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Mapping socio-economic factors in Mali

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Preface

This report is the result of the project 'Assess the demand for weather index-based insurance as a means of adaptation to climate change' (BO-10-009-112). It complements the PRI Wageningen UR report "Mapping maize yield variability in Mali" (Conijn et al., 2011). The work has been carried out within the Policy Support Cluster International Cooperation, which is one of the major programmes for international research and capacity building at Wageningen UR. The Cluster is financed by the Netherlands Ministry of Economic affairs, Agriculture and Innovation.

Activities have been implemented in close coordination with the IFAD WFP Weather Risk Management Facility (WRMF) team. Launched in 2008 with the support of the Bill and Melinda Gates Foundation, the WRMF is a joint initiative of the International Fund for Agricultural Development (IFAD) and the World Food Programme (WFP). It draws on IFAD's experience in rural finance and on WFP's expertise in disaster-risk reduction and management.

The WRMF focuses on four areas:

- Building the capacity of local stakeholders for weather risk management by strengthening partnerships, offering technical assistance, and promoting knowledge exchange in the development and use of risk mitigation mechanisms, including weather index-based insurance (WII).
- Improving weather services, infrastructure and data management for weather risk management, including the development of WII, national weather risk management, early warning systems and vulnerability analysis.
- Supporting the development of an enabling environment by engaging with government partners and advocating national risk management frameworks and appropriate financial and weather risk-management strategies and policies.
- Promoting inclusive financial systems for poor people in rural areas, including innovative delivery channels and client education, which lead to better planning for and coping with weather shocks.

The WRMF strongly appreciated Wageningen UR support and the result of this work, as it will be instrumental to shape the ongoing and future activities in Mali and in other countries.

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1 Introduction

Extreme weather events and natural disasters can trap rural households in poverty, impede development and drain a country's critical financial resources. Smallholders in developing countries are particularly vulnerable to such natural disasters.

The International Fund for Agricultural Development and the World Food Programme have joined forces to reduce the vulnerability of poor rural people in developing countries to the extreme weather events that can be devastating to agricultural productivity. With support international donors, IFAD and WFP are working to improve the access of poor rural people to a range of financial services through the use of weather index-based insurance, a financial product based on local weather indices that are highly correlated with local crop yields.

A demand-driven, technical collaboration between Wageningen University, IFAD and WFP will leverage the experience and capacity of IFAD and WFP, the wider UN family, and a range of partners to reduce the vulnerability of poor farmers in the developing world to weather risks.

Based on the analysis undertaken in the appraisal missions, the IFAD-WFP team has chosen Mali for implementation, taking a staged approach to the commencement of activities. In order to prepare the ground for implementation, additional research is needed. Wageningen UR will conduct research using modeling and field research in Mali to assess the feasibility for weather index-based insurance as a means of adaptation to climate change.

This report describes the first results of the mapping of socio-economic factors that are relevant to index-insurance contracts in Mali. In Chapter 2 the methodology and input data are described. In Chapter 3 the results are presented in maps and Chapter 4 discusses some issues to improve the applied methodology.

2 Methodology

2.1 Gridded socioeconomic data

Reliable gridded (or spatial) socio-economic data for the whole world are barely available, except for population data. Socio-economic data are still typically either available at very local scales (e.g. household) for small pilot areas only, or on highly aggregated levels (e.g. province or district). Most socio-economic data is available in aggregated tabular form, and up to date, few attempts have been made at spatial analysis or representation. The potential of GIS (geographic information systems) to analyse these tabular data, and to translate them into more readily accessible information, has until recently been largely untapped.

Rindfuss and Stern (1998) argue that this may partly be attributed to the fact that socio-economic researchers may not be aware of the value of spatial reference of their data or available respective methods . A major hurdle for current research is therefore the disconnection of socioeconomic and geophysical data. In part, the lack of intersection of the research programs has been due to the disparate interests of the different disciplines working in these two areas (Nordhaus 2006).

Epprecht et al. (2007) list three consequences[1]. First, spatial representations of key socio-economic variables are only available at an aggregated level and consequently there is little knowledge existing about eventual emerging development-relevant spatial patterns. Secondly, the scale gap between the available biophysical and the socio-economic data is just too wide to overcome the involved methodological problems to link these disparate data types appropriately for analytical purposes. Therefore, they argue, it is difficult to make causal links or relations between the biophysical conditions and socio-economic realities, beyond the site specific contexts of local case studies, at a policy relevant meso-scale. Finally, as ultimate consequence, policy- and decision-makers at various levels are not equipped with the necessary information to ensure informed decision-making or to allow for cost effective targeting of certain population groups or problem contexts.

In recent years, however, there have been significant advances in earth observation, computing power, as well as in GIS technologies and applications. As a result, the availability of biophysical data is rapidly increasing across the entire scale continuum and at ever increasing resolutions. This technological progress offers new avenues for the presentation and analysis of spatial data (Epprecht et al. 2007). Moreover, some new technologies have created an abundance of new data, allowing analyses with a previously unseen spatial and/or temporal resolution, and also an analysis of the effects of the social environment or the social interaction network, etc. New terms such " Information Cornucopia", " Data Deluge" or " Information Bonanza" have been coined to refer to the enormous amount of information produced by all these sources (1200 exabytes in 2010, only 150 exabytes in 2005[2]) (Helbing & Balietti 2010).

Visualizing geographical variation in statistical data can enhance their value, especially in heterogeneous regions (Epprecht et al. 2007). There are several difficulties that must be overcome when integrating socio-economic data into maps (see Rindfuss & Stern 1998 for an overview). One main problem is that although socio-economic phenomena vary across space, their exact 'values' can typically not be measured and attributed to exact locations: it is generally not clear precisely to which spatial units they relate. Most socio-economic data are aggregated at different administrative levels, e.g. from village to country. However, different aggregations may result in quite different pictures of 'reality' being portrayed by the different maps (Minot et al. 2006).

Epprecht et al. (2007) describe five different types of maps. In general, socio-economic mapping has the aim to provide a graphic visualization of attribute data in space, in the form of a thematic map.

