TECHNICAL NEWSLETTER
#49 - October 2019

WHEN DROUGHT STRIKES

A weather analysis of China's agricultural production risk

INTRODUCTION

Almost one fifth of the world's population currently lives in China. Although it has the same surface area as the USA, China has four times as many people to feed. In addition, weather extremes and natural disasters pose major challenges to agriculture. One of China's political priorities is therefore to establish and maintain sustainable agricultural production. Supporting farmers is seen as a way to encourage rural development. Since 2007, the Chinese government has massively subsidized agricultural insurance, and today China is the second-largest agricultural insurance market in terms of premium volume in the world, after the USA. Thus, China has increased its insurance premium volume more than tenfold in just a few years. While only 5 insurance companies offered agricultural insurance before 2006, by 2017 the figure had risen to 31.

The agriculture reinsurance market has also grown in a similar manner. Whereas the industry before 2013 was dominated by just a few reinsurers, several new players subsequently entered the market, attracted by its growth figures and very low market barriers. Today, China is the third largest agriculture reinsurance market in the world after the USA and India.

This very rapid growth makes China one of the most dynamic insurance markets of its size. Many new products and pilots have been launched, insurance conditions changed and new rules adopted. As a result, many data series are very short, inconsistent or unrepresentative of today's agricultural production and insurance conditions. The statistical methods used to collect the data, for instance for the statistical yearbook, have also changed. **Adequate risk assessment is therefore a challenge, especially when it comes to major events and extremes.** What does an extreme event mean for a country with the size and market volume of China? Have we experienced a large loss in China over the past few years?

To answer these questions, weather data can provide initial insights, especially since it is an independent and unbiased source of information – independent of agricultural production systems and insurance conditions, and independent of loss adjustment procedures and soil fertility.

Hence, in this newsletter we present a study based on weather data – more specially a drought index – to analyze drought risk in China.

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THE PEOPLE'S REPUBLIC OF CHINA AT A GLANCE

Population

1.4 billion

Surface area

9.6 million km²

Arable land

1.4 million km²

Main crops[1]

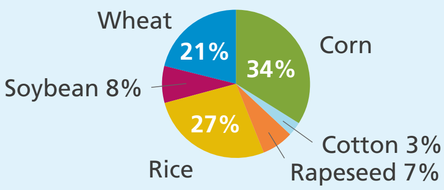


FIGURE 1: MAP OF CHINA

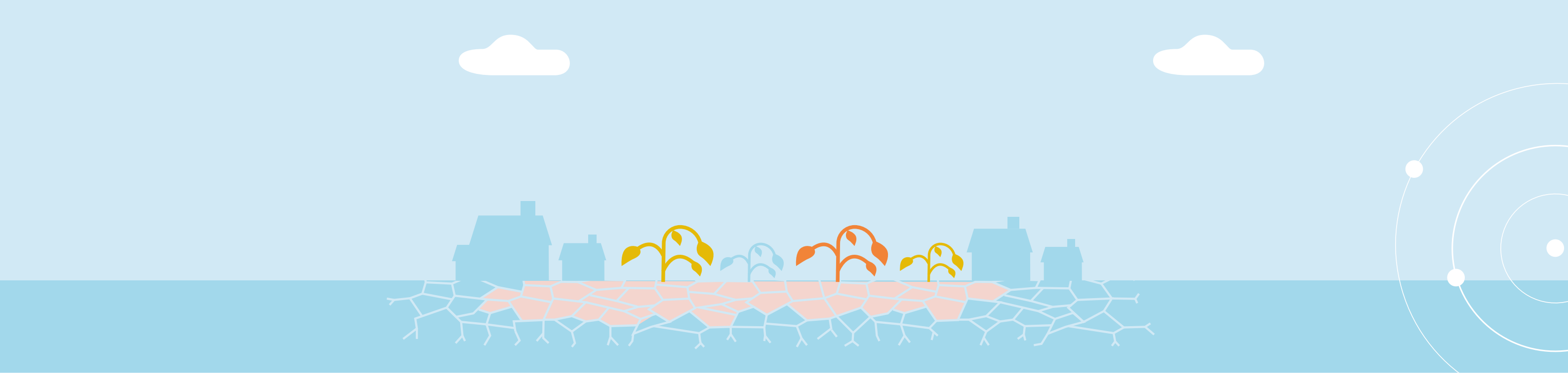
DROUGHT – A SYSTEMIC RISK

Droughts are one of the most devastating natural disasters. A well-known example is the 1930s "Dust Bowl" in the Great Plains in the United States and Canada, where prolonged drought and severe storms affected the environment and the economy. This led to the loss of fertile farmland, which in turn led to migration. This is just one example that highlights the potential of drought to affect large geographical regions at the same time, leading to significant losses.

