crops such as coffee, tea, rubber, tobacco and cardamom.

Table 3: Key features of nation-wide Indian crop insurance schemes

	CCIS (1985-1999)	NAIS (1999-2015)	WBCIS (2007-2015) RWBCIS (2016-)	mNAIS (2010-2015)	PMFBY (2016-)
Index Type	Crop yield	Crop yield (Threshold yield derived from 3 years of data for rice and wheat, 5 years for other crops)	Weather	Crop yield (Threshold yield derived from 7 years excluding max 2 calamity years)	Crop yield (Threshold yield derived from 7 years excluding max 2 calamity years)
Farmers Eligible	Loanee only	Compulsory for loanees, voluntary for non-loanees	Compulsory for loanees, voluntary for non-loanees	Compulsory for loanees, voluntary for non-loanees	Compulsory for loanees, voluntary for non-loanees
Crop Coverage	Cereals, millet, oilseed, pulses	Cereals, millet, pulses, oilseeds, some annual commercial/horticultural crops	Cereals, millet, pulses, oilseeds, annual commercial/horticultural crops (many more than crop yield schemes)	Cereals, millet, pulses, oilseeds, annual commercial/horticultural crops	Cereals, millet, pulses, oilseeds, annual commercial/horticultural crops
Temporal Coverage	Standing (once planted to harvest)	Standing	Split into 3-4 critical growth stages typically during sowing to harvest.	Planting/sowing to post-harvest	Planting/sowing to post-harvest
Peril Coverage	Drought, flood, cyclone, landslide, fire, pest and disease	Drought, flood, cyclone, landslide, fire, pest and disease.	All weather perils.	Planting/sowing: deficit rain or adverse conditions. Standing: Drought, flood, cyclone, fire, pest and disease. Localised: hail and landslide Post-harvest: coastal areas only for cyclonic rain	Planting/sowing: deficit rain or adverse conditions. Standing: Drought, flood, cyclone, fire, pest and disease. Localised: hail, landslide, flooding Post-harvest: all India for cyclonic and unseasonal rain
Insured Unit (IU) Area	Block	Mandul/Taluk/Gram Panchayat for major crops. Individual assessment for local calamities.	Currently, as per PMFBY, village/village panchayat for major crops.	Village/village panchayat for major crops. Individual assessment for local calamities and post-harvest losses.	Village/village panchayat for major crops. Individual assessment for local calamities and post harvest losses.
Premiums*	2% cereals/millet, 1% oilseed/pulses (subsidised by 50% for small & marginal farmers)	3.5% Bajra + oilseed, 2.5% other Kharif crops, 1.5% wheat, 2% other Rabi crops. Subsidised by around 10% for small/marginal farmers. Annual/horticultural crops actuarially based.	Actuarially based, subsidised to be in line with crop schemes. Currently in line with PMFBY.	Actuarially-based up to a cap of 13% (Kharif) and 11% (Rabi) and subsidised up to 75%. Farmers typically paid more than NAIS.	Actuarially based, subsidised by government with farmers paying 2% for Kharif crops, 1.5% for Rabi crops and 5% for annual commercial/horticultural crops.
Sums insured (SI)	Crop loan amount or max 10,000INR	Loanee: Crop loan amount at minimum or extended up to 150% of threshold yield x minimum support price (MSP) Non-loanee: up to 150% of threshold yield x MSP	Currently, as per PMFBY, same for loanee/non-loanee. SI per hectare/crop/district pre-declared by SLCCCI.	Loanee: cost of cultivation pre-declared by SLCCCI. Non-loanee: up to 150% threshold yield x MSP. Under mNAIS, SI became capped as a result of government capping premiums to minimise subsidies. In cases where the actuarial premium was more than the capped limit, SI was reduced leaving farmers under insured.	Same for loanee/non-loanee. SI per hectare/crop/district pre-declared by SLCCCI using Scale of Finance (improvement over MSP).
Indemnity		60%, 80% & 90%	N/A	80%, 90%	70%, 80%, 90%

Settlement Time	Seasonal yield settlement: Long	Seasonal yield settlement: Long due to CCE (8 CCE per Gram Panchayat per crop).	Quick	Seasonal yield settlement: Long due to CCE (8 CCE per Village/Village Panchayat per major crop). Within ~30 days for: - On account-payment for mid-season severe adversity (25 per cent of the likely claim if yield<50% threshold, based on proxy indicators) - Prevented/failed sowing (25% of the sums insured) - Post-harvest losses & localised perils (claim assessed per individual farmer)	Seasonal yield settlement: Improving due to mandatory technology in CEE and reduction of number CCE (4 CCE per Village/Village Panchayat per major crop). Within ~30 days for: - On account-payment for mid-season severe adversity (25 per cent of the likely claim if yield<50% threshold, based on proxy indicators) - Prevented/failed sowing (25% of the sums insured) - Post-harvest losses & localised perils (claim assessed per individual farmer if <25% IU affected)
No. states/UT implemented	18	28	21	21	28
Implementing Agency	GIC	AIC	Private and public insurers	Private and public insurers	Private and public insurers. New crop insurance portal

Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from Crop Scheme Operational guidelines from the Agri-Insurance portal (www.agri-insurance.gov.in), RMS research. *Premiums typically subsidised 50:50 between central and state governments, SLCCCI = State Level Coordination Committee on Crop Insurance.

Lessons learnt prior to PMFBY scheme

Before 2016, 3 crop insurance schemes were in operation between 2013-2015 (NAIS, mNAIS, WBCIS, Figure 9). NAIS was in operation for around 15 years since 1999 and WBCIS for around 8 years since 2007. Figure 10 presents the number of farmers insured per scheme per season for all companies. Since premiums and sums insured have varied during and between schemes, the number of farmers is presented to best reflect the take up of crop insurance over time.

In terms of insurance penetration, statistics show that:

- NAIS was the most successful scheme during this period (Figure 10).
- mNAIS was not as successful as NAIS (despite improvements such as reduced unit area, planting and post-harvest coverage) because of:
    - (i) affordability: higher premiums for the farmers due to the introduction of actuarially-based premiums and
    - (ii) low sums insured: under mNAIS,

  the premiums subsidised by the government were capped at 13% (Kharif) and 11% (Rabi) and sums insured were kept relatively low to maintain subsidised premiums to the disadvantage of the farmers (NCIP Operational Guidelines).
- WBCIS was also not as successful as NAIS, despite the quick claims settlement, due to concerns over basis risk and whether the weather index adequately protects farmers for yield risk.

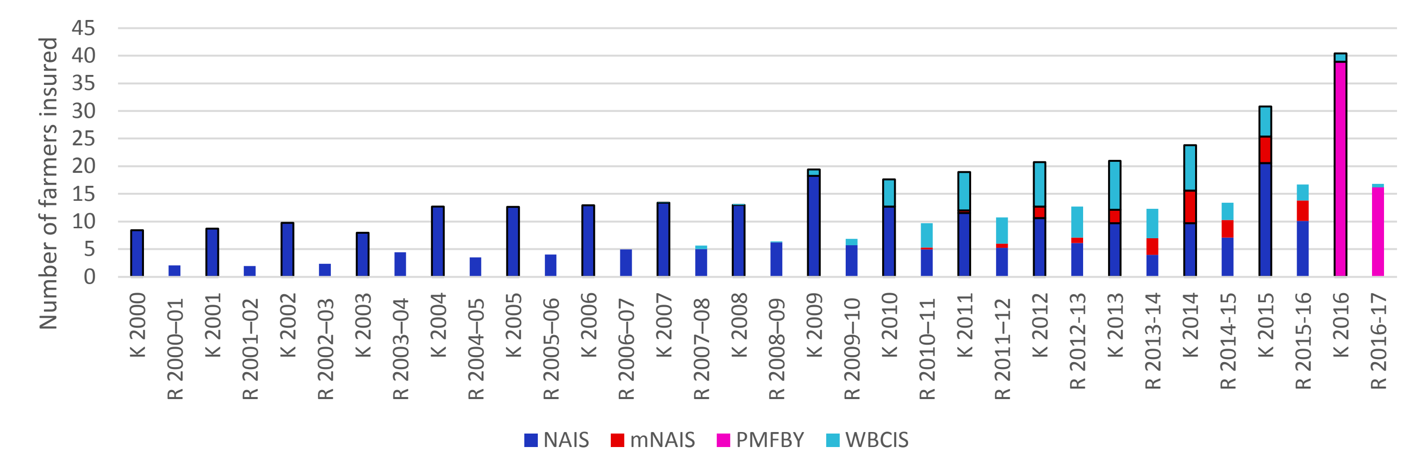
However, in terms of financial viability, the Report of the Committee to Review the Implementation of Crop Insurance Schemes in India (DAC-FW, May 2014) reveals that NAIS performed poorly with an average claims ratio (claims/gross premium) of 3.31 compared to 0.8 (mNAIS) and 0.7 (WBCIS), demonstrating the benefit of actuarially based premiums implemented in mNAIS and WBCIS.

The statistics in Figure 10 also show:

- Insurance is typically purchased in greater volume for Kharif (outlined bars) than Rabi seasons. One likely reason for this behaviour could be because irrigation is more heavily used in the northern wheat Rabi growing regions and thus is less dependent on monsoon irregularities.

While there is generally an increasing trend in insurance over time, there is variability in take up which reflects that some farmers/states purchase insurance either following a bad year, or in a bad year (as the cut off dates for crop insurance can extend into the actual start of the season). For example, in 2009, a bad drought year, Kharif crop insurance increased dramatically that year compared to the previous year. For each scheme, there are specified seasonal notification windows for purchasing Kharif and Rabi crop insurance (Figure 11). However, these deadlines may be extended long enough in the monsoon season with the risk of adverse selection as monsoon forecasts and status updates from the India Meteorological Department (IMD) become available from April onwards. Farmers may opt for crop insurance if they expect damage to crops. Enrolment deadlines for both Kharif 2016 (average monsoon) and Rabi 2016/17 seasons were extended by 10 days for “exceptional” reasons: Kharif 2016 was extended due to some states delaying notification the new scheme and the Rabi notification delay was due to knock on impacts of demonetisation on farmers and the finance sector. Delayed enrolment resulted in farmers not being covered during the planting period. In Figure 10 blue: NAIS, red: mNAIS, pink: PMFBY, light blue: WBCIS. Kharif numbers include a border to easily distinguish from Rabi statistics.

Figure 10: Penetration of crop insurance - number of farmers (millions) with crop insurance per season and scheme)



Source: Lloyd's - Risk Management Solutions, Inc., 2018 based on data from DAC-FW (May 2014) and Gulati et al., (2018). [a] K = Kharif, R = Rabi.

Proposed implementation of PMFBY scheme in 2016

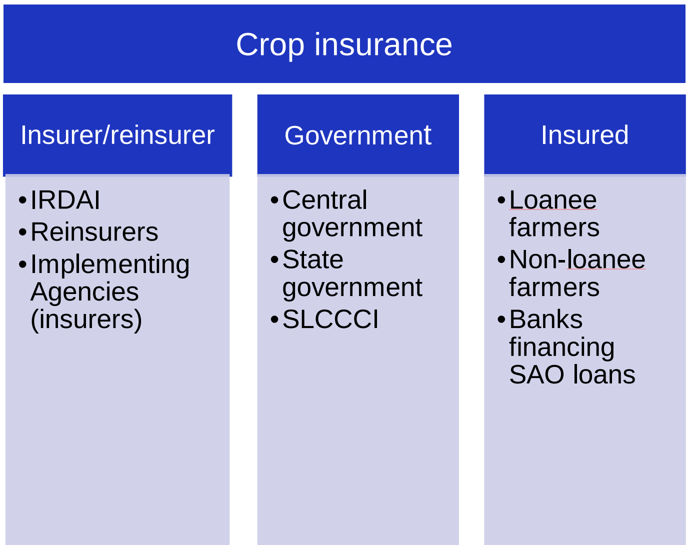
The PMFBY-RWBCIS schemes were implemented in 2016 with new terms as summarised in Table 3 and explained in more detail in the operational guidelines. A summary of the PMFBY implementation process, as per the operational guidelines, is provided here and in Figure 13. The scheme involves many stakeholders (Figure 11).

A few months prior to the crop growing season, states determine via the State Level Coordination Committee on Crop Insurance (SLCCCI), if and which crops and districts to insure and agree the sums insured and indemnity levels per hectare per crop. Districts within each state are grouped into clusters with the intention to diversify risk within a state and so that each cluster has a similar overall risk profile. The number of clusters per state varies from 1 (e.g. Sikkim) to more than 10 (e.g. Karnataka, Rajasthan). Each cluster includes multiple crop types. The number of clusters per state and the district composition per cluster can change between years. Insurance tenders are typically issued per year and season. Although some states opt for multi-year coverage (e.g. Tamil-Nadu has a 3-year contract) and it is becoming more popular to perform the tender process for Kharif and Rabi at the same time (e.g. Rajasthan).

Around two to three months prior to the start of the crop season, insurers (known as "implementing agencies" or IA) tender for insurance clusters via the state governments and are selected purely on lowest premium rates. Premiums rates should be actuarially based as described in the operational guidelines. This would mean considering the pure premium rates derived from historical yield data, plus additional loadings including capital cost, data uncertainty, insurer's margin and basis risk. However due to the bidding process, resulting rates may deviate from these actuarial rates. State Governments should provide 10 years of historical yield data to insurance companies, as per the operational guidelines, for premium and indemnity calculations at the insured unit area but this is not always available. In 2016, 16 insurance companies were approved by the Agriculture ministry to bid for and implement PMFBY/RWCBIS crop insurance: state-owned Agriculture Insurance Company of India (AIC), 4 public sector insurers and 11 private companies (Figure 12). Some states will be insured by 1 insurance company, while others can be insured by more than 5 companies, with each winning 1 or more cluster(s). In July 2017, it was announced that states can now set up their own crop insurance companies (Times of India, 2017).

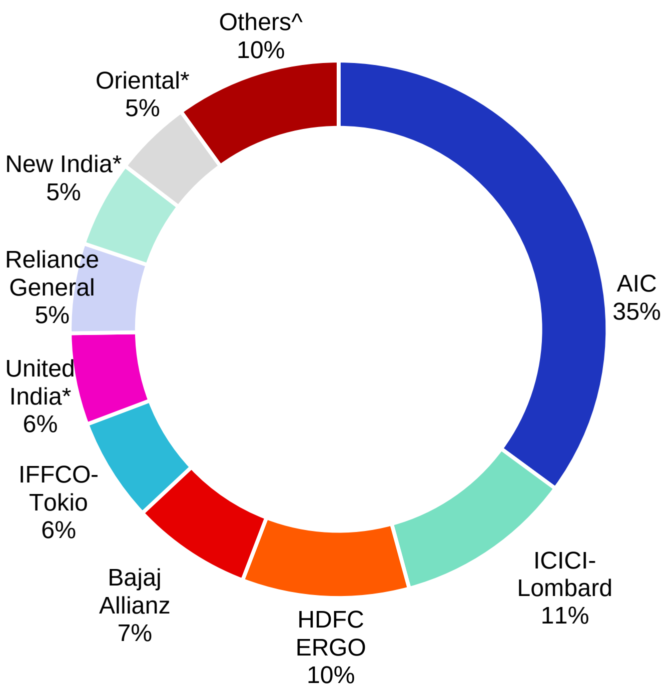
At time of harvest, crop cutting experiments (CCE) to assess crop yields are performed and should be reported to the insurers within 1 month of the final yields, as per PMFBY guidelines. Claims should then be settled within 3 weeks of the yield data being reported. For pre- and post-harvest losses and localised calamities, losses should be assessed within a strict time limit as defined in the scheme guidelines.

Figure 11: Key stakeholders in PMFBY/RWBCIS schemes[i]



Source: Lloyd's - Risk Management Solutions, Inc., 2017.

Figure 12: Crop insurers in 2016/17 & % share of premiums[j] (*Public sector insurers)

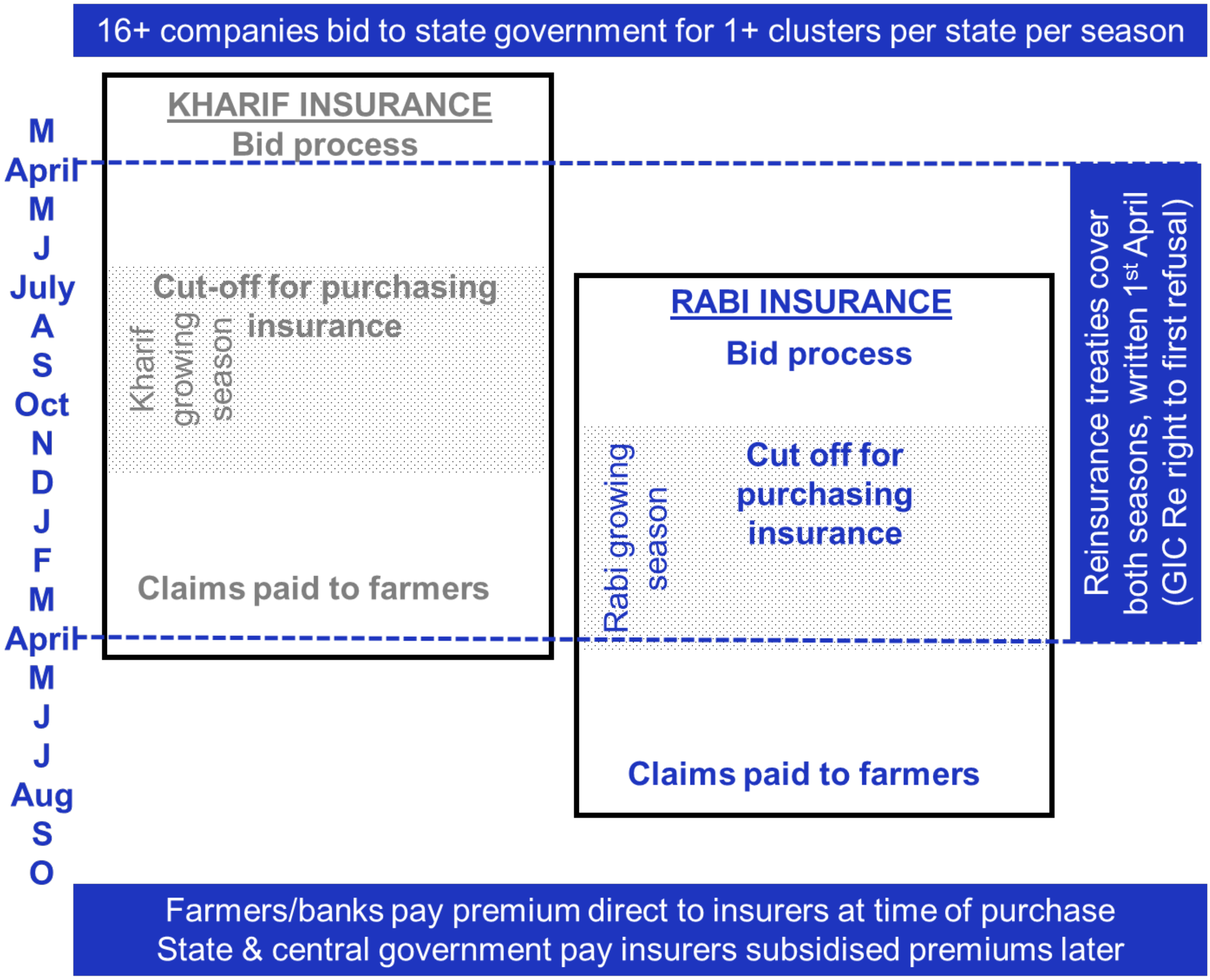


Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from GIC Industry Data Statistics (March 2017)

[i] . (SLCCCI = State Level Coordination Committee on Crop Insurance, SAO = Seasonal Agricultural Operations loans)

[j] (Others include: National*, Shiriam General, Future Generali, Cholamandalam MS, SBI General, Tata-AIG, Universal Sompo)

Figure 13: Schematic of the typical PMFBY implementation process



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from PMFBY Operational Guidelines, 2016.

Impact of PMFBY scheme in 2016

In the first Kharif year of PMFBY, it was estimated that around 30% of farmers were protected by crop insurance, up from 22% in the previous year under the pre-PMFBY schemes (Press Information Bureau Dec 2016 press release). The new scheme followed 2 years of drought and unseasonal rain and hail which may have acted as an incentive for purchasing crop insurance in 2016. It was claimed that the majority of the increased take up was from non-loanee farmers, which had been negligible pre-2016 at around 1 million farmers and jumped to over 10 million during Kharif 2016. However a study by the Centre for Science and Environment (CSE, Bhushan & Kumar, 2017) reports that this is not strictly the case when investigating the details behind the numbers and that only around 5% of farmers insured during Kharif 2016 were non-loanee.

Table 4 summarises the impact of the PMFBY and RWBCIS schemes in 2016 for the Kharif and Rabi seasons. The data suggests that while Kharif crop insurance grew in the first year of the PMFBY scheme, the coverage may have decreased in the first Rabi season (based on the decrease in insured area). Uptake of Rabi insurance may have been reduced as a result of the good monsoon in 2016 and farmers feeling less need to purchase protection or obtain bank loans for the Rabi crops.

Table 4: Comparison of crop insurance statistics (number of farmers insured, insured area, sums insured) for 2015 (pre-PMFBY) versus 2016 (PMFBY+RWBCIS)

	Kharif 2015 (pre-PMFBY schemes)	Kharif 2016 (PMFBY/RWBCIS)	% Kharif Change	Rabi 2015 (pre-PMFBY schemes)	Rabi 2016 (PMFBY/RWBCIS)	% Rabi Change	Total 2015 (pre-PMFBY schemes)	Total 2016 (PMFBY/RWBCIS)	% Total Change
Farmers (mn)	30.8	40.4	31%	16.7	16.8	1%	47.5	57.2	20%
Insured Area (mn Hectares)	33.5	37.9	13%	20.2	19.3	-4%	53.7	57.2	7%
Sum Insured (USD bn)	11.1	21.0	89%	7.3	11.1	50%	18.5	32.1	74%

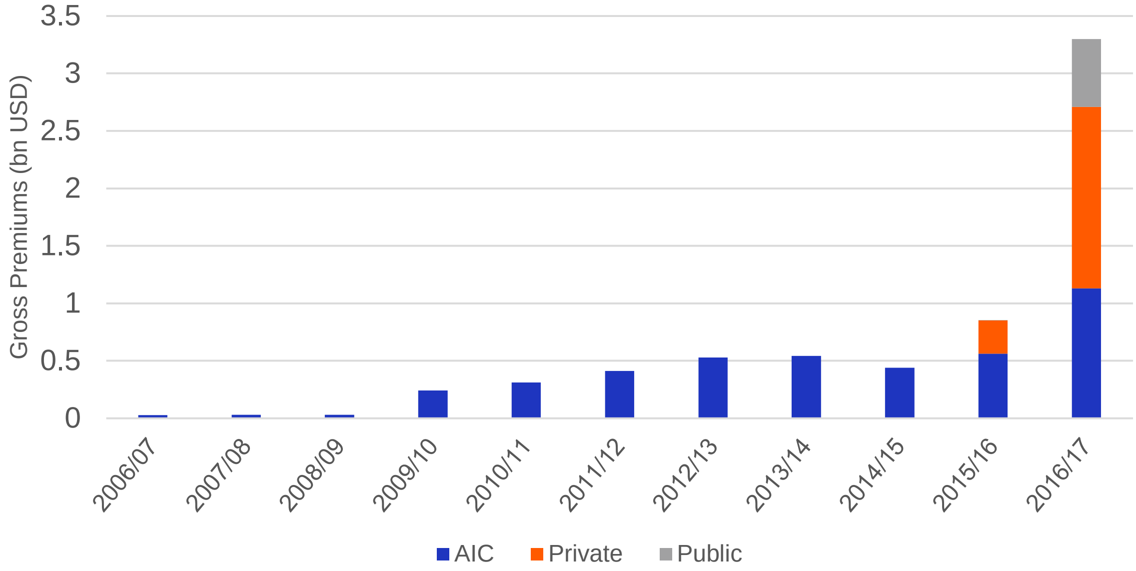
Source: Gulati et al., 2018.

Sums insured have significantly increased for both Kharif and Rabi seasons. As mentioned earlier, one of the shortcomings of previous schemes was that the sums insured typically fell short of covering the farmer's cost of production. To ensure farmers are better protected, sums insured have increased under the PMFBY scheme. In Kharif 2016, while the number of farmers insured rose by around 30% and the insured cropped area increased by 13%, the sums insured nearly doubled. Rabi sums insured did not increase as much as Kharif in the first year of the scheme, although the reduction in the area insured during the 2016-17 Rabi season will contribute to this result. The CSE study (Bhushan & Kumar, 2017) reports that there are still cases where the sums insured are not adequate. However the statistics show that overall the new scheme offers significant improvement.

As a result of the increased sums insured and to a smaller extent, the increased take up rate, premiums increased significantly in 2016 (Figure 14). AIC (blue, 2006-2016), private insurers (orange, only 2015-2016 shown), public insurers (grey, only 2015-2016 shown). AIC premiums doubled in 2016 while market-wide the premiums increased by nearly 300% to around USD 3.3 billion (GIC Industry Data Statistics, March 2017). Thanks to the 2015/16 IRDAI regulatory updates discussed earlier, the market share of private insurers providing crop insurance increased from 34% to nearly 50%.

However increased premiums, heavily subsidised by the state and central government, with no caps, have brought additional financial burden on state agricultural budgets. As a result, some states delayed notifying PMFBY in its first Kharif season which resulted in extending the enrolment deadline, other states did not enrol at all such as Punjab (Bhushan & Kumar, 2017).

Figure 14: Gross Crop Premiums (USD bn)



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from GIC 2015-16 year book (2006-2015/16) and GIC Industry Data Statistics (March 2017).

Lessons learnt from PMFBY scheme in 2016

The consensus after its first year is that the PMFBY scheme is a significant improvement over past schemes in terms of protecting farmers. The government has shown commitment towards developing a robust crop insurance market both in terms of the new scheme and also driving regulatory changes, via the IRDAI, to enable foreign capacity and expertise to enter the market. The uptake of crop insurance has increased as intended with more states opting to implement PMFBY. However there have been implementation issues which need to be addressed.

From the farmers' point of view, shortcomings still remain in the new scheme such as the area approach, concerns over threshold yield calculation used in the index, slow claims process, challenges in enrolment and lack of awareness (Bhushan & Kumar 2017). The scheme is committed to leverage the use of technology such as smart phones, satellites and drones to speed up the claims process and payments to the farmers. A freely available, simple to use, CCE app (CCE Agri Mobile app) has been developed which feeds into the government's national crop insurance data portal. This is taking some time to implement as many states were still in the process of purchasing and implementing this technology during 2016/17 (Bhushan & Kumar, 2017). Tamil-Nadu is one example where satellite technology has been successfully used to assess claims and speed up the claims settlement process during Rabi 2016/17 (Remote Sensing-based Information and Insurance for Crops in Emerging Economies, RIICE) (see Box 4).

It is estimated that by April 2017 only around 32% of claims had been paid for the Kharif 2016 season (Bhushan & Kumar, 2017), with values ranging between 0-100% between states. The reason for the delay in claims is due to delayed payment of subsidised government premiums to insurers, lack of infrastructure to share data between stakeholders and to support the large number of CCE and also the vetting process by some insurers to validate claims. Delayed premiums were not always the main driver of delays as claims were delayed in states which had received their subsidies. Only the state of Karnataka had settled 100% of the 2016 Kharif claims by April 2017 (see Appendix 4 for more detail). To increase confidence in the scheme among farmers and improve the voluntary demand for the scheme, these shortcomings should be addressed, particularly on the loss adjustment process.

Awareness and ease of application of the scheme continues to limit the take up for many non-loanee farmers. Farmers in Trichy district in Tamil-Nadu claimed to be unaware of crop insurance, while many farmers in neighbouring Tiruvarur district have benefitted from crop insurance during the 2016 Kharif season due to drought (Times of India, 2017). The CSE study (Bhushan & Kumar, 2017) reports that some farmers were unaware of the need to report pre-and post-harvest and local calamity losses within a specified time window and were unable to claim for crop damage. Better education is required for all farmers, including current policy holders, so they can fully benefit from the scheme, which should in turn increase the confidence in and take-up of crop insurance.

More effort is also required to increase distribution channels and attract non-loanee farmers. Crop insurance for loanee farmers is automatically deducted from their loan amount, with the banks receiving commission per policy. The non-loanee registration process needs to be simplified and more accessible with incentives to cover the distribution costs for non-loanee policies.

For state governments, sufficient funding is a concern to ensure states can fully subsidise the actuarial premiums and fully implement PMFBY. In some cases, states' share of the premium accounts for up to 60% of a state's agriculture budget (Agroinsurance Sept, 2016). Delay in the notification (Bihar and Gujarat) or reducing the amount of sum insured under the scheme to bring down the premium have taken place. For example, in 2016, Rajasthan introduced a benefit cap, only subsidising farmers owning less than 7 hectares of land. Late tendering in Bihar in Kharif 2016 resulted in high insurance and reinsurance rates as flooding had already impacted Kharif crops in the region before tendering was finalised (Gulati et al., 2018). In another case, the states of Maharashtra and Karnataka had to perform a retendering for Kharif 2017 as they felt the premiums were too high given the monsoon was expected to be normal in 2017 (Economic Times of India, May 2017). The government almost doubled the budget allocated to PMFBY crop insurance for the 2017/18 season to ensure the subsidised scheme can continue to grow (Financial Express, 2017). It has further increased the budget in 2018/19. For the scheme to be a success, farmers must have adequate sums insured coverage and affordable premiums and all stakeholders must have a good understanding of the benefits of regular crop insurance.

From the insurers point of view, there is unease about adverse selection and variability in take up rate and the risk of moral hazard (when an insured deliberately alters his behaviour to increase the magnitude of potential loss) and soft (hard) fraud due to fake or exaggerated claims. The infrastructure is not yet in place to fully perform the large number of CCE and yields cannot always be properly assessed resulting in inaccurate loss adjusting. The CSE report (Bhushan & Kumar 2017) reveals that there were many implementation issues with CCE. Not all CCE took place and of those that did, not all were accurate or processed correctly. There are also concerns around data manipulation of CCE results (e.g. ground-nut yields in Gujarat in Kharif 2016) (Gulati et al., 2018). This can be addressed by the use of technology, such as drones and satellites pre- and post-harvest to assess validity of claims (see Box 4). In some cases, insurers are facing delays in payment of government premiums, which in turn delays claims settlements (Asia Insurance Review, 2017). This is largely a result of the state governments' cumbersome process to verify each policy, per insurance company, before releasing the subsidised premiums.

Low profitability in 'good' monsoon years (such as 2016) is also a concern for insurers along with capacity in the reinsurance sector and a relaxation of solvency requirements for crop insurance. Furthermore, there is a need for more effort to gather and maintain a centralised database of exposure information and high quality historical yield, loss and weather measurements at localised levels, available to all interested parties, that can be used to better assess and price risks. However due to the criteria of the lowest bid winning the tender in each state/district and the gold rush to get a portion of large, attractive crop premiums, there is pressure to reduce premiums below the actuarial rates with some insurers being more aggressive than others. States requesting bid retendering (e.g. Karnataka and Maharashtra in Kharif 2017, Economic Times of India, 2017) further add to this pressure.

With many stakeholders involved in the scheme, there have been challenges in communication and data sharing. The government has set up a national crop insurance data portal (www.agri-insurance.gov) but a greater wealth of data and co-ordination is required to fully meet the needs of the different stakeholders. Some states have also set up state-level crop insurance data portals. Karnataka has been leading the way, setting up a comprehensive state crop insurance portal, SAMRAKSHANE (https://www.samrakshane.karnataka.gov.in/) since the introduction of PMFBY (Gulati et al., 2018), which likely played a key role in the quick claims settlement compared to many states (Appendix 5). The scheme could also benefit from greater coordination amongst the different stakeholders to ensure the scheme works as intended. The PMFBY Operational Guidelines are in the process of revision (not released at the time this report was published) to address many of the implementation issues to date, further demonstrating the government's commitment to improve the scheme for all stakeholders.

Box 4 Using remote-sensing to speed up PMFBY claims settlement process

Remote sensing offers an attractive way to assess crop yields and damage for certain crops for crop insurance purposes. Damage can be assessed quickly and with greater transparency and objectivity than traditional CCEs, resulting in faster claims settlement. The Indian Government has launched several research programmes investigating the use satellite data for agricultural applications including yield and damage estimation:

- FASAL (Forecasting Agricultural output using Space, Agro-meteorology and Land based observations)
- NADAMS (National Agricultural Drought Assessment and Monitoring System)
- CHAMAN (Coordinated Horticulture Assessment and Management using geo-informatics)
- KISAN (C [K] Crop Insurance using Space technology and geo- informatics).

Private companies are also involved in developing remote-sensing applications for the agricultural sector including crop insurance (e.g. Remote Sensing-based Information and Insurance for Crops in Emerging Economies, RIICE). Drones or unmanned aerial vehicles (UAV) are commonly used for precision farming in key agricultural regions such as Canada, Australia, Brazil and Japan. UAV's could also be used for crop insurance claims settlement process, particularly to provide quick and accurate damage assessment of localised calamities such as hail or cyclone damage.

Remote-sensing applications are currently used by individual states or insurance companies for limited crop types (see Tamil-Nadu case study below). These technologies show great potential to assess crop yields in-season and post-harvest and be applied to other crops and states to introduce greater objectivity to the PMFBY claims settlement process.

<u>Case Study: Tamil-Nadu, Rabi 2016/17</u>

During Rabi 2016/17, prevented/failed sowing rice claims due to drought were settled by AIC within 3-4month (8-9 months earlier than usual) thanks to satellite technology to assess in-season areal losses.

Tamil-Nadu Agricultural University (TNAU), working in conjunction with Remote Sensing-based Information and Insurance for Crops in Emerging Economies (RIICE), have been testing remote sensing technology to assess areal crop losses and estimate end of season crop yields for several years, with accuracy rates of around 90%. In 2017, TNAU provided this information to the State Government for the first time to assess and settle prevented/failed sowing rice claims.

Source: Gulati et al. (2018), RIICE (2017).

1.4 Crop reinsurance overview

The Indian Government recognises that insurance offers an effective mechanism to transfer and spread risk nationally and internationally (AXCO,2017). As such the Government and regulators seem to be committed to encourage growth and bring foreign expertise into the local market, such as product design, technology, ratemaking, underwriting and loss adjustment, to bring Indian re/insurance practices in line with well established insurance markets (AXCO, 2017). Big steps have been made towards this goal in the past couple of years through updates to IRDAI regulations in 2015 and 2016 (summarised in Section 1.1). The 2016 reinsurance market regulations now permit Lloyd's and other approved foreign reinsurers to operate through branches in India. Through the new reinsurance purchasing priority order, designed to maximise retention within India, state-run GIC Re has first right of refusal and typically leads most of the crop treaties taking the biggest share of crop risk. Other reinsurers directly cover the remaining business and also provide protection for GIC Re. Thanks to the jump in crop premiums in 2016, GIC Re is now the biggest global agricultural reinsurer, recording an 80% growth in total premiums (USD 1.6 bn crop premiums in 2016-17) since the introduction of PMFBY. GIC Re are opening a syndicate at Lloyd’s of London to diversify and broaden its international portfolio (The Economic Times, 2017). In January this year, the IRDAI issued a draft of updated General Reinsurance Regulations, in response to stakeholder comments, including updates to the reinsurance purchasing priority order (PWC, 2018). However the revisions are yet to be formalised and further changes may be made following stakeholder feedback on the draft regulations (Reinsurance News, 2018).

Current status of crop reinsurance

There are three major challenges currently facing crop reinsurers:

- lack of clarity of exposures at time of underwriting
- lack of transparency of insurance company crop rating methodologies
- delay in receiving premiums

Crop treaties cover an annual period, with renewal typically 1st April, covering both PMFBY and RWBCIS schemes for both Rabi and Kharif seasons. As discussed in Section 1.3, crop insurance tenders are typically performed per season and year. Due to PMFBY timelines and that insurance companies prefer reinsurance to be in place prior to the tendering process, exposures and rates (and expected premiums) at the time of underwriting are relatively unknown. Buffers that account for uncertainty in the final tendering outcome and farmer enrolment are built into the reinsurance contracts. The Kharif tender process should be under way at time of treaty renewals which can give some indication of Kharif exposures. However final confirmation is only available once the cluster bidding process is complete and the scheme enrolment has closed, post-treaty renewals. Changing cluster definitions also adds to further exposure uncertainty. For example, the number of clusters in Andhra-Pradesh jumped from 2 in Kharif 2017 to 4 in Kharif 2018. For the Rabi season, there is very little concrete information and reinsurers have to rely on business plans estimates of premiums insurers hope to win per state. Although it is becoming more popular for Rabi tenders to be performed at the time of Kharif tenders. The only known exposures are any clusters on multi-year contracts (currently only opted for by a few states). Thus, one of the current challenges for the market is obtaining accurate and reliable premiums, exposure and sums insured information. Given the significant changes implemented in PMFBY (such as different premiums, sums insured, and indemnity levels) the market cannot rely on historical information. A further challenge for the reinsurance market is understanding the rating methodologies used by the individual crop insurance companies. It is critical in a sector such as crop that insurance and reinsurance rates are based on actuarial rates and the temptation to bid below this rate to win business is avoided. Rating discipline may be relaxed in some companies under the pressure to win bids in this competitive market, resulting in inadequate protection for both the insurer and reinsurer.

Because of this uncertainty, quota share proportional treaties are most commonly used for Indian crop business as it is an effective way to cede “unknown” risk, usually with low retentions. They are also attractive to insurance companies who do not have sufficient capital to retain their entire crop portfolio. Sliding scale commissions, where commissions are based on ultimate loss ratios, are used as a way to incentivise prudent underwriting. Stop loss treaties are purchased in addition to the quota share treaties to protect companies from very high claim ratios. Traditionally, many Indian crop stop loss treaties have similar attachment and limits regardless of the exposure mix (states, crops, season, scheme) and company (underwriting practices, reserve strength, risk appetite), suggesting that treaty conditions are not technically-based. However this is starting to change with smaller portfolios typically having higher limits. Stop loss treaties usually start around 110-140% and many cap around 200-250% loss ratio. The operational guidelines state that the state and central Government will pay claims beyond a national loss ratio of 350%. However it is unclear how this would work in practice. In 2016, due to the severe lack of clarity around exposures during the first year of the PMFBY scheme, GIC Re purchased additional coverage as the final exposures were larger than expected. In 2017, GIC Re has combined this into 1 treaty having more certainty in the level of exposures.

Reinsurers are also concerned by the delay and uncertainty in the timing and receipt of crop premiums. Insurers face delays in the payment of the government's share of the subsidised PMFBY premiums, which in turn delays the premium collection for reinsurers and claims settlements (Asia Insurance Review, 2017).

1.5 Future of crop (re)insurance in India

It is clear that there are strong social and economic reasons for establishing a robust crop insurance market. The current Government is committed to adequately funding the schemes and supporting them via (re)insurance regulations. Revising the PMFBY operational guidelines to learn from implementation issues further demonstrates the Government's pledge to develop sustainable crop insurance. The crop (re)insurance market needs to ensure business can be financially viable in the long term which can be supported by the influx of foreign expertise currently entering the Indian crop risk sector.

For now, crop insurance schemes will likely remain subsidised and well-funded by the states and central governments to ensure take up rates continue to rise and farmers learn directly of the benefits of crop insurance. This is supported by international experience from the US and China where crop insurance penetration only significantly increased after the Government began heavily subsidising insurance schemes (Gulati et al., 2018). The aim of PMFBY is to improve the penetration rate of crop insurance, particularly in non-loanee farmers, to 50% of the area planted by 2018/19 (Business Today, 2016), and to improve the spread of risk in the sector using actuarial methods of risk assessment and premium rating.

The Indian crop market is unique in many ways. To encourage and maintain capacity in the Indian crop reinsurance market, it is important that there is more data and risk transparency as well as confidence that risks of moral hazard and adverse selection are being minimised by the processes set up in PMFBY such as mandatory use of technology and geolocating the sites of CCE. Much of the framework is in place but proper implementation is required to ensure greater transparency and accuracy and that timelines are strictly adhered to. The issues found in the Indian crop insurance market are not all unique. The crop market in China, although a few years ahead of India, continues to be impacted by concerns of adverse selection.

