How vulnerable is India to climatic stress? Measuring vulnerability to drought using the Security Diagram concept

Lilibeth Acosta-Michlik
Fausto Galli
Université Catholique de Louvain, Belgium

Richard J.T. Klein
Sabine Campe
Potsdam Institute for Climate Impact Research, Germany

Kavi Kumar
Madras School of Economics, Chennai, India

Frank Eierdanz
Joseph Alcamo
Dörthe Krömker
University of Kassel, Germany

Alexander Carius
Dennis Tänzler
Adelphi Research, Berlin, Germany

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How vulnerable is India to climatic stress? Measuring vulnerability to drought using the Security Diagram concept[1]

L. Acosta-Michlik[2], F. Eierdanz, K. Kumar, F. Galli, D. Tänzler, J. Alcamo, R.J.T. Klein, S. Campe, A. Carius, and D. Krömker

Abstract:

There is a consensus that some degree of climate change will most likely occur making adaptation an important focal point of climate change research. For an adequate adaptation support, it is crucial to know who are the most vulnerable. Developing indicators of vulnerability is one step to achieving this end. This paper contributes not only to the derivation of vulnerability indicators but also to the development of a vulnerability framework by drawing a clear link between environmental stress and state susceptibility, on the one hand, and environmental crisis, on the other hand, using the concept of the Security Diagram. The Security Diagram consists of three components, namely environmental stress, state susceptibility and crisis probability curves. The underlying assumption of the Security Diagram is that, the higher the level of vulnerability due to the combined impacts of environmental stress and state susceptibility the higher the probability of crisis. Susceptibility indices were generated from selected social (e.g. infant mortality, illiteracy rates, population, etc.) and economic (e.g. GDP per capita, share of agriculture to GDP, irrigated area, etc.) indicators through application of fuzzy logic method. On the other hand, indices of environmental stress were derived using indicators of water stress, which have been generated from the WaterGap model. Another unique feature of the Security Diagram is the possibility of embedding crisis probability curves on the diagram, which are convenient yardstick for measuring the degree of vulnerability of a state over time, or comparing vulnerability across regions and countries for a particular period. Using the time-series indices on environmental stress and state susceptibility, and time-series data on the occurrence of crisis, the probability curves were estimated with logit and probit regression. Through these combined methodologies, a Security Diagram for the state of Andhra Pradesh in India for the period 1970-1995 was constructed. The diagram revealed that Andhra Pradesh has experienced a

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[2] Author for correspondence: Lilibeth Acosta-Michlik, Senior Research Fellow, Département de Géologie et de Géographie, Université Catholique de Louvain (UCL), Place Louis Pasteur 3, B-1348 Louvain-la-Neuve, Belgium, Tel.: +32-10-47-9182, Fax: +32-10-47-2877, E-mail : acosta@geog.ucl.ac.be

very high level of vulnerability in the past because of frequent occurrence of droughts and little reduction in socio-economic susceptibility. Moreover, the crisis probability curves tend to tilt towards the water stress axis, which implies that the level of vulnerability tends to be more sensitive to the changes in the level of water stress. A water stress index of around 0.7 already yields a very high probability of crisis and requires a very low level of susceptibility (or high level of adaptive capacity) to avoid the occurrence of crisis. A more immediate planned adaptation measure is thus to invest in infrastructure or technologies that could help hinder the intensity of drought.

Keywords: adaptive capacity, climate change, drought, globalisation, Security Diagram, vulnerability, water stress

1. Introduction

Adaptation is now as an important issue as mitigation in climate change research. This is because of the fact that climate change will occur in the coming several decades regardless of efforts to reduce emissions due to the long life span of greenhouse gases in the atmosphere (Downing et al. 2001). “Adaptation is a necessary strategy at all scales to complement climate change mitigation efforts” (IPCC 2001). The major task ahead is to identify the regions or the specific groups of population that will likely be affected by climate change and the strategies to minimise the negative effects of climate change on them. The identification process involves the assessment of the level of vulnerability of the society and the analysis of their adaptive capacity. The choice of appropriate adaptation options requires vulnerability assessment hence the concepts of vulnerability and adaptation are closely interlinked. Although vulnerability science is not new, vulnerability research in the fields of climate change is quite recent. Unlike in the field of economic or social planning in which quantifiable indicators are mostly well developed and applied, policy experts in the field of climate change are still exploring appropriate and relevant indicators. This is a crucial task as “formal indicators of vulnerability and adaptive capacity are useful to help identify vulnerable situations and plan and monitor effective adaptive measures” (Downing et al. 2001:5). Vulnerability research in climate change has adopted ideas and concepts from other fields such as poverty and food/human security.