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[1] They focus on Vietnam, but these issues are applicable for most developing countries
[2] 1 exabyte is 260 bytes

Dot maps, in which each dot represents an equal number or quantity of the attribute being displayed. Geographical distributions and relative densities of absolute numbers, such as populations, can meaningfully be represented with dot maps. The dots are typically distributed randomly within the enumeration area (e.g. the province) for which the attribute exists.

Choropleth maps, in which the entire area is divided into discrete regions such as administrative entities, for which attribute data exist. Political administrative maps are typical examples, where each country or province is depicted in a distinctive colour, and colours change along the boundaries only. Though this wrongly implies uniformity within each entity, and sharp changes at the borders, choropleth maps are frequently used to depict socio-economic data by administrative units. Choropleth maps typically depict relative numbers (i.e. percentages and ratios rather than totals)

Isarithmic maps, in which trends are depicted in continuous data (actually observed, or interpolated from discrete data) through lines of equal values (isolines). Typical examples include meteorological maps of atmospheric pressure (isobars) or temperature (isotherms) and elevation maps depicting contour lines of equal elevation (isohypses). It is not common for socioeconomic data to be depicted as isarithmic maps.

Symbol maps, in which the attributes are represented by symbols (e.g. circles) and the size of the symbols varies according to their attribute value. A special case of symbol maps is the graph map, where statistical graphs are used to show the values of multiple attributes in space.

Trend surface maps, in which continuous surfaces are depicted as a raster grid and are used to visualize individual values for any point in space at the given spatial resolution. Such surfaces are generally obtained either through remotely sensed data (e.g. elevation data), modelled data – such as, for instance, ‛accessibility’ of certain service locations

Dot and choropleth thematic maps are generally the most useful and widely used to represent socioeconomic and agricultural data.

2.2 Data sources

Most of the data used in this study came from FAO, collected at http://countrystat.org/mli for Mali. CountrySTAT is a Web-based information technology system for food and agriculture statistics at the national and subnational levels. Through national and regional CountrySTAT projects, FAO forms partnerships with statistical offices and the ministries of agriculture, fisheries and forestry among others to introduce the system and build the national capacity to use it. In each country, the national government makes a substantial contribution to ensure its deployment and continued training and maintenance.

The Malian data for CountrySTAT is disaggregated per Région (province) or Cercle (lower administrative level), rather than the national level as is common with a number of other data sources. This detail came at the expense of some missing data points and a relatively short data series. In general, series ran for about 5 years, with some exceptions such as maize production in four provinces running between 1985 and 2007. The analysis uses data between 2000 and 2010 where available. It should be noted however that there were a number of gaps in the data and this might have some impact on the inferences drawn.

3 Results: socio-economic maps

This chapter provides several maps that show different socio-economic indicators that may be of importance when targeting districts where a weather index-based insurance could be implemented. All indicators pertain to maize (linking up with the mapping exercise for yield variability of maize in Mali by Conijn et al., (2011)). We selected the following indicators:

1. Maize production
2. Change in maize production
3. Consumer prices of maize
4. Producer price of maize
5. Population
6. Economic difficulty
7. Food difficulty

Mali is divided into eight regions and one capital district (see Figure 3.1). The principal city of each regions bears the name of the region, respectively. The regions are divided into 49 cercles. The cercles and the capital district are divided into arrondissements. Most data is disaggregated at the level of region. Food & economic difficulty are as defined by CountryStat[3] which uses the definition of Système d'Alerte Precoce. The data is sourced from the Malian data in CountryStat.

Figure 3.1: Administrative boundaries in Mali ("regions"))

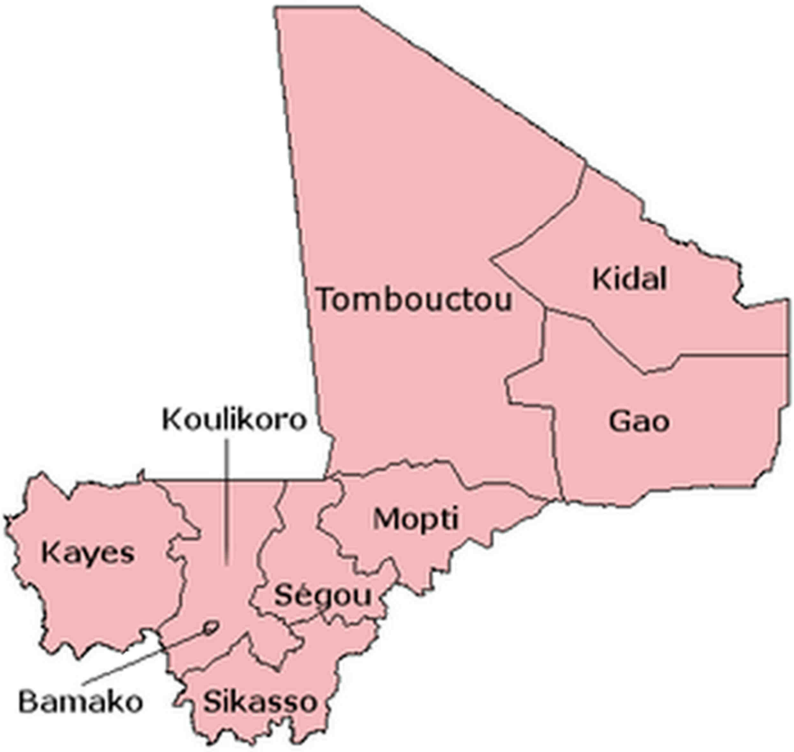


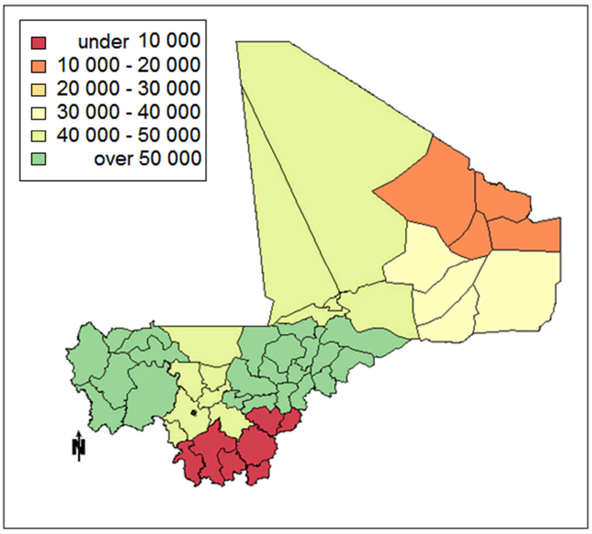
Figure 3.1 shows the population per region. It shows very varying population numbers per year per region, which is rather surprising. This may reflect migration between regions. However, Mopti & Segou have a very incomplete record, only 2005 is really complete for all regions. The 2005 is the most complete for all provinces and might be best to use.