Areas of improvement to ensure business sustainability include:

1. Provide uniform consistent data. A nation-wide effort, with support from the Government and insurers, to digitise, collect and disseminate, exposure, weather, yield and loss data at the finest spatial resolution, in a consistent format within a centralised database would create a historical dataset enabling better support for developing actuarial premiums that reflect the potential risk. The Government has set up a national crop insurance data portal (www.agri-insurance.gov) to collect data related to crop insurance but a greater wealth of information is required to fully meet the needs of the (re)insurers. Digitising data will reduce the time lag for all stakeholders between gathering, processing and analysing information. Data Yield, loss and weather data availability is also essential to ensure rates are technically priced and that insurance companies can support a major adverse year such as a large-scale drought. It is also critical to improve the claims settlement process to give confidence to the (re)insurers that crop claims are valid and verified and that the market can be financially viable in the short and long-term.
   The portal should ideally include all available historical crop yield records at district level down to insured unit level where available, and beyond the past 10 years if available. To best interpret historical loss data, historical exposure and policy information should also be provided. Going forward, exposure information should include as much information as possible including the number of hectares insured, sums insured and farming management information such as planting dates, irrigation levels, seed variety. This data could be designed with a flexible schema compatible with standardised schemas such as the Global Exposure Accumulation and Clash project (GEAC) which aims to provide a more comprehensive and standardised framework for monitoring and reporting exposure enterprise-wide, for different lines of business, across all geographical insurance markets.
   It could also be added to the agricultural datasets available in the Oasis Hub. Digital platforms are being developed to greatly reduce the administrative effort and cost of deploying crop insurance, monitoring fields and reporting claims. The Government is continuing to develop and enforce the use of the centralised national crop insurance portal to gather and maintain all data relevant to crop insurance. Data from Community Service Centres, CCE results via the CCE Agri Mobile app and Aadhaar ID numbers are meant to feed directly into the portal. Any state portals should link into the national data portal and ensure there is no duplication or mis-match of data.

2. Ensure greater transparency and underwriting discipline. It is vital that those involved in the crop risk market have a good understanding of the complexities of crop risk and exercise underwriting discipline so that the market can support a major adverse weather event. Insurance companies should follow consistent and more transparent rating methodologies to calculate their premiums during the bidding process and share these amongst the stakeholders, including the reinsurance market. Some insurers offering crop insurance may lack experience of the complexities of crop underwriting and may not be fully aware of the consequence of bidding below the actuarial rate. Rates are priced around a 75-85% loss ratio which leaves little room for expenses and provide a return to capital providers. However, during Kharif 2017, there were reports of insurers deliberately bidding high to outprice themselves from the tendering process (The Hindu Business Line, 2017).

3. Minimise exposure uncertainty. The lack of knowledge of final risks at time of treaty underwriting impedes a transparent and fair reinsurance market. Concerted action is required between the Government and the (re)insurance market to address this issue and better enforce and align the bidding, enrolment and renewal timelines. Shifting timelines of the bidding process forwards by a few months would provide a firmer idea of Kharif exposures per insurance company before April. However insurance companies prefer to have reinsurance in place before entering the tendering process. There would remain some uncertainty for Kharif premiums as farmers typically enrol for the scheme between April and July. Larger uncertainty will remain for Rabi premiums as the bidding process and scheme enrolment does not begin until much later in the year. Although it is becoming more popular that Rabi tenders are performed at the same time as Kharif tenders. Splitting the treaties into separate Kharif and Rabi six month contracts, would help to reduce Rabi premium uncertainties at the time of treaty inception but would incur extra effort and increased volatility and reinsurance rates. Alternative solutions are to change the tenure of the tenders such as making it compulsory to perform Rabi tenders at the time of the Kharif season or providing incentives to the insurers to bid over several years (such as in Tamil-Nadu),

thus spreading their risk, as well as the risk of the Government and reinsurers over longer time periods. Multi-year contracts are currently not common due to concerns around scheme stability and locking in rates. Such solutions may require different selection criteria based on historical claim processing and sound capacity (The Hindu Business Line, 2017).

4. Improve claims management process. The market needs confidence that claims are reliable and can be settled quickly. The use of new technology to improve the CCEs and/or to replace them by alternative means would reduce time and effort in claim management. Digital insurance platforms could reduce the administrative cost of deploying insurance, monitoring fields and reporting claims. Continued effort is required to implement technology (digital insurance platforms, smart phones, drones, satellite imagery) to identify areas of damaged crops and support a faster, more efficient and audited assessment of crop yields and claims (currently done by CCE requiring a large pool of human resources that are not always available or adequately trained). State and central Government should also provide their share of subsidised premiums in a timelier manner, as per the operational guidelines, to avoid further claims settlement delays. Technology could help to adhere to the timelines of the PMFBY scheme and make improvements in the transparency and speed of the claims settlement process which is in the interest of all stakeholders. Since Kharif 2017, capturing CCEs data on smartphones via the government CCE Agri App and its real-time transfer on the National Crop Insurance Portal (http://agri-insurance.gov.in/Login.aspx) has been made mandatory (DAC-FW, 2018). Furthermore states have to provide an evidence of having conducted CCEs before the Government of India releases its share of the premium subsidy. Some states, such as Maharashtra, are using external agencies for third party independent evaluation of CCE's (Department of Administrative Reforms and Public Grievances, 2017). It is hoped that drones and remote-sensing applications can be used to a greater extent in the future to assist, speed up and add greater objectivity and transparency to the claims settlement process (Box 4). As a further move to help speed up the claims settlement process, it has become mandatory that electronic Aadhaar identification be provided when purchasing crop insurance from Kharif 2017 onwards (Economic Times, March 2017).

5. Ensure timely premiums. The state and central governments are encouraged to pay their premium subsidy in a more timely fashion than has happened to date in the PMFBY scheme. This has many consequences including delayed payment of claims to the farmers and premium to reinsurers. Streamlining the state government process to verify crop insurance policies would help to speed up the delivery of subsidised premiums.

6. Strengthen regulations. If the Indian crop reinsurance market grows as intended, the need for more robust insurance regulations would be required. In response to the enormous jump in premiums in 2016, the IRDAI set up a Reinsurance Expert Committee in May 2017 to review international regulations with the purpose to make the Indian insurance market more transparent to international reinsurers and alternative risk transfer with the aim to increase capacity and lower cost of reinsurance (Reinsurance News, 2017). The IRDAI is currently drafting an update to General Reinsurance Regulations, which should include updates to the categories of reinsurers, order of preference and retention limits (PWC, 2018).

If all these improvements are made, the need for large buffers in crop treaties to account for uncertainties (such as exposure uncertainty, underwriting discipline, data availability to technically price treaties) should reduce which could in turn lower reinsurance rates and feed down the (re)insurance chain to ultimately reduce government subsidies per contract. The following will ultimately impact the overall success of the PMFBY scheme:

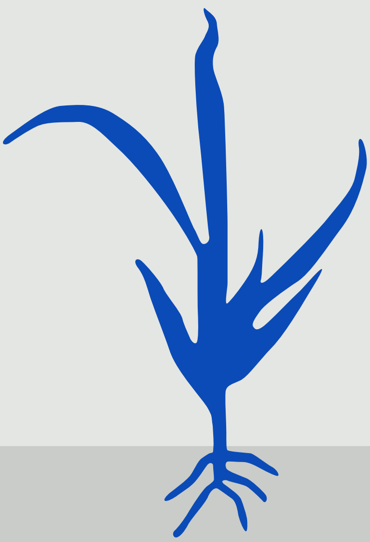
7. Growth. Crop insurance take up and premiums are expected to grow in the next few years, driven by the Government's commitment to increase the coverage of insurance to 50% by 2018, supported by increasing financial budgets allocated to the scheme. The premiums in 2017 and beyond will not increase to the same dramatic extent as 2016 since scheme terms, such as sums insured, remain the same as 2016, and there have been no significant IRDAI regulatory updates. Overall crop premiums are anticipated to grow 15-20% in 2017/18 with projected premiums of around USD 3.7-3.9 billion (INR 24-25,00 crore) (National Insurance Chairman, Times India). Growth will come from attracting non-loanee farmers, as well as onboarding states yet to implement PMFBY. Others in the market think the growth could be as much as 35% resulting in premiums of 28,000 crores (approximately USD 4.3 bn). No official premium reports for the 2017/18 season were

available at time of publication, but the latest gross premiums statistics from the General Insurance Council Industry Data Statistics, for the year ending February 2018, show a 19% increase in Miscellanous gross premiums (of which ~ 80% was attributed to crop in 2016/17), compared to the year ending February 2017. It is hoped that the PMFBY scheme will continue to evolve and address many of the issues described here and give greater confidence to all stakeholders that the scheme can be better implemented and supported in the future. The popularity of weather-based insurance contracts has notably decreased since the introduction of PMFBY (Figure 10), largely due to product design issues (Gulati et al., 2018). There is currently weak correlation between temperature and other weather triggers recorded at the weather station and yield calculation (basis risk) and potential for tampering weather station to "trigger" payments. If these issues are corrected, this product could become more popular providing a quick and simple method to receive compensation for crop damage. India could learn lessons from Kenya where weather-index based insurance contracts are highly successful, distributed via agricultural stockists (Gulati et al., 2018).

8. Attract non-loanee farmers. The main potential source of growth in the agriculture insurance market is the participation of non-loanee farmers. To attract non-loanee farmers and further grow the crop market, agriculture insurance stakeholders (including insurers and government) need to deploy a multiple front effort to educate farmers about the value of insurance and address the reasons for the current low take-up rate, such as lengthy claims payment and the perception that there is no return value in the premiums being paid or that claims will not be paid. In an attempt to further broaden the outreach to non-loanee farmers, simplify the registration process and increase crop insurance uptake, Common Service Centres (CSC) and post offices across the country started to distribute crop insurance from July 2017 (Asian Reinsurance Review, 2017). However there is still reluctance of farmers to insure if they 'feel' there is no need when the monsoon is expected to be average or above. The India Meteorological Department (IMD) generally provides its first long-range monsoon forecast in the latter half of April, months in advance of the enrolment deadlines. A persistent effort to demonstrate the value of long term insurance with the support of subsidies and faster claim processing may ensure more consistent and increasing year-to-year take up. Awareness generation programmes have been running at a localised scale in some districts/states (Department of Administrative Reforms and Public Grievances, 2017) but this is required on a much greater scale. The PMFBY scheme was launched following two drought years when there was a greater appetite for crop insurance. The take-up rate for Kharif 2017 and following seasons will provide an indication of attitudes towards insurance. High-level PMFBY statistics on the 2017-18 season, reported at the time this report was published, have revealed that despite the apparent increase in premiums, the insured crop area, number of farmers and total sums insured have decreased below 2016-17 levels (Financial Express 2018). A drop in coverage could be driven by a combination of factors including risk perception (less need for insurance with good monsoons in 2016 and 2017), mandatory introduction of Aadhaar identification when purchasing crop insurance, loan waivers in states such as Uttar-Pradesh and Maharashtra as well as concerns around claims settlement (The True Picture, 2018). Once greater insight into the 2017-18 season is available, steps can be identified to encourage the scheme to grow as intended by the Government.

9. Innovative product design. As the Indian crop market stabilises and matures, innovative products may become available to better suit the farmers and insurers. In some countries, new products are being developed around the interaction of yield risk with price risk which can expose producers to unexpected revenue shortfalls since commodity price decreases could offset above-average crop yields. Crop revenue protection, as offered in other more mature crop markets such as US, as well as crop yield protection, is starting to appear in India to fully protect farmers. Earlier in 2017, farmers in some states demanded waivers on farm loans and higher prices for their crops as crop prices dropped after a bumper harvest following the good monsoon in 2016 (BBC, 2017). Some believe this was largely due to the impact of demonetisation and lack of liquidity and cash. Others believe it is a deeper-rooted problem and that lack of adequate food storage and processing capacity when there are surplus harvests drives down the price.

The impact of weather and climate on crop yield and crop insurance losses



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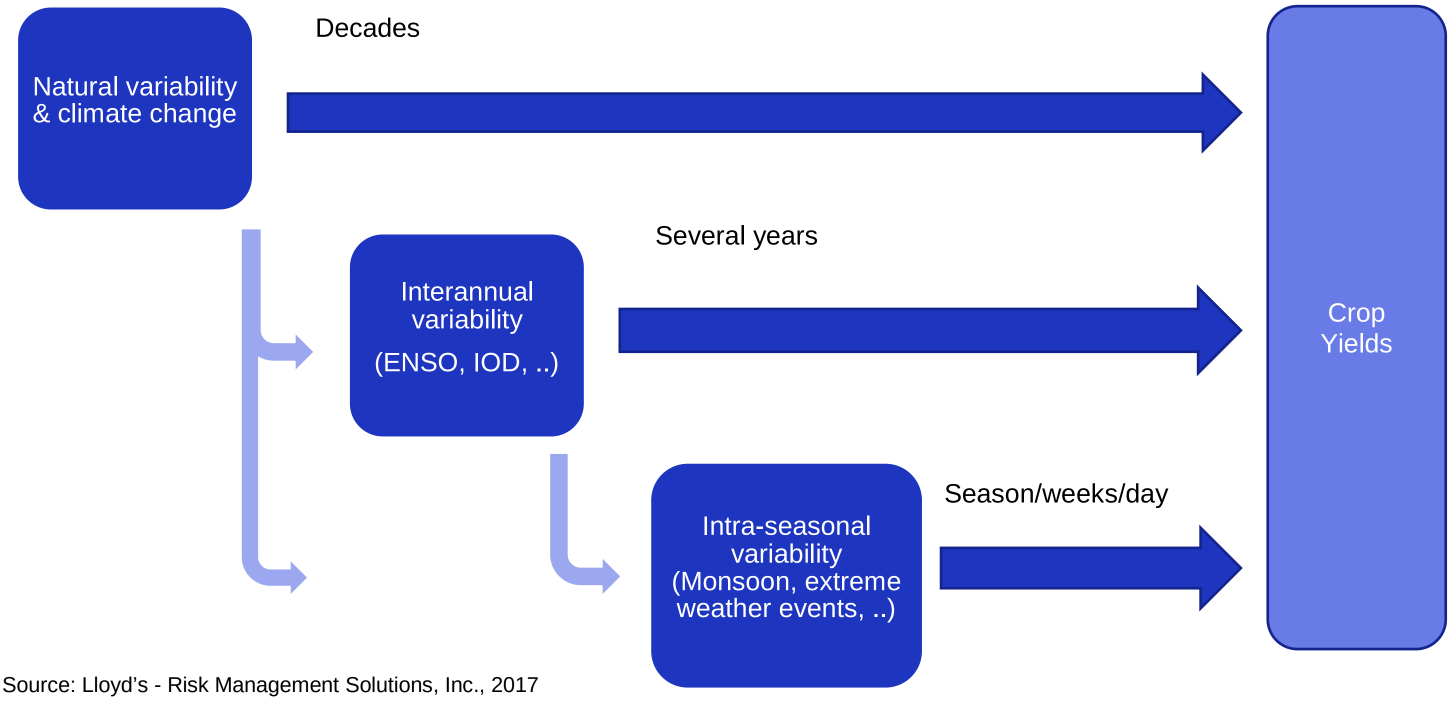
2. The impact of weather and climate on crop yield and crop insurance losses

Crop yield index insurance schemes in India cover against a deficit in the realised crop yield at the end of each Kharif and Rabi season. As summarised in Section 1.2 (Drivers of crop yield variability), crop yield variability can be due to one or combination of several different factors (Figure 6, p23) including attritional and extreme weather events, managerial practices and pests and disease. Nonetheless, weather variability is regarded as the primary cause of the year to year fluctuations in yield (Petr 1991, Kumar et al., 2006). Drought, frost, heat wave, flood, and cyclone are perils that cover generally large geographic areas and contribute in large part to crop yield variability. Other meteorological events such as hail and tornado affect much smaller areas.

Given the important role weather plays on crop yield variability, this section summarises the importance of the monsoon and other extreme weather events on year-to-year crop yield variability. This section is expanded in Appendix 6 to provide greater detail about these weather events and their impact on crop yields and losses, along with their potential to be used as predictors for crop yields in the coming season. The latest research on observed and future climate change related to its impact on Indian climate and crop yields is also summarised in Appendix 6. Figure 15 shows the links between climate and weather and crop yields in a simplified way to highlight the different spatio-temporal time scales that are potentially relevant.

Figure 15: Timescales of climate and weather patterns that impact crop yields



Source: Lloyd's - Risk Management Solutions, Inc., 2017

2.1 Overview

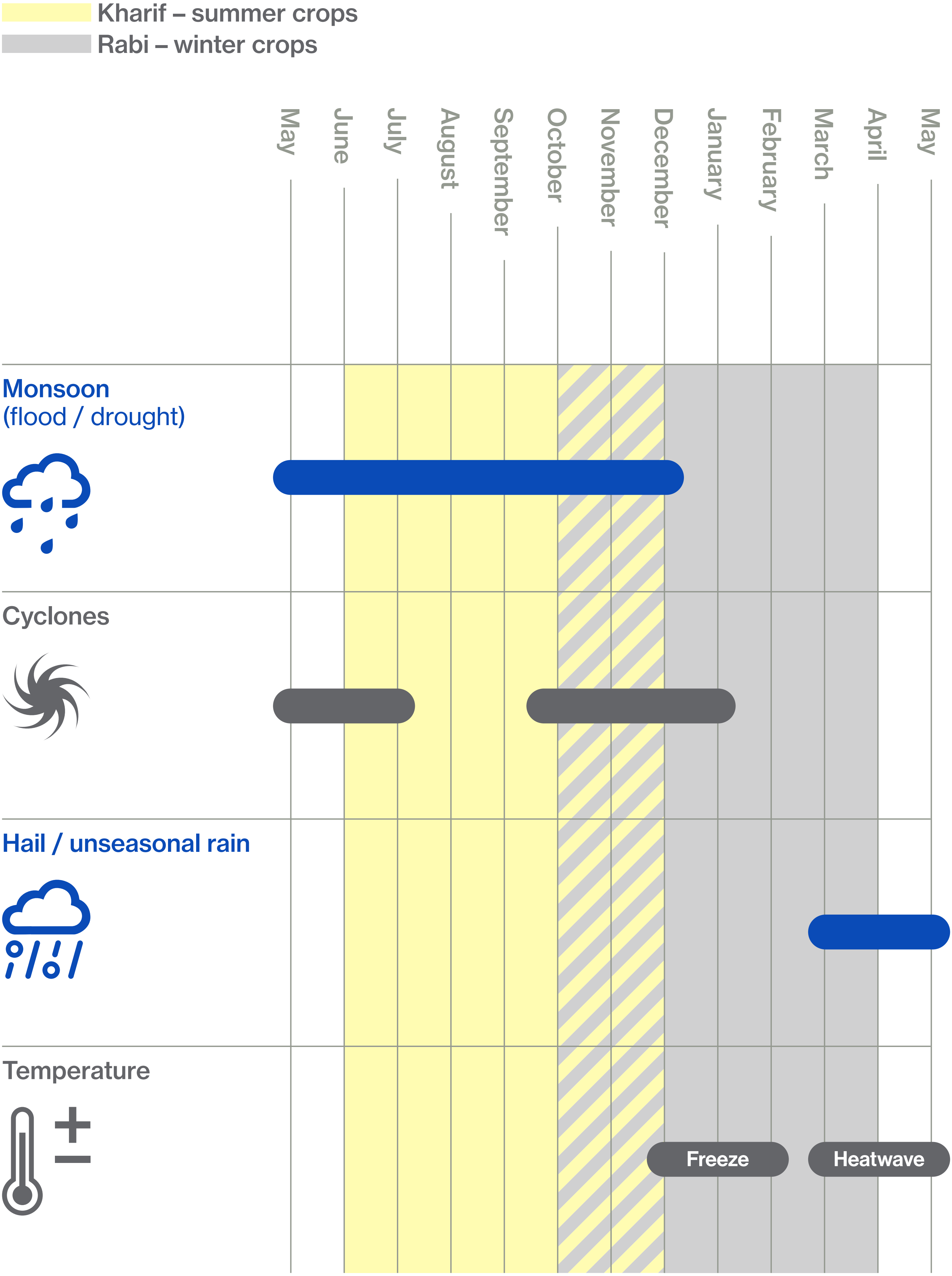
As mentioned in Section 1, India's agriculture sector relies heavily on the timely onset and spatial distribution of monsoon rainfall for successful cultivation of rainfed systems and for the replenishment of water levels for irrigated systems. Not surprisingly, the monsoon is the most studied and tracked weather system in the region and has even been dubbed "real finance minister of India" (Reuters, 2012). Historically India's economic and social core has been bound to the monsoon as it is the main driver of variability in agricultural output.

Outside of the monsoon and its associated floods and droughts, India is also subject to many other extreme events (Figure 8, page 22) which can have severe impacts on crop yields, such as:

- Tropical Cyclones
- Extreme Temperatures
- Unseasonal rain and hail storms

Most climate hazards in India have a distinct seasonality and can impact different crop seasons and growth stages (Figure 16).

Figure 16: Indian crop seasons and peak seasons of major weather perils impacting crop yields



Source: Lloyd's - Risk Management Solutions, Inc., 2017

2.2 Importance of the Monsoon on Indian agriculture

The Indian subcontinent receives 75-80% of its annual precipitation during the Indian summer monsoon (June to September). The Indian summer or Southwest monsoon marks the arrival of warm, moist air carried by winds travelling from the south-west over the Indian Ocean, bringing rain over the Indian subcontinent between June and September. The summer monsoon arrives with a sudden downpour of rainfall that continues for several days, known as the ‘burst’ of the monsoon. During a typical monsoon, the onset begins in southern India in late May or early June, and gradually advances northwards and westwards, reaching the north by early July.

The Northeast monsoon (also known as the retreating or winter monsoon) usually "bursts" around the 20th of October and lasts for about 50 days before withdrawing. In this retreating phase of the monsoon, winds blow from the north-east and bring moisture from the Bay of Bengal. As a result, the South-eastern coastal region of India also receives significant precipitation between October and November. For example, in Tamil Nadu, the Northeast monsoon (and not the summer monsoon) is the main rainy season and some of its coastal districts get nearly 60% of their annual precipitation during this period. The timing of the Northeast monsoon helps crops that are grown in the southern parts of India, often resulting in an extended Kharif season into October and November so the crops can benefit from this additional rainfall. However, at a nation-wide level, the Northeast monsoon is of lesser importance for Indian rainfall and agriculture than the Southwest monsoon.

Fluctuations in the monsoon may present themselves in various ways, for example, as early or late onset or retreat of the monsoon or prolonged phases of extreme weather within the monsoon season such as heat waves and droughts or extreme precipitation and flooding. There can be significant variability in the spatial distributions and intensity of Indian monsoon rainfall, both within the monsoon season (intra-seasonal variability) and from year-to-year (inter-annual variability), which will influence seasonal crop yields. This variability along with observed and future trends in the monsoon are discussed in Appendix 6.

A deficit summer monsoon (drought) generally leads to a reduction in food grain yield particularly for Kharif crops but also for Rabi crops which depend on monsoon rain for irrigation (Prasanna 2014). Excess monsoons often result in higher crop yields nation-wide, although spells of very heavy rainfall can damage Kharif crops, and also impact Rabi crops if the soil remains waterlogged, with a negative impact regionally on crop yields (Revadekar & Preethi., 2012). “Average” monsoons can also result in reduced crop yields due to periods of extreme drought or rain/floods.

Monsoon variability arises due to complex nonlinear feedback among land, atmosphere and ocean systems, some of which are yet not fully understood (Saha et al., 2016). It is well acknowledged that the “climate driver” El Niño - Southern Oscillation (ENSO, Trenberth 1997) has a major influence on weather and climate around the globe (Lloyd’s, 2016), especially in the tropics, including the Indian monsoon. Based on a study mapping time series of historical anomalies of the all-Indian summer monsoon rainfall (ISMR) against ENSO years, over the period 1871-2015, 19 major flood years and 26 major drought years have been identified with ISMR anomalies one standard deviation above or below the long-term mean. During this period, while in ENSO neutral years, the chance of the monsoon ending in a major drought is calculated to be 13%, this possibility increases to 47 % in El Niño years (Table 5). No such signal is seen for major floods, as seen in the table below. Note that most severe droughts are associated with an El Niño event. The impact of ENSO on crop yields via its influence on the Indian climate is explored in Section 4. Other drivers of monsoon variability, along with their potential to be used as predictors for crop yields in the coming season, are discussed in Appendix 6.

Table 5: Impact of ENSO on Indian monsoon (1871-2015)

ENSO Phase	Major Droughts	Major Floods
All years	18%	13%
Neutral	13%	12%
El Niño	47%	0%
La Niña	0%	9%

Source: Lloyd’s - Risk Management Solutions, Inc., 2017 based on data from data from the Indian Institute of Tropical Meteorology, 2017

2.3 Impact of extreme events on crop yields in India

Tropical cyclones

The Indian coast is subject to frequent tropical cyclones which form over both the Bay of Bengal (impacting the eastern coast of India) and the Arabian Sea (impacting the western coast of India). Storms can cause significant damage to crop in coastal areas due to high winds, precipitation-driven flooding and also coastal flooding and sea water incursion due to the low-lying nature of most of India's coastline. For example, the 1999 Orissa super cyclone severely damaged crops, particularly rice and sugar cane, in the state of Odisha (formerly Orissa). Again in Odisha, but in 2013, cyclone Phailin destroyed crops worth USD 4 billion (Neubert and Smith, 2015).

There are two peak periods of tropical cyclone activity in India: pre-monsoon (May to June) and post-monsoon (October-December) when sea surface temperatures are highest. Cyclone activity is typically higher during the post monsoon period coinciding with the later stages of the Kharif season and the start of the Rabi crop period.

The impacts of cyclones are greatest during the Kharif harvest period, because the crops cannot recover from physical damage that may occur.

Extreme temperatures

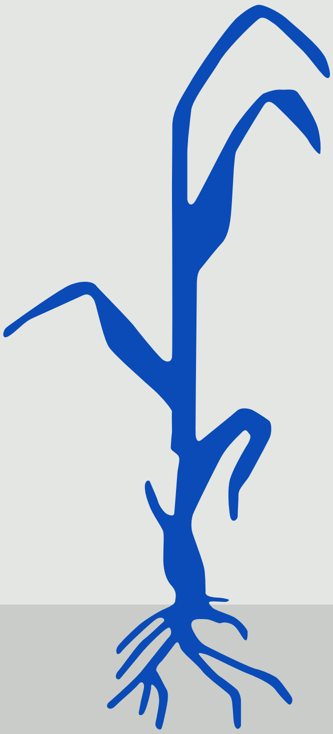
Crops can be severely damaged by extreme hot or cold temperatures, although the impact differs among crop species and the stage of plant development. Extreme hot or cold events typically occur outside of the monsoon seasons and thus have more impact on Rabi crops than Kharif crops. Frost and cold spells during winter months typically occur in the north-western plains of India. Heat waves and extreme high temperatures typically occur just before the monsoon arrives in March/April.

Unseasonal rain and hailstorms

Hailstorms and unseasonal rain can cause severe localised damage to crops across many parts of India (e.g. the February 2018 hailstorm in Maharashtra). Unseasonal weather often occurs pre-monsoon during the hottest part of the year (March to May), just before the Rabi harvest.

Further details about these extreme events and their impact on crops yields are provided in Appendix 6.

Crop risk modelling



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3. Crop risk modelling

Historically crop insurance loss expectations have been modelled using empirical models, relying on historical loss data and/or crop yield and/or weather data from past years. Loss distributions and extreme loss events are extrapolated from the historical observations using statistical distributions.

Crops have some peculiarities that need to be considered. For conventional property catastrophe risk modelling it is important to evaluate the frequency and severity of large events, and for some perils, also the attritional annual impact of events (such as severe convective storms). For crops, it is imperative to consider the attritional impact of many smaller adverse events, as well as the frequency and severity of large events and also account for the timing of each event. Plant vulnerability not only depends on the intensity of the stress but also on the stage of the crop's growth cycle (phenology), which in turns depends on the planting date, the selected variety, the local weather and soil conditions.

There is huge variability in historical crop yields in India (Figure 7, p24). As discussed in Section 1.2 (Drivers of Crop Yield Variability), crop yields are dependent on many, often interacting, factors (Figure 6, p23) including management practices (such as choice of seed, use of pesticides and fertiliser) and weather variables (such as rainfall, maximum and minimum temperatures). Long-term yield trends are driven by enhanced managerial practices including use of new genetics and fertilisers.

However year-to-year variability in crop yields is largely driven by weather (Petr, 1991; Fageria, 1992) as a sequence of attritional events over the growing season and/or extreme events such as a tropical cyclone. Weather also has a major impact on pests and disease outburst which can in turn cause damage to crops.

Given the importance of weather for crop yields and the different time scales of climate variability (Figure 15, p50), to model reasonable crop loss expectations, long-term historical records, considering climate trends, are required to capture weather and crop yield variability today, both temporally and spatially.

With limited historical yield records available to capture the impact of climate variability, crop models can be used to extend the historical record by modelling agricultural production as a function of weather and soil conditions as well as crop management over a longer timescale. Methodologies for assessing the biophysical effects of climate on crop yields include statistical models (e.g., Schlenker et al., 2006; Lobell and Burke, 2010) and process-based models that simulate crop growth as well as soil water and nitrogen balances driven by daily climate data, relying on known relationships of the biophysical process of specific plants (e.g., Keating et al., 2003; Brisson et al., 2003; Jones et al., 2003; van Ittersum and Donatelli, 2003; Challinor et al., 2004).

This section discusses the shortcomings of historical data available for crop risk modelling and explores how crop yield models can be combined with historical and probabilistic simulated weather data to create different classes of crop risk models for (re)insurance purposes (see Table 6).

Table 6: Classes of crop insurance risk models and typical length of data records in India

Crop risk modelling approach	Weather data	Crop Yield data	Insured Crop Loss data
Historical Data	Observed (40-50 years)	Observed (2-10+ years)	Observed (5-10 years)
Historical Crop Risk Modelling	Observed (40-50 years)	Historical modelled yields, derived from crop models using 40-50 years of historical weather data	Historical modelled losses, derived from historical modelled yield data by applying index formula
Probabilistic Crop Risk Modelling	Simulated (1000+ years)	Simulated yields, derived from crop models using 1,000+ years of simulated weather data	Simulated losses, derived from simulated yield data by applying index formula

Source: Lloyd's - Risk Management Solutions, Inc., 2017.

3.1 Limitations of historical records

One of the challenges of risk modelling using only historical observations is to determine whether the loss distribution derived from the observations provides a good understanding of the potential severity and frequency of losses that are either not present in the historical data or present but without perspective of their repeated frequency. Indian historical loss and crop yield data is limited and surrounded by many data quality issues which can make it insufficient for robust pricing. Some of the main data quality issues include:

- Short historical records. Historical crop yield and insurance data is typically quite limited. With new insurers entering the crop market, the length of historical loss cost information can be as little as 2 years to more than 10 years for more established insurers such as AIC. Loss data is typically provided per district, but is not always broken down per crop type. Crop yield data is available from a central database from 1998 onwards, at district level (http://www.dacnet.nic.in/). However, the number of years of data available varies by crop and district, and the quality of the data reported is also challenging. As specified in the operational guidelines, state governments should ideally provide 10 years of historical yield data to insurance companies for premium and indemnity calculations at the insured unit area but this is not always available. Loss benchmarks such as the annual average loss can vary depending on the chosen historical averaging period. For weather-based insurance indices schemes, ground station weather data typically extends back more than 20 years but this data is unlikely to capture the range of extreme events possible over all areas for which crops need to be insured because the stations are generally too far-spaced and do not capture micro regional variation (precipitation in particular). Gridded weather data that have a fine spatial resolution can alleviate this issue.
- Data non-stationarity. Insured crop losses experienced ten years ago would be very different if the same events occurred today, as a result of a combination of factors such as changes to the insurance financial terms and conditions, changes in exposures, improvements in crop management and technology (better methods, more resistant crops), changes in Indian administrative regions (such as states and/or districts) for which crop yield data is typically reported, changes in the season classification for a given crop during the reporting period, potential changes in the Indian weather due to climate change and how crop varieties will respond to changing weather. Thus, historical data must be interpreted, considering all possible trends, and used with caution to ensure a consistent robust data record is used for insurance pricing. Figure 7 (p24) provides an example of changes in crop yields over the past 25 years. Changes have generally amplified over the past decade.
- Data relevance: As the crop insurance schemes improve, the insured unit area decreases and at present the unit area is at village (Panchayat) level[k]. However, crop yield time series are typically available at district resolution and at village level for short periods of time. Thus, to accurately assess and price crop risk, at this level, finer resolution data is required, which presently does not exist across all of India. While longer records of historical weather data exist, longer records may not always be co-located within an insured unit area. Some weather stations may have been recently set up within an insured unit and thus long historical records may not always exist and a station further away may be used for historical weather information.
- Data quality. Historical crop yield data can often have missing data over periods of time, questionable data points (such as integers or extreme outliers) and other data irregularities. For example, for some crops/districts, the season classification associated with yield records, has changed during the reporting period. Thus, the data must be carefully screened before being used for risk assessment. Similar problems can be found in weather data but to a smaller extent.

[k] Village panchayat is either a village with a population greater than 500 people, or a group of 2-3 neighbouring smaller villages. http://www.agriinfo.in/default.aspx?page=topic&superid=7&topicid=619

3.2 Crop models

An alternative method to investigate loss distributions given the lack of long and reliable historical records of crop yields is to use crop models to simulate crop yields given weather data and relevant current crop information, including their characteristics, phenology, crop season and managerial practices such as use of fertilisation, irrigation and pesticides. Crop models play an important role in farming and food supply decisions at strategic, tactical and forecasting levels. The wealth of scientific research advancing crop development and yield modelling can also be applied to (re)insurance risk modelling.

There are three main types of crop models that can be distinguished:

Process-based crop models	Statistical crop models	Hybrid crop models
Process-based crop modelling has been used by the agriculture research community for many years to understand how weather affect specific crop behaviours, under different crop management scenarios, soil types/profiles and topography, to improve crop yield and recently to provide crop forecasting for different lead times. They are also used to model possible yields generated by new crops not yet fully tested in the field. These models include mathematical descriptions of most of the plant growth and development processes as they are currently known in the field of plant sciences (Hoogenboom, 2000). Process-based crop models require many detailed inputs (number variables and resolution) and a complex calibration procedure and are commonly used at very fine resolution (i.e. field resolution), per crop type. Although each physical crop model is based on the same fundamental equations, modifications to these equations are, in some cases, necessary after calibration to improve their adequacy. Process-based models are used at a specific location, although some have been modified to run over multiple locations simultaneously. However, these models still require an amount of detailed information that may not be available or too costly to gather in most cases. An up-scaling methodology is required to assess the results at a broader scale.	Statistical crop models use the correlative relationship between agro-climatic variables (which best, statistically, explain observed historical yield variability) and final historical yields to make yield or loss estimates typically at a coarser spatial resolution such as district or state level. These simpler models can be applied to much larger geographical areas at country or global scales. Although statistical crop models do not explicitly capture all drivers of crop yield variability, they are included implicitly via the modelling process. More advanced statistical models use different sets of predictors per growth period (e.g. planting, flowering and harvest) to differentiate the impact on final crop yields depending on the timing of the event. Some models may first de-trend weather data and crop yields before modelling crop yield variability to remove the long-term impacts of climate change and managerial practices and then model the residual year-to-year yield variability and retrend this to reflect yield variability based on today's management practices and climate.	Hybrid crop models use components of both process-based and statistical crop models, aiming to integrate the advantages of both methodologies. Process-based models or statistical crop yield models have their own challenges and benefits. Valuable information is obtained and both approaches are complementary. The advantage of statistical models is both in the calibration process and availability of suitable data, and in the limited computing power required. In contrast, process-based models are generally complex to calibrate and require many parameters to be estimated at very fine resolution, as well as more computing power.

3.3 Application of crop models to re(insurance) crop risk modelling

Crop models can be incorporated in (re)insurance risk models to provide additional insight into crop insurance loss distributions given the lack of long and reliable historical records. Requirements to develop an Indian crop yield model for (re)insurance risk modelling purposes include good geographic coverage as well as simulating thousands of years of possible yield outcomes. To achieve this, the strengths and weaknesses of crop yield modelling approaches, along with the availability and quality of data, at the right spatial resolution, are considered. It is not usually possible to run process-based models across the whole of India as the detailed data required for the many input parameters is not generally available. The advantage of statistical models is that they can be run for many thousands of years at relatively fine spatial resolution over an entire country such as India, with limited computing power required, making them suitable for (re)insurance modelling applications. Indian probabilistic crop risk models have recently been developed and, as seen in other insurance markets, will increase in complexity over time as more data becomes available as the market matures.

Crop models can be run with either (i) historical weather data and/or (ii) many thousands of years of simulated weather data providing insight into scenarios not experienced in the past.

Crop risk models driven by historical weather data

Historical weather data (after consideration of potential impact of climate change) can be applied to crop models to create records of historical modelled or 'rebased' synthetic crop yields that represent the yields based on today's agricultural technology and land management, if past years' weather occurred today. From this, historical insured crop losses can be calculated by applying the PMFBY crop yield index formula to modelled yield data. In India, nation-wide weather data can be applied to crop yield models going back 40-50 years to provide deeper insight into crop loss variability, which can be evaluated alongside the shorter historical observed yield and loss records.

Crop risk models driven by probabilistic weather data

The concepts of probabilistic risk assessments are not new to the insurance industry (Mitchell-Wallace et al., 2017). Probabilistic models, providing simulations of thousands of years, have been widely used in the property catastrophe insurance industry for over 30 years. The building blocks of the latest generation of these models are now being applied to the agricultural sector making use of existing digitised data, technology and science. Ancillary products, such as insurance exposure databases, also provide valuable insight into the underlying exposures, especially important in emerging markets where reliable exposure information is not always available. Probabilistic models, once understood by their users on how assumptions were made and validations presented, can support decision-making in agriculture insurance pricing risk, from risk assessment and pricing to portfolio management and risk transfer. They also support agriculture (re)insurance underwriters in fully understanding the underlying risk to make the best possible risk transfer and investment decisions.

As mentioned earlier, agricultural risks must consider both the timing and the cumulative impact of each potential adverse peril (typically weather event) that may affect a crop during its growth cycle (simulated via crop yield models) until harvesting. With these considerations incorporated, probabilistic crop models provide a mechanism to integrate and synthesise all the relevant science and data into algorithms, to expand 20+ years of past historical experience to thousands of years of modelled data, and thus better understand the potential pathways to loss and assess the probability of extreme loss events occurrence. These models consist of a suite of components (individual models) that create thousands of plausible realisations of next year's crop yield, based on today's climate, agricultural technology and land management practices, by applying probabilistically modelled daily weather data (e.g., precipitation, minimum and maximum temperature) to crop yield models. Both weather and crop yield models are rigorously calibrated and validated with the best available historical de-trended data. The impact of simulated daily weather data on annual Kharif and Rabi crop yields are the analogue to a stochastic event set in cat modelling. For each simulated year, current insurance terms can be applied to estimate risk metrics such as annual average losses (AAL) and annual probabilities of exceeding losses (Exceedance Probability Curve) for an entire portfolio or parts thereof.

3.4 Benefits of crop risk modelling

Use of crop models that can explain behaviours of crops subject to external events is one step towards simulating crop behaviours under different scenarios for which likelihood of occurrence are modelled as well (for example using weather generators or simulating large scale weather patterns). Thus, carefully calibrated and validated historical or probabilistic crop risk models can provide highly valuable data alongside historical records and be successfully applied to agricultural (re)insurance modelling.