Security research, whose traditional foci were related to the issues of military threats, territorial integrity and political independence, shifted to non-conventional threats including environmental stress brought about by global warming. “It is now accepted that environmental stress, often the result of global environmental change, coupled with increasingly vulnerable societies, may contribute to insecurity and even conflict” (Lonergan et al. 2000). The concept of the security diagram was developed to provide quantitative meaning to earlier studies linking environmental change and human security (Homer-Dixon 1994; Lietzmann and Vest 1999), which have been largely qualitative (Alcamo and Endejan 2001). Among others, it aims to assess the likelihood and the degree of environment-related crisis, identify the locality of the crisis and the affected population, and draw up a broader view of the world security situation due to global climate change. The Security Diagrams Project contributed to this research endeavours by developing indicators of state susceptibility and environmental stress, which are important determinants of vulnerability (Alcamo et al. 2005, Acosta-Michlik et al 2005, Tänzler and Carius 2005, and Krömker et al. 2005). In the project, the susceptibility component has been evaluated according to three dimensions – socio-economic, political and psychological. This paper focuses on the socio-economic susceptibility that links the issue of globalisation to climate change. Besides identification of indicators, the concept of Security Diagram provides further quantitative meaning to the concept of vulnerability by drawing an empirical link between the level of susceptibility and environmental stress, on the one hand, and the ensuing level of risks, on the other hand. Security Diagram thus provides a holistic empirical approach in the assessment of vulnerability to the impacts of climate change. Using the Security Diagram concept, this paper assesses the vulnerability of the state of Andhra Pradesh in India to drought, an extreme climatic event which is increasingly becoming a security issue in many countries. According to the IPCC (2001), demand for water is generally increasing due to population growth and economic development, but water shortages will be exacerbated in many water-scarce regions due to climate change. The next section of this paper discusses the concept of the Security Diagram (Section 2). Section 3 describes the case study region (Andhra Pradesh, India). In section 4, the methods used to compute the different components of the Security Diagram and the corresponding results are discussed. Finally, the paper concludes by assessing the vulnerability of Andhra Pradesh using the Security Diagram.

2. The Security Diagram Concept

The Security Diagram represents vulnerability in three components (i) the “susceptibility” of society (i.e. the converse of adaptive capacity), which is a function of attributes of society such as it preparedness for disasters, (ii) “water stress” which is a reflection of the pressure on society caused by the irregularity (from society’s perspective) of natural processes, and (iii) drought-related societal “crises” (Alcamo et al. 2005). From a socio-economic perspective, Acosta-Michlik et al. (2005) defined these components as follows:

- Water stress is the intensity, extent, timing and duration of a change in normal water resource availability that disrupts economic and human activities.

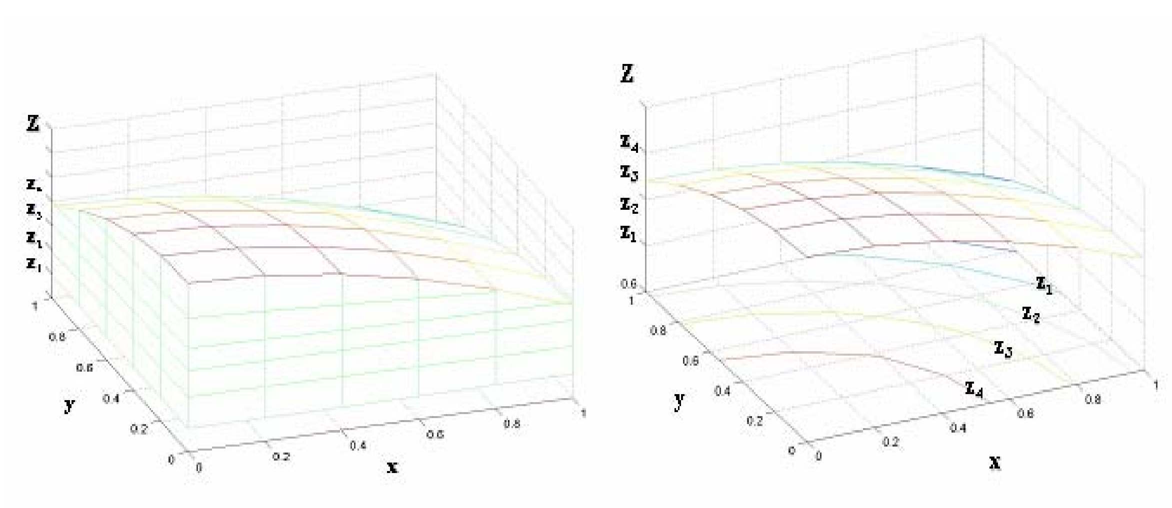
- State susceptibility is the inability of the state to protect and support society from adverse water stress if market mechanisms fail to provide the necessary resources for coping with the stress.
- Drought-related crisis is an unstable or critical economic and human state of affairs caused by the susceptibility of the state and society to water stress, which has serious adverse consequences on economic development and requires national or international emergency support.

In this paper, the Security Diagram is used to characterise vulnerability as dependent on both water stress and socio-economic susceptibility. The assumption behind the Security Diagram is that the higher the water stress, the higher the likelihood of crises. At the same time, the higher the socio-economic susceptibility (i.e. the lower the adaptive capacity), the lower the stress required to cause a crisis. Within the framework of the Security Diagram vulnerability can be expresses in the following functional form:

[1] $$z = f(x, y)$$

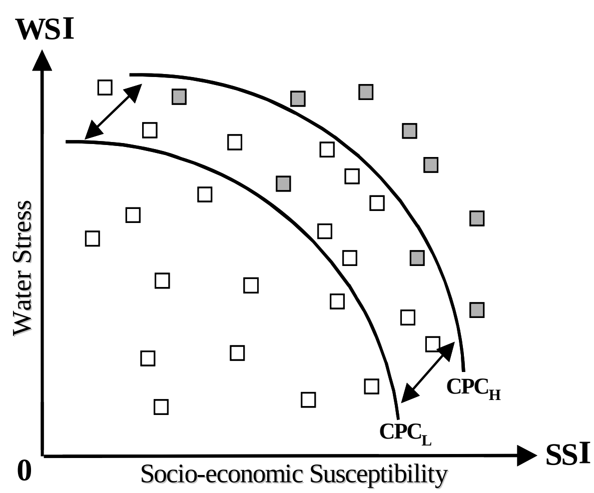
where z are some measurable indicators of the level of vulnerability, which are a function of two explanatory variables – socio-economic susceptibility (***x***) and water stress (***y***). Figure 1 shows a three-dimensional diagram of equation [1]. The two horizontal dimensions represent the two inputs ***x*** and ***y***, and the vertical dimension represents the outcome ***z***. "The surface displays directly how the value of [***z***] changes with the variations in the values of its inputs, and is sometimes termed as *response surface*" (Morgan and Henrion 1990). For example, at point z_4 where (combination of) the values of ***x*** and ***y*** are low, the level of vulnerability is low. In contrast, vulnerability is high at point z_1 where ***x*** and ***y*** are high.