[3] Available at http://bit.ly/5kSaL9. Accessed November 2010

3.1 Population

Figure 3.12 shows the provincial distribution of population in 2005. The main populated areas are in the middle of the country, with Sikasso not reporting data. The data is missing in a number of circles and this will inevitably reduce the population count.

Figure 3.2: Distribution of population per region (2005)



NB This includes 0's in the under 10000- all but 1 are 0. Sikasso is missing data

Figure 3.3: Population per region per year (2005 – 2010)

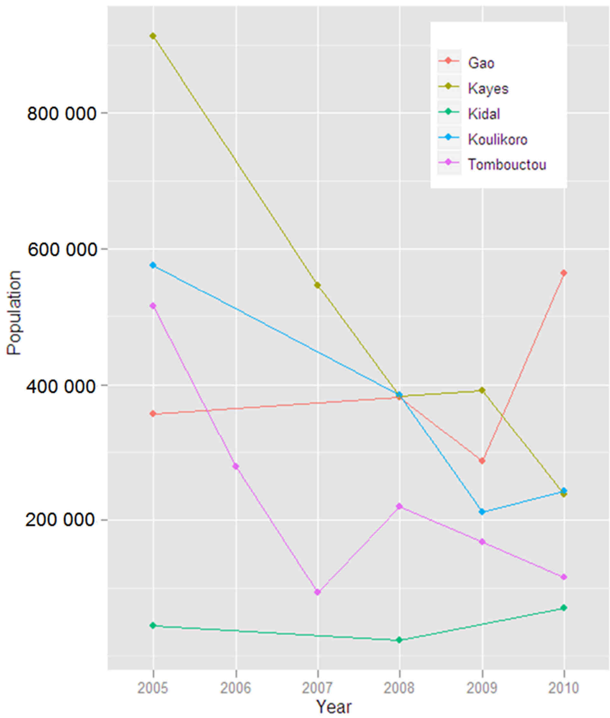


Figure 3.4 shows how levels of maize production are distributed in Mali in 2000. It shows that the northern regions have very low maize production levels. while the higher production is in the south-west.

3.2 Maize production

Figure 3.4: Distribution of maize production per region in MT in 2000

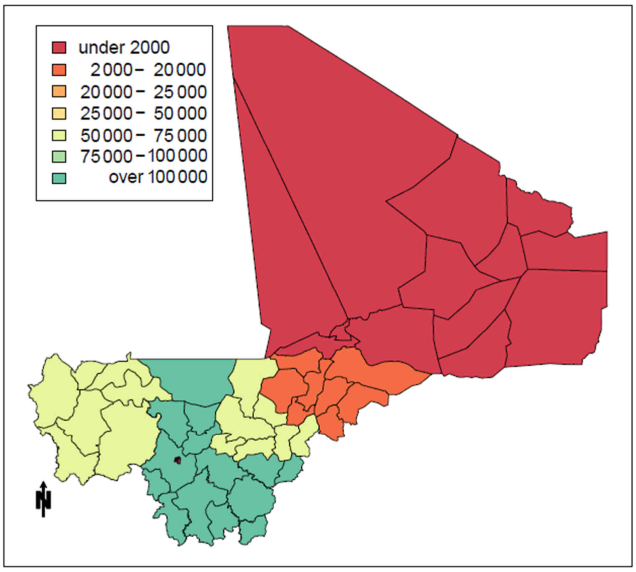
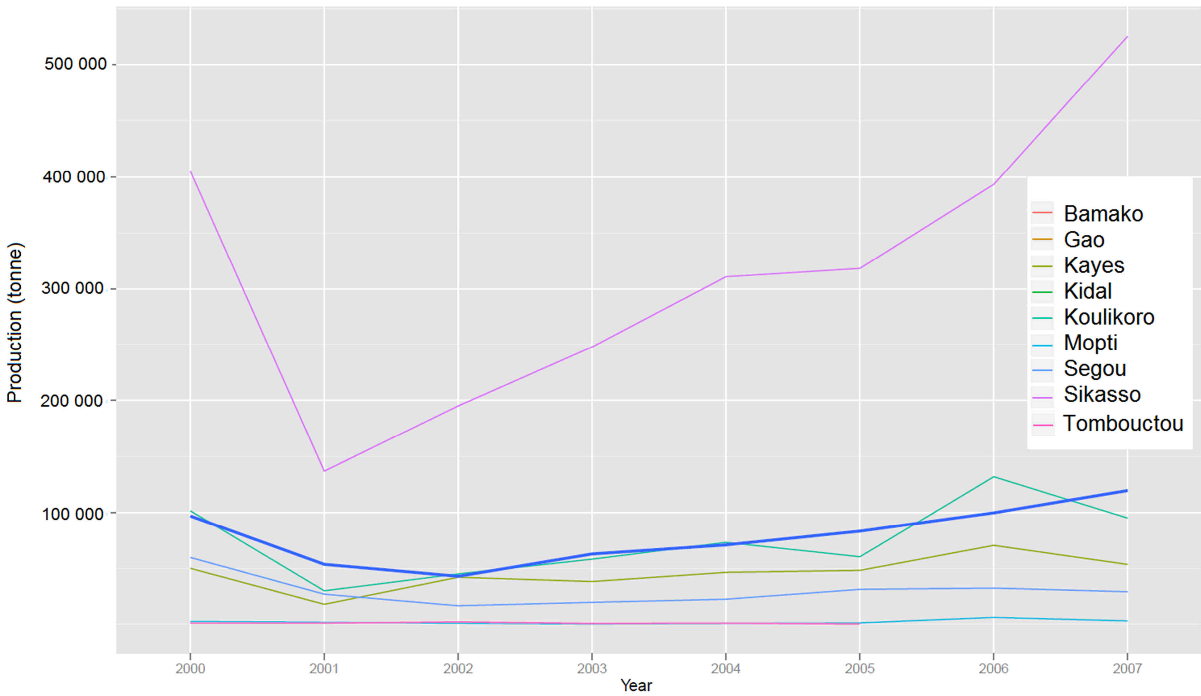


Figure 3.5 show the level of maize production from 2000 to 2007, which shows that the southern region Sikasso has the highest maize production in Mali and also the most variable. In some regions, namely Mopti and Tombouctou the production is not only low, but quite stable in absolute terms.