Drought is also a major threat in China. In 2001 for instance, 33 million people were confronted with a shortage of drinking water, and crop failures totaled USD 6.4 billion[2]. In fact, more than 50% of the losses in Chinese agricultural crop production are due to droughts[3], see Figure 2. Water resources are very unevenly distributed. While it is rather wet in the east and southeast, the north is arid, with some regions receiving less than 100 mm of annual rainfall[4].

Rainfall is also unevenly distributed throughout the year, with the summer months bringing the most. The northern dry regions are particularly dependent on this precipitation, while in the southwestern regions, which are dominated by monsoon rains, deficits can be compensated by (almost normal) precipitation in other seasons. However, southwestern China has also experienced dry periods – for example in the summer of 2009 it was hit by a drought that lasted until spring 2010.

1. Percentage of sown area of main crops, http://www.stats.gov.cn/tjsj/ndsj/2016/indexeh.htm.
2. Shen et al. (2007).
3. Chinese Academy of Agricultural Sciences.
4. Wang et al. (2011).



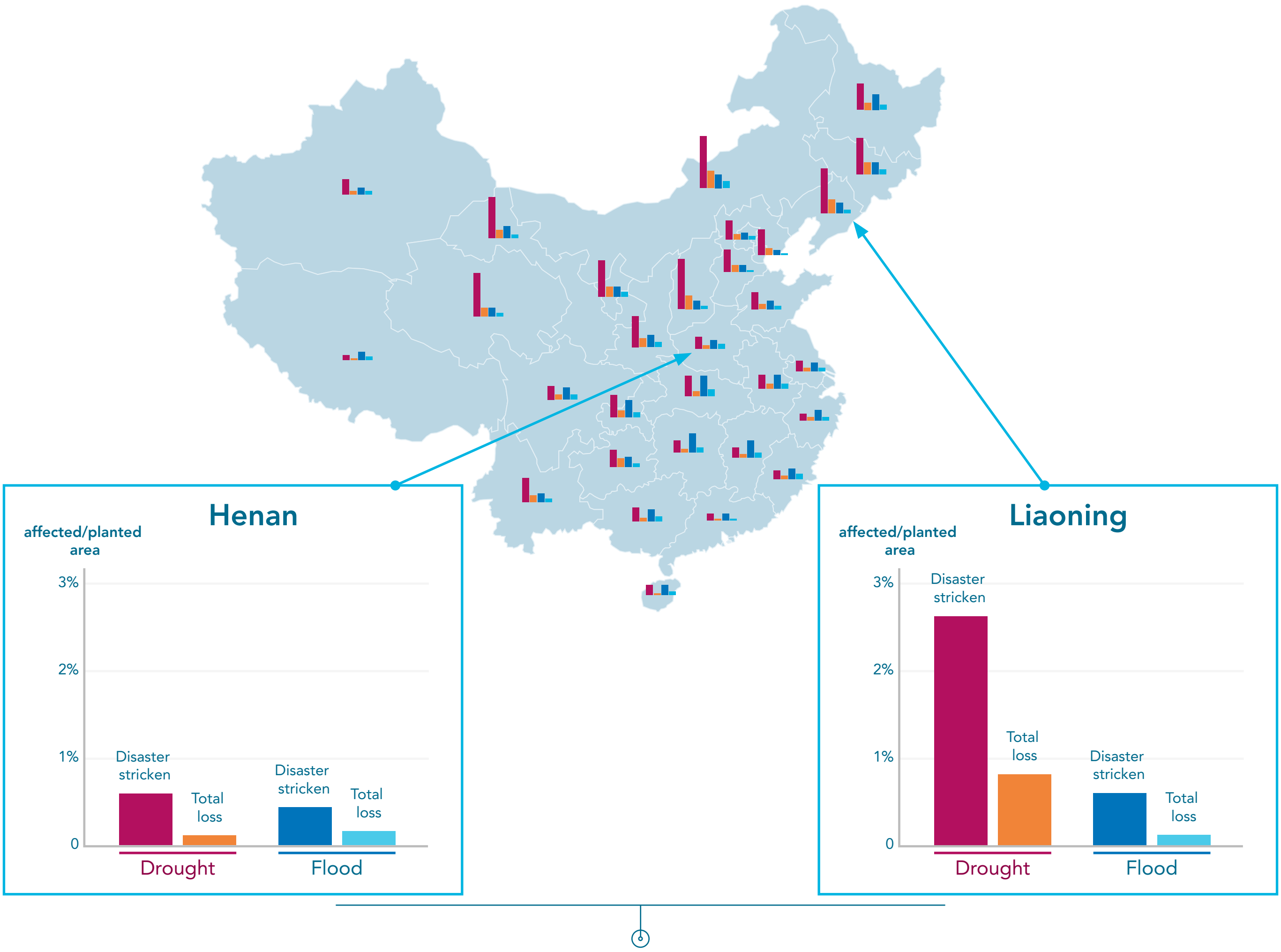


FIGURE 2: PERCENTAGE OF DROUGHT AND FLOOD AFFECTED CROP AREA TO TOTAL PLANTED CROP AREA PER PROVINCE. ALL BARS ARE EQUALLY SCALED. BASED ON 1990-2016 DATA FOR MOST PROVINCES.

Source: Chinese Statistical Yearbook

DEFINING DROUGHT AND DROUGHT-RELATED STRESS ON PLANTS

Drought is a complex phenomenon that is generally defined by below-average precipitation over a long period of time, often accompanied by above-average temperatures. A distinction is made between different types of drought, such as hydrological, meteorological, and agricultural drought. Of course, the different types of drought are interrelated. In the context of agriculture, drought is closely linked to a lack of soil moisture.

A drought event is characterized by its
a) intensity, i.e. the strength of a drought,
b) duration, i.e. the length of the drought event,
c) spatial extent, i.e. the size of the affected areas, and
d) frequency, i.e. the number of drought events occurring over a given period.