Figure 1. Surface (left) and contour (right) plots of the Security Diagram



The surface of the diagram can be compared to a hill, on which one feels or become better off on a higher than lower ground. Hence, equation [1] can also be presented in a contour plot showing lines of constant elevation or height. The contour lines $\boldsymbol{z_1}$, … $\boldsymbol{z_4}$ are the different levels of vulnerability at varying combination of socio-economic susceptibility $\boldsymbol{x}$ and water stress $\boldsymbol{y}$. Correspondingly, vulnerability is quite low at $\boldsymbol{z_4}$ (upper part of the hill), but increases as one moves to $\boldsymbol{z_1}$ (lower part of the hill). Adverse impacts of an environmental stress on the state are thus very high at $\boldsymbol{z_1}$ but low or negligible at $\boldsymbol{z_4}$. The magnitude and scale of water stress can be quantified in terms of crop losses, health risks, reduced income, unemployment, migration, etc. When impacts reach an unprecedented level beyond the capacity of the communities or even the state to adapt and recover, crisis could occur. The Security Diagrams assumes that crisis is likely to occur at say, points between $\boldsymbol{z_2}$ and $\boldsymbol{z_1}$, where the levels of socio-economic susceptibility are highest or, in other words, the adaptive capacity to impacts of water stress are lowest. These contour lines, which we define here as "crisis probability curves" are very important in the context of the Security Diagram. The importance of these curves can be emphasized in a two-dimensional representation of the Security Diagram (Figure 2).

Figure 2. Security Diagram with Convex Crisis Probability Curves



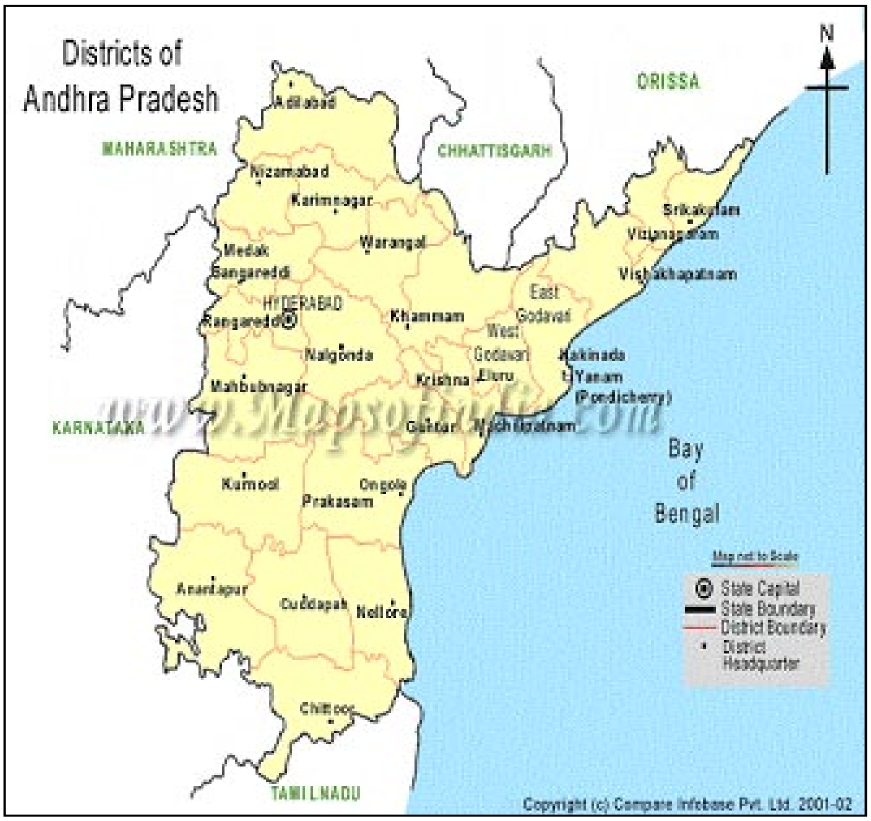
As in Figure 1, the $\boldsymbol{x}$-axis represents socio-economic susceptibility index (SSI) and the $\boldsymbol{y}$-axis represents water stress index (WSI). The scattered boxes in the diagram shows the combined indices of the socio-economic susceptibility and water stress for a given year, and thus indicates the level of vulnerability (or "insecurity") of the state. The low crisis probability curve ($\mathbf{CPC_L}$) and high crisis probability curve ($\mathbf{CPC_H}$) correspond to $\boldsymbol{z_2}$ and $\boldsymbol{z_1}$ in Figure 1, respectively. The probability of occurrence of crisis is higher the further the boxes from the origin and the closer to the **CPC_H**, as represented by the grey boxes. The probability curves are a convenient yardstick for measuring the degree of vulnerability of the state over time. The methods for computing the three components of the Security Diagram and the crisis probability curves are presented after the description of the case study region in section 3.