Figure 3.5: Maize production per year per region (in tonnes)



NB dark bold blue line the underlying trend based on all regions

Figure 3.6 shows the change in maize production between 2000 and 2001 and is accompanied by a map showing the change (in percantage terms, not annualised) between 2000 and 2007. As noted in Figure 3.5, maize production in the northern region is low and not very variable as this is not a major producing region. This map demonstrates the large fall in production in 2001, which was approximately 65% decline in production in Sikasso and Koulikoro. These data and maps are merely indicative and a fuller time series of the changes is available from the authors. The change in Tombouctou appears to be large (over 50% fall) however this was from a low starting point and so should not be over-weighted in the analysis. The largest producing area, Sikasso saw a significant increase over the period of almost 30%, Koulikoro, the other large area of maize production saw a small (6%) fall over the period. Annualised these would approximate to 4.25%pa for Sikasso and -1% for Koulikoro. These annualisation and growth rates should be interpreted with care as these calculations do not take the significant drop in production of 2001 into account.

Figure 3.6: Distribution of change in maize production per region in tonnes (2000-2001)

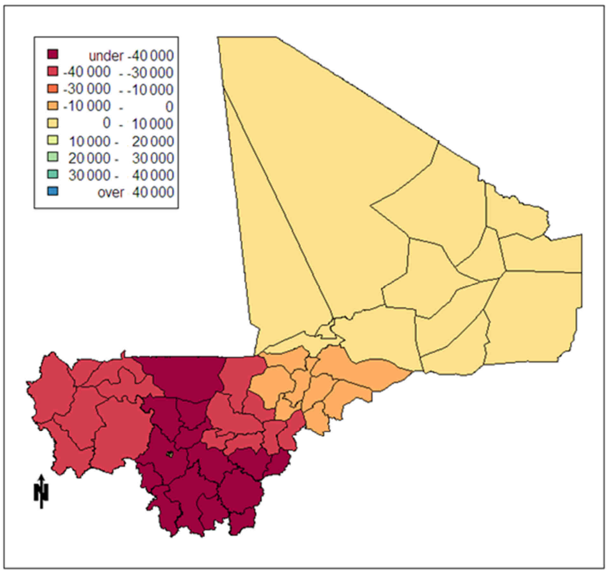
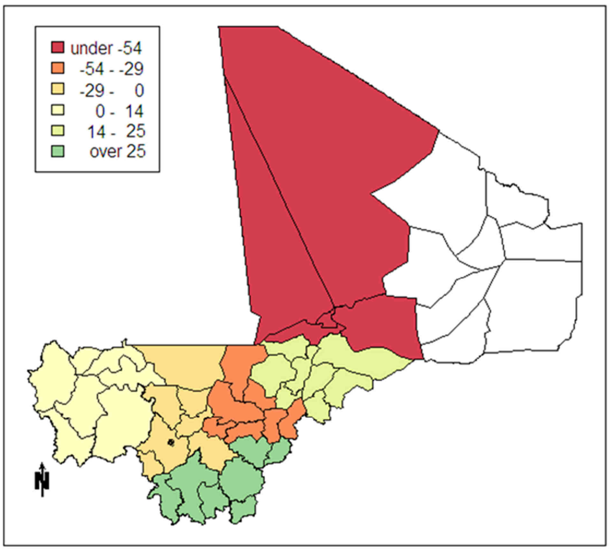


Figure 3.7 is similar to Figure 3.6 but shows the change over a longer period (2000 to 2007) and in percentage change. The figure shows that change in maize production is quite considerable and differs across regions: some regions have had a negative change, while other have had a positive change.

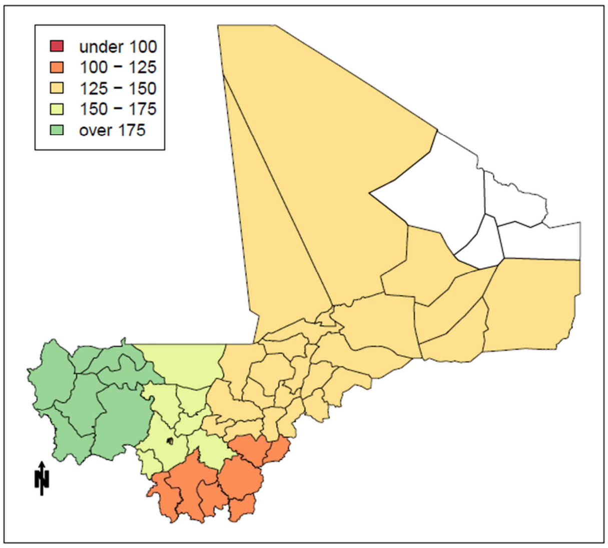
Figure 3.7 Distribution of change in maize production per region in % (2000-2007)