The reactions of crops to drought stress are manifold. The impact on crops depends on the plant variety, the timing of the drought (phenological phase), other stress factors such as nutrient deficit, and adaptation to drought stress. In general, a water deficit reduces plant growth and development and reduces crop yield. It can also affect the quality of yields and, for strong droughts, cause irreparable damage.

DROUGHT INDICES

Drought risk can be quantified in various ways and with different indices, depending on the "aspect" of a drought one is most interested in. For this study, we have chosen the self-calibrating Palmer Drought Severity Index (scPDSI)[5], which has been widely used for drought studies. This index is calculated "using a rather complex water budget system based on historic records of precipitation and temperature and the soil characteristics of the site being considered"[6]. Consequently, this index has a "memory", which is important for drought, since drought is always the product of a longer process. Since the index takes local climatic characteristics into account[7], it is possible to compare different climatic regions such as those found in China. The scPDSI is a standardized index with negative values representing dry conditions (smaller than -4, extremely dry) and positive values describing a wet spell (above 4, extremely wet), see Table 1. The index has a spatial resolution of 0.5°, which means that grid cells cover an area of around 50km x 50km, depending on the latitude. Even though the index is available from 1901 as a monthly value, recent scPDSI values are judged to be more reliable.

scPDSI value	scPDSI category
Above 4.00	Extreme wet spell
3.00 to 3.99	Severe wet spell
2.00 to 2.99	Moderate wet spell
1.00 to 1.99	Mild wet spell
0.50 to 0.99	Incipient wet spell
0.49 to -0.49	Normal
-0.50 to -0.99	Incipient drought
-1.00 to -1.99	Mild drought
-2.00 to -2.99	Moderate drought
-3.00 to -3.99	Severe drought
Below -4.00	Extreme drought

TABLE 1: CLASSIFICATION OF SELF-CALIBRATING PALMER DROUGHT SEVERITY INDEX (scPDSI) VALUES
Source: Adapted from Van der Schrier et al. 2005