The main benefit of historical and probabilistic crop risk models is to extend the historical record and provide greater insight into crop loss variability and distributions over longer timescales, representative of today's climate and land management practices, by means of use of historical climate data and simulations of climate scenarios. These models can be run at fine spatial resolution across the whole of India, for most crop types, to provide a comprehensive view of the agriculture risk and inform reinsurance purchasing decisions as well as loss cost estimation for primary insurance underwriting. Additional potential functionalities of crop risk models could also include:

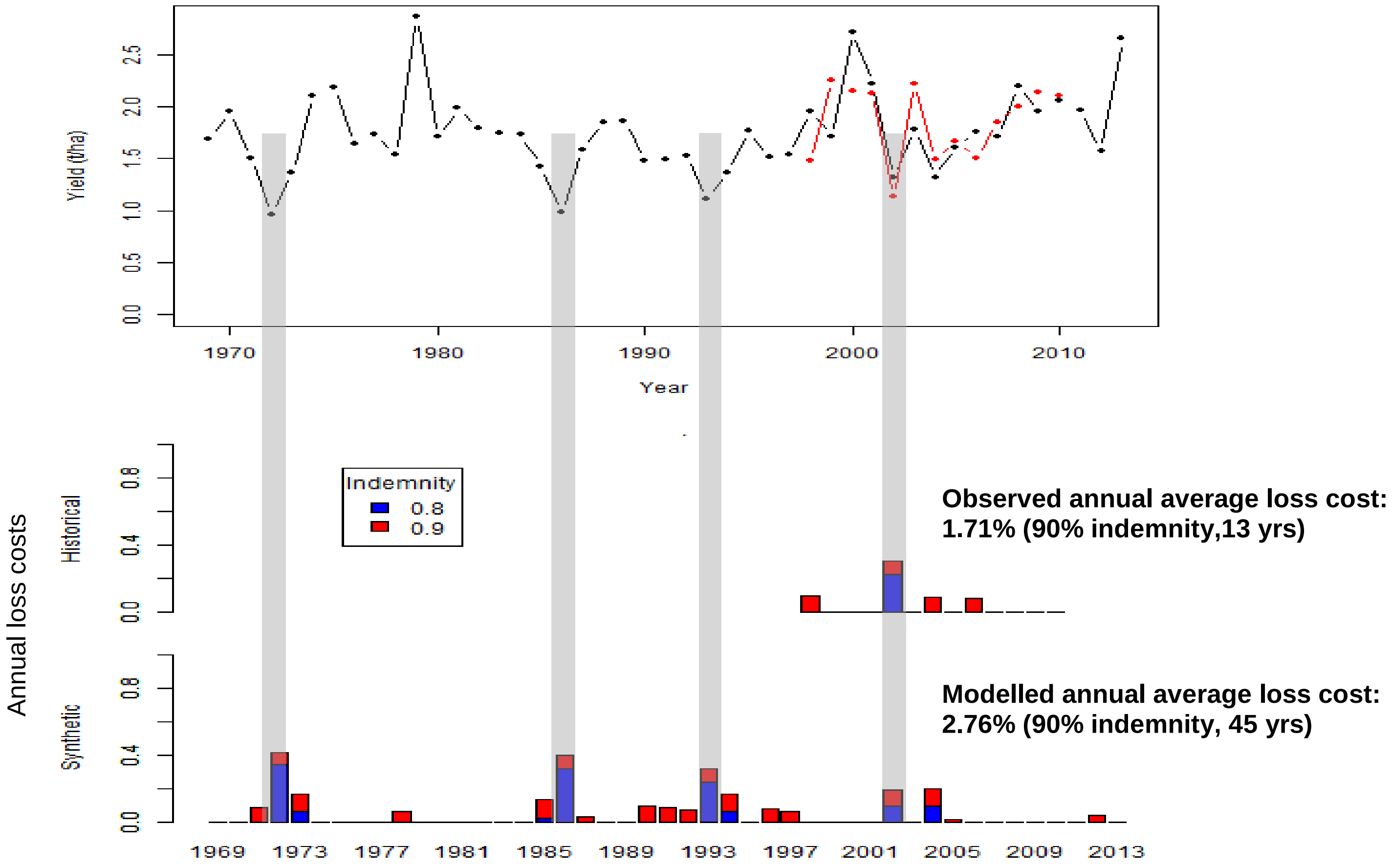
- In-season loss prediction (predictive modelling) by applying forecasted weather data to crop yield models
- Predicting the impact of different managerial practices (such as irrigation) on crop yields/losses
- Estimating crop yield/loss behaviour under different climate scenarios (e.g. El Niño phases)
- Estimating climate change impacts on crop yield/loss behaviour under different IPPC 's Representative Concentration Pathways (RCPs)

To schematically demonstrate the benefits of using historical modelled over historical observed yield data, crop yields and PMFBY loss costs are compared in Figure 17 for Kharif rice in Uttar-Pradesh between 13 years of historical yield records (1998-2010) and 45 years of historical modelled crop yields (1969-2013). For this analysis, historical yield data is obtained from DACNET (Directorate of Economics and Statistics, Indian Ministry of Agriculture). As mentioned earlier, the historical modelled crop yields represent the yields based on today's agricultural technology and land management, if past years' weather (de-trended) occurred today. In this example, the PMFBY loss costs are derived from de-trended observed and modelled historical crop yields using the crop yield index formula (described in Box 2, p28), where for each year, the observed/modelled yield value is used as the "actual yield ($yield_{yr}$)" and the "average yield" is calculated from the observed/modelled yield time series as per the definition in the scheme guidelines.

The top figure, comparing observed (red) and modelled (black) rice yields, shows that using a crop model to extend the time series of yields to 45 years gives context of the regularity of extremely low yield years (highlighted by the grey bars). The lower figure shows historical PMFBY loss costs, for the observed and modelled yields, based on 80% (blue) and 90% (red) indemnity levels. Losses are triggered more often with the higher 90% indemnity value as expected based on the PMFBY index formula (Box 2). Because loss costs are not linearly related to the changes in yields, the impact on the losses could be larger than what is observed. Comparing the modelled and observed annual average loss costs using a 90% indemnity, the modelled loss cost (2.76%) based on 45 years is more than 60% higher than the observed annual average loss cost (1.71%) based on 13 years. Differences would also be expected comparing observed and historical modelled loss costs against probabilistic modelled loss costs based on thousands of years of simulated weather data. Extending the historical record may not always result in higher losses as it will depend on the weather variability and crop type for the region analysed. Grey bars highlight example years with very low yields.

There are some discrepancies between the observed (red) and modelled (black) yields. Crop risk models are not expected to provide a perfect match to historical observations as by design of their intended use, they do not explicitly model all physical process that can drive historical crop yield variability. However these results demonstrate their value in providing greater insight into crop yield and loss variability.

Figure 17: Illustration of the annual loss cost (loss/sum insured) and yield variability for Kharif rice in Uttar-Pradesh comparing observed yield data (red) to historical expected modelled yield (black)



Source: Risk Management Solutions, Inc., 2017 based on data from DAC-NET, 2014 and RMS India Agriculture Model

The example in Figure 17 demonstrates that historical modelled yields based on weather data of 45 or more years can better capture the distribution of frequency and intensity of losses compared to 10-15 years of observed yields. A still better perspective can be appreciated with simulations of weather phenomena representing thousands of years of variability providing insight into the true frequency of recent historical events as well as simulating realistic adverse weather events that have not occurred in the past. Simulating thousands of years of yield and loss behaviour using probabilistic crop risk models provides the foundations for more robust tail risk assessment. The advantages of using thousands of years of simulated yield and loss data compared to 40-50 years of historical modelled data are highlighted in the next section presenting crop risk model results.

Requirements for a probabilistic Indian crop risk model

A probabilistic crop model for the Indian crop insurance market must reflect the way crop insurance is administered and written in India. Thus, the following capabilities are required:

- Major drivers of crop yield variability
- Nation-wide coverage for most perils
- Account for insurance clusters
- Attritional and catastrophe losses
- The impact of irrigation
- Separate models of different crops for Kharif and Rabi seasons
- Model both PMFBY and WBCIS schemes
- Historical and probabilistic simulated loss models
- Exposure management functionality

Under the current status of the Indian crop (re)insurance market, when exposure at risk is not yet known at the time of reinsurance renewals, and there is limited historical data, crop risk models can provide value for sensitivity testing to better understand and account for exposure uncertainty at the time of treaty underwriting, as well as portfolio management decisions once exposures are confirmed.

Note that over the past 25 years, probabilistic NatCat models have evolved with the needs from the (re)insurance industry and are used today with greater confidence throughout the risk management chain. This process is now beginning for the agricultural sector and over time probabilistic modelling should also become an integrated component of crop risk management as data and models improve and the market gains greater confidence in their capabilities.

A study of Indian crop risk

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4. A study of Indian crop risk

The benefits of developing and using probabilistic risk models have been discussed in the previous section. Once calibrated and the assumptions understood by the user, they can then be used in agriculture to explore risk variability in many ways such as: spatially (state, regions, districts), between lines of business or in this case for distinctive crops and for different perspectives such as the annual average loss or low frequency, long return period losses, for example the 200-year loss, as well as for special climate modes (El Nino/La Nina/Neutral) or under climate change scenarios (RCP's).

To illustrate the benefits of crop risk modelling and provide an overview of crop risk in India, the RMS India Agriculture Model is used to model the 2016 PMFBY crop yield index scheme on a hypothetical nation-wide portfolio.

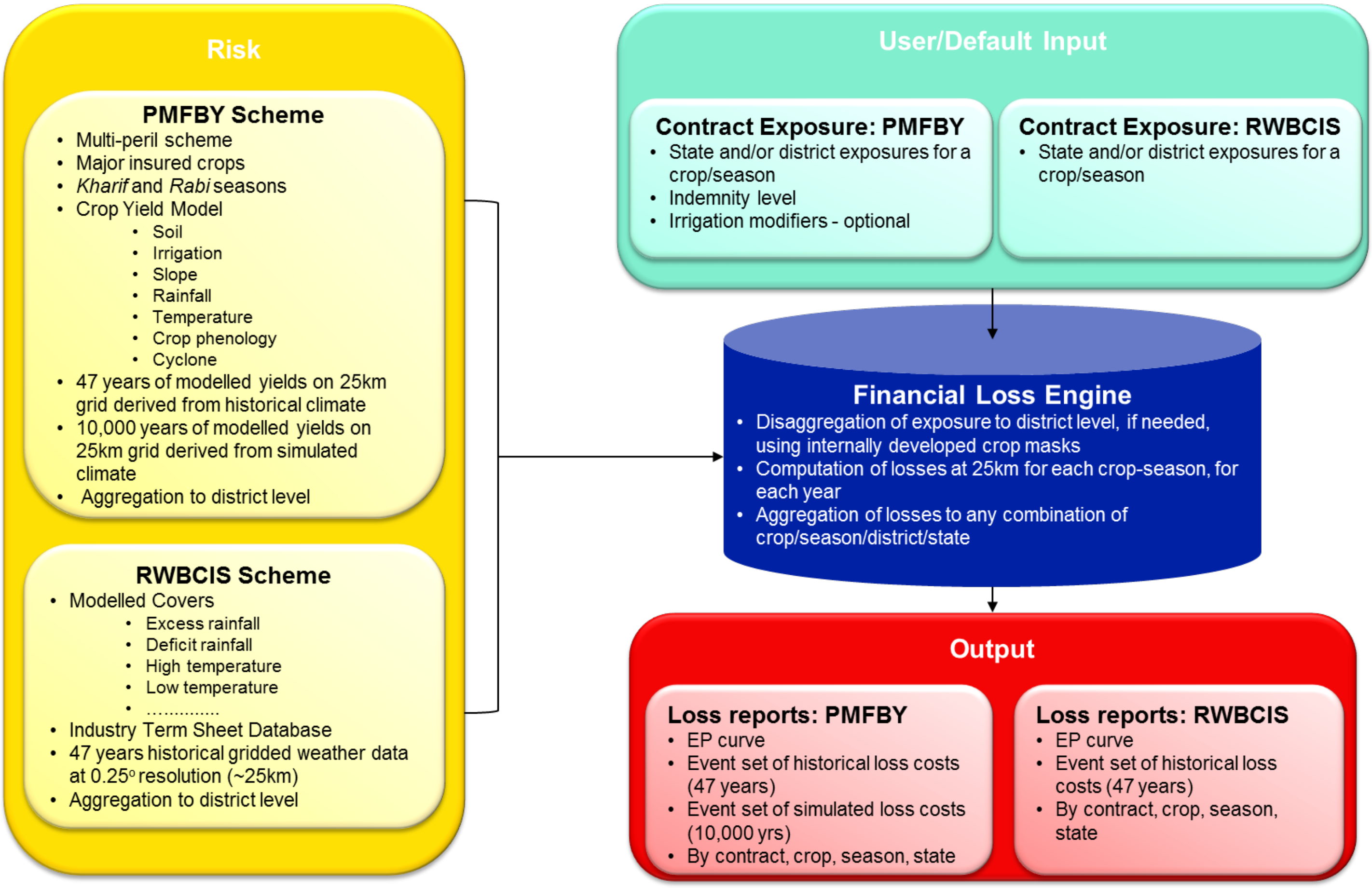
4.1 RMS India Agriculture Model

The RMS India Agriculture Model is a probabilistic crop risk model developed for the (re)insurance market to help risk selection, model and price crop yield (PMFBY) and weather (RWBCIS) indices contracts at district resolution, providing historical and stochastic loss distributions. The RMS India Agriculture Model, run at 25km^2 resolution, was first released in November 2015, and covers all states within India, simulating 10,000 years of weather, crop yield and loss data (based on today's climate and agricultural land management practices) for Kharif and Rabi growing seasons for 13 of the major crops covered in PMFBY.

Over 70 different crop types are modelled via the RWBCIS component. The model has been calibrated and validated with district-level and nationwide yield and weather data to ensure temporal and spatial correlations are properly represented.

The RMS India Agriculture Model consists of separate analytical risk modules covering the PMFBY and RWBCIS schemes (Figure 18). Exposure is specified by scheme, crop, cropping-season (Kharif and Rabi), and geographical location (district or state). Exposure entered at the state level is disaggregated to the district level using the latest available information on crop planted areas. Irrigation details, if known, can also be entered. Otherwise the model will use the irrigation assumptions built into the model. Other drivers of crop yield production, such as crop variety, fertilisers use and other management practices are implicitly considered in the crop model calibration process. The two risk modules apply the appropriate index formula and simulate pure technical losses and their uncertainty on a 25km grid. The results are then aggregated to district-level using the latest available information on crop distribution (crop masks). Model output includes loss and loss cost EP curves with summary tables, annual (attritional) loss and loss costs per historical modelled (assuming present-day conditions) and simulated year, with historical scenarios including El Niño/La Niña years. Model results can be output at a range of resolutions (per state/crop/season or combined).

Figure 18: Key RMS India Agriculture Model components and interactions



Source: Risk Management Solutions, Inc., 2017

PMFBY Crop yield risk module

In the PMFBY risk module, RMS has developed crop yield models which can be applied to both (a) 47 years of historical de-trended weather and (b) a large ensemble (10,000 years) of simulated weather data, to generate crop yield time series from which losses are calculated. The model is based on a set of yearly events that consider the attritional impact of a range of adverse weather events, at daily resolution, per crop and season, to estimate the impact on crop yields and resulting insured losses (calculated using the index formula in PMFBY), on a 25km^2 grid, at the end of each growing season. The model results represent losses based on today's climate and agricultural practices.

Crop yield models are available for the following 16 combinations of 13 major crops commonly included in Kharif and/or Rabi crop insurance:

- **Kharif crops**: rice, arhar, bajra (pearl millet), maize, moong (green gram), urad (black gram), soybean, sugarcane, cotton
- **Rabi crops**: wheat, gram, mustard, rice, potato, moong (green gram), urad (black gram)

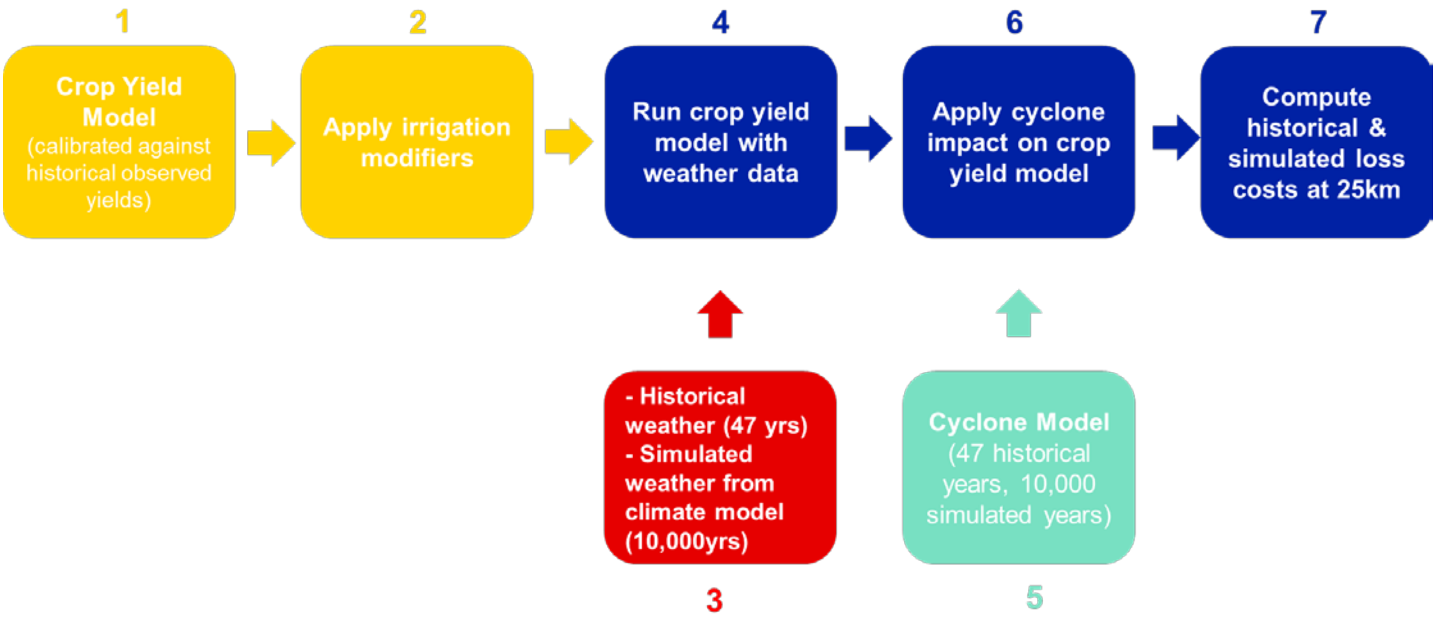
The PMFBY risk module comprises seven different, carefully calibrated, steps and components as summarised below and in Figure 19:

1. Develop crop yield models based on statistical regressions analyses of historical observed crop yields (after detrending) between 1980 to 2014 against agricultural weather indices (after detrending) that can impact crop yields at the different stages of the growing season and acting as proxies of major perils that can impact crop yields, given local soil conditions and levels of irrigations (captured via 15 different Indian agro-climate zones). Examples of weather variables include maximum and minimum temperature, rainfall, number of dry days and potential evapotranspiration. The model uses different sets of predictors for each crop type and different growing stage (planting, development, harvest) to differentiate the impact of the timing of the event on final crop yields.

RMS calibrated the crop yield models using historical observed yields from DACNET (Directorate of Economics and Statistics, DAC-FW).

2. Develop and apply irrigation modifiers: the crop yield model is calibrated to observed district irrigation levels. However modifiers have been developed to adjust this and estimate the impact of no (rain-fed) and full irrigation on crop yields. A user can either use the default assumptions or assign a crop/district as rain-fed or irrigated, if these details are known, or if they wish to explore the sensitivity around irrigation impacts (e.g. for risk selection).
3. Develop a climate hazard model: generate 10,000 years of simulated daily weather time-series at 0.25 degree (approximately 25 km) across all of India, using principal component analyses applied to 47 years of observed historical de-trended weather data. Convert the daily weather time series, for both the observed historical (47 years) and simulated (10,000 years) weather data, to crop specific weather-derived indices to feed into the crop yield models.
4. Run the crop yield model with the historical and simulated weather-derived indices from the climate hazard model
5. Develop a cyclone model, using historical cyclone characteristics and yield data, to simulate the impact of cyclones on Kharif crops for historical cyclones and for 10,000 years of simulated landfalling cyclones
6. Compute cyclone impacts on modelled crop yields (from step 4) for both historical and simulated cyclones
7. Calculate and use historical and simulated yield deviations to model loss and loss costs (ratios of loss to sum insured) on a 25km grid. The financial model calculates losses according to the PMFBY scheme considering the crop-district specific indemnity levels provided as part of the exposure information. The financial model then aggregates the losses and loss costs to district and state level, which are provided as model output.

Figure 19: Components of the RMS India Agriculture Model PMFBY Risk Module



Source: Risk Management Solutions, Inc., 2017

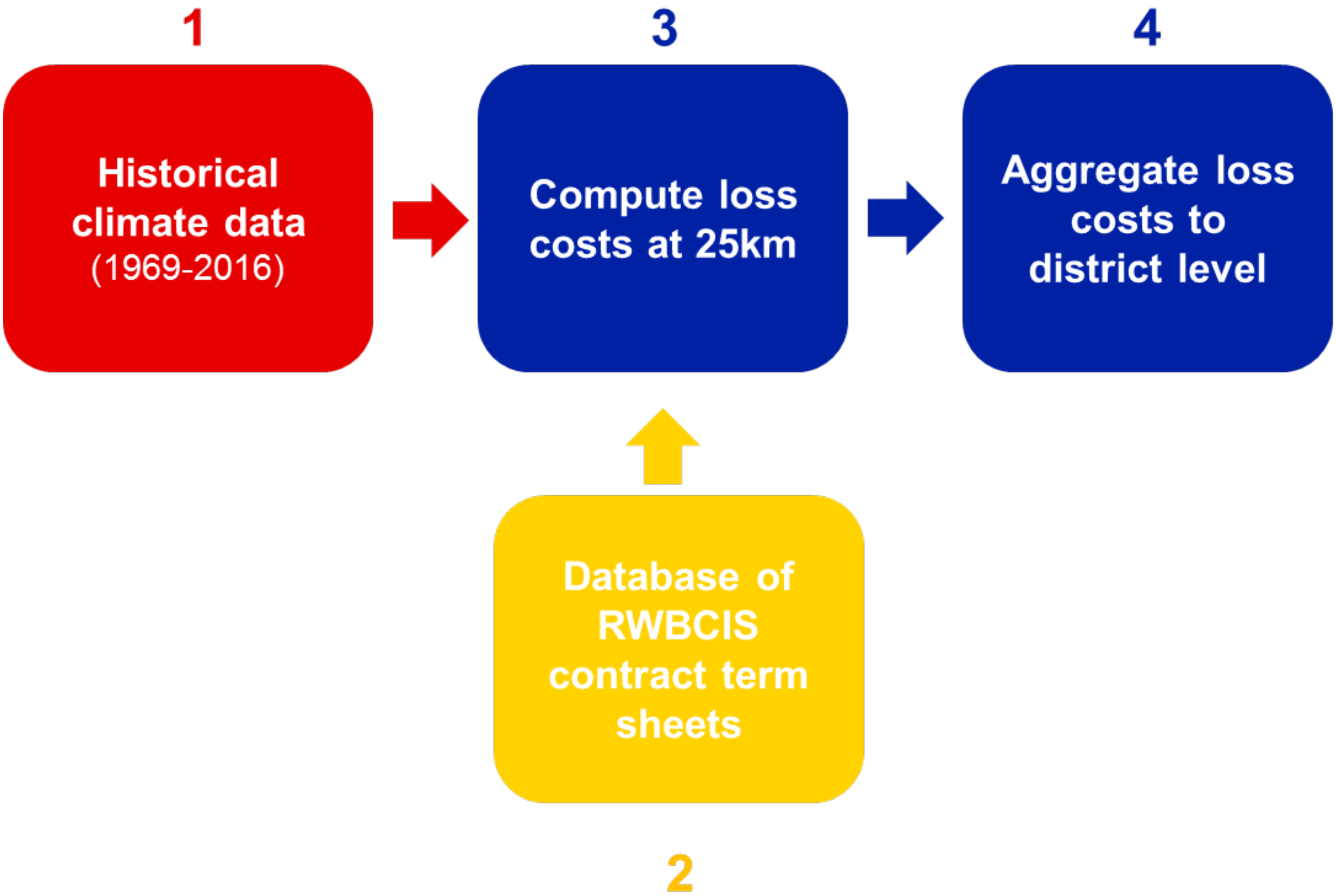
RWBCIS risk module

To provide a historical perspective on losses incurred under the RWBCIS scheme, RMS apply common cover weather-index based cover types to historical weather data (see Appendix 3 for examples). Current term sheets (approximately 1400) containing information on the type of covers prevalent for over 70 crop types have been digitised and combined with 47 years of historical weather data to determine historical indices and associated losses. The term sheets are regularly updated.

The RWBCIS modelling steps (Figure 20) are:

1. Detrending of historical climate data (1969–2016)
2. Collation of term sheets and cover types
3. Index calculation and payout calculation at 25 km
4. Aggregation to district and state using crop masks

Figure 20: Components of the RMS India Agriculture Model RWBCIS Risk Module



Source: Risk Management Solutions, Inc., 2017

4.2 PMFBY model results

The aim of this section is to provide insight into the capabilities of a crop risk model to simulate crop yields and resulting insured losses for the PMBFY scheme in India and demonstrate the volatility of crop yield risk within India for some of the major insured crop types covering the two main growing seasons. Drivers of loss behaviour for a hypothetical portfolio, described below, are investigated both spatially and as well as by crop type. Results are presented for both historical modelled (47 years) and simulated (10,000 years) analyses to demonstrate the advantages of probabilistic modelling. Historical modelled losses are also analysed to show the historical volatility and scenario tests such as the impact of El Niño and La Niña events on crop losses. Maximum insight into crop risk is obtained by considering both historical modelled and simulated results alongside reported loss data.

The following loss metrics are presented in this section:

- Annual Average Loss (AAL): average of loss of all modelled events (historical or simulated event set)
- Annual Average Loss Cost (LC): AAL / sums insured
- Return Period (RP) Loss Cost: return period losses* / sums insured

(*return period loss describes how many years might pass between times when a certain loss might be exceeded. For example, a 0.5% probability of exceeding a loss amount in a year corresponds to a probability of exceeding that loss once every 200 years, or “a 200-year return period loss”.)

The model output represents the pure technical loss based on applying the PMFBY index calculation (performed at 25km resolution) to dis-aggregated exposure information. It does not include uncertainty loadings or any additional loadings that are applied by insurance companies when determining their overall rate. The model results presented in the report are aggregated to district, state and nation-wide resolutions. The results presented here are for a hypothetical nationwide portfolio for 6 major crops (rice, wheat, sugar cane, soybean, cotton & potato), assuming 100% insurance within the districts included in the 2016/17 Kharif and Rabi clusters. As such, the results do not represent any specific insurance portfolio which could experience different results.

Also, actual losses from events may differ from the results of simulation analyses[l].

Exposure summary

A nation-wide hypothetical portfolio, estimating economic exposures, is used for this study. This nation-wide hypothetical portfolio:

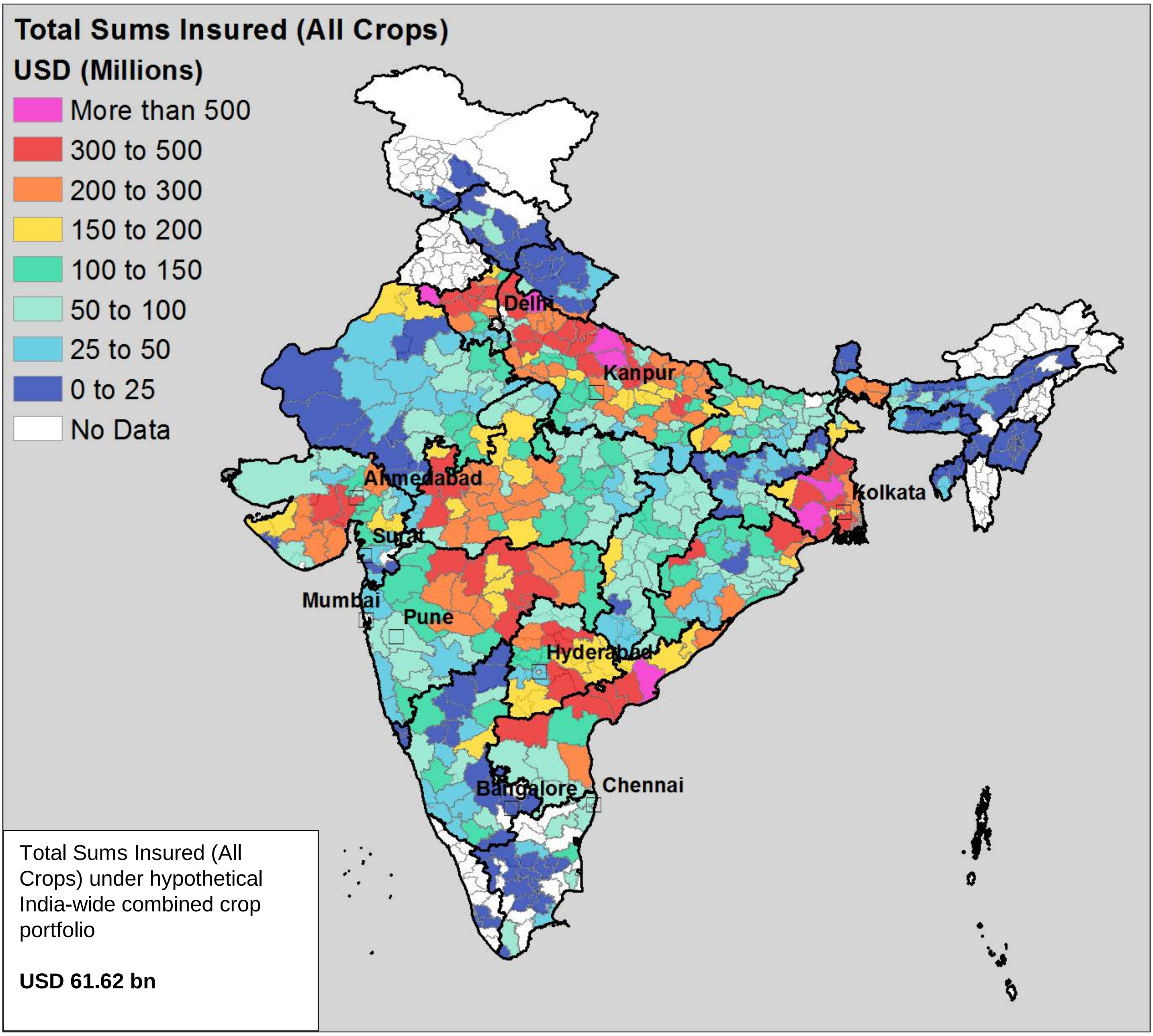
- Includes exposure information that is created at district-level, per crop type, based on the 2016/17 PMFBY policy information available on the agri-insurance portal,
- Includes states and districts that have implemented PMFBY in 2016/17,
- assumes 100% insurance within the total planted area per district per crop,
- covers six key crops: rice (Kharif & Rabi), wheat, sugar cane, soybean, cotton and potato,
- includes sums insured that are derived by multiplying the sums insured per hectare per crop per district for the 2016/17 season with the total planted area per crop per district (from data.gov.in) and
- includes indemnity levels that are based on the 2016/17 terms per district and per crop.

The weather-based RWBCIS scheme is not included in this study. The sums insured were derived by multiplying the Kharif 2016 and Rabi 2016/17 values of sums insured per hectare per crop per district (from the national crop insurance portal http://agri-insurance.gov.in) with statistics about the planted area per crop per district (https://data.gov.in/). Indemnity levels per crop and district reflect the 2016 terms obtained from the agri-insurance portal. Also, a distinction is made between rain-fed and irrigated crops/districts if this information is provided in the agri-insurance portal. If irrigation information is not available, the model will use the spatial distribution of irrigation built into the model.

[l] In view of the hypothetical nature of the modelled portfolio Lloyd's and RMS disclaims any and all liability.

Details of the exposure distribution of the hypothetical nation-wide portfolio are summarised in the next few exhibits. Figure 21 demonstrates the distributions of sums insured at district level. This information, separated by crop type, along with the relevant 2016 indemnity levels and any irrigation information available, is entered into the RMS India Agriculture Model and run with both the probabilistic simulated and historical climate datasets.

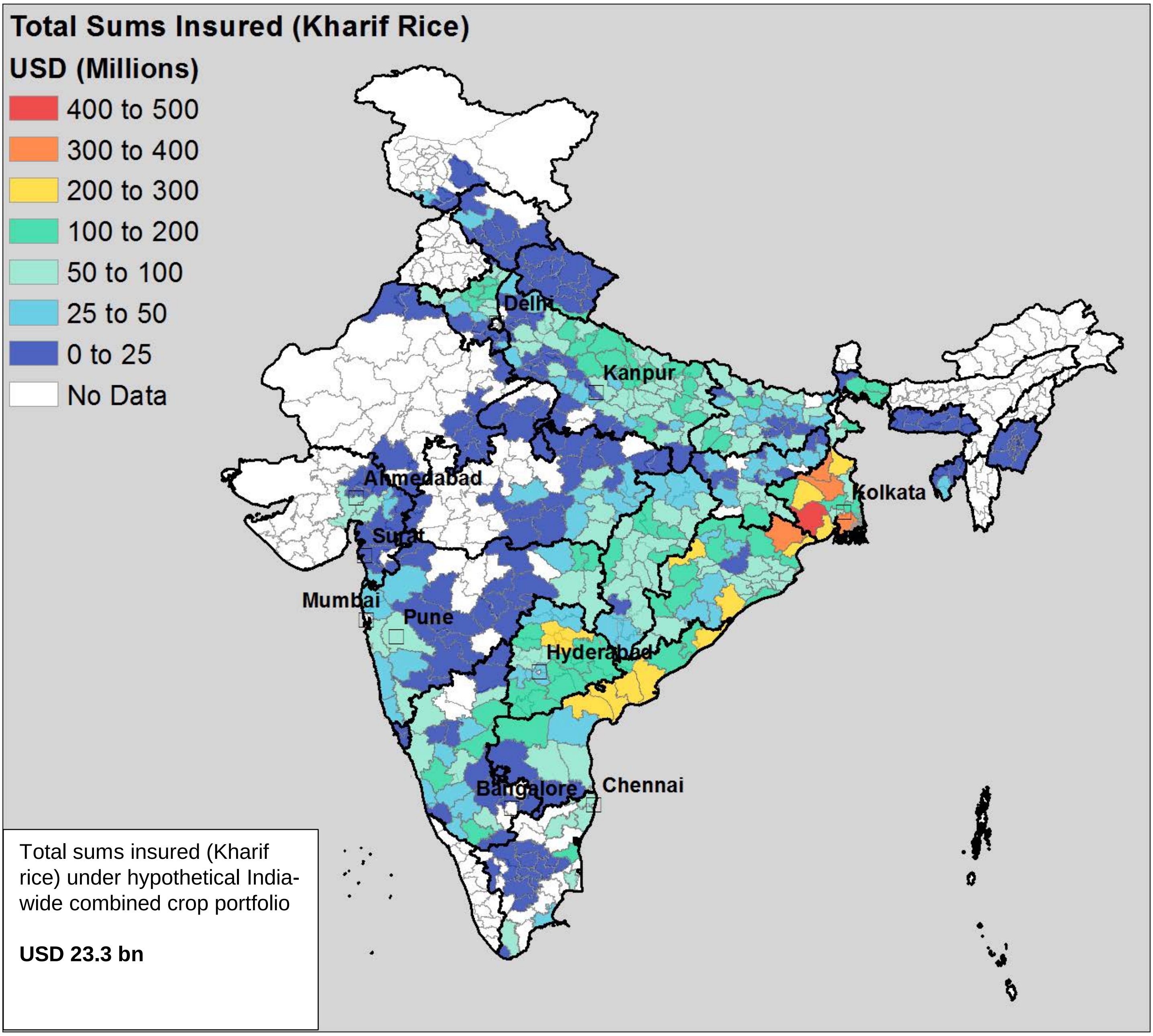
Figure 21: District-level sums insured of hypothetical India-wide combined crop portfolio[m]



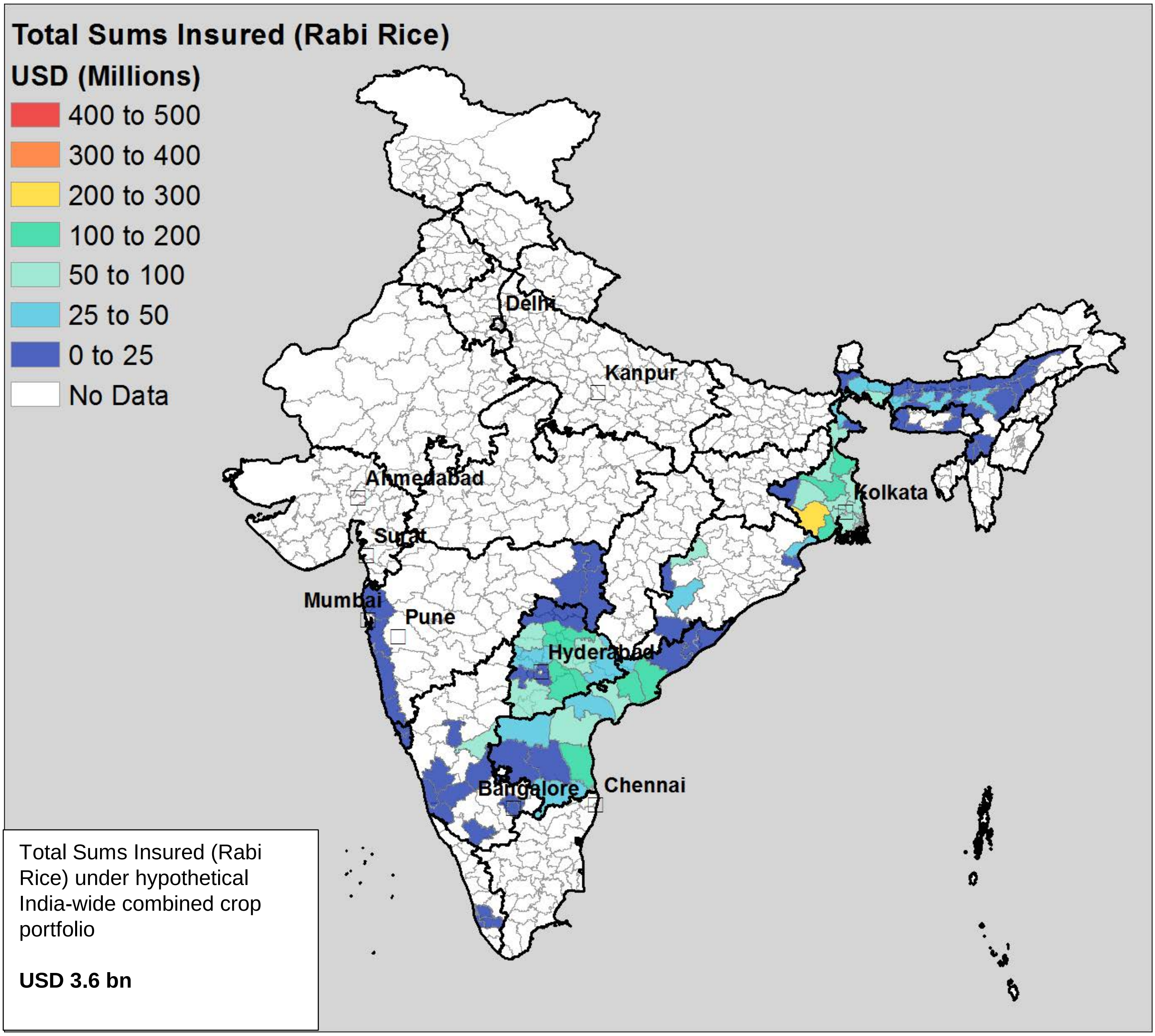
Source: Risk Management Solutions, Inc., 2017 See Figure 2, p19, for map of India's states.

Figure 22 provides an example of the distribution of individual crops such as Kharif and Rabi rice within the portfolio revealing significant differences in the distribution of exposures between the two growing seasons. As demonstrated by Figure 22 and also the breakdown of sums insured between crop type and state (Figure 23), crops can have different spatial distributions reflecting the agro-climatic zones where a specific crop best prospers. The exposure distributions also reflect differences in sums insured per hectare which vary per crop and also regionally. In Figure 22, West Bengal, the top producing rice state (Table 1, p21), has high sums insured compared to the other rice states. No exposure is included in the portfolio for Punjab (3rd biggest rice state) since the state government did not implement PMFBY in 2016/17. Figure 23 reveals large variability in crop distributions between states. Based on the seven crop/season types included in the portfolio, some states only include one crop whilst others can include as many as six crops. Thus more localised portfolios covering only a few states are likely to have quite different exposures distributions compared to a nation-wide portfolio. In reality each state typically has a greater number of crop types than included in the hypothetical portfolio. The total sum insured under the hypothetical India-wide combine crop portfolio is USD 61.62 billion.