3.3 Consumer and producer prices

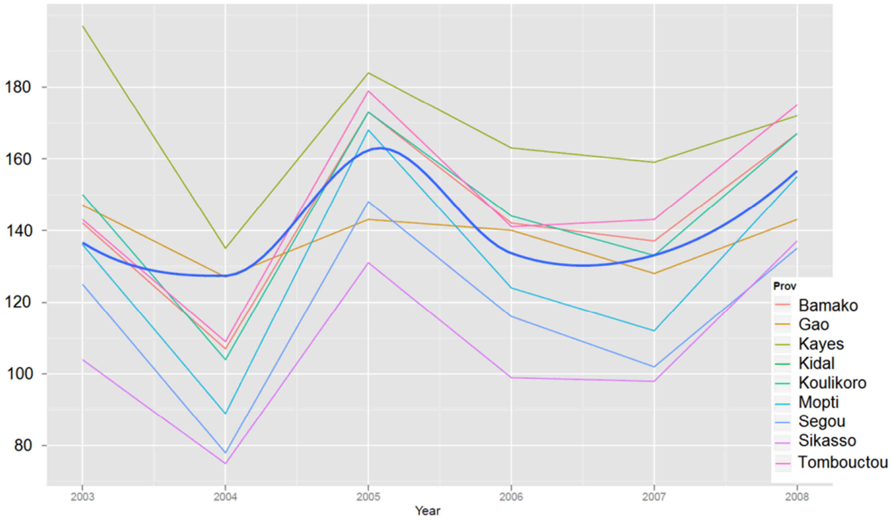
Figure 3.8 shows the different prices in the major market towns, when aggregated to regional levels. There is quite some difference in price levels in 2003, with the highest prices in the East. The fact that there are such price differences may reflect a lack of arbitrage opportunities, e.g. because of high transport costs, lack of information.

Figure 3.8: Distribution of consumer prices of maize per region (in 2003 in Franc CFA per tonne)



As might be expected, consumer prices also vary considerably across years (Figure 3.9), which indicates the expenditure risk that consumers face each year. The figure also shows that prices are consistently higher in Kayes and consistently low in Sikasso, which is surprising, as these two regions are both in the south of Mali and one would expect arbitrage opportunities. This may reflect high transport costs. However, it may also be the case that It might be that Sikasso has problems as there is actually little data generally available here.

Figure 3.9: Consumer prices of maize per year per region (in Franc CFA per tonne)



NB dark bold blue line is the underlying trend based on all regions

Figure 3.10 shows producer prices in the main market towns in Mali. There was no data for the northern regions. Again the prices show a geographical difference between regions.

Figure 3.10: Distribution of producer price of maize per region (in Franc CFA per tonne)

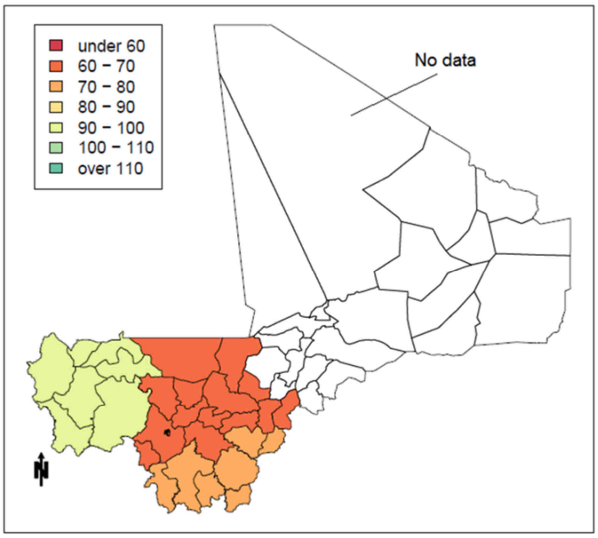
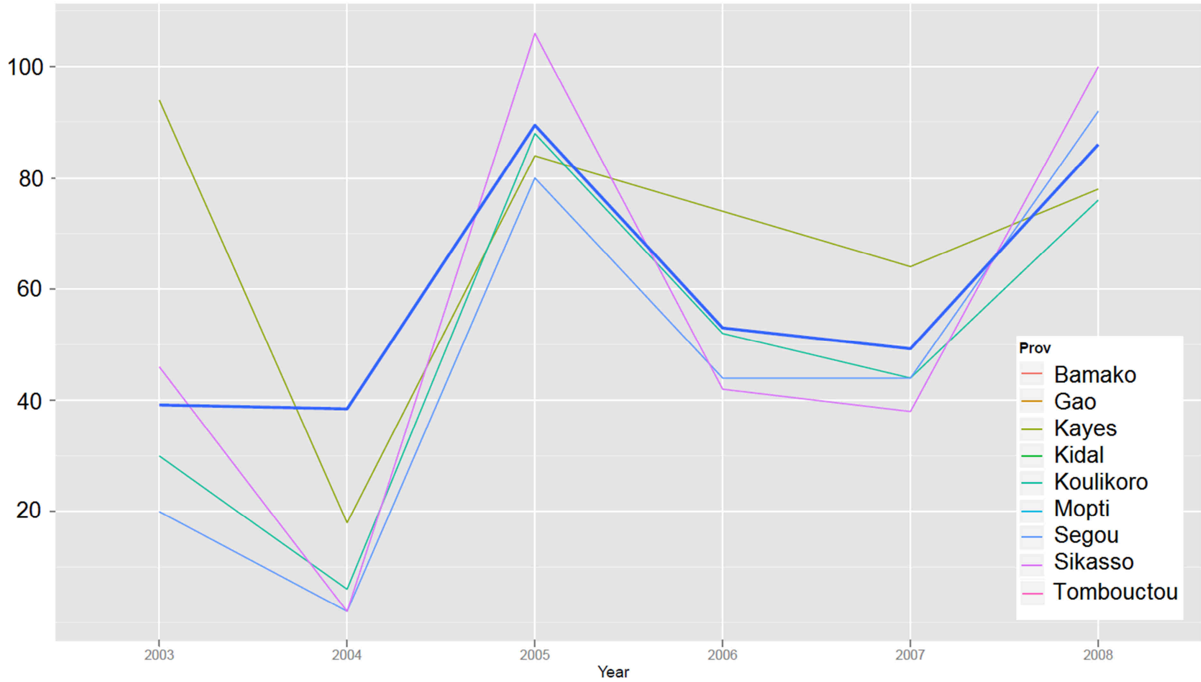


Figure 3.11 show the producer prices across years (2000 to 2008). There is much variation, as in the consumers' prices. This sheds some light on the extent of price risk that farmers face each year. Especially between the years 2004 and 2005 the price jumps considerably. Prices are negatively correlated with yields, therefore a low regional / national harvest will result in high prices, thus levelling off the income of farmers.