3. The Case Study Area: Andhra Pradesh

Covering an area of about 275,000 sq. km. and consisting of 23 districts (Figure 3), Andhra Pradesh is the fifth largest state in India and the fourth most populous. Its population grew from 66.5 million in 1991 to over 75 million in 2001. Nearly three quarters of this population live in rural areas. The state has three major perennial rivers: Godavari, Krishna and Pennar, as well as several other rivers of less significance. The majority of the rivers flow eastwards towards the Bay of Bengal. The state has areas rich in water resources, but also semi-arid regions where agriculture is mainly rainfed. Andhra Pradesh has a typical tropical climate: hot summers but relatively pleasant winters, especially in the plains of the interior. The state has three distinct climatic seasons: summer season from March to May, monsoon season from June to November and winter season from December to February. Scattered rains from April onwards build into heavy showers in August, September and October, tapering off by December. Southwest and northeast monsoons are the two periodic winds, which are important sources of rain; the former covering the months from June to September and the latter from October to December. The hot season starts in March, builds to a peak in June, and begins to drop off with the monsoon rains. Temperatures can rise above 40 degrees centigrade during the summer.

Agriculture is the lifeline of the state's economy, contributing over a third of the state's GDP and providing a livelihood for over 70% of the population. The GDP at constant 1993-94 prices for the year 2000-2001 is estimated to be Rs. 82,434 crores (about US $ 18,320 million) with a growth rate of 5.15 per cent compared to the previous year. Although agriculture has historically been the main source of income and livelihoods, this is changing. The share of agriculture in the state's income has declined from 59 percent to 34 percent between 1960 and 1999. Gains have been made by both the secondary sector (e.g., mining, manufacturing, construction and utilities) - from 12 to 23 percent - and the tertiary sector (services) - 29 to 44 percent. Notwithstanding the fall in the share of agriculture to the Andhra Pradesh's output, the state's economy continues to be predominantly agrarian. The share of rural labour force employed in the sector remained as high as 81 per cent in 1991. Landlessness is high, and statistics show that 10% of the population holds 44% of land. Nearly 59 per cent of the population are agricultural labourers. Thus, the crucial dependence of its rural labour force on agriculture is quite evident and is unlikely to diminish drastically in the near future. Land reforms have not significantly benefited the poor, since the lands identified as ceiling surplus were generally *'banjars'* (wastelands) or of poor quality. Due to the high cost of inputs required to rejuvenate these lands, the beneficiary households have been unable to cultivate them. The state's agriculture is constrained by low productivity, lack of assured supply of inputs, lack of technologies and cropping systems suited to dryland conditions, poor resources and inadequate extension and support services. Roughly 60% of the gross cropped area in the state does not have stable irrigation, and falls in the category of "rainfed drylands".

Figure 3: The case study area Andhra Pradesh with its different districts



Source: (Infobase 2003)

In 2001, Prakasam district (where the social survey on drought conditions was carried out) received 56 per cent less rainfall during June and July. This led to a rainfall deficiency of over 83 per cent in crops sown during these months. Since 1960 many districts in Andhra Pradesh have been frequently affected by droughts, particularly Medak, Nizamabad, Karimnagar, Mahaboobnagar, Nellore, and Hyderabad (Appendix 1). A news article on September 27, 2000 (Jafri 2000) reported that successive crop failures and mounting debts drove some hapless farmers in Anantapur to commit suicide to put an end to their misery and penury. It also added that as many as 159 farmers, mostly cotton growers in Warangal, had ended their lives in 1988 for the same reasons. Less dramatic but nonetheless worrisome consequences of droughts include shortage of safe drinking water, loss of agricultural livelihoods, reduction in milk production due to fodder shortage, temporary migration of families, dependence on usurers for loans, and cumulative indebtedness. Considering the increasing frequency and intensity of droughts in Andhra Pradesh, it is important to assess the vulnerability of the state to this extreme climatic event.