Figure 22: District-level sums insured of (a) Kharif rice and (b) Rabi rice in hypothetical India-wide portfolio

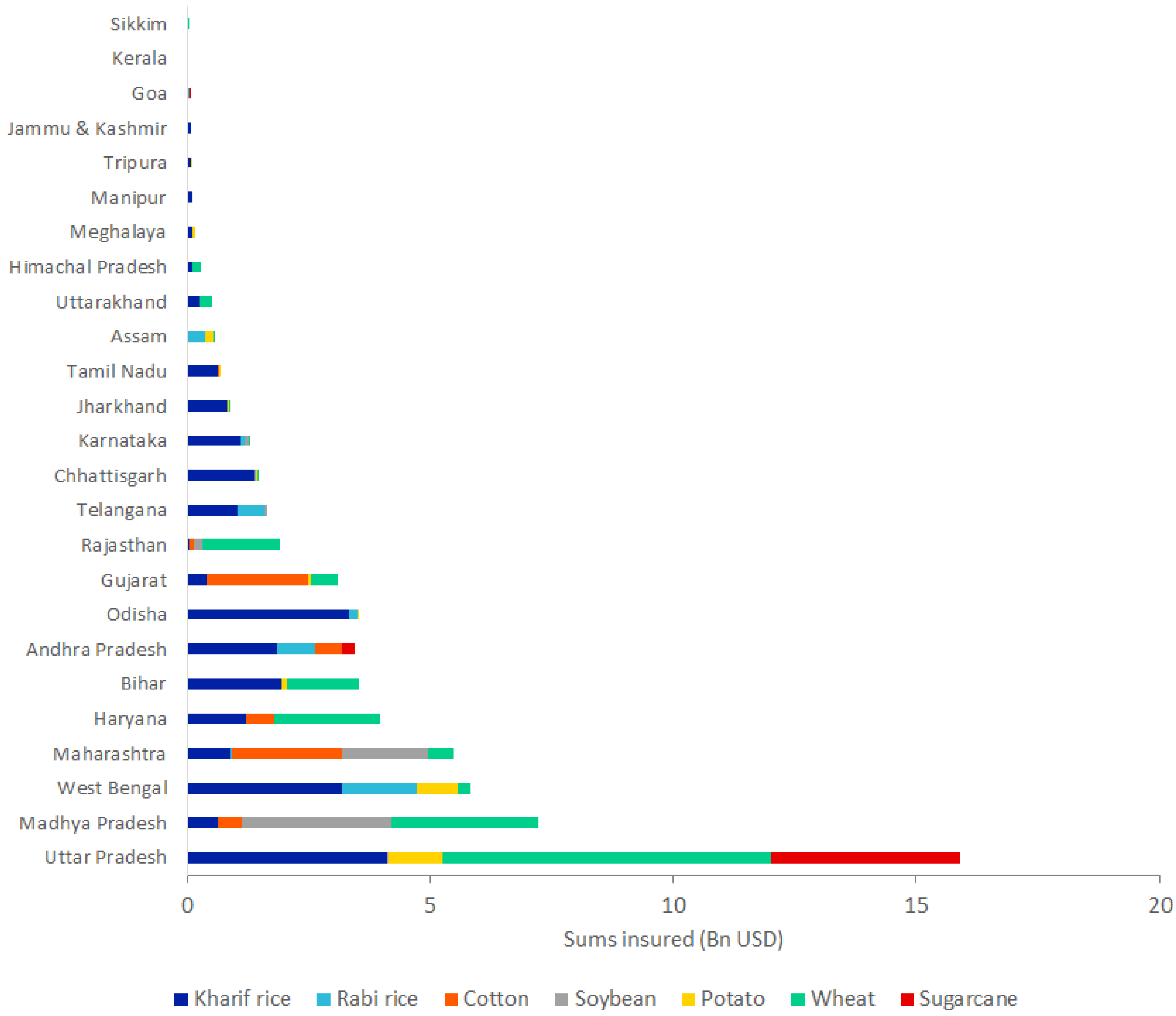


Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.



Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

Figure 23: Sums insured per crop and state in the hypothetical nation-wide portfolio

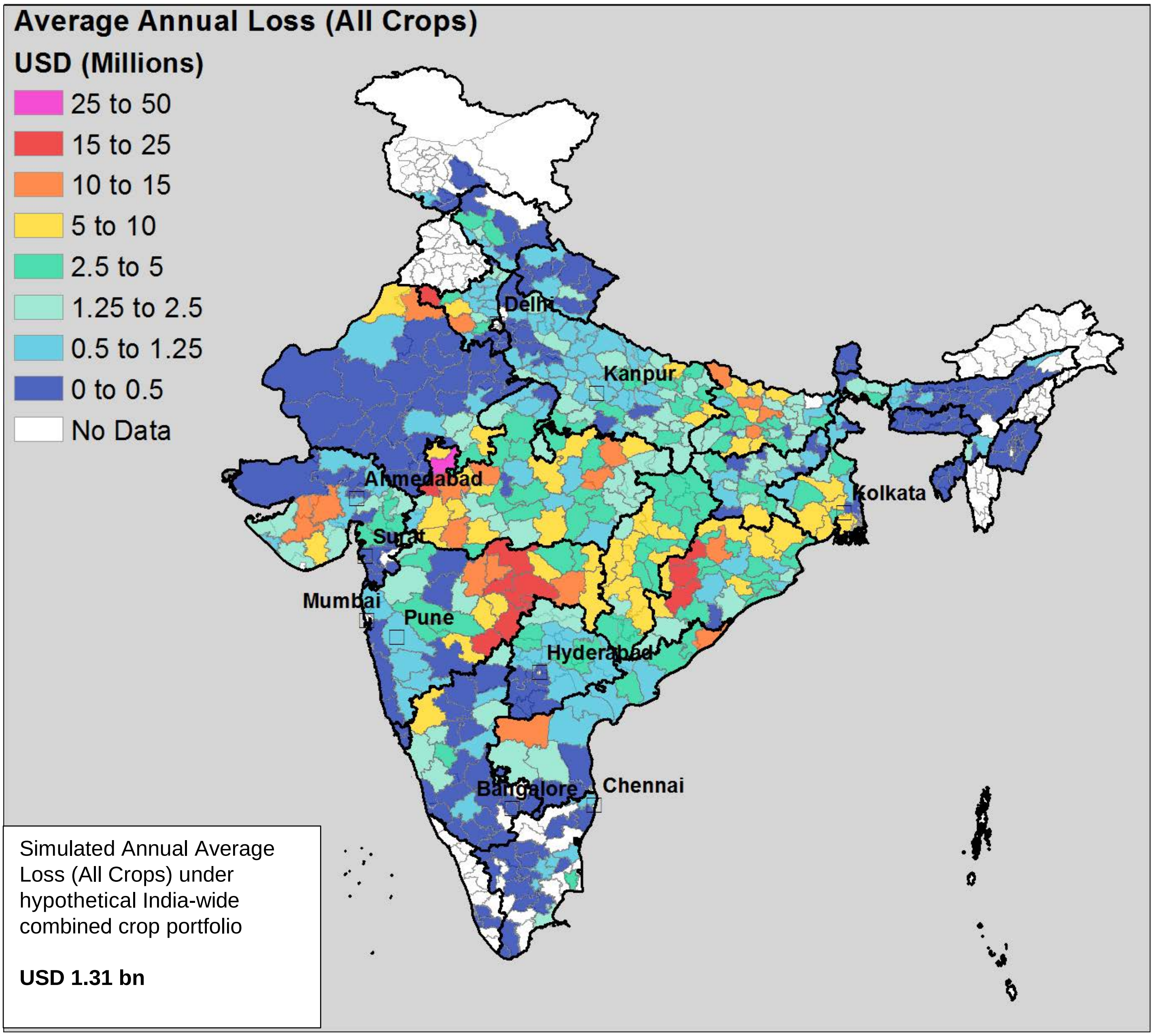


Source: Risk Management Solutions, Inc., 2017

Annual average loss and loss costs

As discussed in Section 3, the key advantage of a probabilistic crop risk model is to provide an extended and more comprehensive view of insured crop losses compared to more limited historical information. The model provides 10,000 years of simulation to enable tail risk assessment. Figure 24 shows the simulated annual average loss (AAL) at district level for all crops combined. District level results represent aggregated PMFBY losses, calculated at 25km^2, for the model grid cells within each district. The distribution of districts with high AAL does not always correspond to the districts with highest sums insured (Figure 21). Total sum insured is highest in Uttar-Pradesh, yet the AAL is lower compared to other states. AAL is highest in central states such as Madhya-Pradesh and Maharashtra reflecting the mix of more vulnerable crop types than other regions, specific weather risks and also lower levels of irrigation compared to northern regions (Figure 5, p22). Irrigation is a key adaptation measure that can dramatically reduce the impacts of droughts. The AAL can be broken down further per crop and state or district. Losses for a particular crop will depend both on differences in the distribution of exposures and what climatic perils they are exposed to as well as differences in the vulnerability of a specific crop to the climate perils and adaptation measures (modifiers) such as the level of irrigation. Thus, the results presented here should not be expected to reflect actual market losses as insured crop clusters will have typically have different crop type composition and different exposure distributions than those included in the hypothetical portfolio and different exposure distributions.

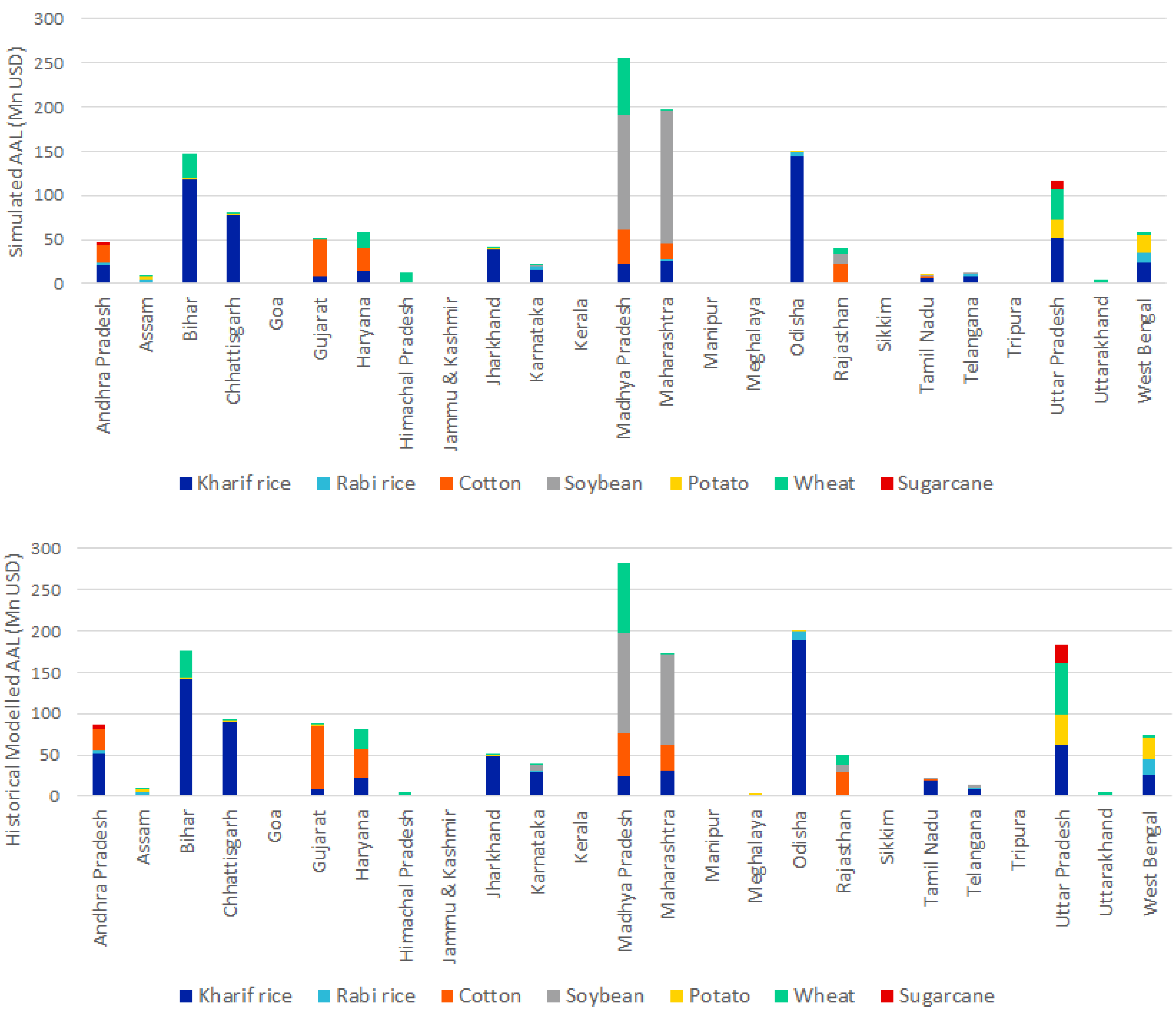
Figure 24: District-level simulated AAL (based on 10,000yr) for all crops combined (USD million)



Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

The breakdown of simulated AAL per state and crop is presented in Figure 25a. The distribution of AAL does not always correspond to the distribution of sums insured (Figure 30, p86). Wheat, rice and sugar cane have a smaller contribution to the nation-wide and state-level AAL compared to their sums insured (Figure 23, p71). In other cases these differences are more localised. For example, while Maharashtra has smaller soybean exposure in the hypothetical portfolio compared to Madhya-Pradesh, the soybean AAL for these 2 states is reasonably similar, indicating that at the overall state level, based on the exposure distribution of the portfolio used in this study, soybean crop risk is higher for Maharashtra compared to Madhya-Pradesh. These variations of risk are further explored by analysing the annual average loss cost (LC). Figure 25b presents the distribution of modelled AAL by state and crop from the historical event set where the AAL is computed from 47 years of historical modelled losses between 1969 and 2015. Differences between Figure 25 a & b demonstrate that the weather events over the past 50 years do not fully reflect the long-term climatology and highlight the sensitivity of historical loss benchmarks such as the AAL to the averaging period chosen. For this portfolio, the overall simulated AAL is lower than the historical modelled AAL. Extending the historical record does not always result in higher losses as it depends on regional weather variability and crop type. Madhya Pradesh, Maharashtra, Odisha, Uttar Pradesh and Bihar would all experience AAL over USD 100 million based on the hypothetical portfolio for both historical modelled (47 years) and simulated (10,000 years) views.

Figure 25: Breakdown of (a) simulated and (b) historical modelled AAL per state and crop

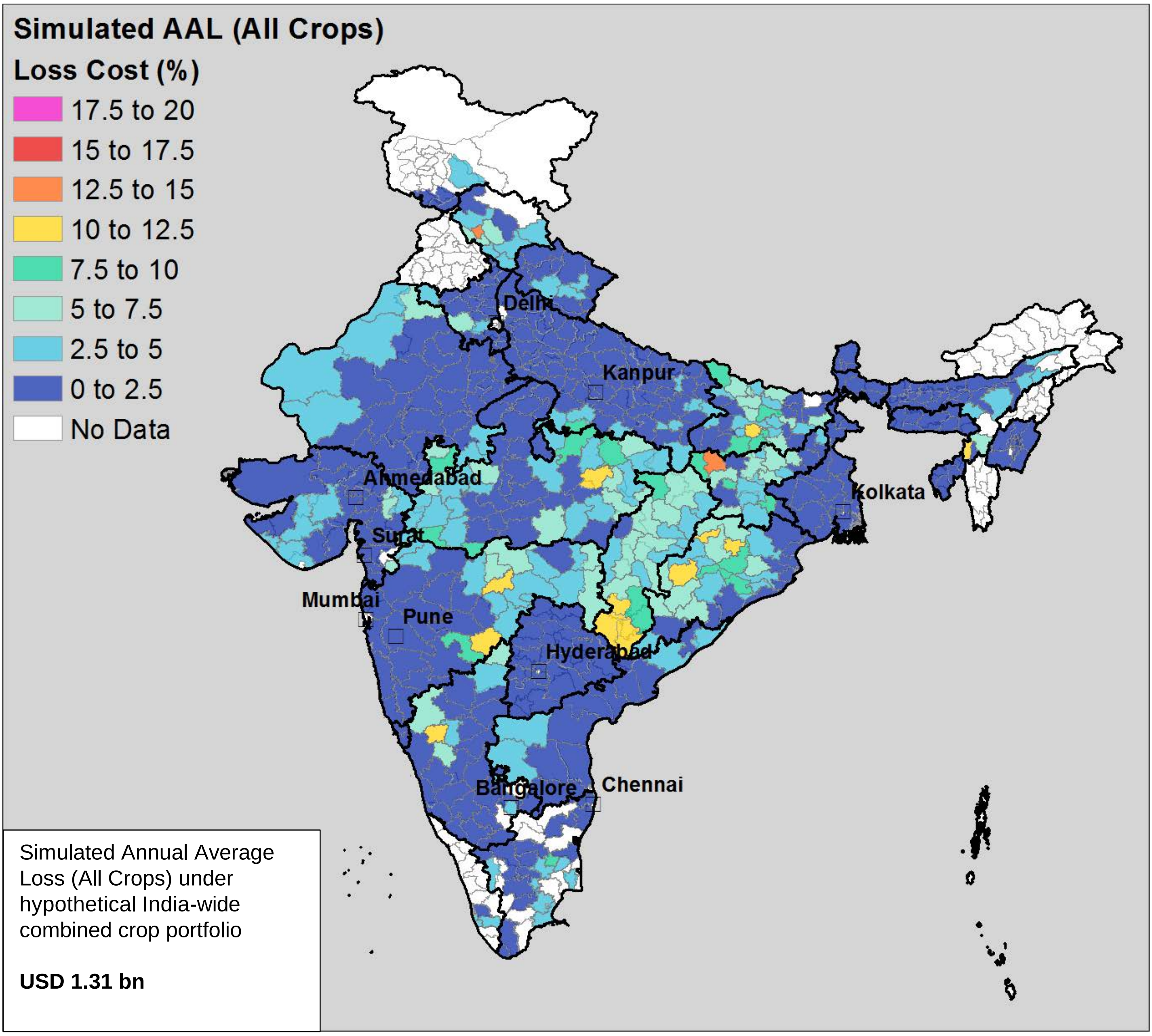


Source: Risk Management Solutions, Inc., 2017

Figure 26 presents the simulated annual average loss cost (LC), for all crops combined, at district level revealing large variability in loss costs between and within states ranging from about 1% to around 20%. Loss costs for individual years can be much higher (more than 80% for certain crops) than the annual average loss costs. These variations are driven by a combination of factors: crop mix per district, typical climate and weather events impacting a certain region, levels of irrigation and indemnity levels per crop/region.

Note that there is also variability in the PMFBY actuarial reported rates per crop and district listed in the agri-insurance portal although the results presented here should not be compared against these actuarial rate values as the underlying exposure within each district is not the same and the reported rates will include additional loadings. The model results represent the pure loss cost.

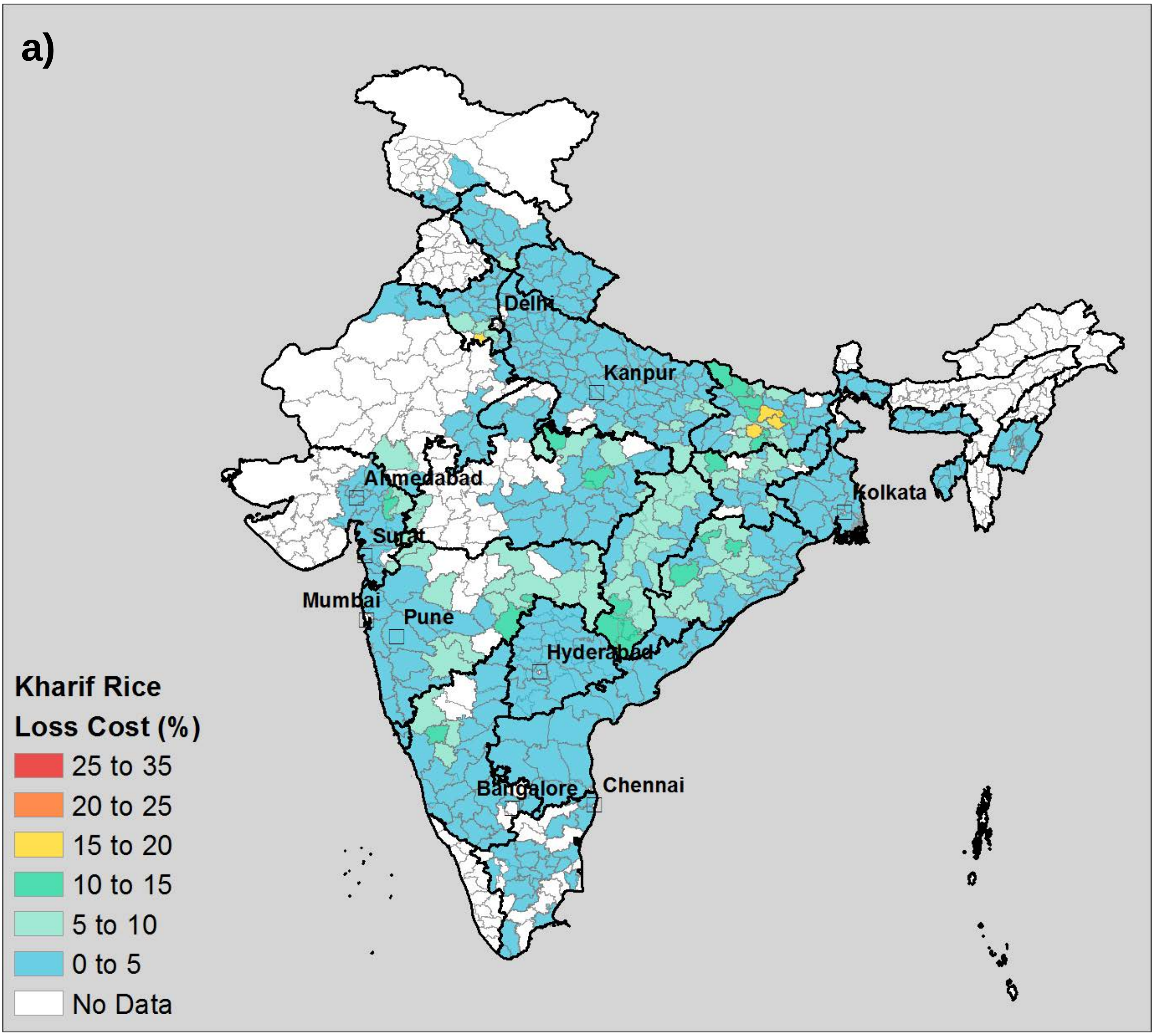
Figure 26: District-level simulated annual average loss cost (based on 10,000yr) for all crops combined

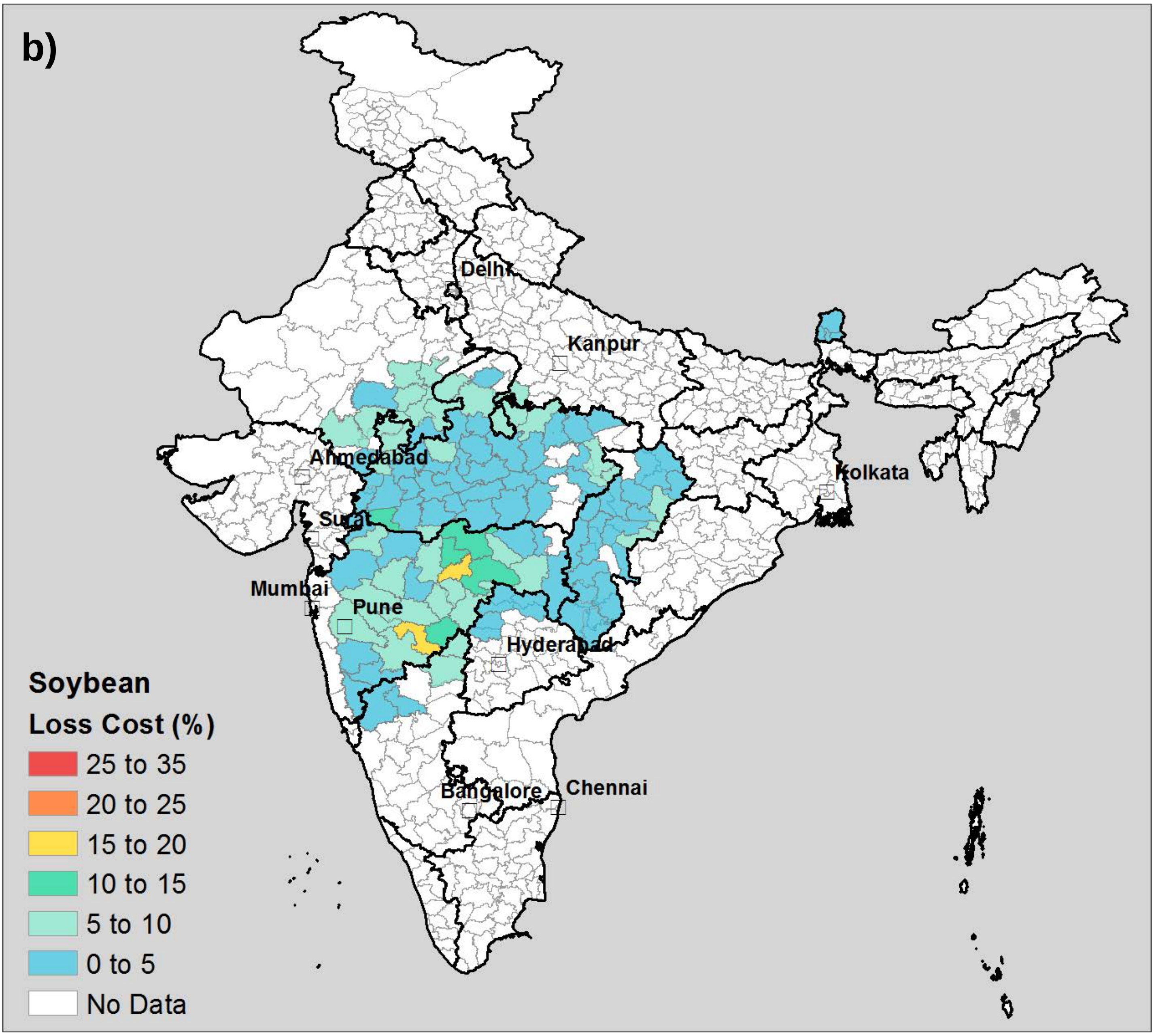


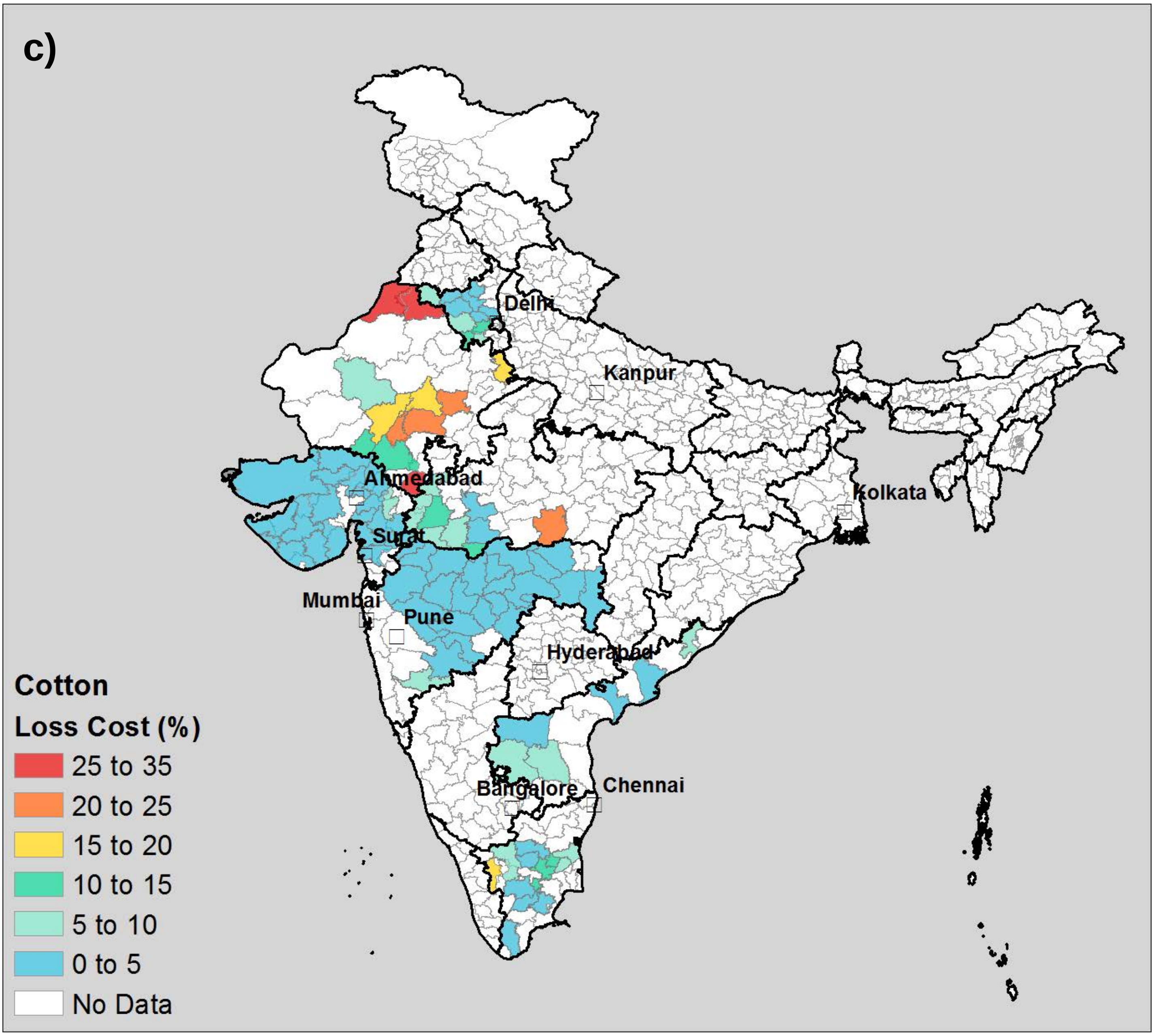
Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

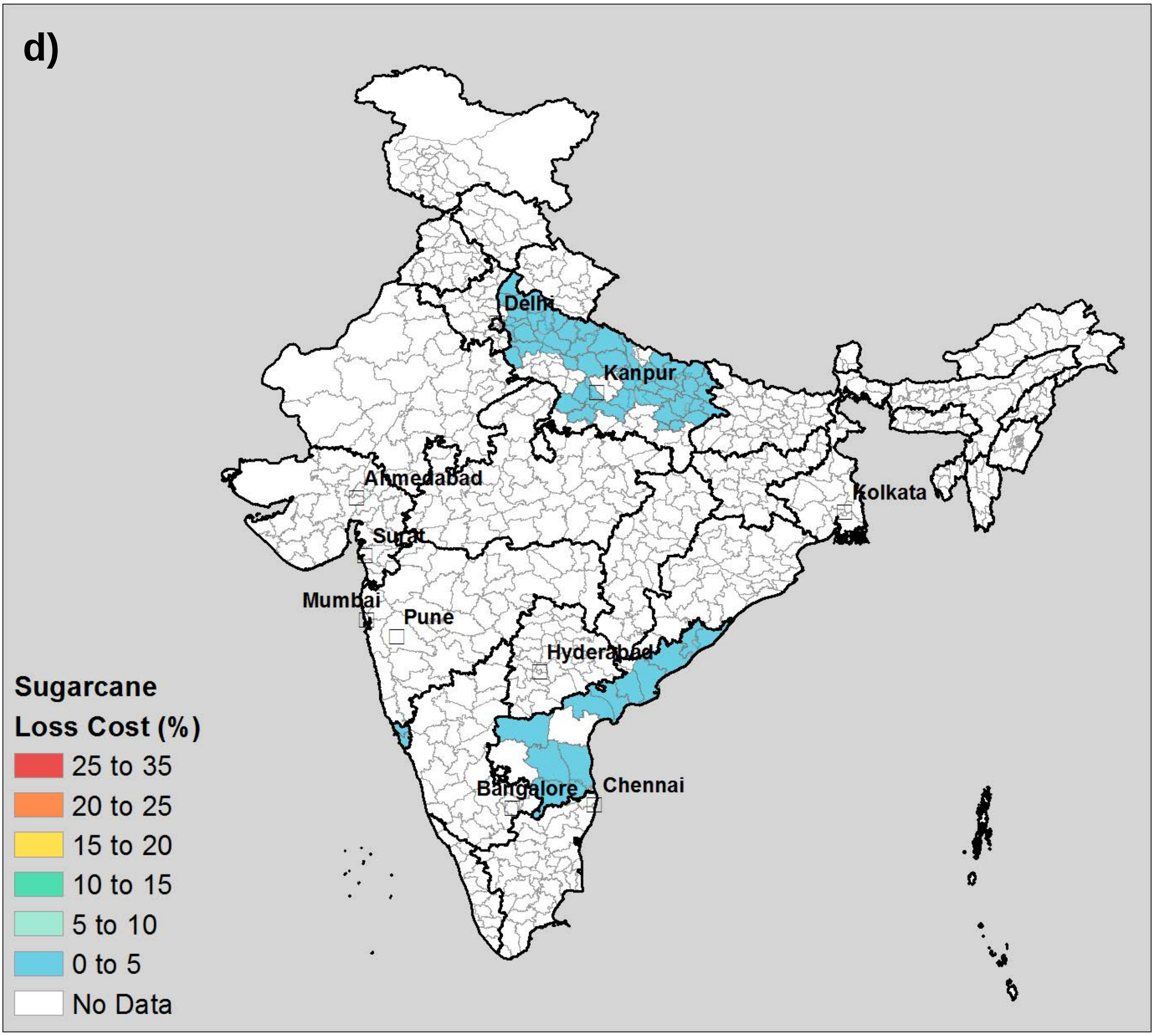
To better understand the drivers of this behaviour, Figure 27 presents annual average loss cost per crop type. From this figure it can be seen that the regions of higher risk (higher loss costs) vary between the different crop types. Kharif rice loss costs are highest in the north-east, whereas for cotton, the north-west shows highest loss costs. Differences in loss cost are driven not only by the crop type and region but also whether the crop is irrigated and the insurance indemnity level associated with each crop and district/cluster. For example, there is a difference between the loss costs for cotton between Gujarat and Rajasthan, both drought prone regions (Figure 4 in Appendix 6), although Rajasthan is generally more arid and dry, particularly in the western half. The indemnity levels for cotton in Gujarat are 70% compared to 80% in Rajasthan, which will contribute in part to this LC difference. As mentioned earlier, the sensitivity of the crop losses to indemnity values and irrigation information can be explored in model by changing the exposure input information associated with these parameters.