Figure 3.11: Producer prices of maize per year per region (in Franc CFA per tonne)



NB dark bold blue line is the underlying trend based on all regions

When we relate the consumer prices to production we can see this relationship (Figure 3.12): when production increases, prices drop. However, this relationship is different for different years, which means that there are other factors that determine prices (and thus price risk). Figure 3.13 shows a similar relationship between producer prices and production. Only 2005 is an outlier: Figure 3.11 shows that in that year, prices were exceptionally high. It is not known what caused this high price. It is interesting that the curves for producer prices are much flatter than those for consumer prices, which means that producer prices are less responsive to production changes. This may reflect the variability of transport or transaction costs. It may also reflect absorption of differences by middlemen.

Figure 3.12: Relation between consumer prices and production (in Franc CFA per tonne)

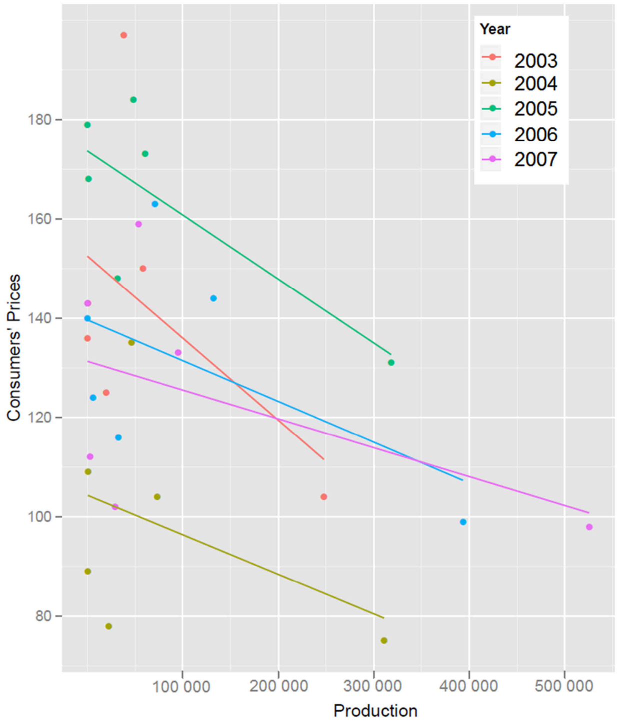
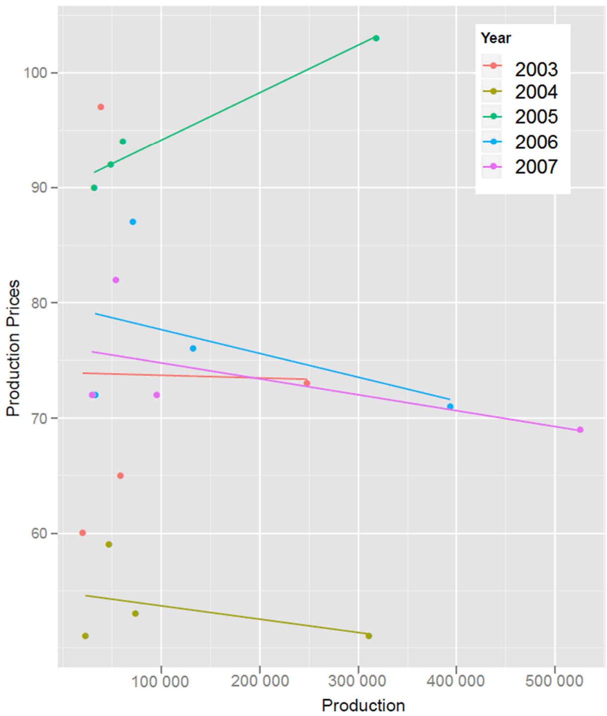
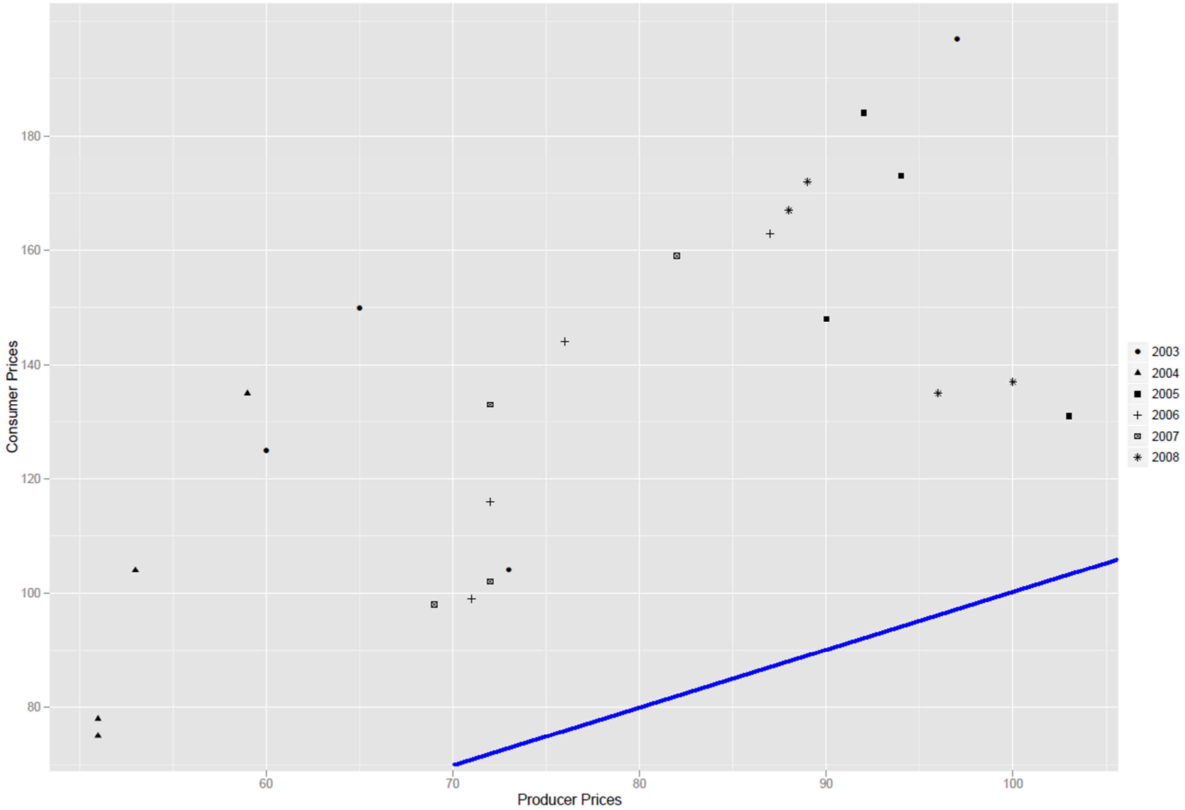


Figure 3.13: Relation between producer prices and production (in Franc CFA per tonne)



Producer and consumer prices are of course related (Figure 3.14) but not perfectly. In all years and regions the consumer price is (much) higher than the producer price.