AGRICULTURAL MAP

With the exception of a few very desert-like regions in Northern China, the scPDSI covers the whole country. However, for this study, we are only interested in agricultural land. Therefore, we use a global land-use map from the European Space Agency, Globcover 2009[8], to derive agricultural production areas. The spatial resolution of the Globcover grid is much higher (300m) than that of the scPDSI grid (about 50km). Therefore, we calculated the percentage of agricultural land per scPDSI grid and "resampled" in such a way that the Globcover matches the scPDSI grid. Figure 3 shows the derived agricultural map, with the percentage of agricultural land with lower resolution per resampled pixel cell.[9]

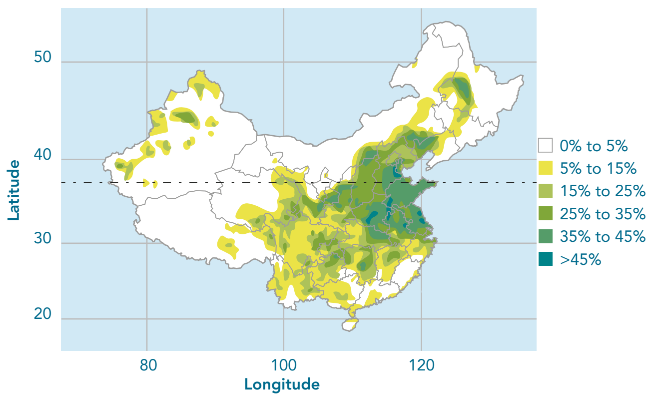
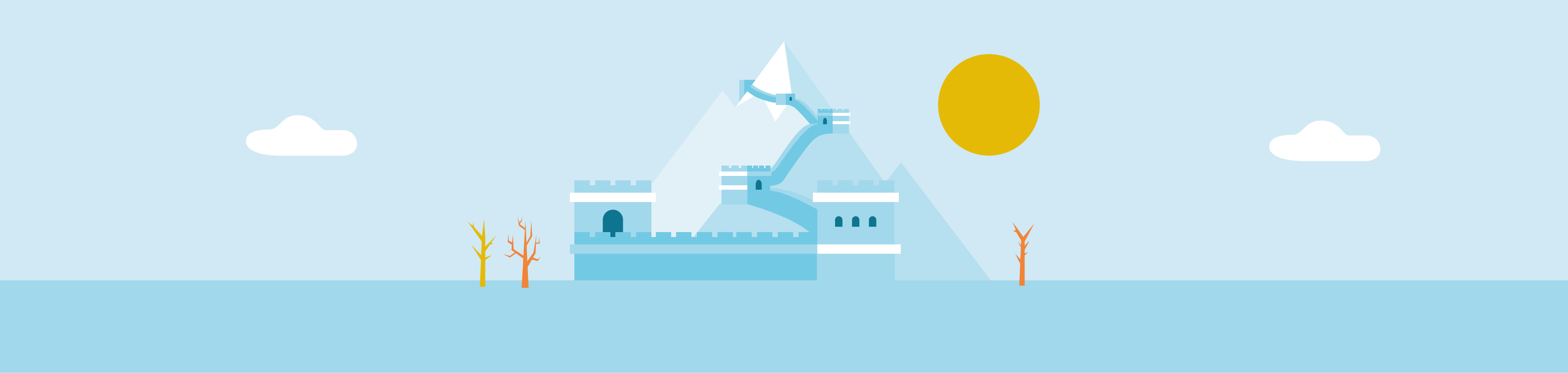


FIGURE 3: AGRICULTURAL AREA DERIVED FROM THE GLOBCOVER DATA WITH LOWER RESOLUTION AND RESAMPLED TO THE scPDSI GRID. THE DARKER THE GREEN, THE HIGHER THE SHARE OF AGRICULTURAL LAND IN THE RESPECTIVE PIXEL CELL.
Source: SCOR

5. Climatic Research Unit, University of East Anglia.
6. Van der Schrier et al., 2005, p.2818.
7. Wells et al., 2004.
8. © ESA 2010 and UCLouvain, http://due.esrin.esa.int/page_globcover.php
9. By reducing the spatial resolution of the Globcover map, much information is lost. This is justified for this nationwide analysis and necessary to match the grid of the scPDSI. For a more detailed analysis, the original resolution of 300m should be maintained.