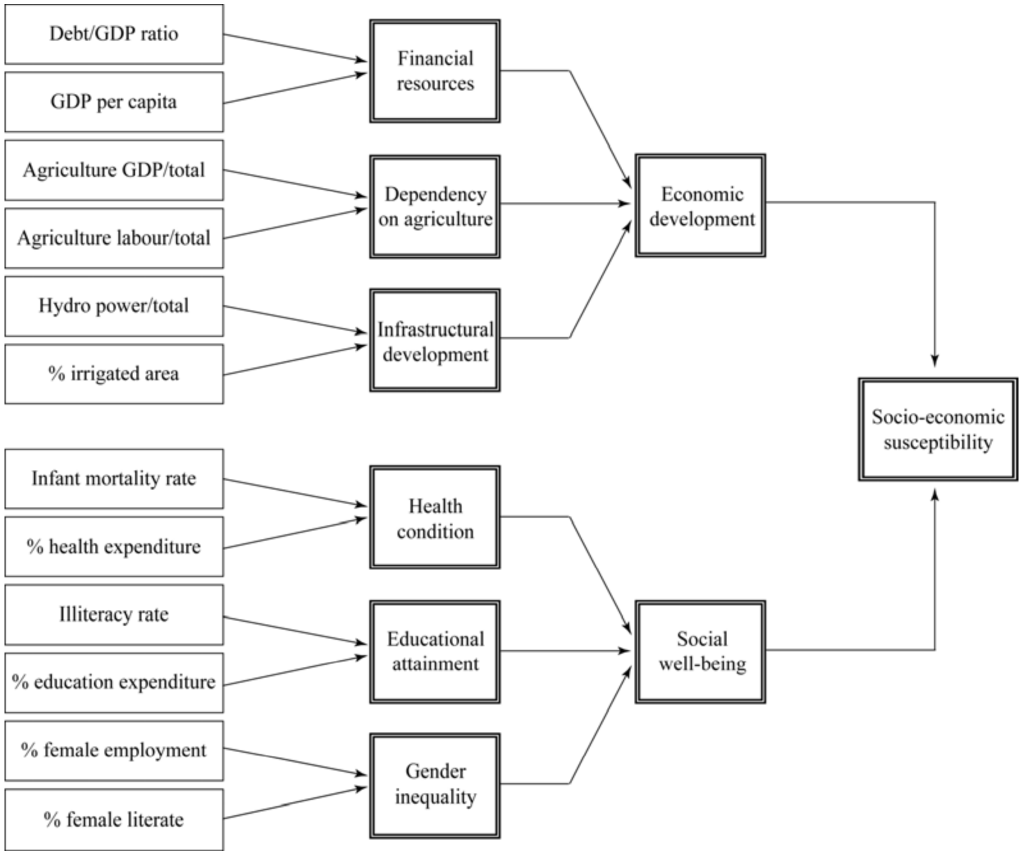
4. Methods and Results

Different methods were combined to construct a Security Diagram that assesses the vulnerability of Andhra Pradesh to droughts. These include fuzzy logic to develop indices of socio-economic susceptibility, statistical analysis to test the significance of water stress, and logit model to estimate the probability of crisis occurrence. This section briefly presents these methodologies and discusses the results of the analysis. Details on methods are available in Acosta-Michlik et al. (2005), Alcamo et al. (2005), and Acosta-Michlik and Galli (in preparation).

4.1 Developing susceptibility indices with fuzzy logic

In the Security Diagram, the framework on socio-economic susceptibility is based on the idea that susceptibility is related to the inability of the market and state to provide sufficient economic and social resources to society for coping with water stress (Acosta-Michlik et al. 2005). It was built on the assumption that susceptibility at the different geographical scales is influenced by globalisation. There are several economic theories explaining the effects of globalisation on economies and societies. Acosta-Michlik et al. (2005) discusses the relevance of economic development theories of modernisation and trade dependency in the development of the socio-economic susceptibility framework. These theories propose two opposing ideas on economic growth and human well-being across countries as a result of globalisation, in particular free trade. Whilst modernisation theory recognises the important role of globalisation in raising the economic and social well-being of society in many industrialised and newly industrialised countries, the trade dependency theory argues that global trade and industrialisation, which are central to globalisation, fail to bring about economic growth in many developing and least developed countries. In designing the socio-economic framework of susceptibility, we considered both theories to take into account the indicators that reflect the unequal distribution of gains and losses from globalisation. This is consistent with the concept of double exposure (O’Brien and Leichenko 2000), which suggests that communities characterised by economic marginalisation and high-risk environments are potential double losers.

Figure 4. Conceptual framework for socio-economic state susceptibility.



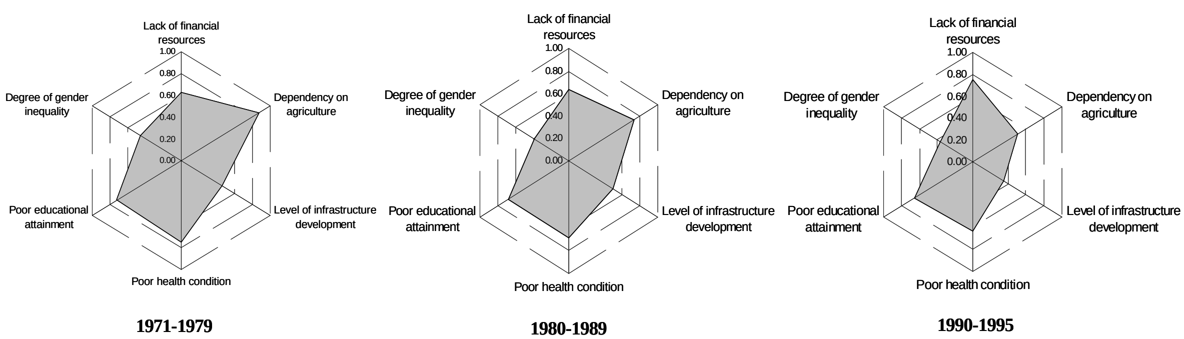
The framework on socio-economic susceptibility includes selected indicators on financial resources, agriculture dependency, infrastructure development, health condition, educational attainment, and gender inequality (Figure 4). However, the choice of indicators was partly restricted by the availability of time-series data for the district of Andhra Pradesh. Using fuzzy logic, a stepwise aggregation of the indicators was applied to develop indices ranging from 0 to 1. An index of 1 implies a very high level of susceptibility, whilst at 0 susceptibility is negligible. In fuzzy logic, it is possible to attach linguistic values such as low, moderate and high to certain index value ranges. Linguistic values are useful for fuzzy concepts to "quantify the vagueness and imprecision of interpretations" (Mays et al. 1997). "Thus, they are useful for evaluating state susceptibility, which does not have an objective yardstick to assess its relative magnitude" (Acosta-Michlik et al. 2005). Eierdanz et al. (2005) discuss in details the three components of the fuzzy logic – fuzzification, fuzzy inference and defuzzification – and their application to the concept of susceptibility.

The stepwise fuzzy aggregation yielded three sets of indices:

- First level of aggregation – indices of the determinants of susceptibility
- Second level of aggregation – indices of economic and social susceptibility
- Third level of aggregation – indices of socio-economic susceptibility

The results of the fuzzy models for the first level of aggregation are presented in web diagrams, where each co-ordinate refers to the six determinants of socio-economic susceptibility (Figure 5). The level of susceptibility for these determinants increases from the centre to the edge of the web. This implies that the larger the area in the web, the higher the susceptibility. According to these web diagrams, the susceptibility of Andhra Pradesh with respect to the six groups of indicators has generally declined from 1970s to the 1990s. This trend is largely attributed to the significant decline in agriculture dependency, improvement in infrastructure and increase in gender equality. However, India has experienced increase in susceptibility in terms of lack of financial resources due to the increase in foreign debt. This in turn limited the government's capacity to provide important basic services to the population such as education and health. As a result the susceptibility of Andhra Pradesh with respect to these social indicators remain relatively high until 1995.