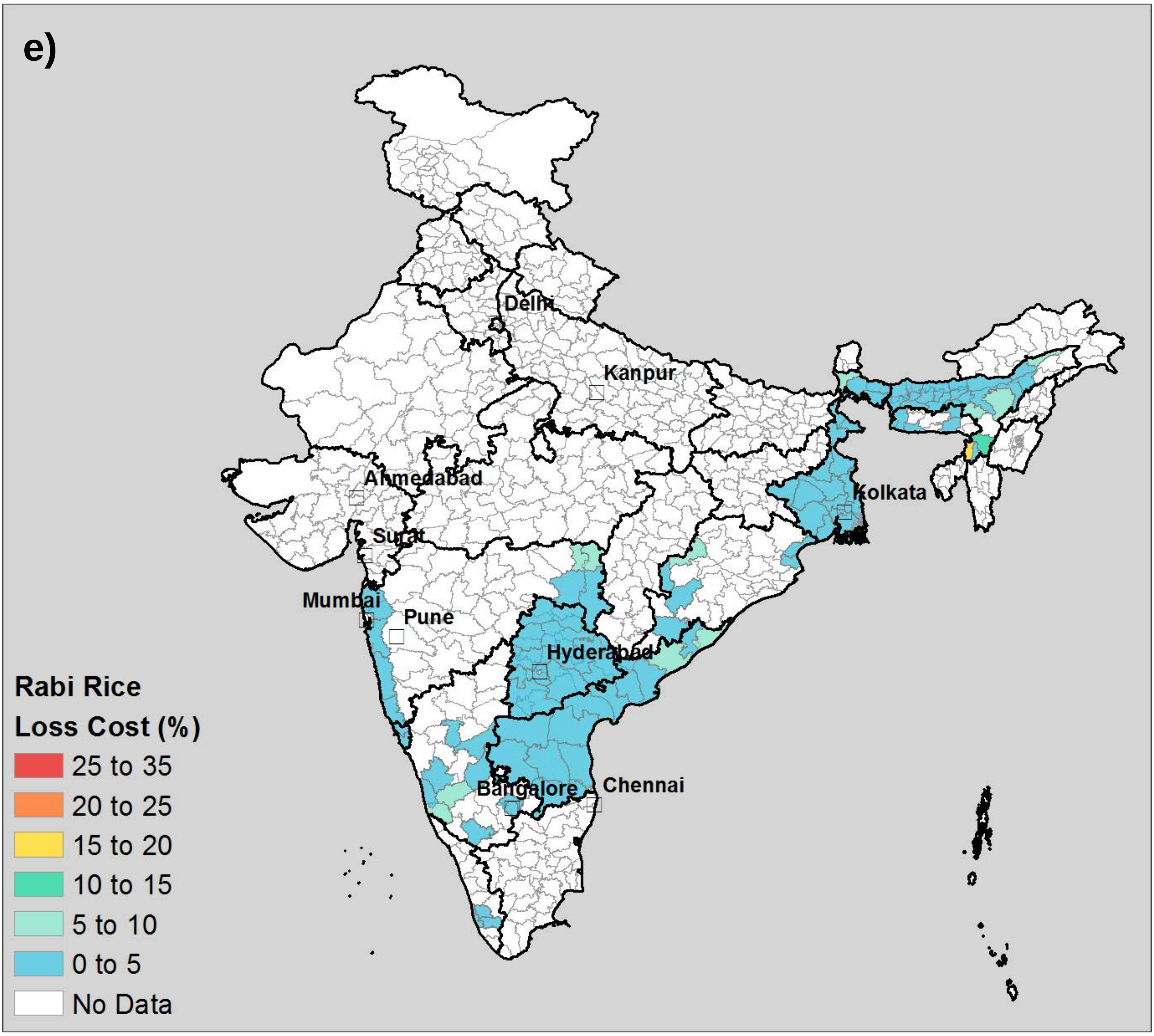
Figure 27: District-level simulated annual average loss cost (based on 10,000yr) per crop a) Kharif rice, b) soybean, c) cotton, d) sugarcane, e) Rabi rice, f) wheat, g) potato

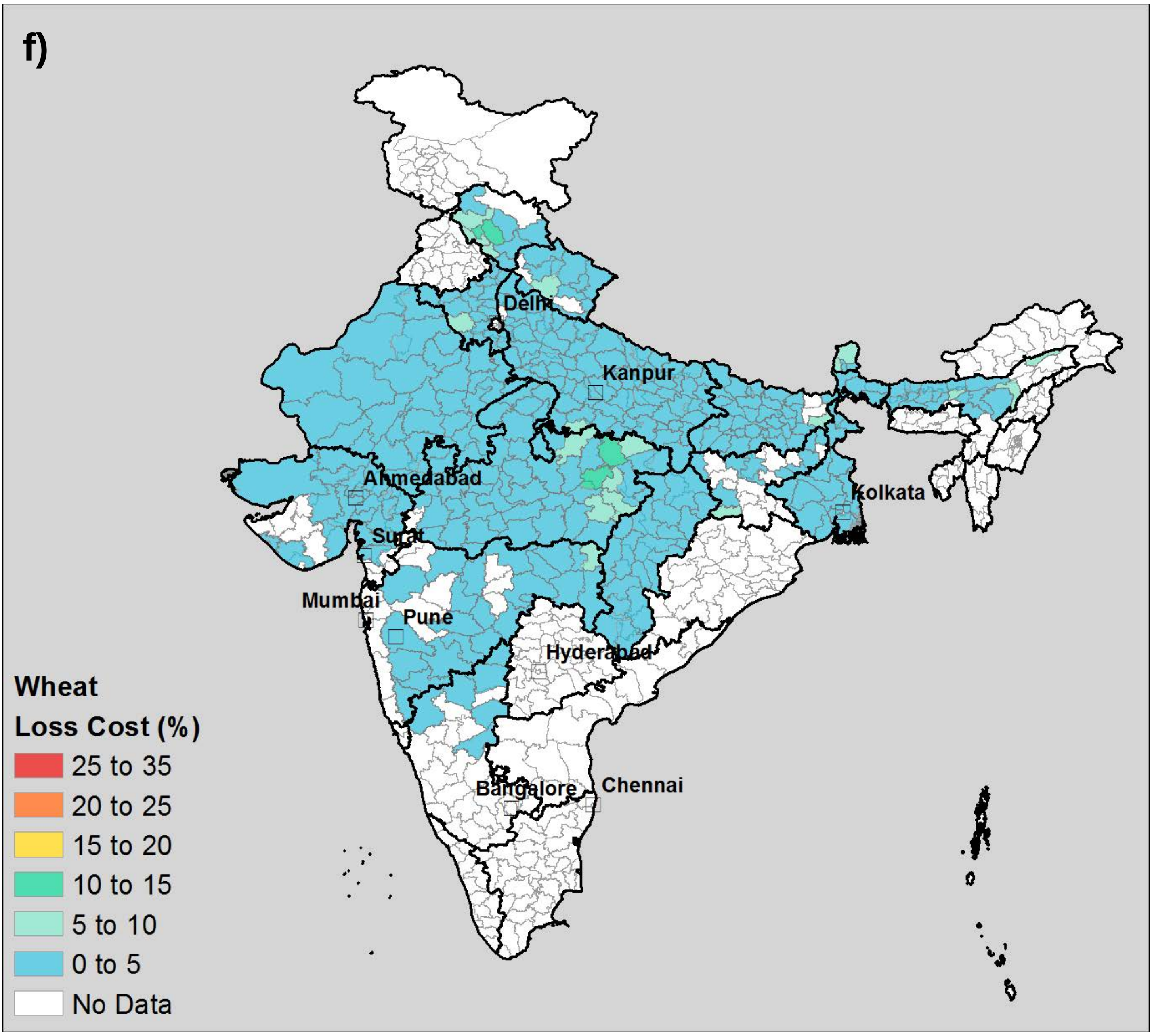


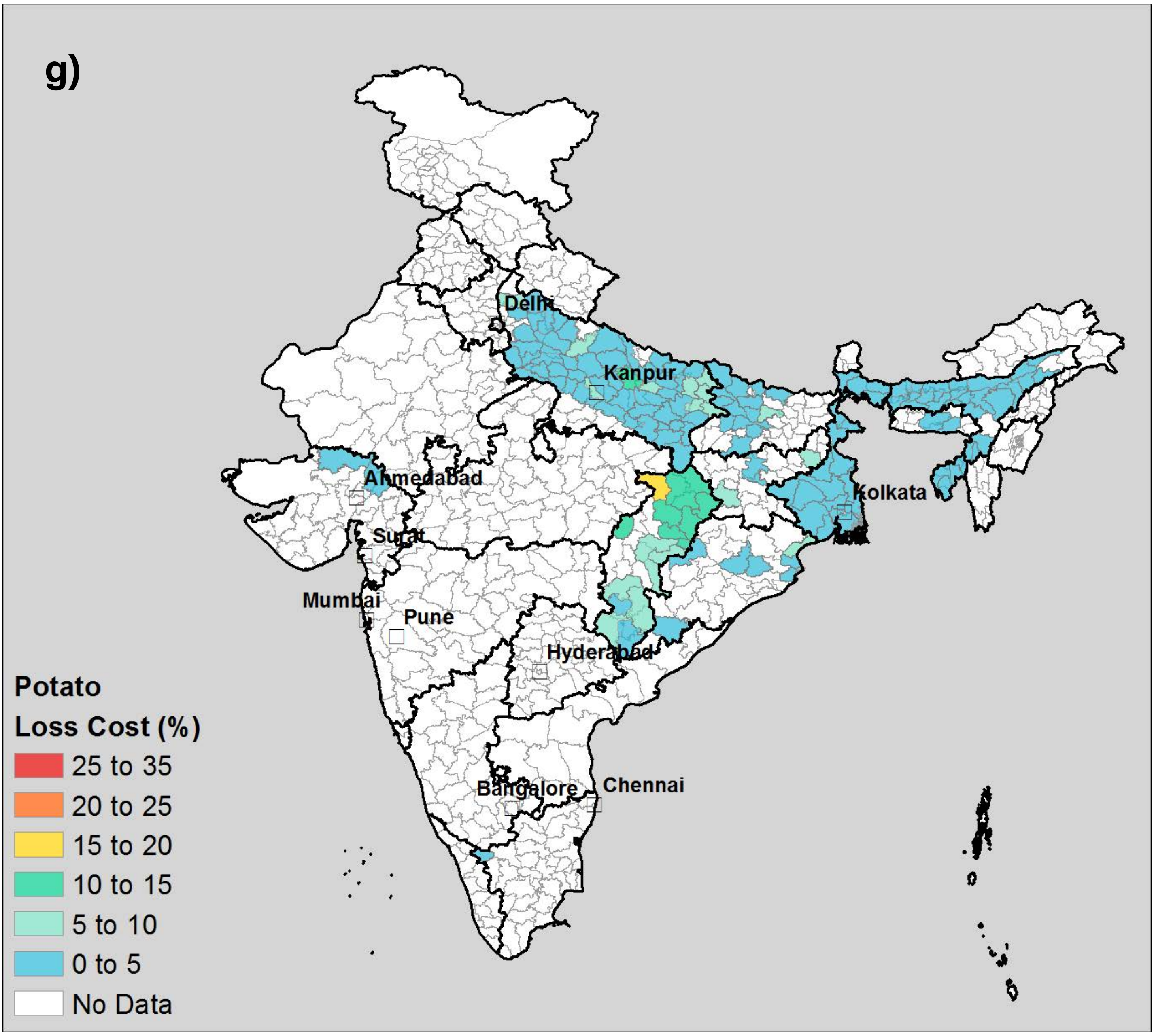

b)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
Soybean
Loss Cost (%)
25 to 35
20 to 25
15 to 20
10 to 15
5 to 10
0 to 5
No Data


c)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
Cotton
Loss Cost (%)
25 to 35
20 to 25
15 to 20
10 to 15
5 to 10
0 to 5
No Data


d)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
Sugarcane
Loss Cost (%)
25 to 35
20 to 25
15 to 20
10 to 15
5 to 10
0 to 5
No Data


e)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
Rabi Rice
Loss Cost (%)
25 to 35
20 to 25
15 to 20
10 to 15
5 to 10
0 to 5
No Data


f)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
Wheat
Loss Cost (%)
25 to 35
20 to 25
15 to 20
10 to 15
5 to 10
0 to 5
No Data



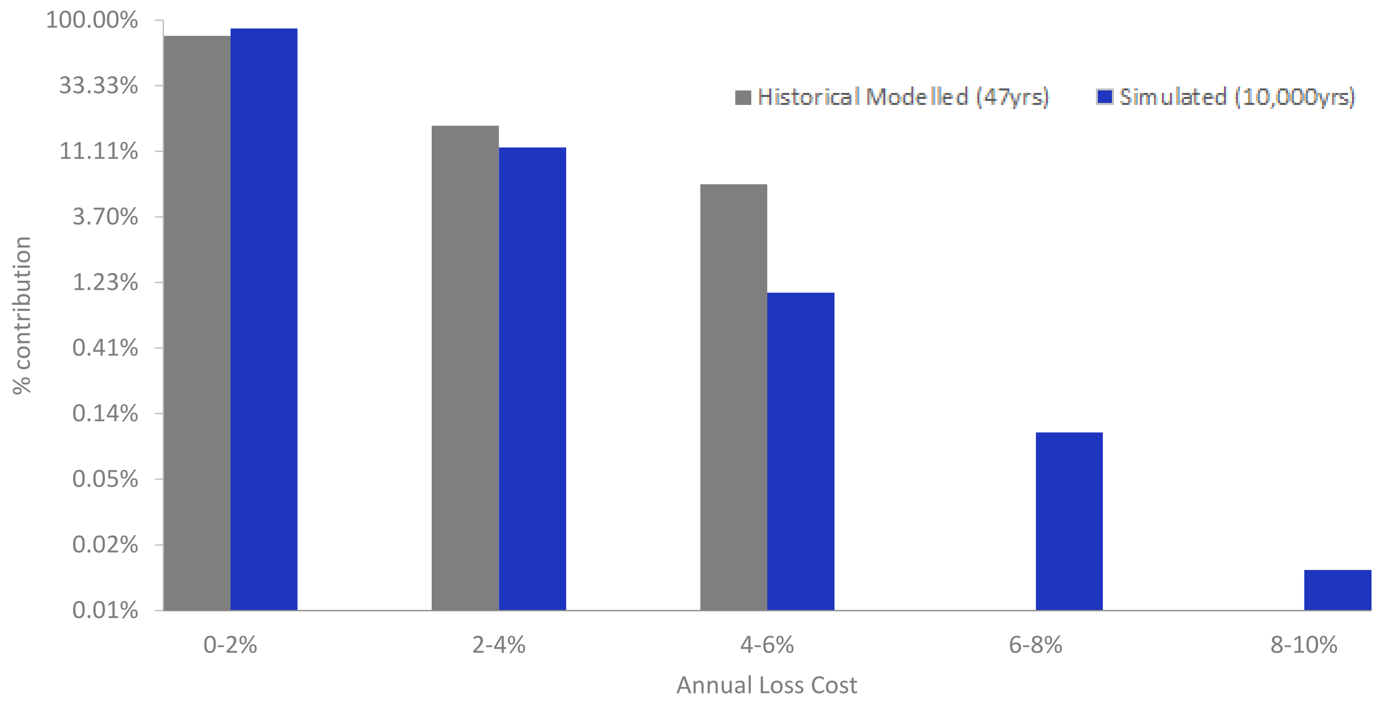
Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

Comparing historical modelled losses (47 years) and simulated losses (10,000 years)

To demonstrate the use of simulated over historical modelled losses for crop risk modelling, Figure 28 compares the distributions of the modelled annual loss costs, at portfolio-level, between the historical (47 years) and the simulated (10,000yrs) event sets for Rabi-only crops in the portfolio (wheat, Rabi rice and potato). The simulated model contains years with larger loss costs than those of the past 47 years demonstrating the benefit of further extending the historical modelled records to get a better representation of loss distributions.

The overall historical modelled annual average loss cost, at portfolio-level, for the Rabi crops is larger compared to the simulated set (1.6% versus 1.1%) but misses the tail risk. As one would expect the historical modelled loss cost distribution is narrower than the simulated one. The maximum historical modelled loss cost, at portfolio-level, for the Rabi crops is 5.5% compared to 8.3% in the simulated yearly results. These results suggest that the past 50 years represents only a short period whose mean annual loss cost happens to be somewhat higher than the average over the 10,000 simulated years.

Figure 28: Distribution of portfolio-level[n] modelled annual loss costs for the historical modelled (47 years) and simulated (10,000yrs) event sets for Rabi-only crops (wheat, rice and potato) in the nation-wide hypothetical portfolio

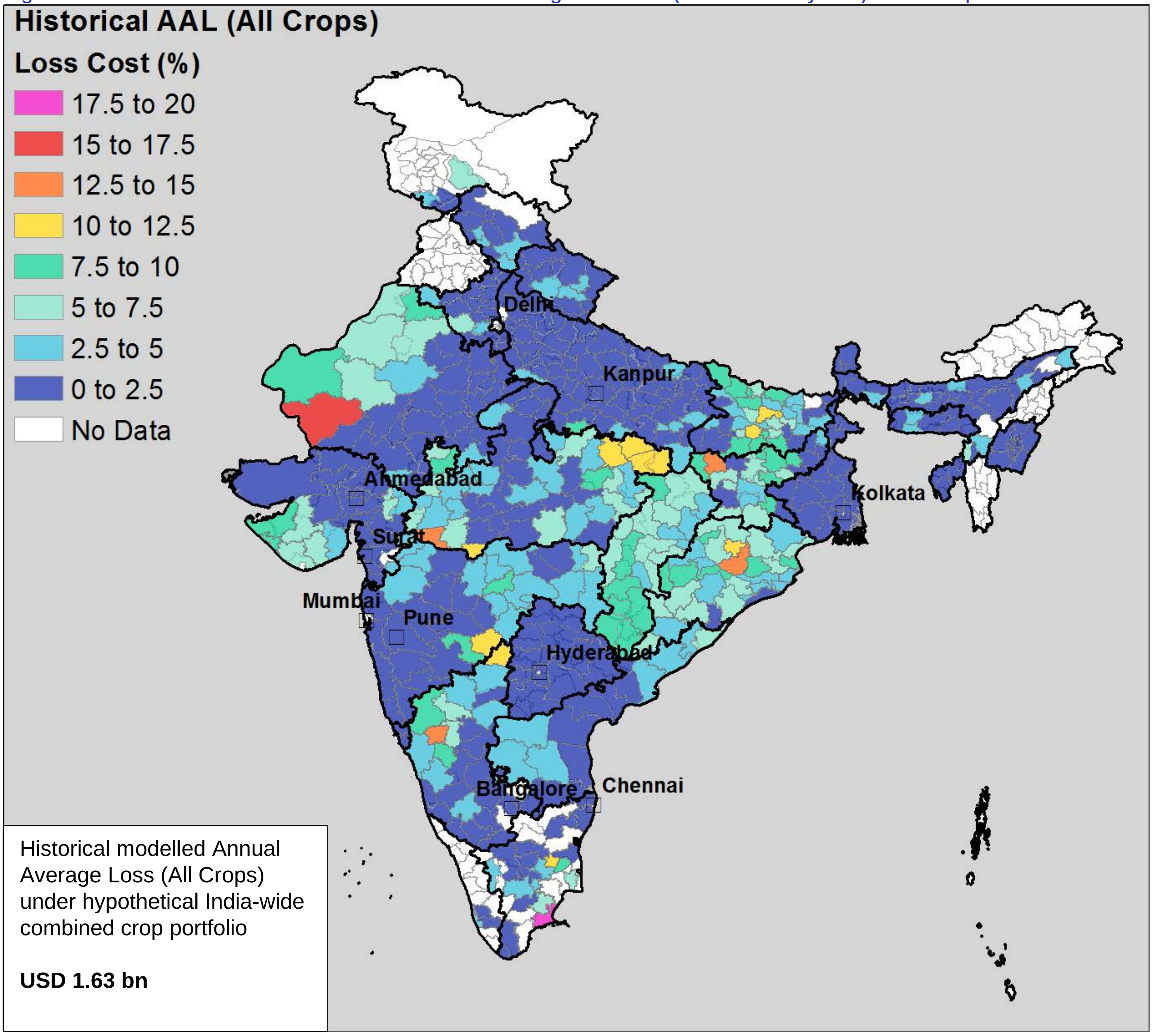


Source: Risk Management Solutions, Inc., 2017

[n] Portfolio-level loss costs represent the combined loss costs of all the districts with Rabi exposure in the hypothetical portfolio

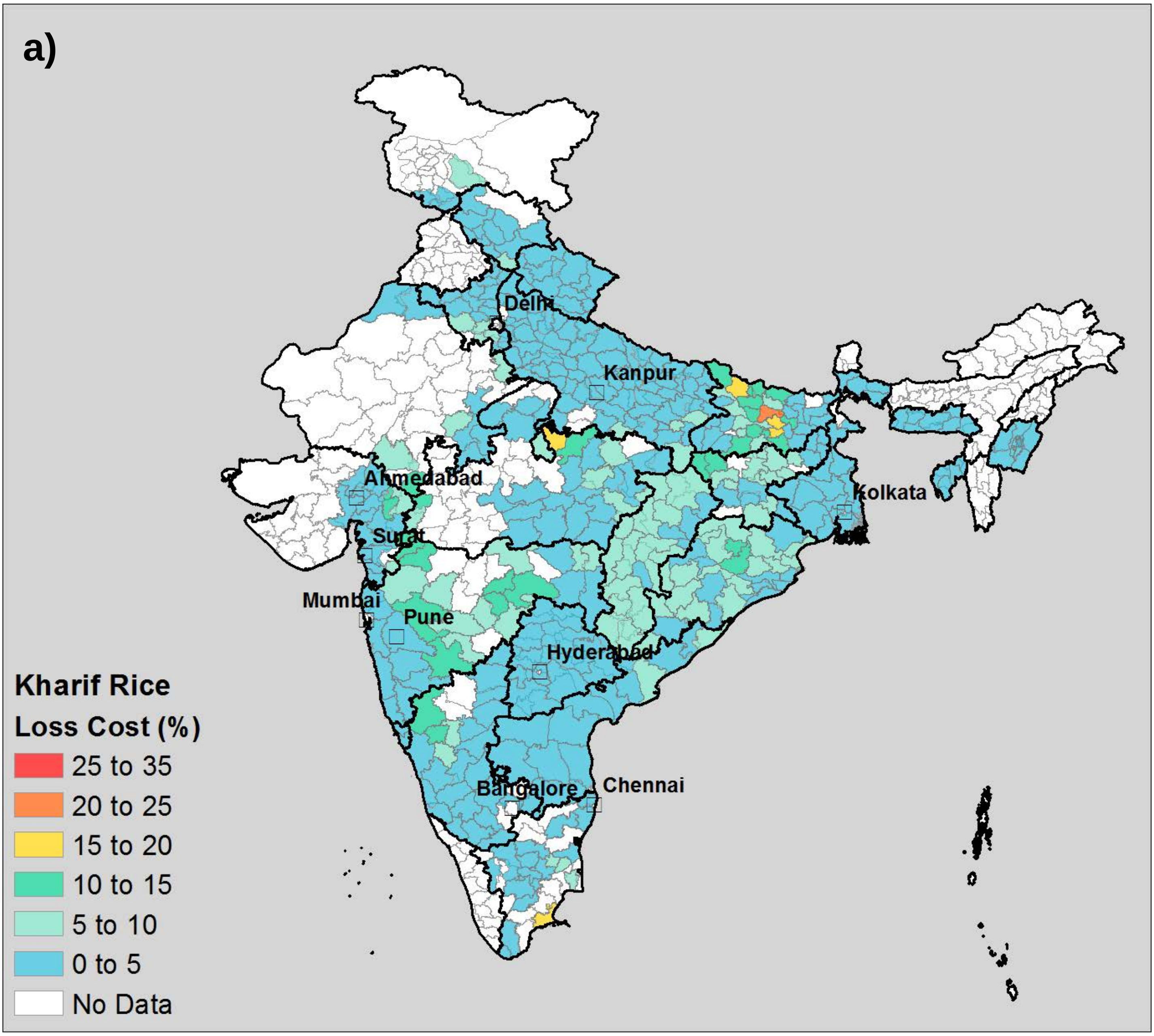
Comparing district level historical modelled annual average LC (Figure 29) to the simulated results (Figure 26, p76), differences in loss costs are more notable in some regions compared to others (e.g. Rajasthan), indicating regional variations in the agreement between the recent historical record (past 47 years) and all range of possible weather events (represented by 10,000 years simulated weather). Model results can also be broken down further per crop to explore differences between historical modelled and simulated losses. Figure 30 presents examples of the historical modelled loss cost per district for Kharif rice and Kharif soybean which can be compared against the simulated loss costs Figures 27a and b (p77). Comparing the historical modelled versus simulated loss costs, there are examples where historical modelled loss costs are higher for some districts (e.g. Maharashtra for Kharif rice). For soybean, there are cases where the simulated loss costs are higher (e.g. Maharashtra). Also higher loss costs extend into adjacent areas in the simulated results revealing the true extent of the perils when considering the full range of possible adverse events These results indicate regional variations in the agreement between the recent historical record and the range of all possible events and also how different crops will have higher/lower lost costs (e.g soybean versus Kharif rice in Maharashtra) under the same climate conditions (driven by differences in crop characteristics as well as any differences in irrigation and indemnity levels).

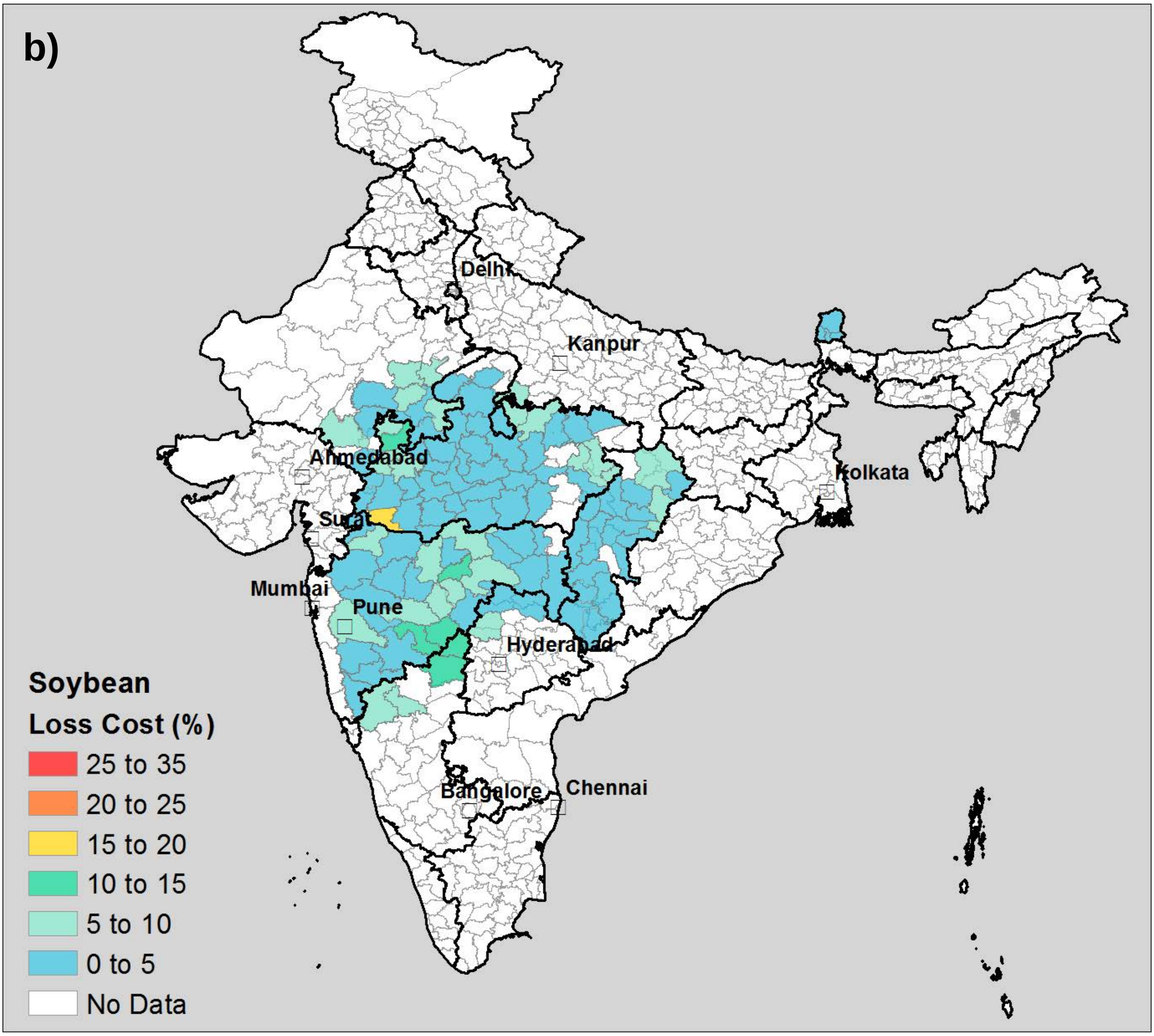
Figure 29: District-level historical modelled annual average loss cost (based on 47 years) for all crops combined



Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

Figure 30: District-level historical modelled annual average loss cost (based on 47 years) for (a) Kharif rice and (b) Kharif soybean



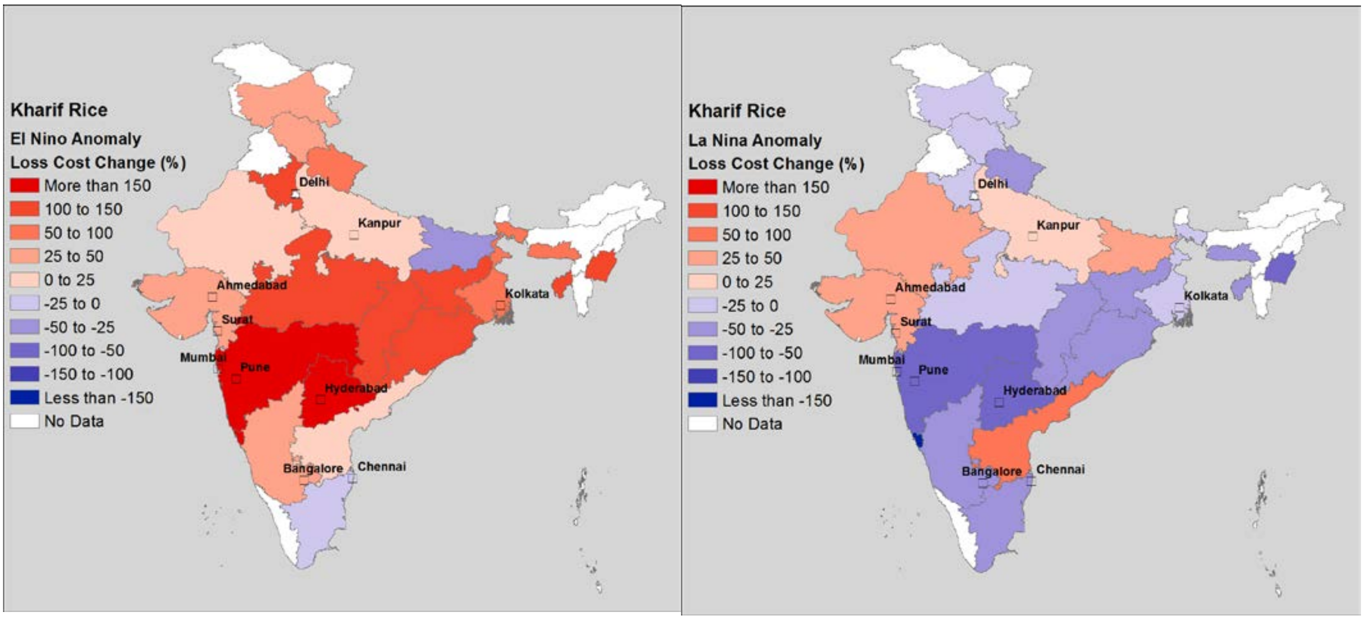


Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

Historical modelled losses are also useful in terms of model validation and scenario stress-testing of particular past years. The historical losses can also be used to estimate the impact of El Niño and La Niña by calculating the AAL from the historical years which coincided with an El Niño/La Niña event. Figure 31 shows the impact of El Nino and La Nina years on the historical modelled annual average LC for Kharif rice. The loss costs are generally higher than the 47 year average during El Nino years and generally lower during La Nina years.

The historical modelled annual average LC at portfolio-level for Kharif rice during El Niño years is 5.82% compared to 2.91% during La Niña years, and 3.37% for all 47 years, demonstrating the relationship described in Section 2 and Appendix 6 (Figure 3 in Appendix 6) whereby El Niño events are often (but not always) associated with droughts that reduce crop yields and increase losses whereas La Niña events are often associated with excess monsoon rainfall, overall higher crop yields and lower losses. However excess monsoons can also result in localised flooding and lower yields which is reflected by the smaller decrease in PMFBY losses during La Nina years compared to the larger increase during El Nino years. This sensitivity can be explored in more detail regionally and for each different crop type or season.

Figure 31: Impact of ENSO phases on annual average LC: % change in state-level historical modelled annual average LC for (a) El Niño years and (b) La Niña years, compared to the 47 year mean, for Kharif rice



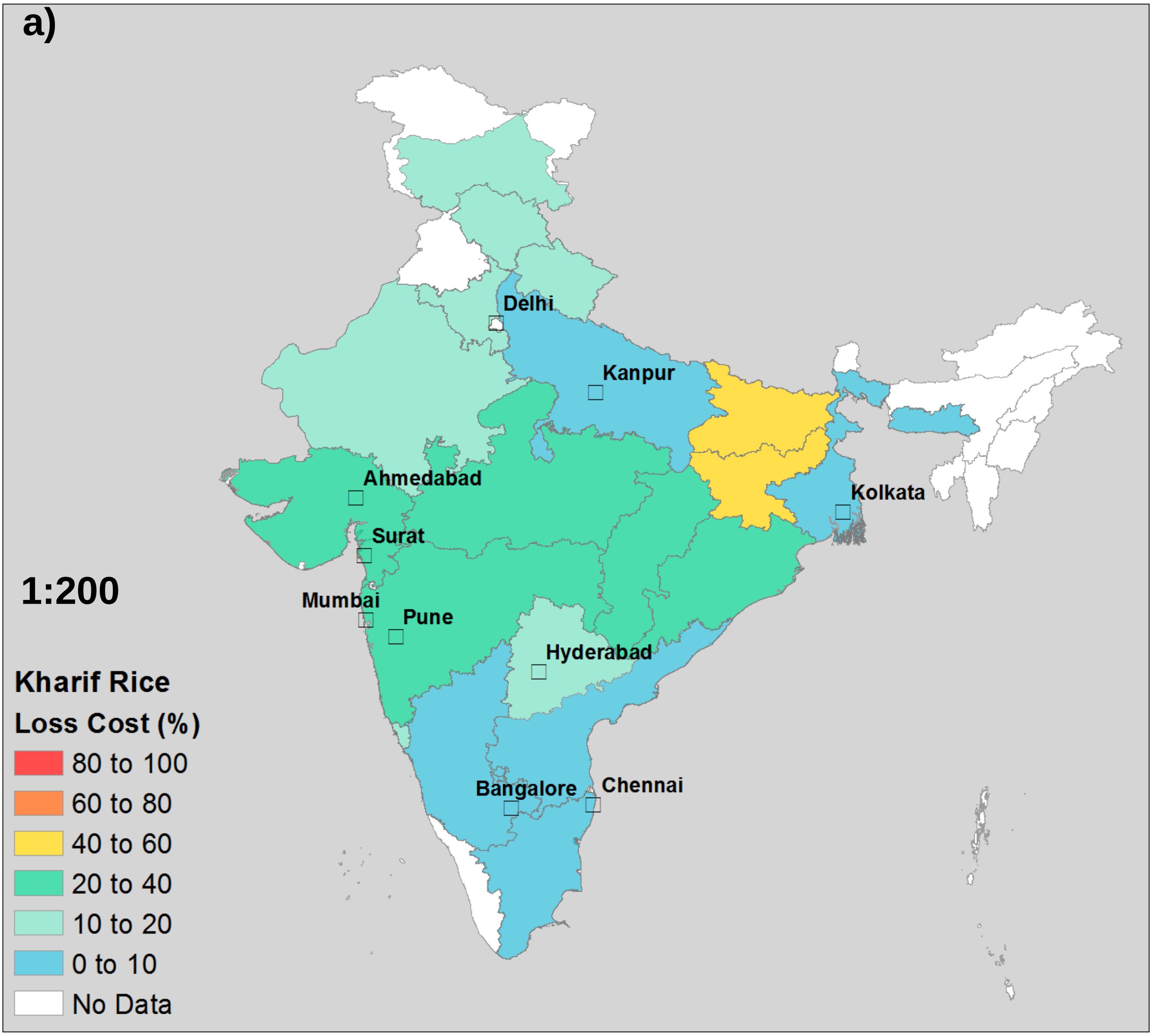
Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

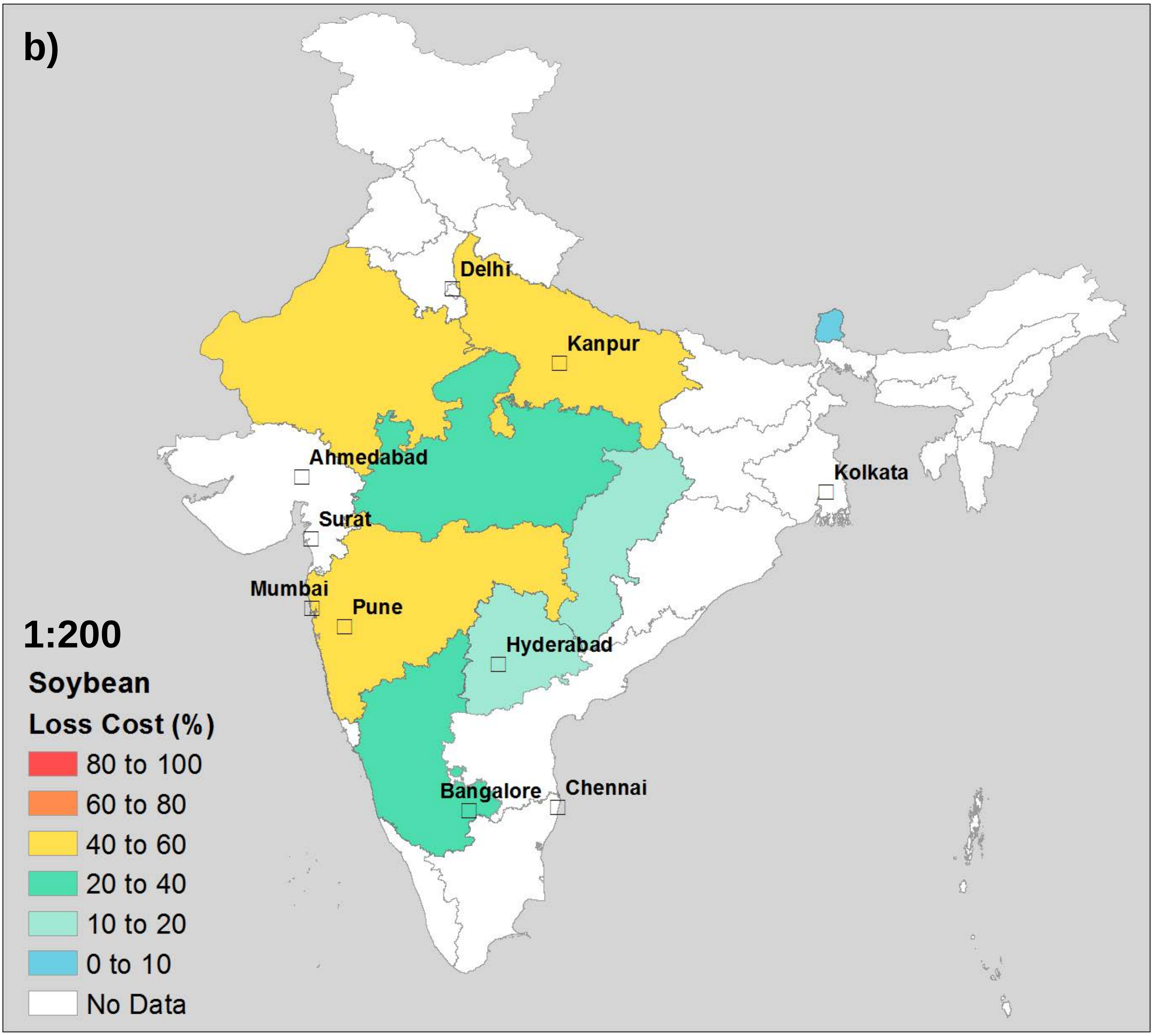
Tail risk loss distributions

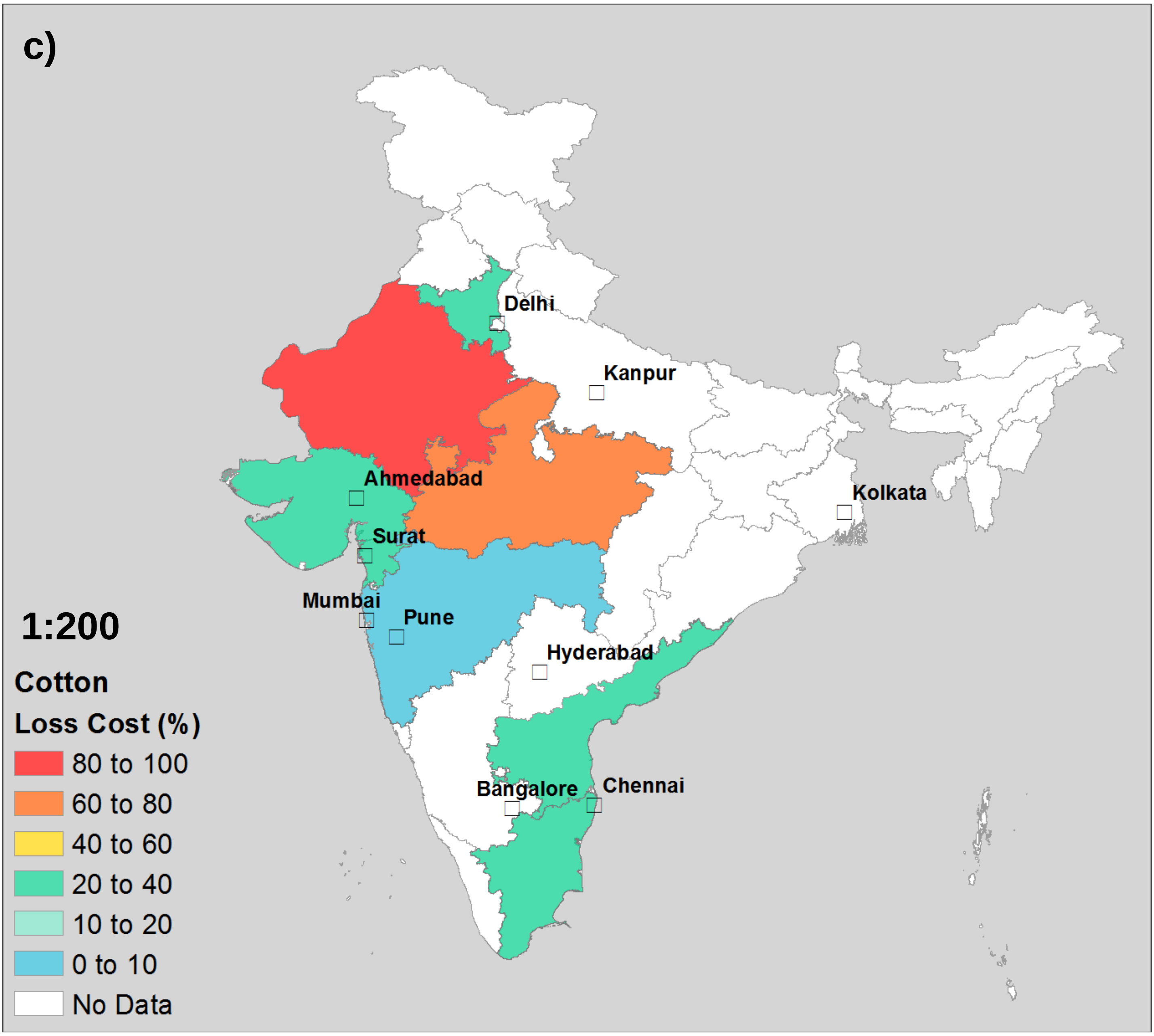
Probabilistic model output includes several return period losses and loss costs that define Exceedance Probability loss or Loss Return Period curves. As an example, 200-year loss costs at state level per crop type are presented in Figure 32. The state-level loss costs represent the combined loss costs of all the districts with exposure in each state. For certain crops, exposure in the portfolio may only for a small proportion of the state (e.g. in Uttar-Pradesh only 2 southern districts have soybean exposure in the hypothetical portfolio, the majority of the state has no soybean exposure). Thus care should be made when interpreting state-level results. As per the annual average loss cost, the variation in return period loss costs between crops and states will depend on the crop type, exposure distributions, the perils impacting each state and also the indemnity and irrigation levels which can vary between crops and states.