PHENOLOGICAL PHASES AND INDEX VALUES

The growing season in China is shifted considerably due to the country's strong north-south expansion. The vegetation in the south is a few months ahead of that in the north. We use a simplified approach and divide the country into a northern region (≥ 37.25° latitude) and a southern region (< 37.25° latitude), selecting the scPDSI index value accordingly: the July values for the south and the September values for the north, to cover the main crop season. At first glance, this late selection of the months may seem surprising. However, since the scPDSI takes previous conditions into account, one still captures dry conditions happening early in the season. This selection of July for southern regions and September for northern regions is used consistently for the analysis.

SPATIAL CORRELATION OF DROUGHTS

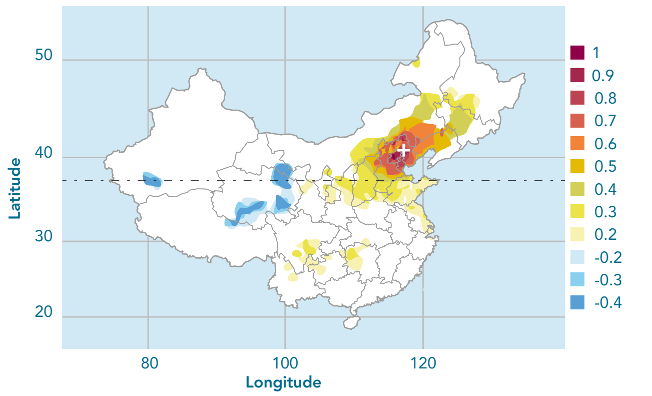
The correlation of grid cells can be used to quantify spatial extent and dependencies. This results in a large table of pairwise correlation values, which are difficult to interpret due to their dimensionality. Therefore, we show the so-called 1-point map, in which a reference cell is chosen and the correlations with respect to this cell are displayed. The reference cell is selected using Principal Component (PC) analysis, whereby only agricultural areas and significant correlations are considered[10]. Consequently, some significant correlations are not shown as they have not been categorized as agricultural land.

In Figure 4, the reference cell with the strongest correlation pattern (i.e. first principal component with maximum explained variance, PC1) is shown with a white cross. Using the same approach one can also calculate the 2^{nd}, 3^{rd}, x^{th} strongest correlation pattern and its corresponding reference cell (i.e. PC2, PC3 etc.). Here, the reference cell lies in the northeast, on the border of Beijing and Hebei province.

Possible correlation coefficients range from -1 (negative linear correlation, shown here in blue shades) to 1 (positive linear correlation, shown here in yellow-red shades). The darker the yellow to red color, i.e. the closer to 1, the higher the positive correlation. The higher the positive correlation, the higher the chance that grid cells / regions will be drier (or wetter) in the same season. The black dotted line shows the 37.25° north-south division – see *"Phenological phases and index values"* section.

It is not surprising that neighboring grid cells have more similar conditions and hence a higher positive correlation coefficient than more distant grid cells. What is interesting, however, is how fast and strong this decrease is, and the fact that there are also distant regions with significant correlations.

Positive correlations from the reference cell decline with distance – but not uniformly. There is a strong correlation between the reference cell and the surrounding provinces Tianjin, Beijing and Hebei, and some moderate correlation with Liaoning, Inner Mongolia, and Shanxi. Also, a few more distant cells show a positive correlation, although this is only weak. It would be interesting to see if these results could be explained by weather patterns and underlying physical processes. The agricultural area with significant positive correlation, as shown in Figure 4, adds up to around 31% of the total agricultural area of China.



White area: either no significant correlation or no agricultural land (or both).

FIGURE 4: SIGNIFICANT CORRELATION COEFFICIENTS OF AGRICULTURAL LAND ARE DISPLAYED IN RELATION TO A REFERENCE CELL MARKED WITH A WHITE CROSS. THE BLACK DOTTED LINE IS ON THE 37.25° LATITUDE, WHICH FORMS THE DIVIDING LINE FOR THE SELECTION OF INDEX VALUES.

Source: SCOR

One can observe a moderate negative correlation between the reference cell and a few grid cells of West China, mainly located in Qinghai province. The share of agricultural area corresponding to these negative correlated cells is virtually negligible, adding up to just 2.4% of the total agricultural land in China.