Figure 3.14: Correlation between producer and consumer prices (in Franc CFA per tonne)



NB bold blue line is 45° where consumer and producer price are equal

3.4 Economic difficulty

Economic difficulty[4] is show in Figure 3.15 for each cercle. It shows that there are quite some differences. In Sikasso the data is missing. In Kidal at the far east and Gao, data is present with populations in economic difficulty recorded as 31 082 and 98 288 respectively. It should be noted at Menaka in Gao recorded 0 and this may lead to an under-estimate of the numbers.

[4] The dataset of CountrySTAT does not define how economic or food difficulty is measures. There are no units given beyond that it is number of people.

Figure 3.15: Distribution of population in economic difficulty per region (in 2005)

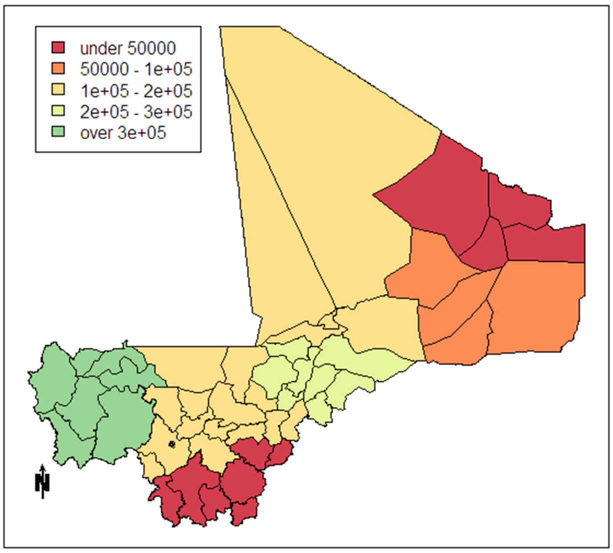
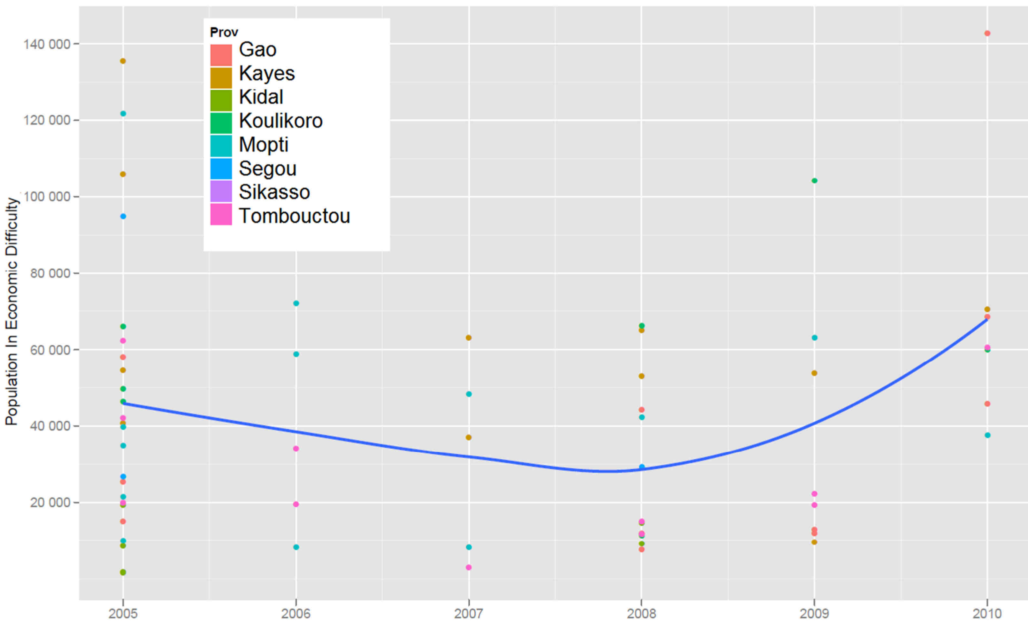


Figure 3.16 shows that also across years, the number of people in economic difficulty differs greatly. From 2008 to 2010 this population increases sharply. This shows the vulnerability of the Malian population across years: vulnerable groups are not fixed, or stable, some people fall into economic difficulties in some years, while coping in other years. The data is most complete for 2005, hence there are more points.

Figure 3.16: Population in economic difficulty per year per region



NB dark bold blue line is the underlying trend based on all regions

3.5 Food difficulty

A similar map was made for food difficulty (Figure 3.18), which closely follows the map for economic difficulty, as expected. The most food insecure cercles are in the south and north-east. However, while

Mopti comes out as food insecure, it appears to be that it is recording more than others. Thus its status as food insecure might suffer due to better reporting.