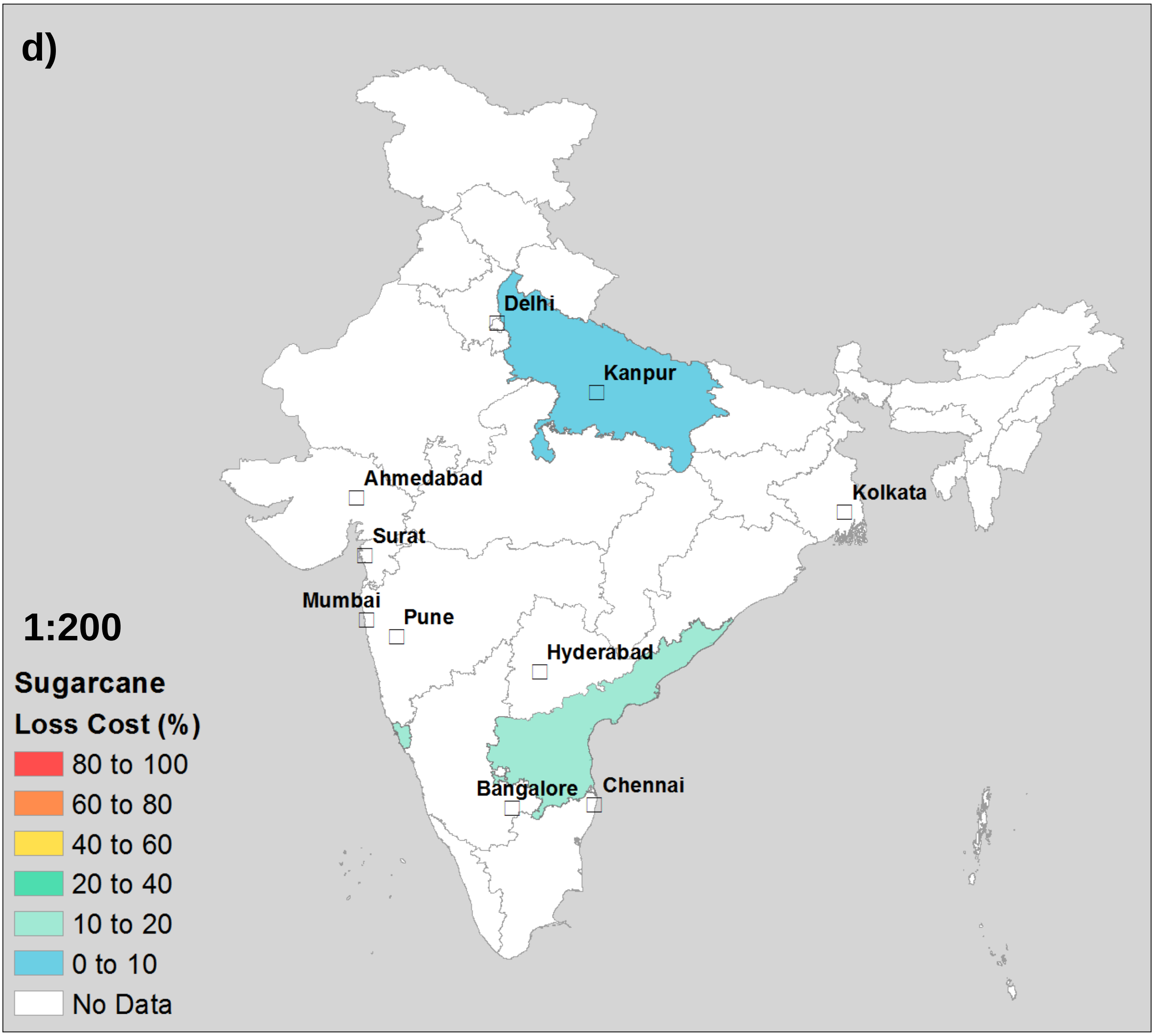
For many of the Kharif crops, the regions of highest 200-year loss cost coincide with the main drought regions. The results demonstrate that tail loss costs can be large, particularly for more vulnerable crops such as soybean and cotton. Tail losses exceed maximum historical modelled values highlighting the value of probabilistic modelling to expand knowledge and capture new plausible loss scenarios not experienced before. For example, at a nation-wide level, the largest historical modelled loss cost for potato is 14% over the past 47 years compared to 26% in the simulated results (10,000 years). Similarly the largest historical modelled loss cost for soybean is 25%, compared to 49% in the simulated results.

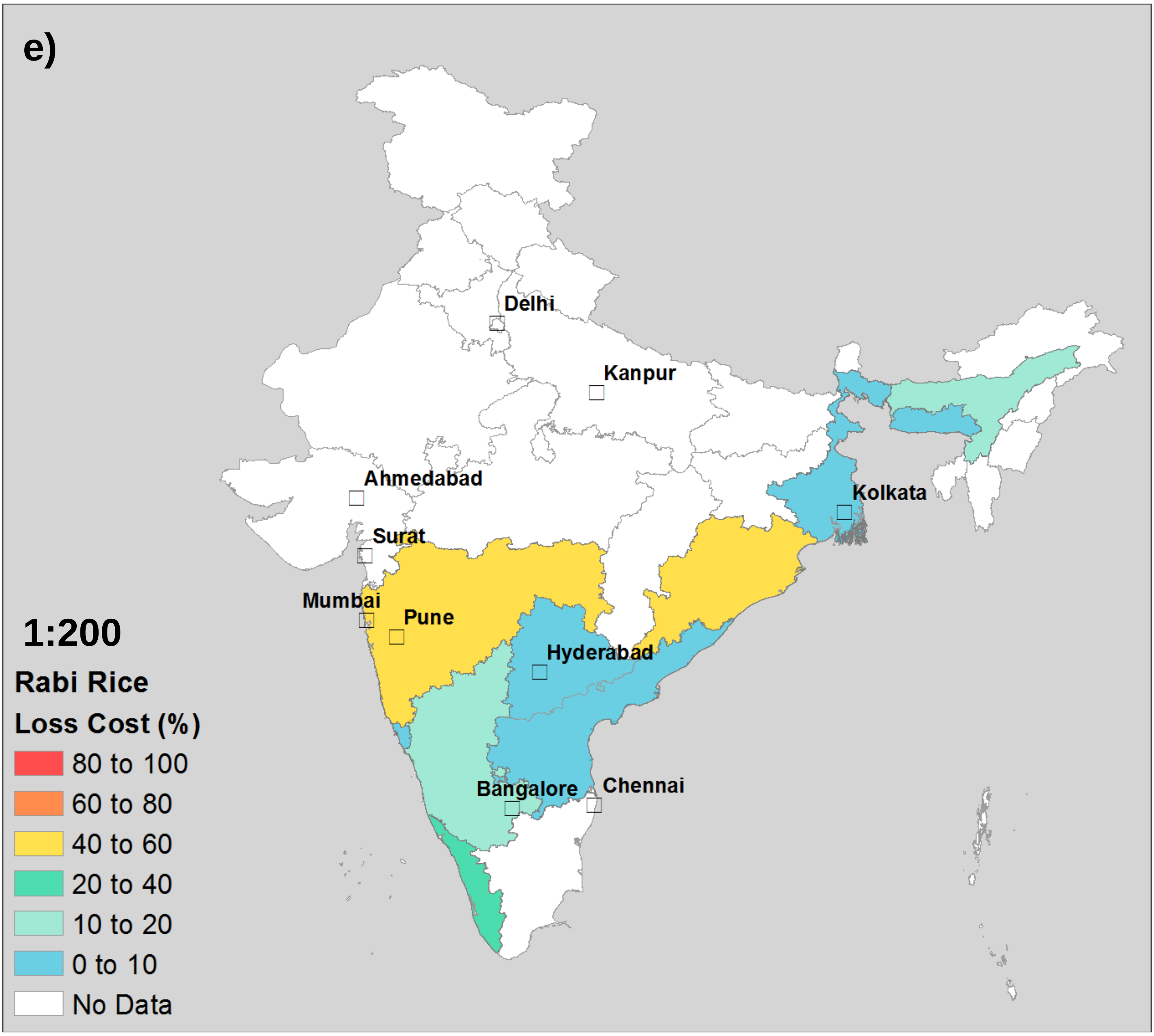
Figure 32: State-level simulated 200-year return period loss cost per crop a) Kharif rice, b) soybean, c) cotton, d) sugar cane, e) Rabi rice, f) wheat, g) potato

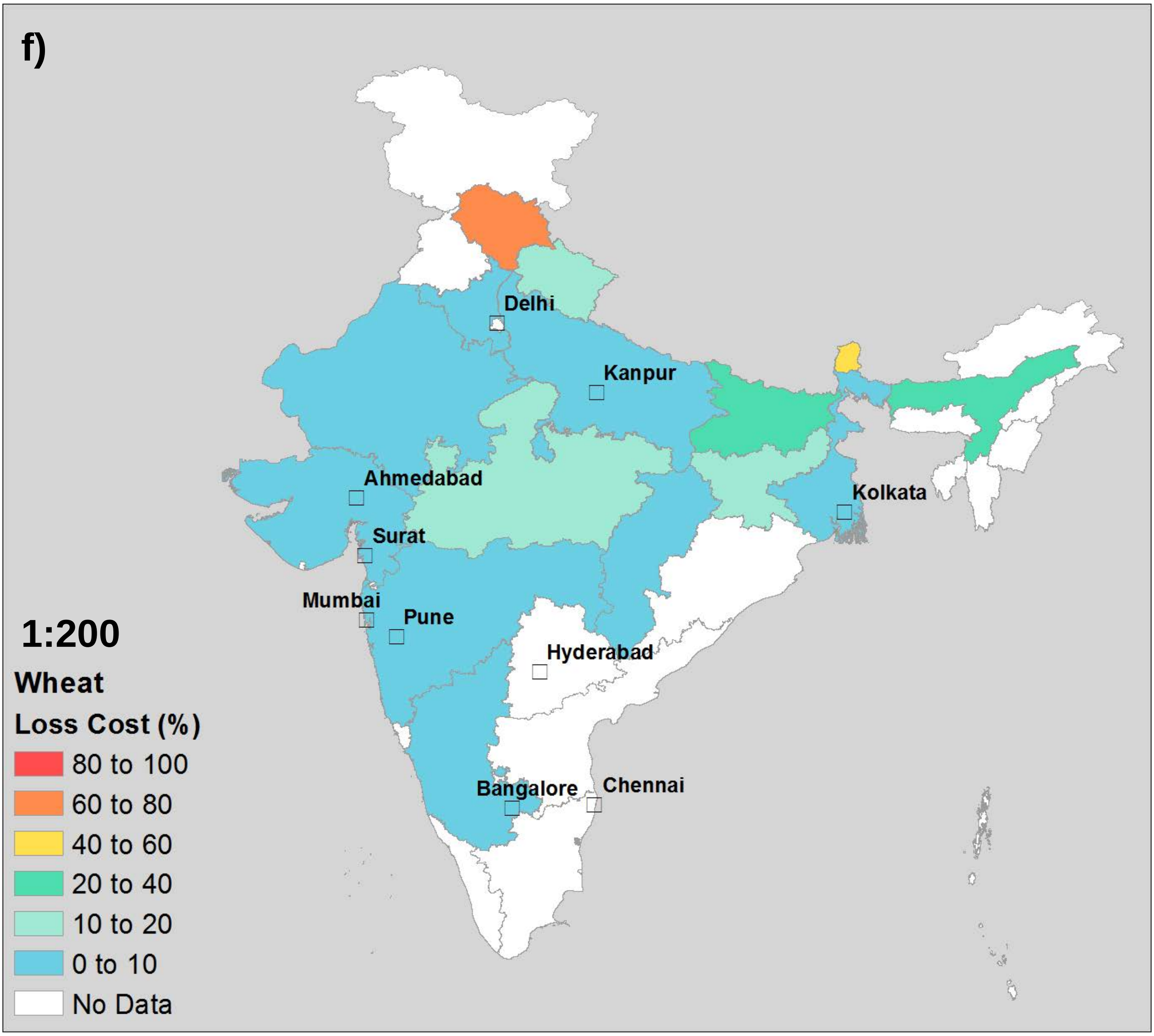


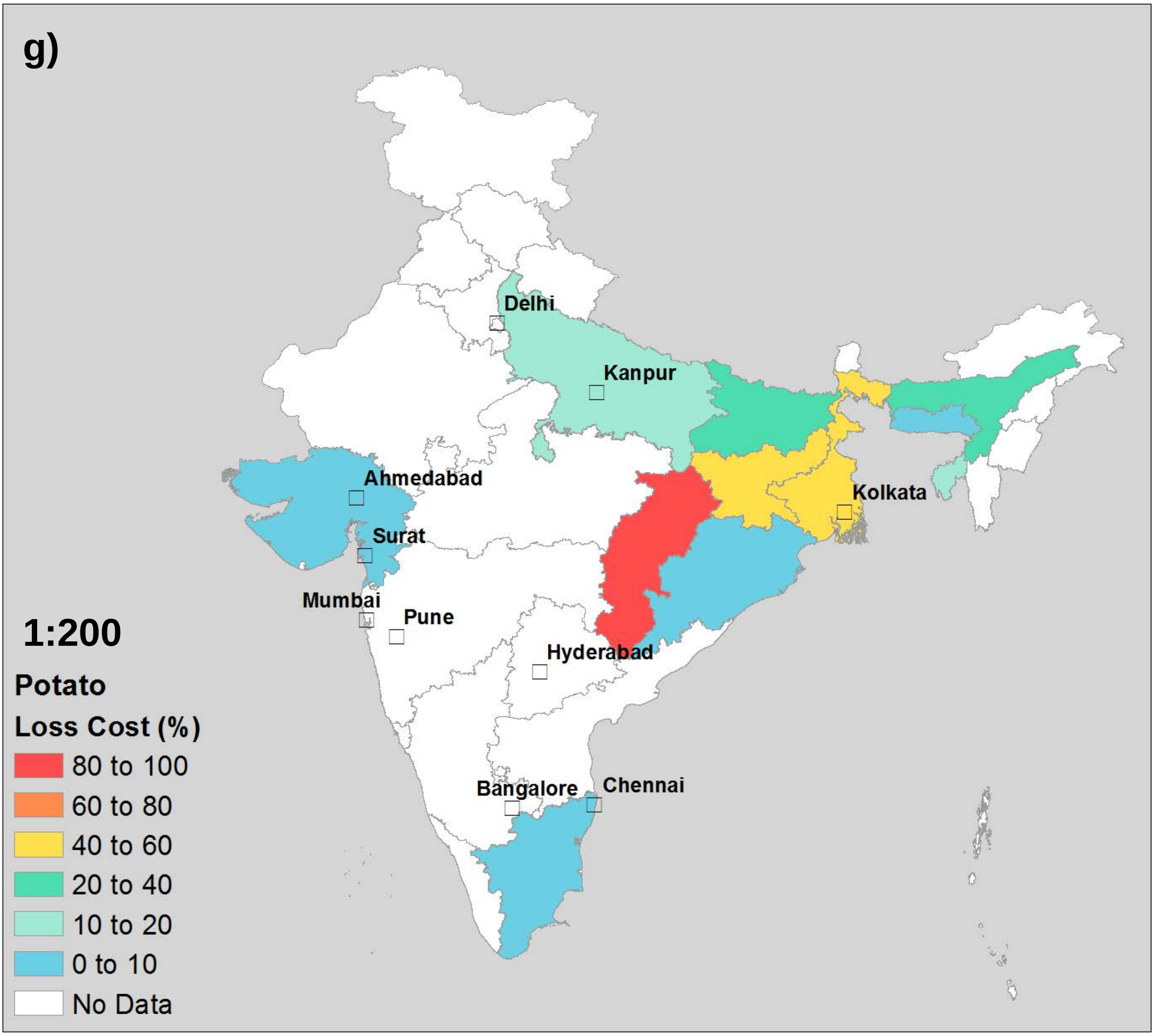

b)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
1:200
Soybean
Loss Cost (%)
80 to 100
60 to 80
40 to 60
20 to 40
10 to 20
0 to 10
No Data


c)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
1:200
Cotton
Loss Cost (%)
80 to 100
60 to 80
40 to 60
20 to 40
10 to 20
0 to 10
No Data


d)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
1:200
Sugarcane
Loss Cost (%)
80 to 100
60 to 80
40 to 60
20 to 40
10 to 20
0 to 10
No Data


e)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
1:200
Rabi Rice
Loss Cost (%)
80 to 100
60 to 80
40 to 60
20 to 40
10 to 20
0 to 10
No Data


f)
Delhi
Kanpur
Ahmedabad
Kolkata
Surat
Mumbai
Pune
Hyderabad
Bangalore
Chennai
1:200
Wheat
Loss Cost (%)
80 to 100
60 to 80
40 to 60
20 to 40
10 to 20
0 to 10
No Data

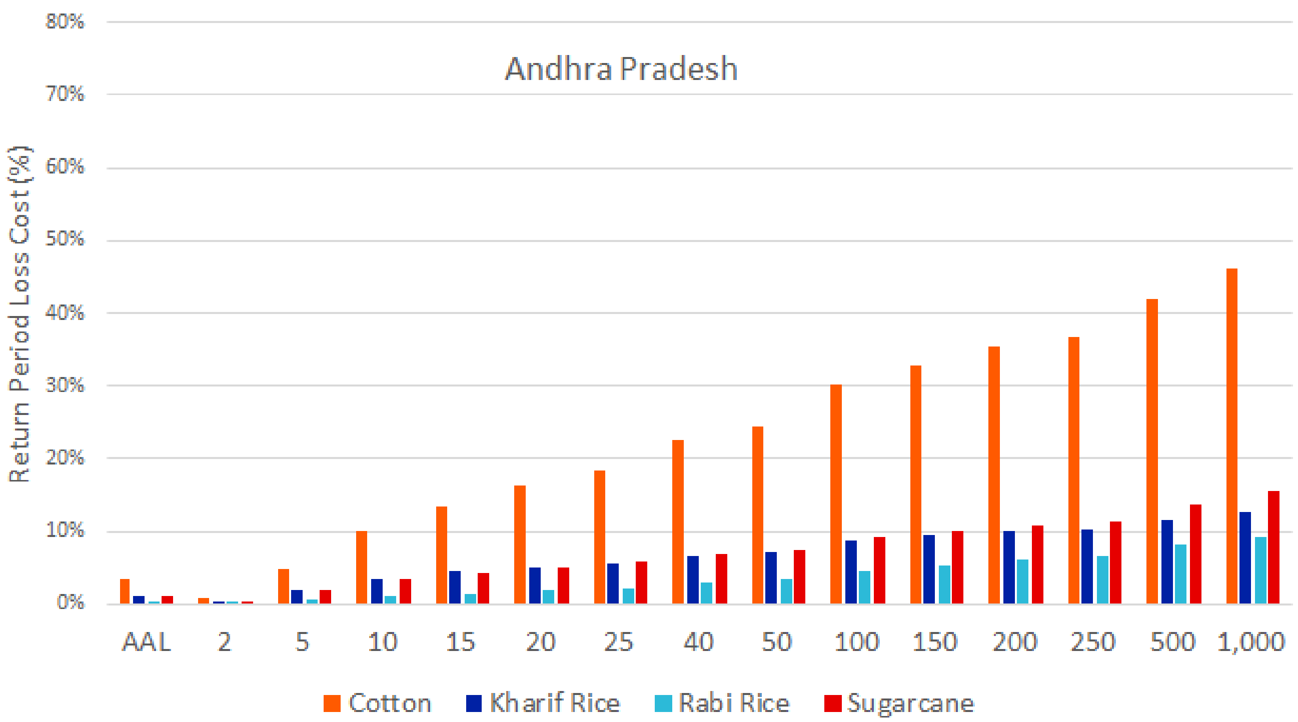


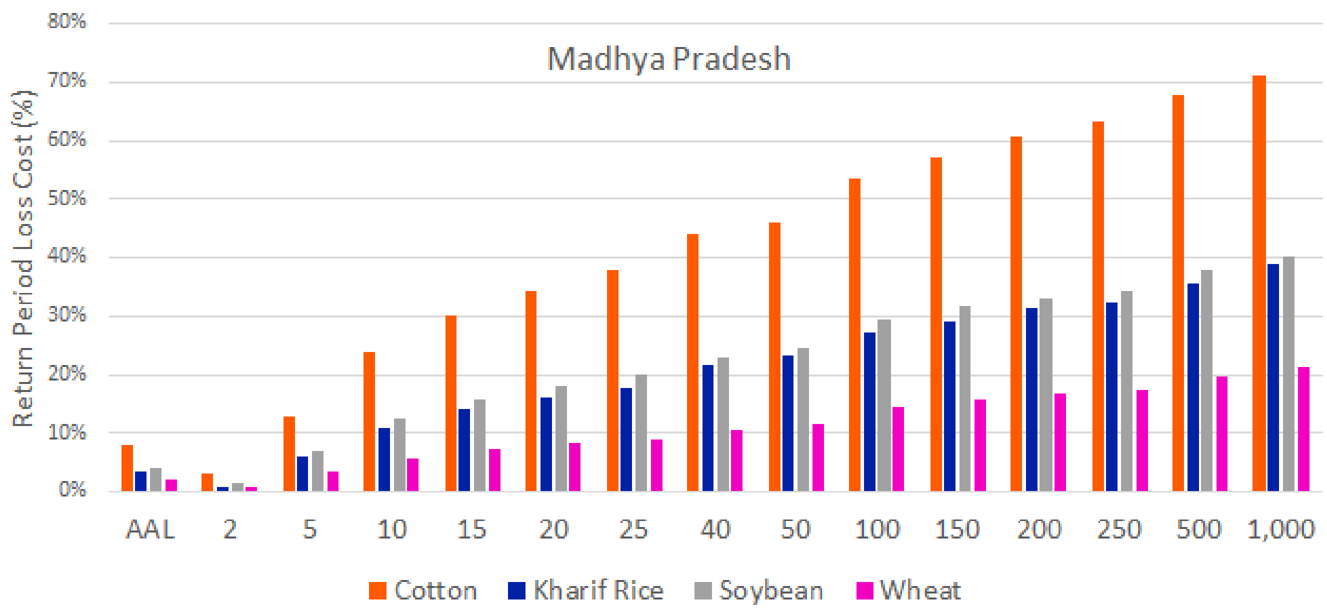
Source: Risk Management Solutions, Inc., 2017. See Figure 2, p19, for map of India's states.

Figure 33 provides a further example of how loss distributions can vary quite significantly between states and crops by comparing simulated return period loss costs between the states of Andhra-Pradesh and Madhya-Pradesh. The loss costs are much higher for Madhya-Pradesh than Andhra-Pradesh for all crop types, largely reflecting differences in adverse weather events between these two different climatic regions. The indemnity levels are reasonably similar, 80% on average, per crop for each of these states. In both states there is a mix of irrigated and rain-fed land (Figure 5, p.22).

The relativity between some crops differs between the two states. Cotton loss costs are larger than Kharif rice in Andhra-Pradesh compared to Madhya-Pradesh. These results further demonstrate the complexity of crop risk assessment as many factors can influence the overall risk.

Figure 33: Simulated return period loss costs for (a) Andhra-Pradesh and (b) Madhya-Pradesh





Source: Risk Management Solutions, Inc., 2017

4.3 Modelling summary

The results for the hypothetical portfolio presented in this section demonstrate the additional insights that can be obtained by coupling probabilistic climate datasets with crop models, assessing different views of risk for historical scenarios, specific projections (ENSO) and explicit adaptation measures (irrigation). With such a dramatic change in the crop insurance market since the introduction of PMFBY, historical reported loss data offer limited information and insights for pricing today's crop schemes. Thus, the use of probabilistic modelling is recommended to provide grounded, scientific and data-driven approach to assess and model Indian crop risk under the new PMFBY scheme. Models can also support validation of premium rates of crop insurance clusters to identify cases where clusters may be priced below the risk based rates and sensitivity testing around the impact changing cluster definitions.

Historical crop risk models, extending the historical loss records back 40-50 years, help to better understand the frequency and severity of historical crop losses. They also provide opportunities to stress test the model, modelling specific scenarios such as the impact of El Niño and La Niña years and performs model validation exercises. Probabilistic models, applying thousands of years of simulated weather data to crop yield models, provides greater insight into loss years that have not been observed before and provides a more robust framework to assess tail risk.

The model presented in this report provides results aggregated from 25km^2 to different spatial resolutions (whole portfolio, per state or district level) per crop (for those currently covered in the model) or combined, enabling the market to analyse individual insured clusters or multiple books of crop risk. The results have highlighted the complexity of crop risk modelling and the sensitivity of losses to the exact mix of crop types and their exposure distributions (in terms of exposure to different perils) considering different levels of irrigation and indemnity levels that are defined at cluster/district level per crop. Such models can be run with different levels of indemnity and irrigation information to explore the sensitivity of these important parameters.

If the amount of insurance coverages continue to grow as intended by the Government, crop risk models can provide a meaningful tool to assess the impact of new exposures in terms of their geographic distributions and crop mix. Given the current gap in time between treaty renewals and confirmation of crop exposures, crop models can be used to perform sensitivity analyses around business plans at renewal time, such as adding or dropping cluster(s), and should be flexible enough to allow quick and simple portfolio optimisation as exposures are confirmed. As the Indian crop risk market matures and stabilises, and more data becomes available, modelling companies should work hand-in-hand with all relevant stakeholders (Figure 12, p38) to develop more sophisticated models which can be used throughout the risk management chain.

Correlation between crop and property insurance risk

Emerging Risk Report 2018

Society & Security

5. Correlation between crop and property insurance risk

Rapid urbanisation, in conjunction with the high concentration of economic assets which comes with it, has exposed increasing portions of population and economic value in India and across many other parts of Asia, to natural hazards. Recent events, such as cyclone HudHud in 2014 or the flooding in Chennai (Madras) in December 2015, highlight the risk of large economic losses to multiple lines of business including crop and property. Today a large protection gap remains between economic and insured losses in India. In the future, if insurance penetration across non-life sectors increases as anticipated (AXCO, 2017), the correlation strength between crop and property will become more important for the insurance industry. This section explores the risk of large correlated losses between crop and property lines of business to increase insurers' awareness as the Indian insurance market grows.

To explore the potential of correlation between crop and property insured losses, the following was considered:

- perils impacting both lines of business,
- exposure distributions and
- insurance penetration.

Non-life insurance penetration in India is around 0.8% (IRDAI, Annual Report 2016-17) compared to 4.3% in the U.S, 2.6% in the U.K. and 1.8% in China (Swiss Re Sigma Explorer Database, 2018). Property business contributes to around 9% of Indian non-life premiums (USD 1.9 bn) while agriculture accounts for 16% (USD 3.3 bn) (Figure 1, GIC Industry Data Statistics, March 2017). Property insurance take up is higher for commercial and industrial lines compared to residential, where there is a lack of awareness of the benefit of insurance amidst concerns homeowners will not be adequately covered nor receive prompt and full claims settlement (The Tribune, 2014).

5.1 Natural peril risks impacting crops and property

Both property and crops can, theoretically, be impacted by large scale risks such as flooding and extreme wind with potential correlation between them (Table 7, p100). For more localised perils such as hailstorms and landslides, correlation may be less likely as the spatial extent of the event may not cover both agricultural and urban regions.

Property and crops are not always vulnerable to the same perils. For example, while drought and heat waves can devastate crops, it will not result in heavy direct property loss, although it can have negative impacts on revenues for energy and infrastructure (Carter & Moss 2017, World Bank 2016). During prolonged droughts, there is a risk of subsidence, depending on the soil type, which may/may not be covered by property insurance policies. Furthermore, crop damage can be caused by the attritional impact of several different adverse weather conditions over a growing season rather than attributed to one particular event like a property loss.

A total risk perspective should focus on the correlation of large scale perils, specifically monsoon driven floods and cyclones. There would also be some correlation between catastrophe events with small annual frequency of occurrence (large return periods) such as earthquake (localised) and secondary perils such as tsunami. Earthquake can damage crops directly for example by landslides or flooding via dam breaks and indirectly by farmers unable to tend to crops due to damage to infrastructure (not covered by crop insurance schemes). Given the size of India, any natural catastrophe will impact only a portion of the whole country and so nation-wide portfolios will be less impacted by an event than regionally focused portfolios. However even nation-wide crop and property portfolios can have a regional bias as discussed next.

Table 7: Summary of Indian natural catastrophe perils which could impact crop and property lines of business

Peril	Crop	Property	Correlation (C+P)
Monsoon Flood	Y (mainly Kharif crops)	Y	Y
Cyclone wind	Y (mainly Kharif crops)	Y	Y
Non cyclone extreme winds	Y	Y	Y
Cyclone flood	Y (mainly Kharif crops)	Y	Y
Drought	Y	small (subsidence)	N
Freeze	Y (mainly Rabi)	N	N
Heatwave	Y (mainly Rabi)	N	N
Landslide/mudslide	Y	Y	Unlikely (due to size of event footprint)
Hailstorm/unseasonal rain	Y (mainly Rabi)	small	Unlikely (due to size of event footprint)
Tsunami	Y	Y	Y
Earthquake	small	Y	Y

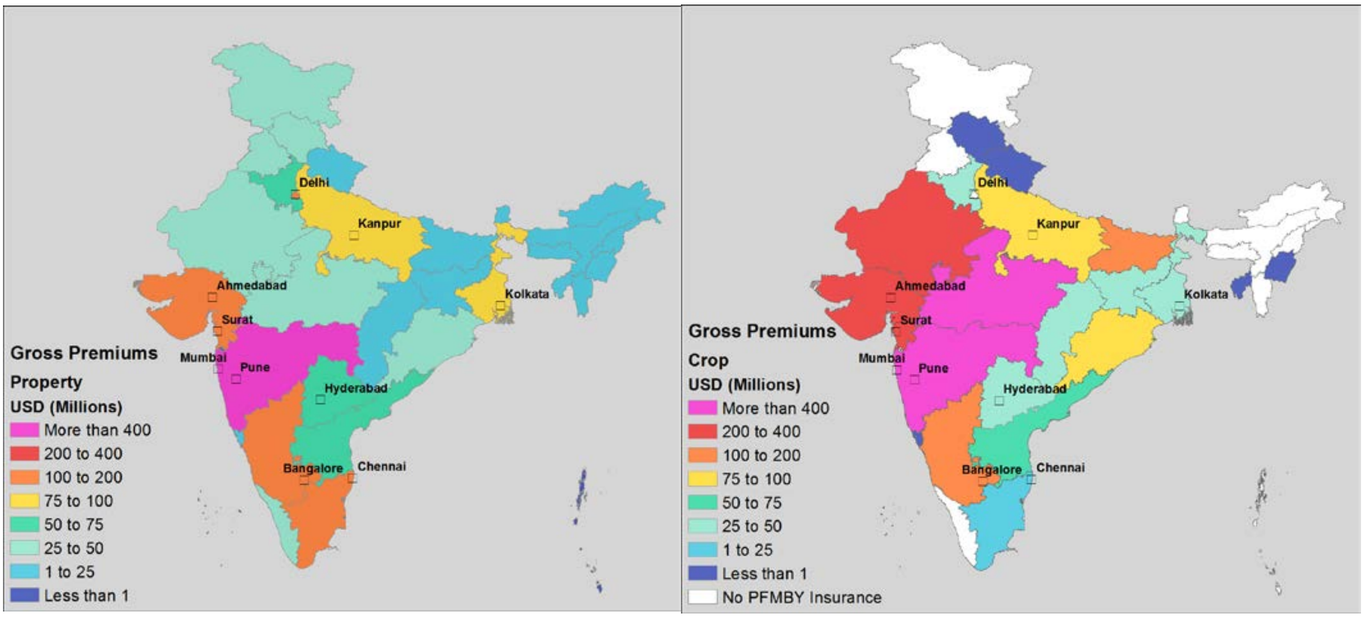
Source: Lloyd's - Risk Management Solutions, Inc., 2017. Y=yes, N=no.

5.2 Exposure distributions

To help understand the degree of dependency between property and crop risks, it is important to consider the distribution of crop and property exposures across India. Crops by their nature are spread out across large geographic areas. In contrast, India's populated regions are densely concentrated by recent rapid urbanisation. Around 80% of non-life insurance in India covers urban regions (GIC 2016-17 Year Book). Thus flooding or cyclones will have a bigger nation-wide impact on property portfolios than crop due to the concentration of property exposures. Drought, which has the biggest nation-wide impact on crops, will have a small impact on property.

As a way to compare coincident property and crop insured risks, Figure 34 compares state-level gross premiums between crop and property. In Table 8 this is overlaid with the top 10 cities in India with highest annual average GDP along with statistics about property and Kharif crop insurance in the associated state. Analysis based on data from the Cambridge Centre for Risk Studies identifies flood as the top natural threat to GDP in India's large cities. The impact of cyclones on GDP is low for most of the cities included in the analysis, with the exception of Kolkata. However while cyclones are less likely to occur they can cause greater losses. While premiums are spread across all states for both crop and property, more than a third of both Kharif crop and property premiums are concentrated in Maharashtra and Gujarat (Figure 34).

Figure 34: Property Premiums (2016/17) and 2016 Kharif Crop Premiums



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from GIC 2016 year book and CSE 2017 report (Bhushan & Kumar, 2017). See Figure 2, p19, for map of India's states.

Table 8: Top ten cities in India in terms of annual GDP with summary of state-level crop and property gross premiums (USD bn unless stated differently)

City	Annual GDP	Annual GDP@risk	State/UT	FL (GDP@risk)	CY (GDP @ risk)	EQ (GDP@risk)	DR (GDP@risk	Property Premiums by state (USD mn)	% to nation -wide 2016-17	Crop Premiums by state (USD mn)	% to nationwide 2016 (Kharif)
Delhi	108.5	3.52	Delhi UT	0.39	0.01	0.01	0.00	129	12	N/A	N/A
Mumbai	101.0	3.14	Maharashtra	0.18	0.03	0.01	0.00	504	27	632	25
Bangalore	74.10	2.53	Karnataka	0.18	0.02	0.00	0.03	131	7	137	5
Kolkata	32.60	1.72	West Bengal	0.12	0.56	0.10	0.01	81	4	44	2
Chennai	29.70	0.91	Tamil Nadu	0.05	0.01	0.00	0.01	161	8	2	<1
Ahmedabad	27.70	0.90	Gujarat	0.10	0.01	0.00	0.00	198	16	369	15
Hyderabad	26.00	0.90	Andhra Pradesh	0.10	0.01	0.00	0.01	73	4	70	3
Pune	24.50	0.89	Maharashtra	0.09	0.00	0.08	0.00	504	27	632	25
Surat	22.40	0.79	Gujarat	0.08	0.01	0.00	0.00	198	16	369	15
Kanpur	4.80	0.14	Uttar Pradesh	0.02	0.00	0.00	0.00	98	6	98	4
TOTAL	451.3	15.45		1.29	0.65	0.19	0.07				

Source: Lloyd's - Risk Management Solutions, Inc., 2018 based on data Cambridge Centre for Risk Studies, 2018, GIC 2016-17 year book, Bhushan & Kumar 2017. FL=Flood, CY=cyclone, EQ=earthquake and DR=drought.

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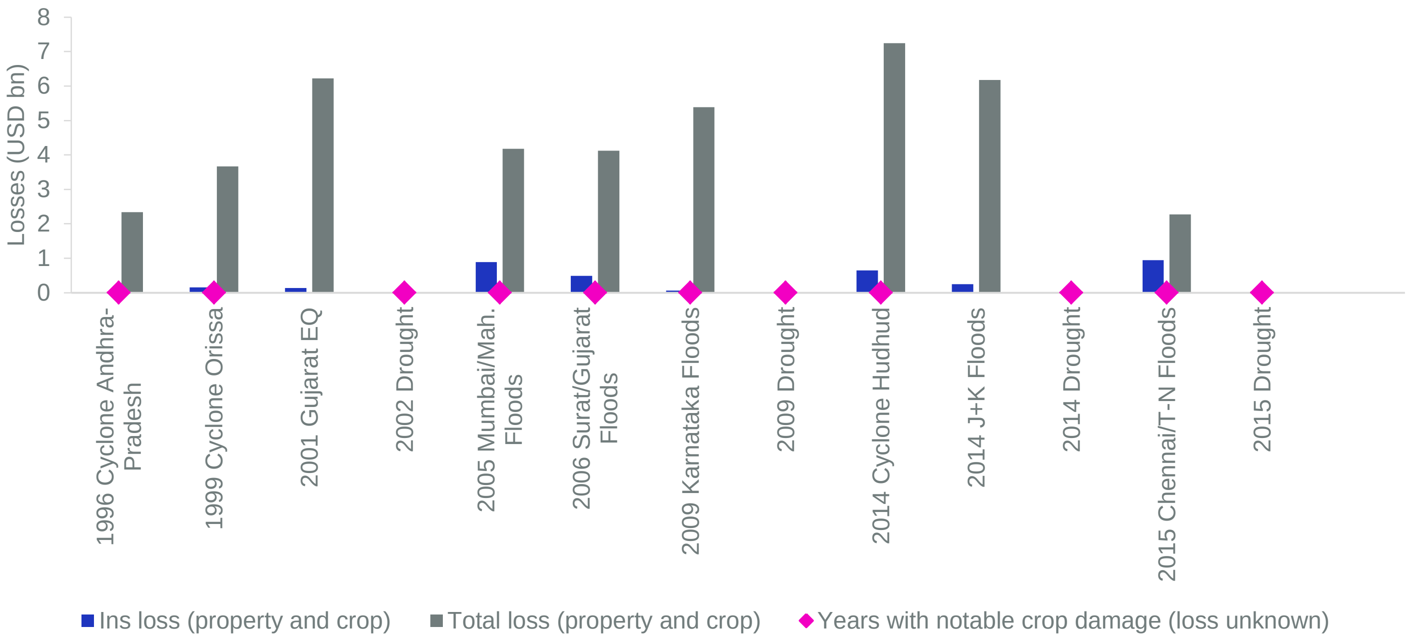
5.3 Potential drivers of correlated loss

Properties will always be at risk of a natural catastrophe regardless of the timing or seasonality of the event. Crop damage will depend on the timing of the event with regards to the growing season of crops (Kharif vs Rabi) in the impacted areas.

Most natural disasters faced by India have distinct seasonal variability (Figure 16, p52), except earthquakes/ tsunami which can occur at any time of year. Figure 35 lists recent natural catastrophes that have impacted either or both crops and properties. Total and insured losses are provided for the biggest events since 2000 from Swiss Re Sigma database. Years with significant droughts and reports of notable crop damage are flagged with pink diamonds (although the crop losses associated with these events are not clearly quantitatively reported).

Figure 35: List of major natural disasters for properties and/or crops losses



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from Swiss Re Sigma database (2017)

As seen in Table 8 flood is typically the top natural threat to GDP in India's large cities. The impact of cyclone is low for most of the cities included in the analysis, with the exception of Kolkata. However Figure 35 demonstrates that while cyclones have lower probability, they can cause greater losses. Since flood and tropical cyclones are important perils for both property and crop risk, the correlation of crop and property risk for these two perils is explored in this section. Hail and extreme temperatures are not considered for this investigation as they have a more localised impact and will not drive major correlated losses. Drought and earthquake, with less correlation between crops and property (with the exception of tsunami), are considered later when discussing the relative impact of natural catastrophes on crop and property losses.

Tropical cyclones

Tropical cyclone risk and its impact on crops have been discussed in Section 2 and Appendix 6. Post-monsoon cyclones tend to have greatest impact on Kharif crops along the eastern coast of India, if they arrive just before/during/post-harvest, which extends into October/November/December in this region thanks to the north-east monsoon. These storms can also cause significant damage to property due to high wind, precipitation-driven flooding and also coastal flooding due to the low-lying nature of most of India's coastline. Many buildings, particularly residential structures, are highly vulnerable to wind and flood damage. Pluvial flooding in urban areas has amplified over recent years driven by rapid urbanisation (Lloyd's, 2017).

The amount of damage caused by a cyclone will depend both on its severity but also where it makes landfall. Given the size of India, cyclones have a significant chance to impact heavily populated areas. For example, while Cyclone Phailin, in October 2013, was the second strongest cyclone to make landfall in India in recorded history. It resulted in relatively low property losses since it made landfall in a less populated region of Odisha, but caused severe loss to crops destroying crops worth USD 4 billion (Neubert and Smith, 2015). If this cyclone had hit a more populated region, the economic and possibly insured losses would have been significantly higher. Cyclone Hudhud in October 2014, while less severe in hazard, caused more damage as it hit a more populated region (Visakhapatnam - third largest city on the east coast of India).

The eastern coast of India, particularly the north, is most prone to tropical cyclones (Figure 5 in Appendix 6), with major coastal cities such as Kolkata and Chennai falling in their pathway. Chennai was damaged most recently by cyclone Vardah in December 2016, which also damaged crops in Tamil-Nadu, causing around USD 1 billion total loss but only USD 52 million insured loss (Swiss Re, 2017). Kolkata was last directly hit in May 2009 by cyclone Alia, but with records of more severe cyclones in October 1846 and 1737 causing devastating damage.