10. Grid cells with less than 5% agricultural land were not included in the analysis. Significance level of 1%.

DROUGHT FREQUENCY

In the previous section, we analyzed spatial dependency. Another important aspect of droughts is the frequency and intensity with which they occur. For this purpose, we calculate the share of the agricultural area threatened by strong drought each year. We differentiate between 3 categories in Figure 5: "severe" (scPDSI <-3), "severe to extreme" (scPDSI <-3.5) and "extreme" (scPDSI ≤-4) drought, and use the different index values for the north and south as discussed in the *"Phenological phases and index values"* section.

As Figure 5 clearly shows, agricultural land has been exposed to far more severe droughts in some years than in others, and periods with frequent droughts are followed by periods with low drought activity. In the last 10 years for instance, on average less than 3% of the agricultural area has suffered from extreme drought in the months under consideration. The two years with the highest share of extreme drought (around 15%-18% of the agricultural area) were in 1942/43 and 1920/21. Aside from 2001, when mainly northern China was hit by a drought[11], comparable drought events have not occurred in recent history.

In Figure 5 we show the whole agricultural area of China under drought conditions. However, such analysis can also be made for individual provinces or regions, in which local drought events can be identified and their intensity assessed. Such analysis can also serve as a starting point for determining return periods of drought events.

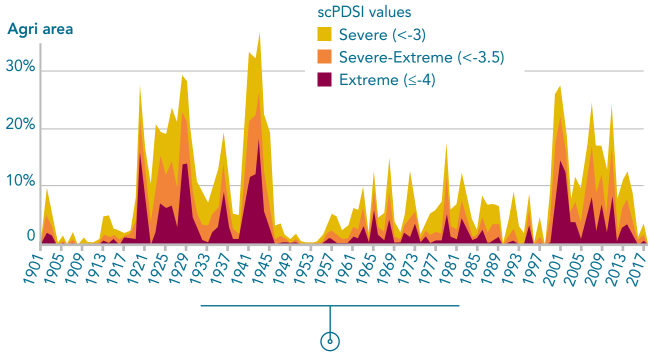


FIGURE 5: AGRICULTURAL AREA UNDER SEVERE TO EXTREME DROUGHT IN CHINA FROM 1901-2018. DIFFERENT scPDSI VALUES SELECTED FOR THE NORTH AND SOUTH OF CHINA.

Source: SCOR

RISK CLUSTERS

For most applications in China, the province is the most important geographical unit, as subsidies, regulations and original insurance conditions are set per province. Therefore, we use this level of aggregation to calculate the percentage of agricultural land suffering moderate drought (i.e. scPDSI < -2).

As before, we have divided China into a southern and a northern region. The provinces located in both areas have been assigned to either the north or the south, depending on where more agricultural land is located. We use a hierarchical clustering approach[12] to define the similarities (or dissimilarities) between the 31 provinces. The vertical axis ("height") in Figure 6 indicates the dissimilarity between provinces. In other words, the higher the point of fusion, the less similar the provinces.

The aim is to find homogeneous regions that share similar characteristics in terms of drought. Generally, this approach works better for some provinces than for others because some provinces are themselves very inhomogeneous (e.g. Anhui, Sichuan). Therefore, this approach has some limitations, although it is essential in this context to carry out the analysis at a provincial level.

In order to avoid segmentation and maintain information stability, we select only 4 clusters. The strongest dissimilarities are between the north and northeast provinces (red areas) and the south and northwest provinces (blue areas) in Figure 6. Both clusters divide into 2 sub-clusters at about the same height. The blue cluster is divided into a southern and a northwestern to eastern sub-cluster, and the red cluster into a northern and a northeastern sub-cluster.

These clusters or risk zones can be used to build a well-diversified portfolio, with an even distribution of exposure across the different clusters. Regional limits can be set to avoid too much exposure within a cluster and to reduce the volatility of the whole portfolio. Besides portfolio steering, knowledge of dependencies can also support capital allocation.

11. See for instance Yu et al. (2014), Shen et al. (2007) and Wang et al. (2011).
12. We use the Euclidean distance and the Ward2 method as linkage function.