Figure 3.17: Distribution of population in food difficulty per region (in 2005)

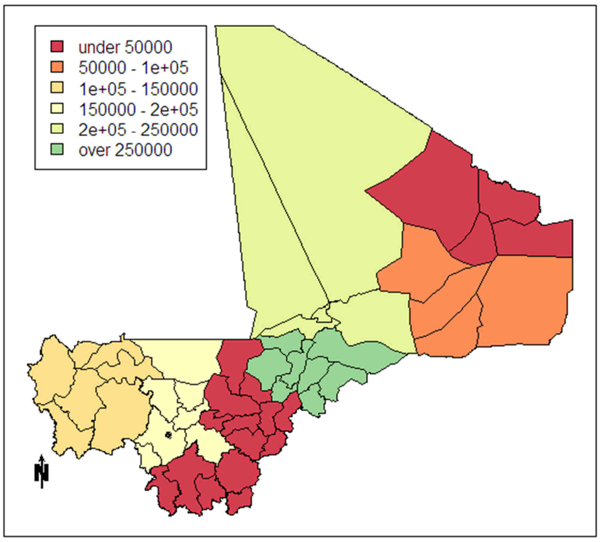
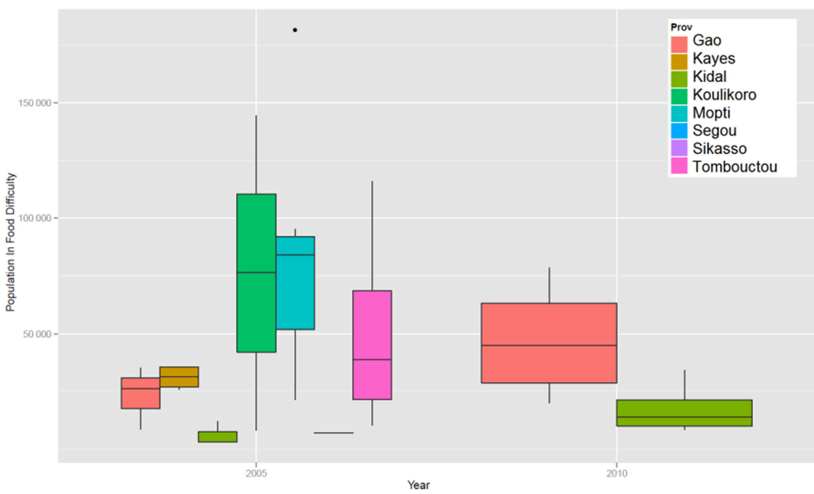


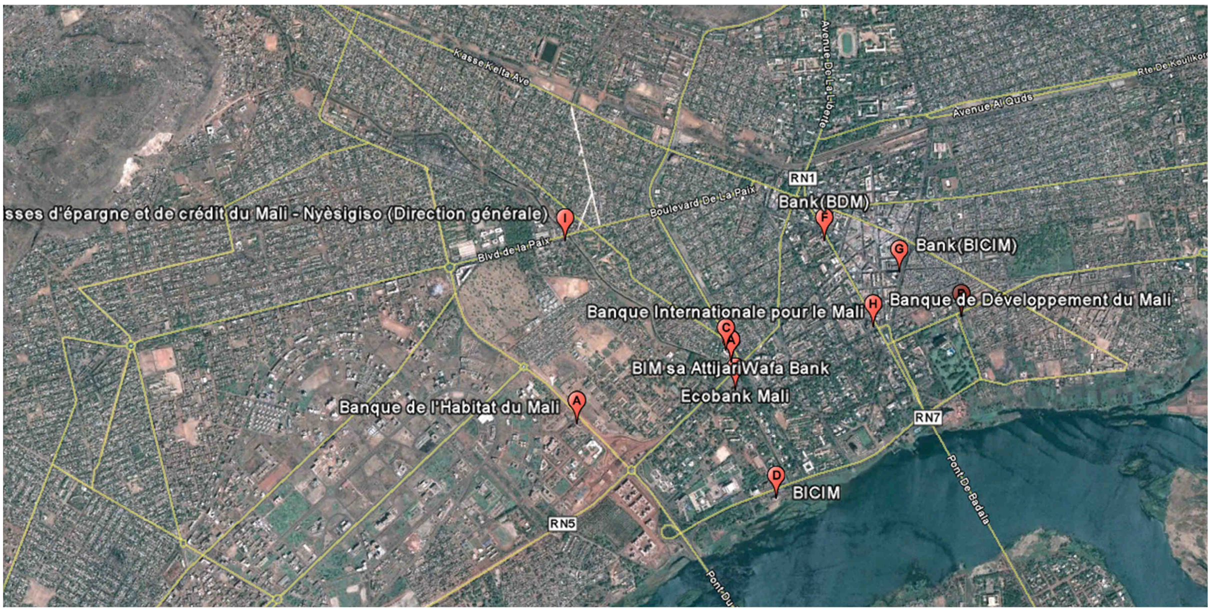
Figure 3.18 shows a slightly different figure than Figure 3.16 for food difficulty per year per region, but it also shows that food insecurity is dynamic: it changes over the years. The boxes represent the interquartile range of the data, i.e. it is a measure of the spread of, in this case the population in food difficulty. The horizontal line in the middle of the box is median. Small boxes represent highly concentrated data and if the median is towards one end of the box then the data is skewed with higher population nearer that quartile. Kidal in 2005 & 2010 both have relatively small differences within their region, however Koulikoro has some regions that have considerably higher problems than others. Further the Mopti region has some differences in the distribution of those in food difficulty with a clustering towards the upper region, with one very badly effected region (denoted with the point).

Figure 3.18: Population in food difficulty per region and year



3.6 Financial institutions

Figure 3.19: Location of main banks in Bamako



Using publically available information, banks were sited in Bamako and a number of other regions (Figure 3.19). This data can be used to give an initial estimate of the number and distribution, though it should be noted that the data appears to reflect the major commercial banks rather than any smaller micro-financial institutions that might be utilised in the implementation of the insurance policies. The data acquisition for this information will not be simple.

4 Conclusion

This study showed the results of several socio-economic mapping exercises. For targeting vulnerable groups for which an index insurance could be made possible, socio-economic data is not very precise: most of the data are on a region level, or at cercle level at best. The data also suffers from "missing data". We found many zeroes in the data, which probably are not zeroes but missing. There may be more disaggregated data available in the form of household surveys, that could then be transformed into gridded data.

However, the data do show the extent of vulnerability to volatile prices for both producers and consumers. As many farm households are not only producers but also net consumers, this reflects the fact that many farm households are disadvantaged. Although a low harvest will lead to higher prices, thus raising income, this will also mean that later in the year, when stocks have been emptied, farm households will need to buy food (such as maize) at much higher prices later in the year.

The socio-economic mapping exercise should be combined with the mapping exercise for yield variability (see Conijn et al., 2011) to see how the different risk factors are related. This will be done in further research.

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