While the probability is lower, major cities on the western coast of India are also at risk of tropical cyclone damage. Mumbai (Bombay) has been directly hit in the past (such as June 1882 Great Bombay cyclone, November 1948, and November 2009 - Phyan).

Due to the large spatial extent of cyclone damage, and considering the distribution of crop and property exposures (Table 8, p102), there is a risk of coincident large crop and property cyclone losses if cyclones impact Chennai, Kolkata or Mumbai. Based on the current distributions of crop and property premiums (Figure 34, p101), a cyclone making landfall in Mumbai and moving inland over Maharashtra could create potentially the greatest correlated cyclone loss given the concentrations of crop and property risk. If both property and crop insurance penetration continues to increase, as expected, the risk of large correlated losses will increase.

Box 5: Recent historical cyclones causing both crop and property damage

Cyclone Orissa 1999: In late October 1999, a tropical cyclone developed in the Bay of Bengal and intensified to a Super Cyclone Storm with wind speeds of up to 162mph (260 km/hr, Cat 5 equivalent on the Saffir Simpson Hurricane Wind Scale) at landfall. The storm made landfall in the state of Odisha (known as Orissa in 1999), between Puri and Kendrapara, on the morning of the 29th October, causing wide spread damage in at least 14 districts from winds and inland and coastal flooding. The IMD reported storm surge between 5- 6m (16-20ft) along some parts of the coast, penetrating as far as 35 km inland, causing major property and crop damage and loss of life. Unlike most cyclones, the storm did not dissipate and move inland but stalled over land near the coast retaining its intensity and causing prolonged high winds and rain and further exacerbating the effects of the storm. Over 10,000 lives were lost, largely due to storm surge and is it is estimated that around 1.7mn properties and 1.8mn hectares of crops were damaged (IMD report, 2000). Residential properties with little or no engineering suffered worst damage. Damage was more limited in better engineered commercial and industrial properties in urban areas (Francis et al, 2001). Over 1 million hectares of Kharif crops were damaged (Action Aid report, 1999) including sugar cane and rice (Oxfam report, 1999). Coastal flooding affected standing crops and soil fertility preventing immediate replanting (Khatua & Dash, 2000). Total losses at the time were estimated at around USD 2.5 billion with insured losses of around USD 100 million (Swiss Re, 2000). Today, total losses are estimated at USD 3.7 billion with insured losses of USD 150 million (Swiss Re, 2017).

Cyclone Hudhud 2014: On 12th October 2014, cyclone Hudhud (classified as a Very Severe Cyclonic Storm by the IMD and the biggest storm of the Indian Ocean season) made landfall near the port city of Visakhapatnam in Andhra Pradesh, the state's largest city and third largest on the east coast of India. The IMD reported maximum sustained wind speeds of 107-113 mph (170-180 km/hr, Category 3 equivalent), and a storm surge of 1.4m (4.5 ft) was recorded at the tide gauge in Visakhapatnam (National Disaster Management Authority, 2015). Strong winds and precipitation-driven and coastal flooding resulted in 68 casualties and caused wide spread damage to property, including the airport, and crops in Viskahapatnam and neighbouring districts in Northern Andhra-Pradesh and southern Odisha (National Disaster Management Authority, 2015). The system moved north-east wards across Chhattisgarh, Madhya-Pradesh and Uttar Pradesh causing further widespread flooding and crop and property damage. Total economic losses were estimated at USD 5.5-7 billion (Munich Re, Swiss Re, 2015), the largest of all natural catastrophes in the world in the year 2014 (Swiss Re, 2014). Insured losses were reported as USD 350 to 600 million (Munich Re, Swiss Re, 2015). The state government of Andhra-Pradesh reported overall losses of USD 3.5 billion (INR 219 billion) of which around 10% were attributed to crop and horticultural damage, 15% housing and around 28% to private industries (Times of India, 2014). Cyclone Hudhud caused damage to around 150,000 homes and 0.25 to 0.45 million hectares of crops, including rice, sugar cane and bananas, in Andhra-Pradesh (Sphere India report 2014, Times of India, 2014).

Box 6: Recent historical monsoon floods causing both crop and property damage

Mumbai/Maharashtra 2005 floods: During the month of July 2005, almost 1,000 millimetres (39 in.) of rain fell on Mumbai in a 24-hour period, almost double the previous rainfall record in July 1974. The flooding was further aggravated when seawater entered the system during high tide, adding to water levels and preventing drainage of the rainfall out to sea. The floods in Mumbai and the neighbouring districts resulted in over 1000 casualties (Ministry of India report, 2011) and caused widespread damage to property and crops. More than 100,000 properties were damaged in Mumbai alone (Gupta 2007) and with reports of 10,000 homes having collapsed (UN, 2005). Over 225,000 hectares of Kharif crops across 15 districts in Maharashtra were damaged (UN, 2005). Sugar cane crops were extensively damaged. Total losses at the time were reported to be between USD 3-5 billion (Swiss Re, Munich Re, 2006). Today, total losses are estimated at USD 4.2 billion with insured losses of USD 890 million (Swiss Re, 2017).

Mumbai is susceptible to flooding due to its geography, both natural and man-made. Typically, 50 percent of the rainfall occurs during July and August, falling in just two or three events. This situation is aggravated by the man-made geography. Large areas of the city are situated only just above sea level and below the high tide level which inhibits natural runoff of surface water. The complicated network of drains, rivers, creeks and ponds drain directly to the sea, meaning that during high tides, sea water can enter the system, preventing drainage and in extreme cases, lead to saltwater deluge. Mumbai experienced severe flooding again in August 2017 and while there was better emergency disaster management following on from lessons learnt in 2005, there has been slower progress in terms of urban flood and drainage management (Indian Express, 2017).

2015 Chennai/Tamil-Nadu Floods: On November 15 through 16, Chennai received 246.5 millimetres (10 in.) of rainfall during a 24-hour period (highest since 1975) resulting in floods over most of the city. Chennai received 1,060.2 millimetres (41.7 in.) of rainfall in the month of November, the second highest amount recorded in November since 1918. Then on November 30, Chennai received an additional 374 millimetres (14.7 in) of rainfall over 24 hours, almost twice the historical average for all of December and the highest since 1901, making 2015 the worst 24-hour period of rainfall ever recorded in December since record keeping began in 1847.

The culmination of these heavy rainfalls resulted in significant flooding in Chennai and the surrounding areas in Tamil-Nadu and also parts of Andhra-Pradesh, resulting in nearly 300 casualties and severely damaging properties and crops to the estimated cost of around USD 2-3.5 billion (Munich Re, Swiss Re, 2016). Many large commercial and industrial facilities, including motor and IT manufacturing companies, in Chennai were damaged by the floods and insured losses were estimated at around USD 500 – 800 million (Munich Re, Swiss Re, 2016), making it the costliest insured disaster in Indian history according to Swiss Re Sigma records. The floods damaged around 2.5 million properties and 0.4 million hectares of crops in Tamil Nadu (Sphere India report, 2015). Many Kharif crops, harvested later than other parts of the country to benefit from the north-east monsoon, were damaged including rice and sugar cane crops.

Monsoon flooding

Flood is the riskiest peril in India, with more than 2/3 of India Nat CAT losses attributed to flood, based on UN Statistics. Flooding is a common phenomenon in India, driven by periods of heavy rainfall and exacerbated by the silting up of rivers, reduced soil absorption, lack of urban planning and deforestation. Flooding is most commonly caused by heavy bursts of rain during the monsoons or downpours from tropical cyclones (described in Section 2 and Appendix 6). While many of India's floods occur during the south-west monsoon during June to September (e.g. Mumbai 2005, Uttar Pradesh 2013), rainfall during the north-east monsoon can also trigger severe flooding (such as Chennai December 2015 floods). Antecedent conditions (soil moisture content, river levels before heavy rainfall) play a key role in the extent of flooding that a particular period of heavy rain can trigger.

Monsoon driven flooding risk and its impact on crops has been discussed earlier in Section 2 where we noted that. Kharif crops are most at risk from flood damage. Property flood damage has increased over the past few decades as a result of population growth. As people look for more space to live, floodplains are becoming populated and natural drainage systems are covered reducing capacity to handle heavy rainfall. Recent flooding events have been aggravated by increased urbanisation and unplanned growth resulting in severe pluvial flooding (e.g. Mumbai 2005 & 2017 and Chennai 2015). Industrial risks are particularly susceptible to flooding as they are usually located close to rivers.

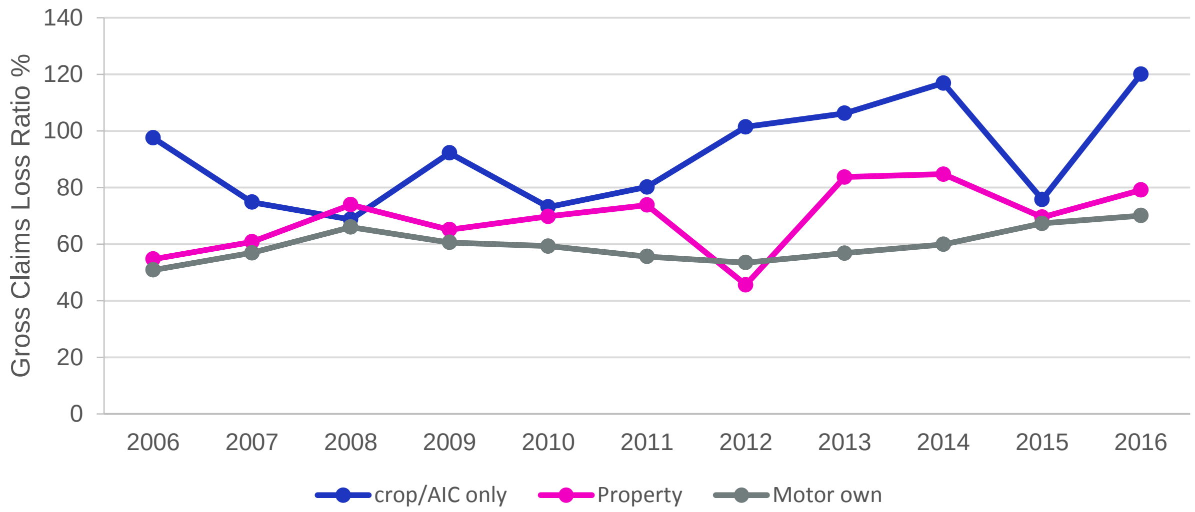
Due to the scale of monsoon rainfall, flooding impacting major cities could also extend over neighbouring arable land and thus result in significant property and crop losses. Some of the most severe recent floods, have damaged both crops and properties. An analysis into historical crop and residential property damage between 1980-2011 reported by the Central Water Commission, suggest that at a nation-wide level major loss on property does not often imply a larger than average loss on crop and vice-versa. The fact that this database separates damage for crop versus property reflects that flood can cause significant damage and loss to both lines of business. At a regional scale, there are cases where moderate to large crop and property losses have been reported such as the Karnataka 2009 floods and floods in West Bengal in 1999 and 2000. Data was not available for the state of Maharashtra and Gujarat to investigate the statistics for the 2005 and 2006 floods.

No state in India is safe from floods but the north/north-east has greatest flood risk (Figure 4 in Appendix 6). These regions contribute a smaller amount to crop and property premiums, thus today, the risk of a large correlated crop and property loss is less likely. However as insurance penetration increases, these losses could become larger.

5.4 Overall risk of correlated insured losses

To put into overall context how correlated property and crop insured losses are, we consider the contribution of the major perils driving crop losses (drought/flood/cyclones) and those driving property losses (earthquake/flood/cyclones). At a nation-wide level, the risk of coincident large crop and property losses is minimal due to two main factors. Firstly differences in exposure distributions: insured property exposures are typically densely concentrated unlike crop. Secondly differences in vulnerability to India's range of natural disasters: drought or an unlucky succession of adverse weather events drive major nation-wide crop losses which have no/little impact for properties. While a cyclone has the potential to cause large insured property losses if it makes landfall at or near a major urban area, since crops by their nature are not concentrated, the impact on a nation-wide book for crop would be relatively small. Earthquake and tsunami's can also cause significant property losses if it impacts a major urban region, but again impact but the impact on crops at a nation-wide scale would be small. Comparing historical claims loss ratios for property, motor and crop (AIC only) lines of business, crop loss ratios are poorly correlated to either property or motor (Figure 36). For example, the peak in crop loss ratio in 2009 (drought, Karnataka floods) is not evident in property and motor ratios indicating that at a national-level, the correlation of large losses between crop and property is weak.

Figure 36: Historical market-wide* gross claims loss ratio reported in the General Insurance Council 2015/16 Year Book (*for crop, only AIC results are shown)



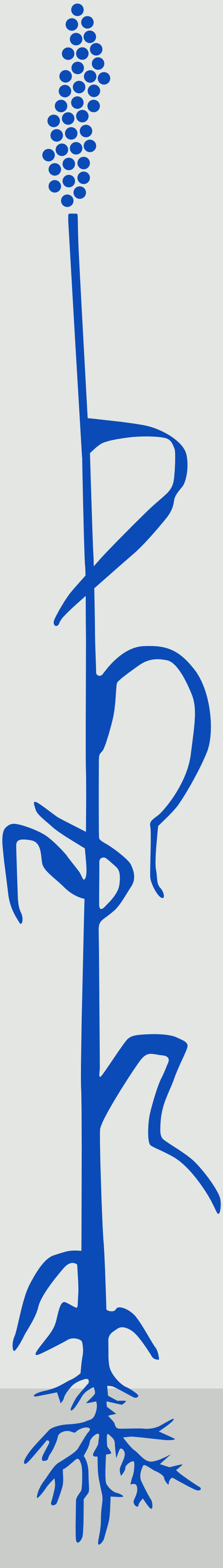
Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from GIC year book reports

At a regional level, there can be correlations in crop and property loss due to cyclones or episodes of regional flooding during the monsoon season as discussed earlier. There is also potential for earthquakes and tsunamis to impact at a regional scale – such as the 2004 tsunami. Thus there is a risk that insurers operating at a regional level in both the crop and property sectors, could be at risk from large correlated losses, compared to more geographically diverse portfolios. However since a large majority of both crop and property insurance premiums are currently concentrated in the western and north-western states of India such as Maharashtra and Gujarat, a major cyclone or flood hitting key cities in these states such as Mumbai, Pune, Surat or Ahmedabad and also impacting large areas of neighbouring arable land could result in large crop and property losses at a national level. While this has not happened in recent history, events such as the 1882 Mumbai cyclone are a reminder of what is possible in the future.

In summary:

- Correlation between large crop and property losses is likely to be at regional scale and event dependent. The insured and total loss statistics presented in the case studies (Section 5.3) highlight the risk of large losses and the current large protection gap.
- As the non-life insurance market grows in India to reduce this gap, it is vital that this is supported by the reinsurance market to better protect India against natural disasters.
- Due to the large number of different types of natural disasters that impact India, it is important to have a solid understanding of crop and property exposures, particularly as both markets are anticipated to grow over the next few years.

- A more holistic risk modelling approach might be required for major lines of business such as crop, motor and property, covering key perils such as flood, cyclone, earthquake and specifically for crops, the impact of droughts and attritional weather events.



Conclusions

6. Conclusions

For Lloyd's, the Indian reinsurance market is a very important one and we look forward to working closely with clients to craft policies that meet specific needs and address the insurance gap in this evolving market.

Looking towards the future

The Indian crop market is unique in many ways. To encourage and maintain capacity in the Indian crop reinsurance market, it is important that there is more data and risk transparency as well as confidence that risks of moral hazard and adverse selection are being minimised by the processes set up in PMFBY such as mandatory use of technology and geolocating the sites of CCE. Much of the framework is in place but proper implementation is required to ensure greater transparency and accuracy and that timelines are strictly adhered to. The issues found in the Indian crop insurance market are not all unique. The crop market in China, although a few years ahead of India, continues to be impacted by concerns of adverse selection. Areas of improvement to ensure business sustainability include:

1. Provide uniform consistent data
2. Ensure greater transparency and underwriting discipline
3. Minimise exposure certainty
4. Improve claims handling process and assessment
5. Ensure timely premiums
6. Strengthen regulations

Future of modelling

Over the past 30 years, probabilistic natural catastrophe models used to assess and manage property insurance have evolved dramatically driven by the increasing needs of the (re)insurance industry. These are used today with great confidence throughout the risk management chain. This development has largely been driven by advances in science, the digitisation of data, technological advances, including computing power, along with the evolution of (re)insurance business practices and regulatory requirements. The threats to agriculture are very similar to those of property: they arise from catastrophic and attritional natural events that cannot be appropriately modelled using actuarial methods alone. The building blocks of the latest generation of natural catastrophe models are now being applied to the agricultural sector. These make use of existing digitised data, technology and science. With agricultural risk increasing from a growing demography coupled with the related impacts of land-use changes, water scarcity and climate change, many governments are concerned with building more resilient agroecosystems in which (re)insurance can play a key role in transferring risk. Over the next few years, as the global agriculture insurance market grows, probabilistic modelling will also become an integrated component of agriculture risk management as data and models improve, and the market gains greater confidence in its capabilities.

The Indian Government continues the drive to implement and embed technology into the agricultural sector. It is also showing commitment to address stakeholder feedback after the first couple of years of the PMFBY scheme, with potential updates to the PMFBY operational guidelines and implementation. In India, data availability is the main factor limiting the progression of crop risk modelling. As with any form of modelling, the quality of model results is reliant in part on the quality of input data. Model uncertainty can be reduced with better exposure, weather, yield and loss data provided at the finest spatial resolution possible. The Government national crop insurance data portal requires a greater wealth of data to fully meet the (re)insurance market needs. Gathering detailed and real time exposures at the time of planting (such as crop variety, planting dates, irrigation levels) and better monitoring the different growing stages, via the latest technologies such as remote sensing, will help to improve crop risk modelling. Some countries, such as the US, already rely on precision-farming technologies to gather such information and feed into crop insurance schemes.

As the Indian crop risk market matures and stabilises, modelling companies should work hand-in-hand with all relevant stakeholders to gather better data and develop models that can be used throughout the risk management chain. As better data becomes available, crop models can become more sophisticated to consider the impact of different managerial practices (such as seed varieties and the use of fertilisers). Models can also evolve to allow in-season loss prediction by applying forecasted weather data to crop yield models, as well as estimating crop yield and loss behaviour under different climate scenarios (e.g. El Niño phases) as well as under different IPCC 's Climate Change Representative Concentration Pathways.

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Appendices

Appendix 1: Priority ordering for Indian re-insurance purchasing

The 2016 IRDAI regulations have outlined the priority procedure for the offering of Indian reinsurance business to local and cross border reinsurers, as follows:

1. Indian Reinsurer (GIC) with right of first refusal
2. Category I (min 50% retention) Foreign Reinsurer/Lloyd's with office in India
3. Category II (min 30% retention) Foreign Reinsurer/Lloyd's with office in India
4. Reinsurers with offices set-up in Special Economic Zone
5. ITI Re or other Indian Insurers
6. The balance may then be offered to Cross Border Reinsurers (outside India)
7. Indian Reinsurers given option to match CBR's quotes

The IRDAI are currently drafting an update to the General Insurance-Reinsurance Regulations following stakeholder feedback (PWC, 2018), including updates to the priority order for reinsurance purchasing. However the revisions are yet to be finalised (Reinsurance News, 2018).

Source: IRDAI

Appendix 2: Worked example of the PMFBY index

This appendix provides a worked example of the PMFBY scheme.

- **Crop**: Wheat
- **Season**: Rabi 2016/17
- **Sums insured**: 30,000 INR/hectare
- **Number of Hectares (ha)**: 1
- **Indemnity level**: 80%
- **Historical reported yield**: The table below presents the historical yields for the past 7 years.

Year	Historical reported yield (kg/ha)	Calamity year (declared by state)
2009/10	4500	
2010/11	3750	
2011/12	2000	x
2012/13	4250	
2013/14	1800	x
2014/15	4300	
2015/16	1750	x

Average Yield: This is calculated as the average yield excluding up to 2 calamity years.

In this example, the 2 calamity years with lowest yields would be excluded from the average yield calculation (2015/16 & 2013/14). The threshold yield is (4500+3750+2000+4250+4300)/5 = 3,760 kg/ha.

Actual Yield (reported from crop cutting experiments for 2016/17): 2,900 kg/ha.

The PMFBY index is defined by the loss cost (loss/sums insured) as follows:

$$\mathrm{LC_{yr}} = \max\left[0, \frac{\mathrm{TY} - \mathrm{Yield_{yr}}}{\mathrm{TY}}\right]$$

where

$$TY = Average\ Yield\ x\ Indemnity$$

Based on this definition:

- **Threshold yield (TY)** = 3760 x 80% = 3,008 kg/ha
- **Loss cost LC_{yr}**= (3,008-2,900)/3,008 = 3.6%
- **Claim** = 3.6% x 30,000 (sums insured) = 1,077 INR/ha

Source: Risk Management Solutions, Inc., 2017 based on data from PMFBY Operational Guidelines

Appendix 3: Worked example of the RWBCIS index

This appendix provides a worked example of the RWBCIS scheme for a policy with 3 different weather indices. It is common to have multiple indices per policy. Source: RWBCIS Operational Guidelines.

- **Crop**: Rice
- **Season**: Kharif 2016
- **Number of Hectares**: 1

Cover A: Excess Rainfall Cover (maximum cumulative rainfall in mm of any 2 consecutive days during the cover period)

Period	1: 15 Jul – 31 Aug	2: 1 Sep - 30 Sep	3: 1 Oct - 31 Oct	Total: 15 Jul - 31 Oct
Strike 1 (mm)	80	33	15	
Strike 2 (mm)	175	95	45	
Exit (mm)	285	200	134	
Notional 1 (INR/mm/ha)	7.37	6.45	9.67	
Notional 2 (INR/mm/ha)	20.91	24.76	30.45	
Period Limit (INR/ha)	3,000	3,000	3,000	
Cover Limit (INR/ha)				9,000
Observed index	79	120	20	
Claim Payable	0	1,019	48	
Total Claim (INR/ha)				1,067

(Notional 1 = standard loss rate between strike 1 and 2. Notional 2 = standard loss rate between strike 2 & exit.)

The claims are calculated as (Observed – Notified index values) x Notional Payout.

- **Period 1**: In this case notified first loss trigger (strike 1) value is 80mm. Observed index value is 79mm. In this case there would be no claim payable as the notified trigger is not breached.
- **Period 2**: In this case notified first loss trigger (strike 1) value is 33mm and the second trigger (strike 2) value.is 95mm. Observed index value is 120mm, which is greater than the second trigger but below the Exit (200mm). In this case a claim would be payable as follows: claim = [(strike2-strike 1) x notional1] + [(observed-strike 2) x notional2] per hectare.
- **Period 3**: In this case notified first loss trigger (strike 1) value is 15mm and the second trigger (strike 2) value is 45mm. Observed index value is 20mm, which is greater than the first trigger but below the second trigger. In this case a claim would be payable as follows: claim = [(Observed-strike 1) x notional1] per hectare.

Total Period: The overall claim is the sum of the 3 periods, (0+1019 + 48) = 1,067 INR/ha.

Cover B: Deficit Rainfall Cover (Aggregate rainfall in mm during the cover period)

Period	1: 25 Jun - 15 Aug	2: 16 Aug - 30 Sep	Total: 25 Jun - 30 Sep
Strike 1 (mm)	475	200	▪
Strike 2 (mm)	270	95	▪
Exit (mm)	25	10	▪
Notional 1 (INR/mm/ha)	7	21	▪
Notional 2 (INR/mm/ha)	24	62	
Cover Limit (INR/ha)	7,500	7,500	
Cumulative Cover Limit (INR/ha)			15,000
Observed index (mm)	230	125	
Claim Payable (INR/ha)	2,395	1,575	
Total Claim (INR/ha)			3,970

(Notional 1 = standard loss rate between strike 1 and 2. Notional 2 = standard loss rate between strike 2 & exit.)

The claims are calculated as (Notified index values – Observed) x Notional Payout.

- **Period 1**: In this case notified first loss trigger (strike 1) value is 475mm and the second trigger (strike 2) value is 270mm. The observed index value is 230mm which is below the second trigger but above the Exit (25mm). In this case a claim would be payable as follows: claim = [(strike1-strike 2) x notional1] + [(strike 2-observed) x notional2] per hectare.
- **Period 2**: In this case notified first loss trigger (strike 1) value is 200mm and the second trigger (strike 2) value is 95mm. The observed index value is 125mm, which is less than the first trigger but greater than the second trigger. In this case a claim would be payable as follows: claim = [(strike 1-observed) x notional1] per hectare.

Total Period: The overall claim is the sum of the 2 periods, (2395+1575) = 3,970 INR/ha.

Cover C: Consecutive dry days

(Maximum number of Consecutive Dry Days,CDD, where a 'dry day' is a day with rainfall <=2.5mm)

Period	15 Jul - 31 Aug
Strike 1 (CDD's)	4
Strike 2 (CDD's)	10
Strike 3 (CDD's)	14
Strike 4 (CDD's)	19
Exit (CDD's)	24

Payout (INR/ha) for Strike 1 <CDD <= Strike 2	328
Payout (INR /ha) for Strike 2 <CDD <= Strike 3	720
Payout (INR /ha) for Strike 3 <CDD <= Strike 4	1,800
Payout (INR /ha) for Strike4 <CDD <= Exit	3,600
Cover Limit (INR /ha) for CDD > Exit	6,000
Observed CDD (days)	12
Total Claim (INR/ha)	720

The claims are calculated depending on the maximum number of dry days in the period. The maximum number of consecutive dry days observed is 12 days. This number is above strike 2 but below strike 3. In this case the claim payable would be: 720/ha for the period.

Combined Policy Limit = 9,000 (Cover A) + 15,000 (Cover B) + 6,000 (Cover C) = 30,000 INR/ha

Combined Policy Claim/hectare = 1,067 (Cover A) +3,970 (Cover B) + 720 (Cover C) = 5,757 INR/ha

Source: Risk Management Solutions, Inc., 2017 based on data from RWBCIS Operational Guidelines

Appendix 4: The table below lists some of the most common weather indices used in RWBCIS

Cover Type	Index Calculation
Deficit Rainfall	Cumulative rainfall (mm)
Consecutive Dry Days (CDD) or Dry Spell Duration (# consecutive	Number of consecutive dry days with precipitation less than trigger (gaps
Excess Rainfall I R	Cumulative or Maximum of sum of excess rainfall (mm) over N consecutive
Excess Rainfall II (total number of wet days)	Total number of days with precipitation greater than trigger
Excess Rainfall IIA Wet Spell Duration (# consecutive wet days)	Number of consecutive days with precipitation more than trigger (gaps
Excess Rainfall III (cumulative total rainfall)	Cumulative rainfall (mm)
HDD (cumulative or Max excess temperature)	Cumulative or Maximum of excess temperature (= deviation from trigger)
LDD (cumulative or Max deficit temperature)	Cumulative or Maximum of deficit temperature (= deviation from trigger)
Extreme Temperature (HDD + LDD)	HDD + LDD
Maximum Temperature (cumulative upward deviation)	Total of fortnightly upward deviation of Average, or Maximum, daily
Low Temperature I (minimum of average temperature over N	Minimum of average daily temperature over any N Consecutive days
Low Temperature II (minimum temperature)	Minimum of daily Temperature
Excess Rainfall IV (daily payouts)	List of Index values over trigger for the entire phase
Excess Rainfall I NR	Cumulative or Maximum of sum of excess rainfall (mm) over N consecutive

Source: Risk Management Solutions, Inc., 2017

Appendix 5: Status of payment of Kharif 2016 claims (as of April 2017) per state

State	Percentage of claim paid for Kharif 2016
Andhra Pradesh	28%
Bihar	0%
Chhattisgarh	13%
Gujarat	0%
Haryana	2%
Himachal Pradesh	70%
Karnataka	100%
Madhya Pradesh	3%
Maharashtra	75%
Manipur	0%
Odisha	0%
Rajasthan	0%
Telangana	0%
Uttar Pradesh	98%
Uttarakhand	99%
West Bengal	0%
TOTAL	32

Source: Risk Management Solutions, Inc., 2017 based on data from Bhushan & Kumar 2017, Department of Agriculture, Cooperation & Farmers Welfare April 2017.

Appendix 6: Analysis of weather and climate variability on crop yield and losses

This appendix expands Section 2 to provide greater detail about the following key weather events that may impact crop production and losses in India:

- Monsoon
- Tropical cyclones
- Extreme Temperatures
- Unseasonal Rain and Hailstorms

The latest research on climate change related to its impact on Indian climate and crop yields is also summarised here.

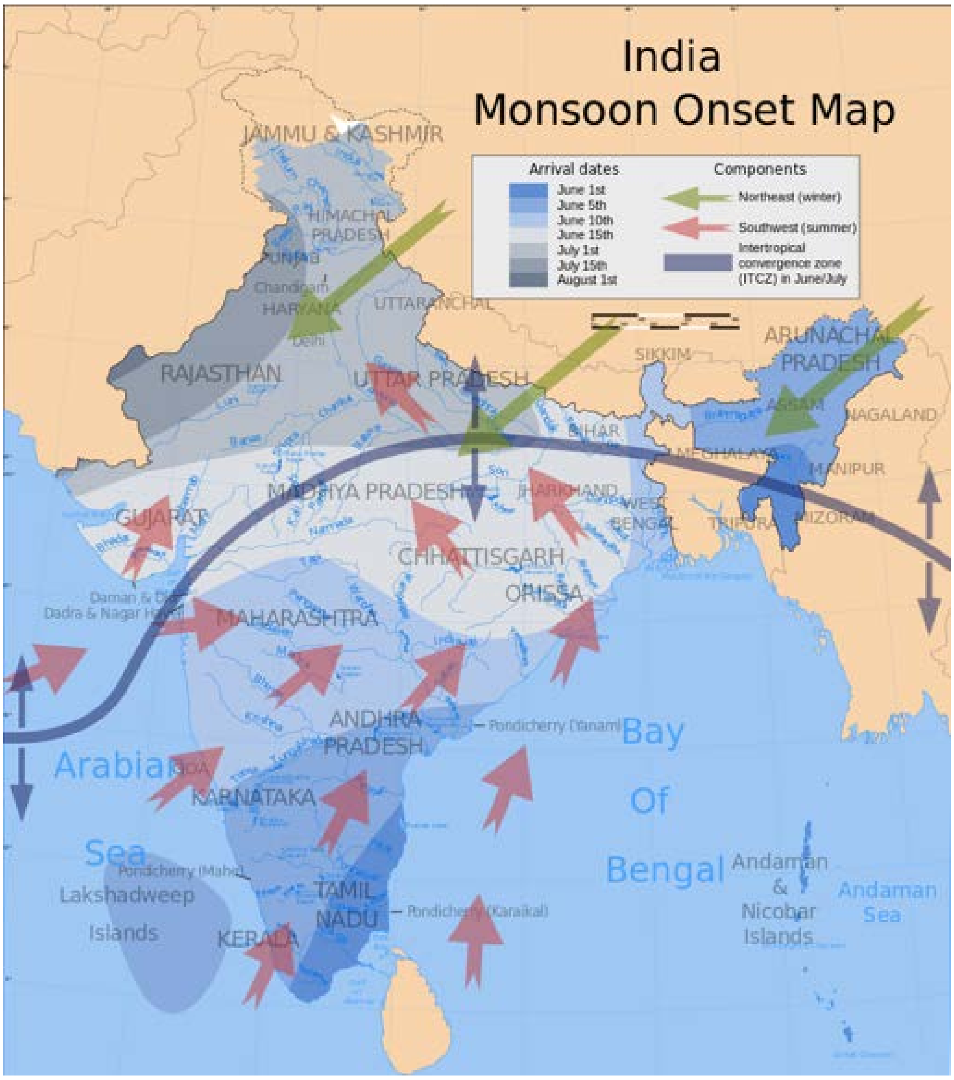
Importance of the monsoon on Indian agriculture

India's agriculture sector relies heavily on the timely onset and spatial distribution of monsoon rainfall. The Indian subcontinent receives 75-80% of its annual precipitation during the Indian summer monsoon (June to September). The winter or Northeast monsoon is important for some eastern coastal states bringing as much as 60% of their annual precipitation. Although the monsoon is a periodic phenomenon that occurs every year, driven by the seasonal changes in the differential heating of continents and oceans, there can be significant spatial and temporal variations extending from synoptic to intraseasonal, inter- annual, decadal, and longer time scales, driven by natural variability and climate change. This section describes a normal monsoon season and explores the drivers of monsoon variability that operate at different timescales and their predictability.

A typical monsoon

The word "Monsoon" is derived from an Arabic word 'Mausim' which means season. Monsoons typically occur in tropical areas and are often defined as a seasonal reversing wind accompanied by corresponding changes in precipitation associated with the anomalous heating of land and sea. The Indian Meteorological Department defines the Indian monsoon as the seasonal reversal of the direction of winds along the shores of the Indian Ocean, especially in the Arabian Sea, which blow from the southwest for half of the year and from the northeast for the other, as depicted in Figure 1. The Indian Summer Monsoon is part of the northward movement of the Inter-Tropical Convergence Zone (ITCZ), a belt of low air pressure and heavy rainfall, where easterly and westerly trade winds meet, that moves seasonally. However, there are more atmospheric and oceanic conditions influencing the monsoon which will be discussed further in this section.

Figure 1: Schematic of the Indian monsoon onset



Source: Saravask, based on work by Planemad and Nichalp - Own work, International Borders: University of Texas map library - India Political map 2001Disputed Borders: University of Texas map library - China-India Borders - Eastern Sector 1988 & Western Sector 1988 - Kashmir Region 2004 - Kashmir Maps.State and District boundaries: Census of India - 2001 Census State Maps - Survey of India Maps.Other sources: US Army Map Service, Survey of India Map Explorer, Columbia UniversityMap specific sources: Onset dates: Normal dates of onset of south-west monsoon over Indian regionWind currents/ITCZ: Burroughs, WJ (1999), The Climate Revealed, Cambridge University Press, ISBN 0-521-77081-5, p. 138., CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=1844314)

Impact of monsoon variability on crop yields

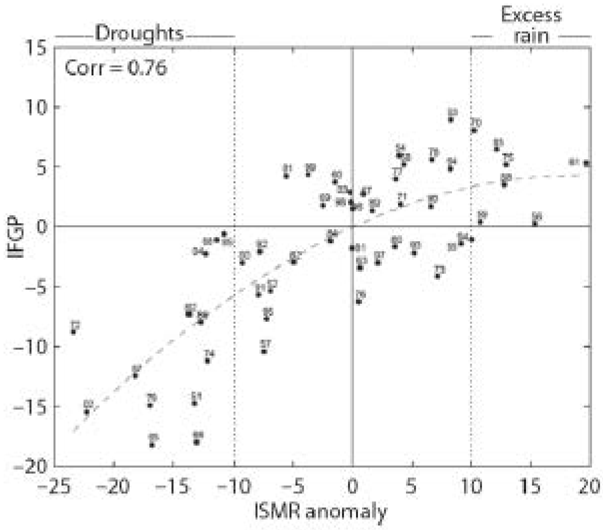
The intra-seasonal and inter-annual variability of the Indian monsoon has a major influence on crop yields. At a nation-wide level, years with drought have a more significant negative impact on crops than years with excess rainfall. This is clearly demonstrated in Figure 2 which shows the effect of drought (negative Indian summer monsoon rainfall anomaly - ISMR) and excess rain (positive ISMR) on the Indian food grain production (IFGP). Droughts generally result in reduced (negative) food grain production with very few with positive results (probably due to irrigation). This is driven by two reasons:

- Flooding will always be more localised than the large-scale nature of drought and
- excess rain can result in positive as well as negative impacts on crops depending on the antecedent conditions, soil types and capacity to retain water, and the severity and timing of rainfall (in line with the crop responses described in Section 1.2).

Due to the large intraseasonal variability of the monsoon, there can be localised flooding during drought years (e.g Karnataka floods in 2009) and vice versa. Figure 3 shows the variability of the summer monsoon over the past 60 years. At a national level, there have been more deficit/drought years than excess years in this time period. Observed and future trends in monsoon rainfall are discussed later in this section.

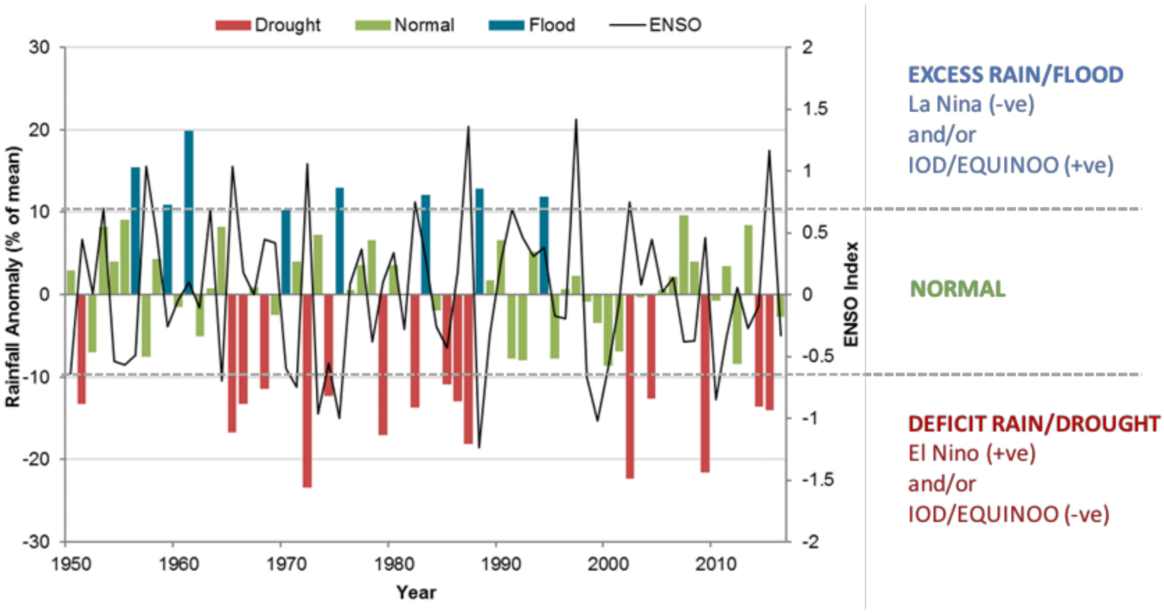
"Average" monsoons can also result in reduced crop yields due to periods of extreme drought or rain/floods. For example, the 2016 and 2017 summer monsoons were reasonably average in terms of overall rainfall but there were episodes of severe flooding (Gujarat, July 2017; Maharashtra, August 2017) and drought (Tamil-Nadu, 2016). The 2016 summer monsoon drought impacting Tamil-Nadu (-19% deficit) was followed by the driest north-east monsoon since 1876, impacting Kharif and Rabi crop yields. The dots, labelled with individual years, present the ISMR anomaly (x-axis) and the Indian Food Grain Production (IFGP) anomaly (y-axis) for each year between 1950 - 2009.