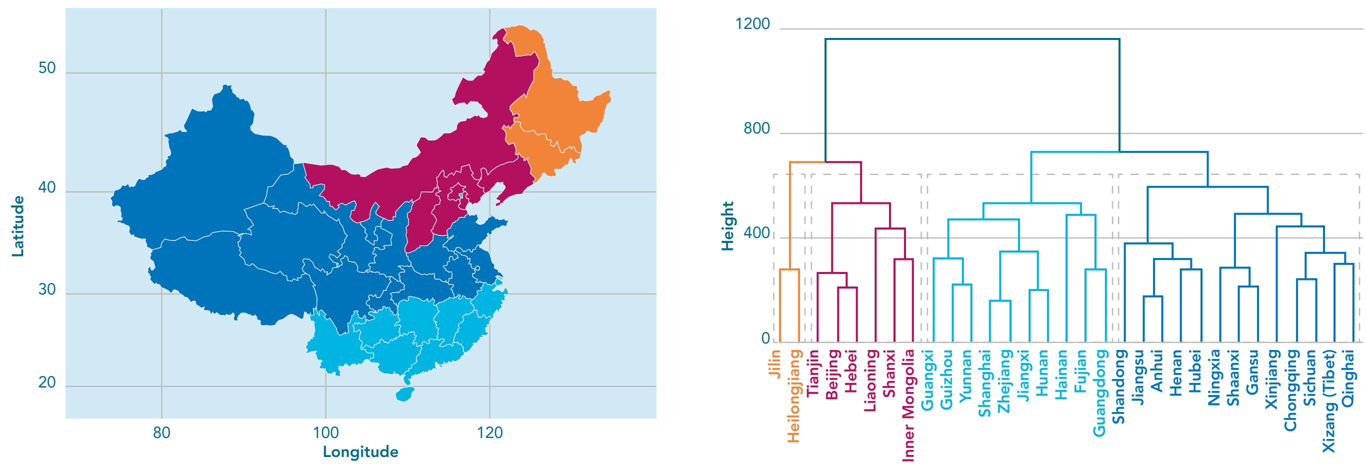


FIGURE 6: HIERARCHICAL CLUSTERING OF PROVINCES

Source: SCOR

CONCLUSION AND OUTLOOK

This newsletter presents a general approach to the analysis of drought risks in agriculture, using a land cover map and a drought severity index. We analyzed the spatial aspects, i.e. the correlation pattern of droughts, and obtained evidence that up to one third of China's agricultural land is more likely to have similar weather conditions during one harvest season. This means, for example, that a drought could hit large areas at once, and that the diversification potential could be lower than is often assumed due to China's size.

In addition, we investigated the frequency and intensity of drought events. We saw that extreme drought years occurred mainly at the beginning and end of the 1920s, the beginning of the 1940s, and the beginning of this century. **So according to our analysis, China has not experienced a catastrophic drought since the emergence of the current insurance market in 2007.**

Furthermore, we presented a clustering approach to partition China's provinces into (more) dissimilar subgroups, which can be used for capital allocation or portfolio steering. Based on the drought index, the strongest dissimilarities exist between some northeastern provinces and provinces located more in the south and northwest.

Of course, this newsletter contains only a few possible applications and analysis can be deepened and more targeted to the respective questions (e.g. peril, crop season) or to the main exposure of (re)insurers.

A logical extension of this work would involve the "translation" of drought risks, indicated by the index, into drought damage to crops. However, this additional step would require taking into account regional specificities such as the adaptation of crops to water scarcity, irrigation systems and general agricultural practices. This kind of analysis is much more data-intensive and may also be subject to changes over time (e.g. changes in agricultural practices). Improvements could also be achieved by using higher spatial resolution data, in order to better capture local drought conditions and phenomena. In addition, observations could be linked to physical processes and weather patterns, such as the East Asian monsoon or the North Atlantic Oscillation. Finally, this is a backward-looking analysis. Due to climate change, drought patterns may change in intensity, duration, frequency and location. Most studies on this topic support this assumption[13]. Drought could therefore become an even greater threat to the Chinese agricultural system in the near future.

This analysis provides a good starting point for further analysis of the main peril faced by the Chinese agricultural production system. It can provide support for risk assessment, portfolio steering and pricing, thereby helping us to prepare for future agricultural (re)insurers growth in the Chinese market.

At SCOR, we are constantly improving our risk modelling capabilities to support our clients with technical advice and customized solutions.

13. For instance, Leng et al. (2015) and Su et al. (2018)

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Editor: SCOR P&C Strategy & Development
ISSN: 1967-2136

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