Figure 5. Indices of the determinants of socio-economic susceptibility, 1970-1995



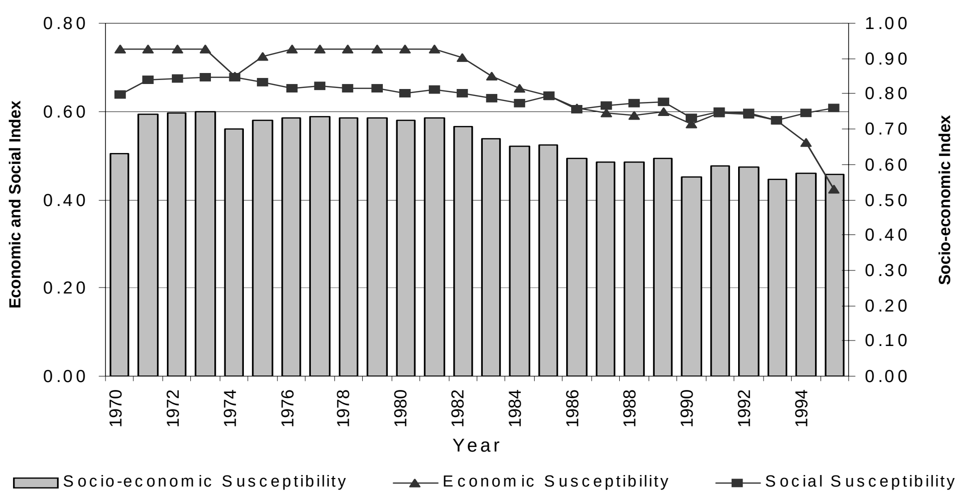
Available programmes to assist the large number of people affected by drought are also rendered ineffective partly on financial grounds. For example, some of the criticisms on the *Drought Prone Areas Programme* (DPAP) launched to tackle problems in fragile areas constantly affected by severe drought, were related to budget constraints. The DPAP is the main programme implemented by the central and state governments in response to drought-related problems.[3] The Technical Committee on DPAP (Hanamutha Rao Committee, 1994) attributed the unsatisfactory performance of the programme inter alia on implementation activities over vast areas and dispersed manner, inadequate budget allocations and expenditures thinly spread over large problem areas, and little participation of the local

[3] The DPAP can be traced back to the Rural Works Programme initiated in 1971-72. It has evolved gradually over time, initially covering a wide range of labour-intensive activities such as soil and water conservation, revegetation and afforestation, and development of irrigation and infrastructure. Over time the program gradually focused more sharply on area development to prevent drought. By the late 1980s, the DPAP became exclusively a watershed development programme focusing on soil conservation, water harvesting, pasture development, and afforestation.

people. Although Andhra Pradesh accounted for the highest level of the DPAP funding (Appendix 2), only 11 out of 23 districts of Andhra Pradesh are presently covered under the DPAP. Funds are allocated annually for the DPAP. The Mid Term Appraisal (1997-2002) of the Planning Commission of the Government of India reports that there is no guarantee for the funds to be released in time by the Government of India or other funding agencies. A more recent study by the Indian Council for Agricultural Research (ICAR) concludes that the insecurity about the availability of funding at the grassroots level limits the effectiveness of the programme (Planning-Commission 2003).

The results of the fuzzy models for the second and third levels of aggregation are presented in Figure 6. The index on the left-hand side refers to the economic and social susceptibility (second level of aggregation), whilst the right-hand side the socio-economic susceptibility (third level of aggregation). Note that the scale of the former index in the diagram is restricted to 0.80 to provide better view of the trend in economic and social susceptibility. The level of economic susceptibility is generally higher than social susceptibility until the mid 1980s. However, economic susceptibility has decreased significantly after 1993. The economic susceptibility is as low as 0.42 in 1995, which is almost half the level in 1970 (index of 0.74). This improvement is a result of the combined effects of good infrastructure development and less agriculture dependency. The level of socio-economic susceptibility, which is represented by the bar graph in the Figure 6, is relatively higher from 1970s to the mid-1980s, and lower from late 1980s to the mid-1990s. Andhra Pradesh experienced the highest level of socio-economic susceptibility in 1971, 1972 and 1973 with indices of about 0.75.

Figure 6. Indices of economic and social susceptibility, 1970-1995



4.2 Testing and Validating Water Stress Indices

In the Security Diagram, testing and validating indices of water stress is equally important as developing indices of socio-economic susceptibility. This section summarises the methods applied in Alcamo et al. (2005) to generate water stress indices for the Security Diagram. The authors used several indicators in water assessments to measure water stress. These indicators and their corresponding thresholds have been supported largely by expert judgement rather than scientific evidence. As an example, they mentioned that many large scale water assessments use the ratio of annual water withdrawals to water availability to indicate levels of water stress, although there have been no independent studies indicating critical values of this indicator (Cosgrove and Rijsberman, 2000; Raskin et al., 1997; Alcamo et al.; 2003b.). However, to provide some empirical meaning to the derivation of water stress index, Alcamo et al. (2005) used the occurrence of drought-related crisis as an independent variable for testing water stress estimates. Data on the occurrence of drought-related crisis were generated from media analysis and impacts reports from local surveys (Taenzler et al. 2005). The occurrence of crises were used to statistically test a wide variety of different water stress indicators. The WaterGAP model (Alcamo, et al. 2003a, b) was used to compute the values of 13 water stress indicators for Andhra Pradesh. Table 1 shows which of the water stress indicators are statistically significant.[4]