Figure 2: Impact of the monsoon (ISMR anomaly) on Indian food grain production (IFGP)



Source: Gadgil & Gadgil, 2006

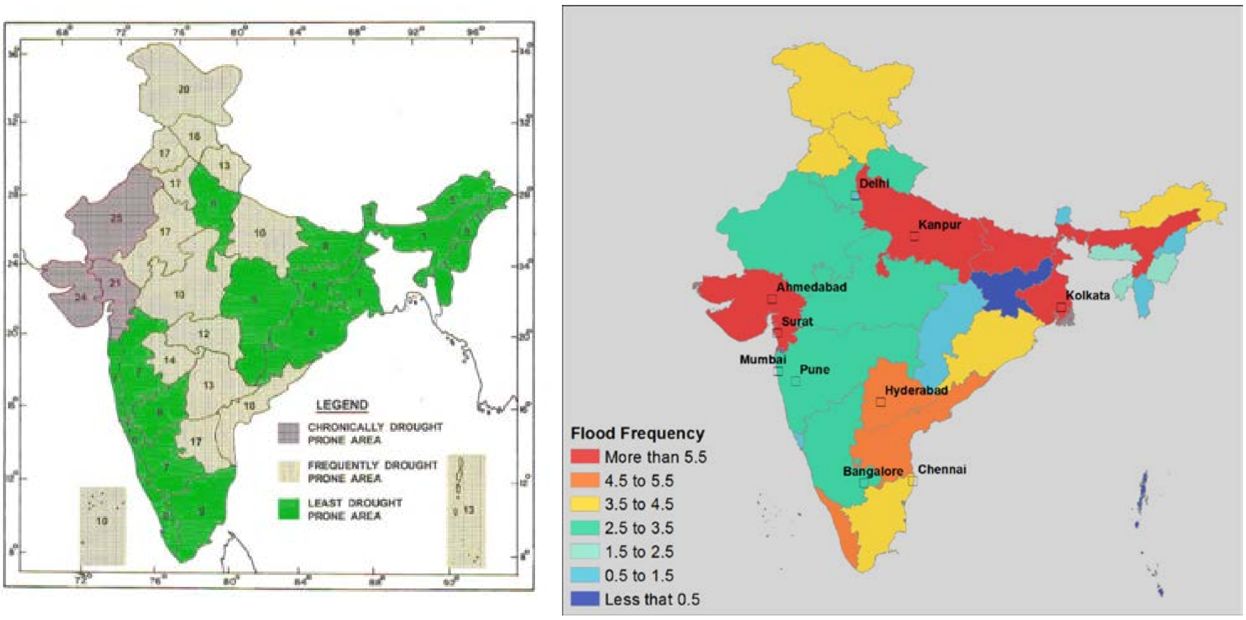
Figure 3: All India summer monsoon rainfall anomaly index (based on departure from long term mean 1871-2016) overlaid with the SSTv4 Ocean El Niño index anomaly (black line, based on departure from a 30year centered base since 1950). Drought (flood) years are assigned when the ISMR anomaly is less than (greater than) -10% (10%).



Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on ISMR data from Indian Institute of Tropical Meteorology, 2017 and ENSO index data from NCEP Climate Prediction Centre, 2017. IOD: Indian Ocean Dipole. EQUINOO: Equatorial Indian Ocean Oscillation

Figure 4 shows the regions that are most prone to drought and floods. States in the north west are most prone to drought, followed by the central states of India running from north to south. Many of these states are also key crop regions (Table 1, p20).

Figure 4: (a) Climatology of drought prone states in India and (b) frequency of floods per year per state based on past 90 years



Source: (a) IMD drought climatology (Shewale & Kumar, 2005), (b) Risk Management Solutions, Inc., 2017 based on data from EM-DAT

Drought typically has greatest impact on Kharif crops but can also impact Rabi crops by reducing water available for irrigation. Flooding is a common phenomenon across India, driven by periods of heavy rainfall (mainly attributed to the monsoon but also tropical cyclones and unseasonal heavy rain) and exacerbated by the silting up of rivers, reduced soil absorption, limited urban infrastructure, and deforestation. More frequent flooding often occurs across the north which is important for both Kharif and Rabi crops. Kharif crops are at greater risk to monsoon flooding since their growing season coincides with the monsoon. Rabi crops can also be damaged by monsoon floods if the ground remains waterlogged during the start of the Rabi season. Uttar Pradesh, the top wheat (Rabi) producing state and the second largest rice (Kharif) producing state, is one of the states most at risk from flooding. Other Kharif rice growing regions such as West Bengal and Andhra-Pradesh in the east and the cotton growing region of Gujarat in the west also have frequent floods. Along the eastern coastline, flooding can occur during the north-east monsoon as well as the summer monsoon. In many of these regions, rice production extends into the winter to make the most of the additional rainfall.

The flood frequency presented in Figure 4 is also impacted by state boundaries changes. Chhattisgarh & Jharkhand are separated from Madhya-Pradesh and Bihar respectively in 2000 and thus have lower frequency. Telangana is given the same values as Andhra-Pradesh to which it belonged to until 2014.

Intra-seasonal fluctuations in the Indian monsoon

The monsoon can experience large intra-seasonal fluctuations, meaning that the spatial distribution, intensity and duration of the wet monsoon season varies within the season. The weather during an individual monsoon season will oscillate between “active” spells associated with widespread rains over most parts of the country and “breaks” with little rainfall activity and high temperatures and humidity over the plains but heavy rains across the foothills of the Himalayas. These heavy rainfalls under the “break” conditions can result in flooding in the plains. The timing and duration of active and break periods account for much of the year-to-year variation in the monsoon.

Frequent, long-lived breaks in monsoon rainfall can trigger severe droughts as experienced in 2002 where rainfall deficits reached 24% below average over the growing season, with a 55% deficit during July, leading to a drop of around 18% in nationwide grain production. In contrast, particularly active periods within the monsoon, with unusually heavy and prolonged rainfall, can lead to localised flood damage to Kharif crops. Recent distribution and dynamics of “active” and “break” phases of the Indian monsoon are well documented (Krishnan et al., 2000, Pai et al., 2016, Rajeevan et al., 2010).

Despite fluctuations in this annually recurring pattern, it is important to acknowledge that fundamentally the monsoon happens with remarkable reliability.

Inter-annual fluctuations in the Indian monsoon

As well as large intra-seasonal variations in monsoon, there can also be significant year-to-year fluctuations in monsoon rainfall. Given its serious impact on the region’s socioeconomic development, understanding the drivers of monsoon intra- and inter-annual variability is an area of ongoing research. Monsoon variability arises due to complex nonlinear feedback among land, atmosphere and ocean systems, some of which are yet not fully understood (Saha et al., 2016). It is well acknowledged that the “climate driver” El Niño - Southern Oscillation (ENSO, Trenberth 1997) has a major influence on weather and climate around the globe (Lloyd’s, 2016), especially in the tropics, including the Indian monsoon. Northern hemisphere temperatures, sea surface temperatures and Eurasian snow cover are also believed to influence monsoon variability.

The discovery of ENSO originates from scientific investigations into the failure of the Indian Summer monsoon rains in 1876 and 1877 which lead to the Great Famine. El Niño is a warm ocean current originating along the coast of Peru that replaces the usual cold Humboldt Current. The reverse condition is known as La Niña. Its atmospheric counterpart is referred to as the Southern Oscillation (describing the variability of the strength of the Walker Circulation). ENSO, as the combined ocean-atmosphere effect is referred to, can drive inter-annual monsoon variability by influencing the strength of the southwest monsoon over India, with the monsoon being weak (and thus causing droughts) during El Niño years, while La Niña years bring particularly strong monsoons (Li & Ting, 2015). As discussed in Section 2, the chance of the monsoon ending in a major drought is greatly increased in El Niño years (Table 5).

While ENSO plays an important role in monsoon variability, it is not the only driver (Kripalani and Kulkarni, 1997). Studies have tentatively explained why not all El Niño events, such as the 1997 event, classified as the worst event of the century, have not always produced severe droughts in India (Kumar et al., 2006). Since 1900, there have been about 30 El Niño events, with the 1982-83, 1997–98 and 2014–16 events among the strongest on record (NCEP). However, despite the occurrence of strong El Niño events, not all of them led to below average monsoon rainfall while the most recent strong El Niño in 2014-16 caused droughts over India (Figure 3). There has been a large amount of research into explaining the behaviour of the 1983 and 1997 monsoons and more generally the recently observed weakening relationship between ENSO and monsoon (Kumar et al., 1999; Kinter et al., 2002). Natural variation on a multi-decadal scale and climate change have both been proposed as explanations for this weakening ENSO-monsoon relationship (Wang et al., 2015, Kitoh et al., 2013), however further research is needed.

The interaction of ENSO with the Indian Ocean Dipole (IOD) mode (Saji et al., 1999) (also known as the Indian El Niño) has been investigated as cause of the apparent change in the ENSO-monsoon relationship (Ashok et al., 2004). The IOD is - just like ENSO in the Pacific Ocean - a similar seesaw ocean-atmosphere system in the Indian Ocean but with much more localised impact. IOD develops in the Equatorial Indian Ocean from April to May and peaks in October. With a positive IOD, winds over the Indian Ocean blow from east to west. This makes the Arabian Sea (the western Indian Ocean near the African coast) much warmer and the eastern Indian ocean around Indonesia colder and drier. In negative dipole years, the reverse happens, making Indonesia much warmer and rainier. A positive IOD index is known to assist the Indian monsoon and thus often negates the suppressing effect of ENSO, resulting in increased monsoon rains in years such as 1983, 1994, and 1997. Other studies explain the changing behaviour of the monsoon with two different types of El Niño where El Niño events with warmest sea surface temperatures in the central Pacific rather than the east are more effective in drought producing (Kumar et al., 2006). These latter El Niño events are also referred to as El Niño Modoki ("El Niño-like", Ashok et al., 2007) and their occurrence, as well as their link with the All India Rainfall Index (AIRI), appears to have strengthened after 1940, compared to the traditional El Niños with east Pacific warming (Wang et al., 2015).

Purely atmospheric oscillation modes have also been investigated as predictors for monsoon rainfall. The Equatorial Indian Ocean oscillation (EQUINOO, Gadgil et al., 2004) is generally accepted to be the atmospheric counterpart to the IOD. EQUINOO is an oscillation of atmospheric cloudiness between the Eastern & Western parts of the Indian Ocean. Generally, positive EQUINOO with enhanced cloudiness over the Western part as compared to the Eastern region is favourable to the monsoon, and thus a favourable EQUINOO is believed to have mitigating effects on the impact of the El-Nino. At present, identifying and understanding the complex drivers of monsoon variability is still an area of ongoing research.

Predicting the monsoon

Given the critical impact of monsoon variability on crop yields and subsequent economic and societal consequences, predicting the strength and intra-seasonal variability of the monsoon suitably in advance would provide an opportunity to better plan and prepare. Prediction efforts in the monsoon started as early as 1886 to aid with agricultural and economic planning. The IMD releases initial operational long-range monsoon forecasts in April, followed by a second forecast in June and follow ups during the progress of the monsoon. Government, farming and media reports regularly comment on the monsoon forecasts and status of El Niño in the lead up to the monsoon season. However, up to today there has not been satisfactory success in predicting the monsoon, largely because the complexity of land-ocean-atmospheric feedbacks, that can influence intra- and inter-monsoonal variability, is not yet fully understood. Research is ongoing to improve intra-seasonal as well as inter-annual monsoon variability in various Indian research centres (such as IITM, IMD and NCMWRF) under the Ministry of Earth Sciences, Government of India as well as internationally.

Many studies apply statistical methods to predict the monsoon, starting from the simple climate drivers described previously. Eurasian snow cover has been recognised as one of the important predictors, which causes memory in the soil through moisture from melting of snow during spring (Hahn and Shukla 1976; Vernekar et al. 1995; Kripalani and Kulkarni 1999; Fasullo 2004; Singh and Oh 2005). During summer, positive soil moisture anomaly caused by melting of excess snow reduces surface temperature through increased evaporation, which affects the upper level tropospheric temperature and the atmospheric circulation (Sankar-Rao et al. 1996; Liu and Yanai 2002). Observation shows that there is a strong and significant negative correlation between Indian Summer Monsoon Rainfall (ISMR) and snow depth over western part of Eurasia during previous December-January-February (DJF) (Saha et al 2013).

Automating the identification of suitable predictors from gridded fields of variable may be the most advanced of the statistical methods. The IMD uses such a statistical approach using several ocean and atmospheric parameters in their statistical ensemble forecasting system (SEFS) (IMD, 2017). However, for the years 1989–2012 the IMD SEFS correlation skill is slightly negative (Wang et al., 2015), although this is largely driven by the failure to forecast 4 extreme years 1994 (excess), 2002, 2004 and 2009 (drought).

The IMD releases forecasts based on a dynamic global climate model since 2012 (IMD, 2017). However, these complex atmospheric and coupled ocean-atmosphere general circulation models (GCM's) are also unable to replicate all monsoonal variability due to limitations in simulating climatic modes such as ENSO and the IOD and their associated teleconnections accurately (Saha et al., 2016). Wang et al., 2015 suggest that failure to replicate monsoonal variability is largely due to models' inability to capture new predictability sources emerging during recent global warming. This will continue to be an area of ongoing research. For now, there is not enough skill in forecasts to reliably predict monsoon variability.

Impact of extreme events on crop yields in India

Outside of the monsoon and its associated floods and droughts, India is also subject to many other natural hazards (Figure 8, p23) which can have severe impacts on crop yields, such as:

- Tropical Cyclones
- Extreme Temperatures
- Unseasonal rain and hail storms

Most climate hazards in India have a distinct seasonality and can impact different crop seasons and growth stages (Figure 16, p52). Earthquakes can also have an impact on agriculture, often more indirectly via the impact on infrastructure and the inability for farmers to tend to fields, store harvests etc, than impacting crops directly. Earthquakes can happen at any time, making the impact on crops less predictable. In this section, the main climatic hazards which can impact crop yields are discussed in more detail.

Tropical cyclones

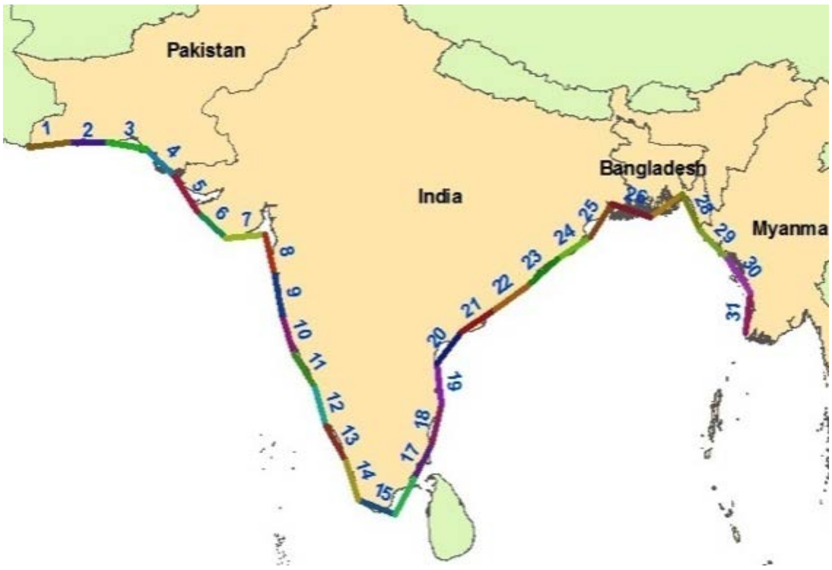
The Indian coast is subject to frequent tropical cyclones which form over both the Bay of Bengal (impacting the eastern coast of India) and the Arabian Sea (impacting the western coast of India). Storms can cause significant damage to crop in coastal areas. High winds can cause physical damage and knock-over standing crops, whilst heavy rainfall can lead to disease and damage due to flooding. Sea water can kill crops, erode and contaminate the soil, reducing its fertility and compromising the success of cropping for several years. Crops can also be damaged by cyclones further inland as heavy rainfall associated with cyclones can cause significant flooding as storms travel hundreds of kilometres inland. Tropical cyclones in India are categorised by severity using an IMD classification rather than the Saffir-Simpson scale. Storms defined as Category 1-3 on the S-S scale, are classed as Very Severe Cyclonic Storms by the IMD and those defined as Category 4-5 are known as Super Cyclonic Storms.

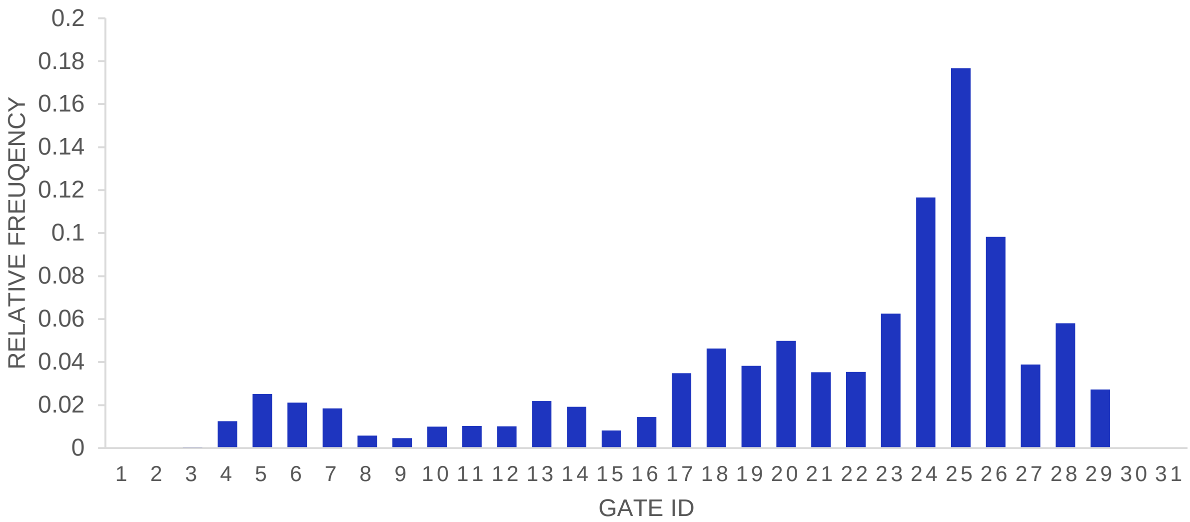
There are two peak periods of tropical cyclone activity in India: pre-monsoon (May to June) and post-monsoon (October-December) when sea surface temperatures are highest.   Cyclone activity is typically higher during the post monsoon period coinciding with the later stages of the Kharif season and the start of the Rabi crop period. The impacts of cyclones are greatest during the Kharif harvest period, because the crops cannot recover from physical damage that may occur. The frequency of tropical cyclones forming in the Bay of Bengal is almost five times higher than the Arabian Sea (Sahoo & Bhaskaran, 2015), with the north-eastern coastline of India most prone to tropical cyclones (Figure 5). The semi-enclosed nature of this basin in conjunction with its funnel shape steers the cyclone pathway striking the land.

The major crop grown along the coastline of India is the Kharif rice crop which is sown in May-July and harvested in September-December, depending on the region. In some eastern parts of India, rice crops are harvested later than the rest of the country to benefit from the north-east monsoon rains that reach this region and thus are at greater risk to cyclone damage than other rice growing regions. Cotton and sugar cane (east coast only) are also important crops for some coastal states such as Andhra Pradesh, Gujarat and Maharashtra.

Table 1 below lists some of historical cyclones that have impacted India. The 1999 Orissa super cyclone is the strongest storm to date to hit the Indian coast from the time instrumental records were kept with a minimum central pressure of 912 mbar. The storm severely damaged crops, particularly rice and sugar cane, in the state of Odisha (formerly Orissa). Observed yield reductions, from the 1998-2012 average between districts close to landfall and districts further away, were around 40% for rice and 25% for sugar cane. Since the 1999 Orissa cyclone, the most intense storm to hit India was cyclone Phailin that made landfall on October 12, 2013 on the coast of Odisha (Orissa). Most recently cyclone Vardah damaged crops in Tamil-Nadu in December 2016. Although recently Indian crops have largely been damaged by Bay of Bengal cyclones, Table 1 and Figure 5 demonstrate that key crop growing regions in western states such as Gujarat and Maharashtra are also at risk.

Figure 5: Historical frequency (1950-2013) of frequency of landfalling Indian cyclones hitting regional coastal "gates"





Source: Risk Management Solutions, Inc., 2017, based on data from the International Best Track Archive for Climate Stewardship (IBTrACS)

Table 1: Major land falling tropical cyclones affecting India (*Super cyclonic storms at landfall)

Location (Name)	Date	Number deaths	Total (Insured) Losses (at time, USD)	Crop Impact
West Bengal	October 1864	50,000[1]		
West Bengal	October 1737	300,000[1]		
Mumbai	June 1882	100,000[1]		
West Bengal	October 1874	80,000[2]		
Andhra Pradesh	November 1946	750[2]		
Mumbai	November 1948	12		
Tamil Nadu	December 1972	80		
Bengal	September 1976	40		
Andhra Pradesh*	November 1977	14,204	498Mn	40% food grains destroyed[3]
Tamil Nadu/A-P	May 1979	594	12Mn	
Gujarat	November 1982	500	625 Mn	
Odisha	May 1989	43		
Andhra Pradesh	May 1990	957	580Mn[1]	
Bengal	April 1993	125		
Andhra Pradesh	November 1996	708	1.5Bn	
Gujarat	June 1998	2871	469Mn	
Odisha* (Orissa)	October 1999	10,000	2.5Bn[4] (0.1Bn)[4]	
Gujarat (Phyan)	November 2009	20	300Mn[1]	
West Bengal (Aila)	May 2009	137	500Mn[1]	
Andhra Pradesh (Laila)	May 2010	32		
Tamil Nadu (Jal)	November 2011	22		

Tamil Nadu (Thane)	December 2011	47	375Mn	
Odisha (Phailin)	October 2013	58[1,4]	1.5-4.5Bn[1,4] (0.1Bn) [1,4]	1.3Mn hectares crops damaged[4]
Andhra Pradesh (HudHud)	October 2014	68-84[1,4]	5.5-7Bn [1,4] (0.35-0.6Bn) [1,4]	0.35Bn crop loss[4], 0.25-0.45Mn hectares crop damage[4]
Tamil-Nadu (Vardah)	December 2016	12[4]	1Bn[4] (0.52Mn) [4]	

Source: Lloyd's - Risk Management Solutions, Inc., 2017 based on data from EM-DAT unless specified. [1]Munich Re, [2]RMS research, [3]Government Disaster Management in India 2011 Report, [4]Swiss Re.

Predicting cyclone activity

Predicting the activity of the Indian cyclone season in advance provides an opportunity for all sectors to better plan and prepare. Indian Ocean cyclones exhibit inter-annual and inter-decadal variability with phases of more active/quiet activity. For example, 12 landfalling typhoons were reported in the Bay of Bengal post monsoon between 2000-2010 compared to 24 between 1980-1990 (Sahoo & Bhaskaran, 2015). El Niño (and/or the positive phase of its atmospheric counterpart Southern Oscillation) are known to suppress the formation of tropical cyclones in the North Atlantic and Australia while enhancing activity in the Northwest Pacific. No such strong relationship in terms of frequency exists between ENSO and Indian cyclones, however, a shift in the genesis location of tropical cyclones in the Indian ocean has been reported by several researchers (Lloyds, 2016). Furthermore, there has been some new research indicating that ENSO will play a role when El Niño co-occurs with other Earth system drivers such as the Pacific Decadal Oscillation (Girishkumar et al., 2015) and El Niño Modoki (Sumesh & Kumar, 2013). Sumesh & Kumar (2013) concluded that there are more tropical cyclones over the Arabian Sea and less over Bay of Bengal during the El Niño Modoki years as compared to the traditional El-Nino years (Sumesh & Kumar, 2013). Two other teleconnection patterns, the Boreal Summer Intraseasonal Oscillation and the Madden Julian Oscillation have been also discussed impacting Indian ocean cyclone formation, however these two climate drivers have short time scales and may only explain intraseasonal fluctuations. In summary, cyclone formation over the North Indian Ocean is a complex phenomenon and influenced by Earth system drivers in a complex way and thus a reliable forecast ahead of the Indian cyclone season(s) is presently not possible. Extreme temperatures

Crops can be severely damaged by extreme hot or cold temperatures, although the impact differs among crop species and the stage of plant development. Extreme hot or cold events typically occur outside of the monsoon seasons and thus have more impact on Rabi crops than Kharif crops.

Frost and cold spells during winter months typically occur in the north-western plains of India. Crop yields can be severely impacted depending on the maturity of the crop and the length of the cold spell. When temperatures are below freezing, ice forms inside the plant tissue and damages plant cells. This frost damage can have a drastic effect upon the entire plant (reducing yields / killing) or affect only a small part of the plant tissue, (impacting product quality). Crops of gram, onion, wheat and potato were reported to have been badly damaged by frost in January 2017 in north-western states (Agroinsurance.com).

Heat waves and extreme high temperatures typically occur just before the monsoon arrives in March/April. Extreme temperatures have most damaging impact during the flowering and grain filling stages with potential to greatly reduce crop yields. For example, despite favourable conditions for most of the 2009-10 Rabi season, an abrupt rise in temperature in March 2010 during the important grain filling stage of wheat adversely affected yields in the main production region of north-west India by as much as 40% in some states compared to the previous year (Directorate of Economic and Statistics, Dept. of Agriculture and Cooperation, 2017). Rabi crops were less impacted by the heatwave in May 2016, where temperature records were broken, as many crops were already harvested by this point.

Unseasonal rain and hailstorms

Hailstorms and unseasonal rain can cause severe localised damage to crops across many parts of India. Unseasonal weather often occurs pre-monsoon during the hottest part of the year (March to May), just before the Rabi harvest. Based on an analysis of hailstorms between 1981 and 2015 (Chattopadhyay et al., 2017), the state of Maharashtra is at highest risk of hail, with thunderstorms and hailstorms occurring frequently during the pre-monsoon season between March and May. Rabi crops in Maharashtra have been damaged by hail and unseasonal rain for the past four consecutive years (2014- 2017). The unseasonal weather in 2014 was unusually prolonged battering 8 states over 20 days in late February/early March and causing severe crop damage (up to 25%) in 28 districts. Other states at high risk from unseasonal rain and hail include Himachal Pradesh, Punjab, Assam and Madhya Pradesh.

Potential impact of climate change on crop yields in India

Another consideration for estimating future long-term weather impacts on crop yields and avoiding unforeseen losses to the insurance sector is the impact of climate change. Indian Agriculture is more sensitive to climate change than developed countries, in part because of limited financial resources for mitigation and resilience to climate change. While some aspects of climate change such as warmer temperatures and increased carbon dioxide may bring benefits in crop growth and yield, there will also be a range of competing adverse impacts due to reduced water availability and more frequent extreme weather conditions. Thus, assessing the overall impact of climate change on agriculture is complex.

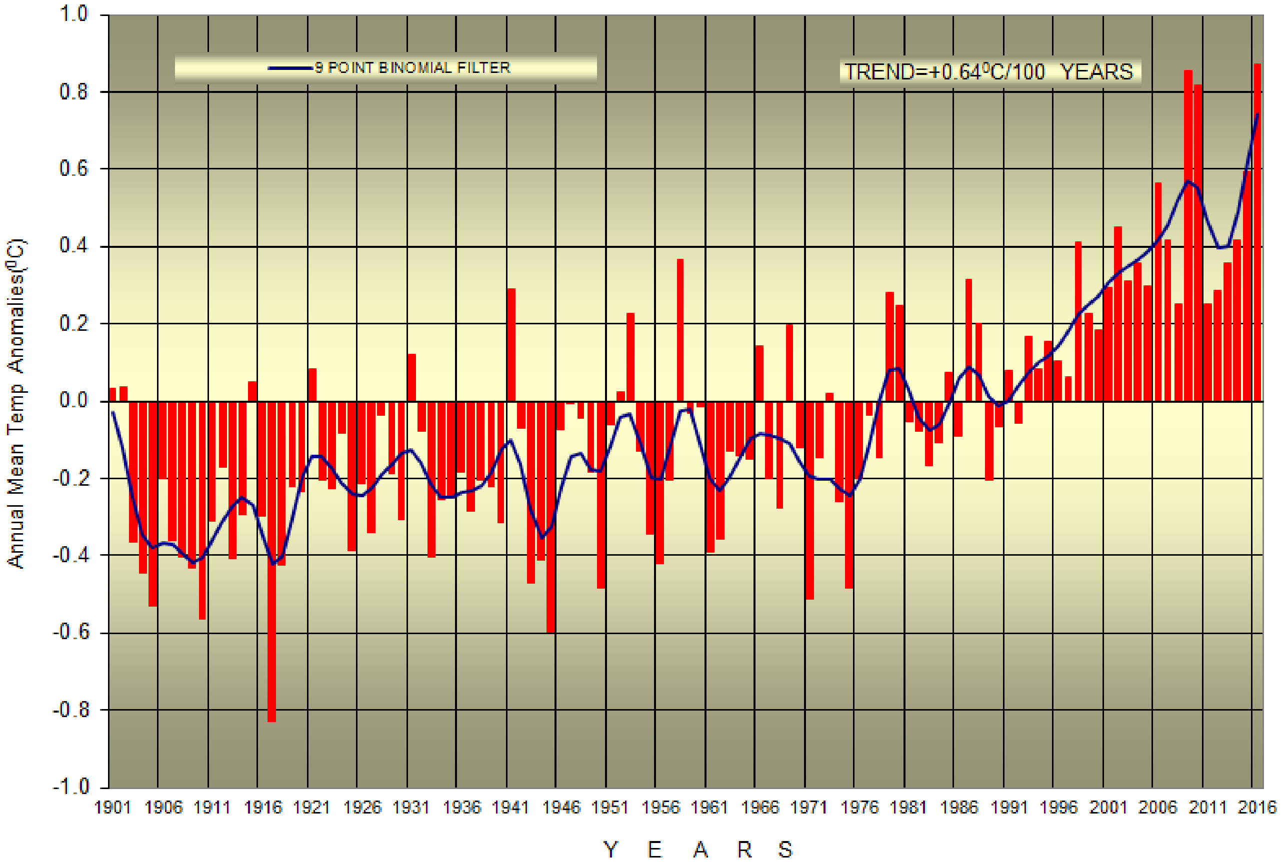
This section summarises climate change observed over the past few decades and its impacts on agriculture and then considers current climate projections for future climate change and how they may impact agriculture in India in the future.

Observed past climate trends and impact on crops

India has a good network of weather stations, many with long records, which have been used to investigate climate trends up to today in the observed record (Kumar et al., 2011). High-level findings from these climate studies can be summarised as follows:

- **Temperature**: There has been a positive temperature trend in India-wide annual mean temperature which has increased by 0.64 C over the past century, with the annual mean temperature above normal since the 1990s (Figure 6, IMD 2017). This warming is primarily due to a rise in maximum temperature, however, since 1990 also the minimum temperatures are steadily rising. These positive temperature trends are found over most of the country except parts of Rajasthan, Gujarat and Bihar, which show significant negative trends. There are also seasonal differences in these trends (Arora et al., 2005) with a stronger warming trend in winter compared summer and trends of heatwaves becoming longer in duration.

Figure 6: All India annual mean temperature anomalies for the period 1901 to 2016 (based on the 1971-2000 average)



Source: Annual Climate Summary, IMD, 2017

- **Precipitation**: Studies investigating observed trends in the Indian summer monsoon reveal a patchwork of trends with significant local and regional differences. Some regions are characterised by an increase in rainfall, while other adjacent areas show an increase of droughts. (Singh et al., 2014, Kothawale & Rajeevan, 2017, Malik et al., 2016). All India annual and monsoon rainfall has not shown any significant trend based on the analysis of a 145-year record of the Indian summer monsoon rainfall by the Indian Institute of Tropical Meteorology (Kothawale & Rajeevan, 2017) for both the full record (1981-2016) and more recently the past 30 years (1981-2016). Regionally, there are significant positive and negative trends, one of the most significant being a decline in precipitation in North East India. This result supports earlier studies with similar findings such as Guhathakurta and Rajeevan (2008).

  Other studies report that summer monsoon rainfall has intensified since 2002 (Jin & Wang., 2017). It is generally accepted that monsoon variability has amplified recently (Goswami et al., 2006, Singh et al., 2014; Vinarasai & Dhanya, 2016, Malik et al., 2016) and there has been a rise in the frequency and severity of extreme rainfall events (Goswami et al., 2006, Roxy et al., 2017), particularly across the central belt of India, along with an increase in the number of monsoon break days (Dash et al., 2009, Singh et al., 2014).
- The drivers of monsoon variability are complex as described earlier in this section. Recent studies analysing the links between changes in ENSO phases and in the mean state of Pacific climate suggests potential increased volatility in the occurrence of both extreme El Niño and La Niña phases as a result of the weakening of the Walker circulation.
- **Atmospheric Composition**: Anthropogenic climate changes are a result of emissions of long lived greenhouse gases and short-lived climate pollutants, both of which can have direct and indirect (via their influence on the climate) on crops. Long lived greenhouse gas emissions have increased since the pre-industrial era, resulting in atmospheric concentrations of certain gases, including carbon dioxide, that are unprecedented in at least the last 800,000 years (IPCC 4th and 5th Assessment reports). Short-lived pollutants such as tropospheric ozone and black carbon have also increased (IPCC 4th and 5th Assessment reports). These concentrations have increased quite dramatically over the last 3 decades in India (Burney & Ramanathan, 2011).

- **Tropical Cyclones**: Due to problems with data availability, quality and consistency of historical cyclone observations, it is difficult to robustly investigate long-term changes in tropical cyclone activity (IPCC AR5 report, Chapter 2, Hartmann et al., 2013). However it has recently been shown that anthropogenic forcing has likely increased the probability of severe tropical cyclones occurring post-monsoon in the Arabian Sea since the preindustrial era (Murakami et al., 2017). There is also some evidence of increased tropical cyclones post-monsoon in the Bay of Bengal (Sahoo & Bhaskaran, 2015).

Impact on crops

Although limited, the literature on climate impacts on Indian agriculture is growing (Birthal et al.,2014; Jayaraman, 2011; Kumar et al., 2014). Changes in different climate variables can result in contrasting effects and demonstrate non-linear interactions and thus the overall impact on crop yields must consider all feedbacks.

Increasing temperatures result in shorter crop growing periods as plants will jump faster from one developmental stage to the next, reaching maturity in less time (Iqbal et al., 2009). A shorter growing period reduces the amount of photosynthesis which results in reduced yields. Grain production is also negatively impacted by extreme temperatures (greater than 30^{o}C) during the flowering period (Moriondo et al., 2011). Higher concentrations of carbon dioxide can have a positive feedback enhancing photosynthesis and increasing yields. However some other greenhouse gases, such as black carbon and tropospheric ozone, can reduce crop yields (Burney and Ramanathan, 2011), with impacts most severe over India and China (Van Dingenen et al., 2009). Black carbon aerosols alter the quantity and nature of solar irradiation and tropospheric ozone is directly toxic to plants.

The findings in the observed past climate data for India, summarised earlier, are consistent with summary statements made with “high confidence” by the IPCC in its most recent assessment report (AR5, Porter et al.) published in 2014 on Food Security and Food production systems:

- The effects of climate change on crop and terrestrial food production are evident in several regions of the world (*high confidence*).
- Studies have documented a large negative sensitivity of crop yields to extreme daytime temperatures around 30°C. These sensitivities have been identified for several crops and regions and exist throughout the growing season (*high confidence*).
- At scales of individual countries or smaller, precipitation projections remain important but uncertain factors for assessing future impacts (*high confidence*).
- Evidence since the IPCC 4th Assessment Report (AR4, 2007) confirms the stimulatory effects of carbon dioxide (CO2) in most cases and the damaging effects of elevated tropospheric ozone (O^3) on crop yields (*high confidence*).
- The IPCC Food Security and Food production systems report (Porter et al., 2014) also summarises the impacts of observed climate changes on crop yields over the past half century from a variety of studies for different regions, using different data and methods. There is *medium confidence* that climate trends have negatively affected wheat and maize production for many regions (*medium evidence*, *high agreement*). Climate trend effects on rice and soybean yields have been small in major production regions and globally (*medium evidence*, *high agreement*).

Projected climate trends and impact on crops

Numerical climate and earth system models are the state of the art instrument for a climate scientist to project climate trends into the future. These models are in a continuous cycle of improvements, increasing resolution and the number of phenomena that are explicitly considered. No models are perfect and their limitations are well understood, as summarised in the IPCC 5th Assessment Report (AR5) (Flato et al., 2014). These models are used to assess the impact of representative concentration pathways (RCPs), consistent with a wide range of possible changes in future anthropogenic (i.e., human) greenhouse gas (GHG) emissions from the most optimistic RCP 2.6 (assuming that global annual GHG emissions, measured in CO2-equivalents, peak between 2010-2020, with emissions declining substantially thereafter) to the most pessimistic “business as usual” RCP 8.5 (where emissions continue to rise throughout the 21st century if there are no policy changes to reduce emissions).

Results of these scenarios for the changing climate in Asia are presented in the IPPC AR5 (Hijioka et al., 2014) and summarised as follows:

- **Temperature**: warming is very likely in the 21st century for all land areas of Asia in the mid- and late-21st century under all four Representative Concentration Pathway (RCP) scenarios. In India, increases in mean annual temperature will likely exceed 2°C above the late-20th-century baseline in the mid-21st century under the extreme RCP8.5 with northern India likely seeing larger increases while it is likely to be less than 2°C under the most optimistic scenario RCP2.6.

- **Precipitation**: increases are very likely at higher latitudes by the mid- 21st century under the RCP8.5 scenario, and over eastern and southern areas by the late-21st century. Under the RCP2.6 scenario, increases are likely at high latitudes by the mid-21st century, while it is likely that changes at low latitudes will not substantially exceed natural variability. These results indicate that there is more uncertainty around the impact of climate change on precipitation than there is for temperature. Uncertainty provides additional incentives for actions since effects can be worse than expected and the economic impacts are asymmetric.

- **Precipitation Extremes**: Future increases in precipitation extremes related to the monsoon are very likely in East, South, and Southeast Asia. More than 85% of the CMIP5 (Coupled Model Inter-comparison Project 5) models show an increase in mean precipitation in the East Asian summer monsoons, while more than 95% of models project an increase in heavy precipitation events. All models and all scenarios project an increase in both the mean and extreme precipitation in the Indian summer monsoon while the inter-annual standard deviation of seasonal mean precipitation also increases. It has been announced that the 6th IPCC Assessment Report will discuss the science of attributing extreme events to a changing climate and their impacts (IPCC, 2017).

- **Tropical cyclones**: the future influence of climate change on tropical cyclones is likely to vary by region, but there is low confidence in region-specific projections of frequency and intensity. However, there are some indications that precipitation will likely be more extreme near the centres of tropical cyclones making landfall in West, East, South, and Southeast Asia.

The 2012 IPCC SREX (Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaption) report (Field et al., 2012) discusses the risk of abrupt and possibly irreversible climate change, such as the shutting down of the Atlantic Meridional Overturning Circulation (AMOC, often referred to as the thermohaline circulation) (Vellinga & Wood 2008, Lenton et al., 2008), or melting of the Artic, Antarctic or Greenland ice sheets (Lenton et al 2008). While the confidence and probability of abrupt change is low, the impacts on climate and agriculture are high. For example, several observational and modelling studies (summarised in Delworth et al., 2008) demonstrate that changes in the AMOC could induce a near-global-scale set of climate system changes, including a weakening of the Indian monsoon. A weakened AMOC cools the North Atlantic, leading to a southward shift of the Inter Tropical Convergence Zone ITCZ, with associated drying in several regions including the Indian and Asian monsoon region.

Impact on crops

- The projected future temperature and precipitation changes summarised above will affect food production and food security in various ways in specific areas throughout Asia. There is uncertainty on the overall effects of climate change, such as negative impacts of rising temperature versus positive impacts of increased CO_2 fertilisation, for important food crops such as rice, wheat, sorghum, barley, and maize, among others. The impact of climate change on crop yields impact can vary regionally and by crop type. For example, cereal production increasing in north and east Kazakhstan and wheat decreasing in the Indo-Gangetic Plain.

- The IPCC AR5 Food Security and Food Productions report (Porter et al. 2014) also discusses the impact of future climate change on cropping systems, with results indicating that the majority of regions around the world, including India, will experience negative crop impacts in the next century while some regional locations may benefit. These impacts will vary depending on region, crop type and adaptation scenario. Furthermore, climate change will increase crop yield variability in many regions (*medium confidence*).

- Over the timescale of the next few years (<5 years), it is unlikely that climate change impacts will result in significantly different climate and crop yields in India beyond what has been observed in the past (IPCC reports), but on a longer term climate change could more significantly impact weather events in India. There are conflicting views on the contribution of climate change to recent extreme events in India. However, it is generally agreed that the warming climate has intensified the hydrological cycle in the tropics and is contributing to more severe extreme rainfall events over India. As a result, the risk of flooding may increase in the future with important socio-economic implications for India, including the agricultural and insurance sectors. It is clear that unless the Paris agreement pledges are met, the RCP 8.5 scenario or something similar, is the trajectory society will have chosen, and thus impacts of climate change must be considered by the (re)insurance industry, across all sectors, including agriculture, to avoid unexpected losses.

Research is ongoing to refine the impacts of global warming on crops and weather patterns, including the monsoon and extreme weather events in India (Sandeep et al., 2018), to better understand the consequences for agriculture. Combining this information with the interplay of other factors, such as a growing demography, land use changes and water scarcity, will enable governments to develop more resilient agroecosystems in which (re)insurance can play a key role in transferring risk.