Table 1: Results of t-tests for the occurrence of crises for the water stress indicators[a/]

Indicators of Water Stress	Results of t-tests[b/]
1. Annual groundwater recharge in mm	–
2. Deviation of evapo-transpiration from long time average	+
3. Deviation of groundwater recharge from long time average	+
4. Deviation of precipitation from long time average	–
5. Deviation of water availability from long time average	+
6. Groundwater discharge per capita	–
7. Internal renewable water availability per capita	–
8. Percentage of area under stress	–
9. Percentage of population under stress	–
10. Runoff deficit index	+
11. Water availability per capita	–
12. Water withdrawal to availability ratio	+
13. Water withdrawal to internal availability ratio	–

Source: Alcamo et al. (2005)

Notes: [a/]Annual data are used for computing the indicators. “Statistically significant” indicates significance at the level of α=0.05.

[b/]+ significant, – not significant

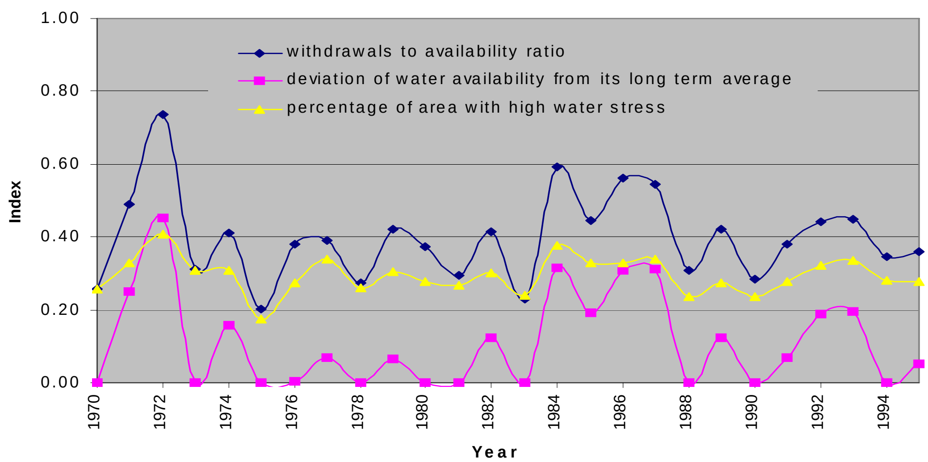
[4] The level of significance is based on testing the relationship of the water stress indicators to the occurrence of drought-related crisis from 1980 to 1995 in three case study regions in India, Portugal and Russia.

After testing and validating the indicators, an approach called "MaxIndex" was applied to generate water stress indices for the period 1970-1995. MaxIndex takes the maximum value of three indicators (i) the withdrawal to availability ratio, (ii) the deviation of water availability from its long term (climate-normal) average, and (iii) the percentage of area with high water stress (defined as water withdrawal to availability ratio of 0.4 or higher) (Alcamo et al. 2005). These indicators were selected in the computation of MaxIndex for the following reasons:

- the indicator "withdrawals to availability ratio" covers regions where water use appropriates a large fraction of total available water resources;
- the indicator "deviation of water availability from its long term average" covers situations in which a short term but sharp decrease in water availability affects a region; and
- the indicator "percentage of area with high water stress" covers situations in which there is an uneven spatial distribution of water resources across a region.

The values of the water stress indicators, which was used in computing the MaxIndex, are presented in Figure 7.

Figure 7. Indices of water stress indicators used in computing MaxIndex, 1970-1995



Among the three indicators, the withdrawals to availability ratio show the maximum index value from 1970 to 1995, except for 1983. The withdrawals to availability ratio showed an average index of 0.40 in the period 1970-1995, whilst the indices for the deviation of water availability from its long term average and the percentage of area with high water stress were only 0.11 and 0.30. According to the MaxIndex approach, this implies that the water stress index assumes the value of the indicator withdrawals to availability ratio for the period 1970-1995. The highest indices for the withdrawals to availability ratio were found in 1972 and 1984 at 0.74 and 0.59, respectively. Alcamo et al. (2005) explained that the frequency of occurrence of crisis events in three case study regions including India increases as values of MaxIndex increase, and crises seldom occur when the value of this index is below 0.4.

4.3 Estimating crisis probability curves with binary models

The crisis probability curves are important component of the Security Diagram because they provide a convenient and simple measure of the level of vulnerability of the state. However, the empirical estimation of the $\mathbf{CPC_L}$ and $\mathbf{CPC_H}$ are necessary in the Security Diagram for the following reasons (Acosta-Michlik and Galli, in preparation):

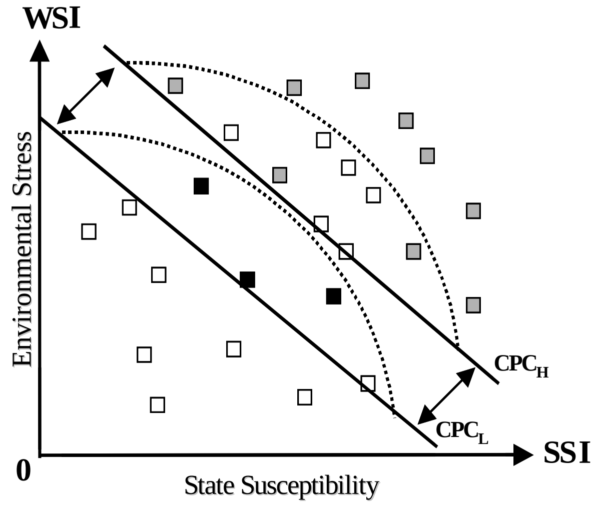
(a) The distance between the two crisis probability curves, low probability curve ($\mathbf{CPC_L}$) and high probability curve ($\mathbf{CPC_H}$), defines the critical zone where the state could be prone to crisis. The larger the gap between these curves, the weaker the power of the diagram to predict the probability of crisis incidence since many countries will tend to be covered by the critical area.

(b) The distance of the curves from the intersection tells also a lot about predictive capability of the diagram. If the curves are further away to the upper right of the diagram, crisis incidence is less frequent as it gives ample space for crisis-free zone.

(c) The shape of the curves influenced the probability of the frequency of crisis events. For example, crisis probability curves with straight contours increase the probability of crisis occurrence as compared to those that bends upward.

To elaborate argument (c), the $\mathbf{CPC_L}$ and $\mathbf{CPC_H}$ are presented in the form of straight lines in Figure 8. Straight crisis probability curves increase the number of events (if the assessment is done for one country) or number of countries (if cross-country assessment is carried out) falling within crisis zone, as exemplified by the black boxes in the diagram. In contrast, these boxes are below the critical levels when the $\mathbf{CPC_L}$ and $\mathbf{CPC_H}$ are convex. Consequently, it is important to investigate whether the crisis probability curves take a straight line or bend upward. To sum up, the strength of the Security Diagram depends on the precision of the estimated $\mathbf{CPC_L}$ and $\mathbf{CPC_H}$, which in turn is dependent not only on the indicators chosen to measure the level of susceptibility and water stress, but also on crisis data. Using the vulnerability function in equation [**1**], it is possible to estimate the probability curves. However, the appropriate statistical method to estimate a function as given in equation [1] and depicted in Figure 8 depends on the available information. There is dearth in crisis data related to drought. To complement the small amount of information on crisis available in the EMDAT database, media analysis was undertaken to generate additional qualitative data (Tänzler and Feil 2003). This implies that the dependent variable $\boldsymbol{z}$ in equation [1] is a discrete rather than continuous variable "so that conventional regression methods are inappropriate" (Greene 1993).

Figure 8. Security Diagram with Straight Crisis Probability Curves



In order to analyse empirically the crisis probability curves it is possible to use a well-known statistical framework, the binary choice model. This paper applied this model to identify the shape of the crisis probability curves and to determine their relative position in the Security Diagram. In this kind of model, the dependent variable represents a finite set of alternatives that can be chosen and has a discrete statistical distribution. In the case of the Security Diagram, the choices are either the presence or the absence of a crisis, thus the dependent variable will be binary, taking a value of 1 when a crisis arises and 0 when it does not. In the binary choice framework, explanatory variables can have a continuous distribution, as in this case, where both water stress index (WSI) and socio-economic susceptibility index (SSI) are continuous between 0 and 1. Applying a simple linear regression on a function with a binary dependent variable would result in conceptual problem such as the need to impose unrealistic hypotheses on the distribution of the errors and in statistical problem such heteroskedasticity. To overcome these problems, a theoretically based solution is as follows: a latent variable, measuring some unobservable indicator of the chance that the binary event will take place is linearly regressed on the explanatory variables and the probability of the event is computed by evaluating the latent variable in a function whose values can range between 0 and 1 (Greene 1993).

To elaborate on this, consider the following regression function:

[2] $$Y_t = \beta_0 + \beta_1 X_{1t} + \cdots + \beta_n X_{nt} + ut$$

where $X_{1t}, \cdots, X_{nt}$ are the explanatory variables at time t and Y_t is the unobservable latent variable. The probability that an event, say crisis, will take place will then be:

[3] $$P(D_t = 1) = F(Y_t)$$

where D_t is the binary variable at time t, taking value 1 if the event occurs and 0 if it does not, and $F(Y_t)$ is the function mapping the latent variable Y_t into the probability of an occurrence. Given function $F(Y_t)$, the event will take place when the latent variable takes a positive value and will not take place when it takes a negative one, that is:

[4] $D_t = 1$ if $Y_t > 0$ and $D_t = 0$ if $Y_t < 0$.

In econometrics literature, there are two common choices for the function $F(Y_t)$: the standard logistic distribution function and the standard normal distribution function, which leads to the so-called "logit" and "probit" models, respectively. The functional relationship for logit is

[5] $$F(Y_t) = \frac{1}{1 + \exp(-Y_t)}$$

and for probit

[6] $$P(D_t = 1) = \int_{-\infty}^{F(Y_t)} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \ .$$

Both models can be estimated using maximum likelihood. The logistic and normal distributions are very similar and yield estimates that are relatively comparable after some scaling in the parameters is performed. Nevertheless, both models were estimated to determine which of the two would better represent the probability of drought-related crisis in Andhra Pradesh. Prior to model specification and estimation, a stationarity test has been performed on all the variables to check for eventual unit roots and any ensuing spurious regression. With a rather high degree of significance, the null hypothesis of the presence of a unit root has been rejected for the dependent variable CRI_t (i.e. occurrence of crisis at time t) and for both the explanatory variables WSI_t (i.e. the water stress index at time t) and SSI_t (i.e. socio-economic susceptibility at time t).

Following equations [2] and [3], the regression function to estimate the latent variable is given in equation [7] and the probability of a crisis in equation [8]:

[7] $$Y_t = \beta_0 + \beta_1 WSI_t + \beta_2 SSI_t + \delta(\beta_0 + \beta_1 WSI_t + \beta_2 SSI_t)^2 + ut$$

[8] $$P(CRI_t = 1) = F(Y_t)$$

In equation [7], the linear relation between the latent variable and the explanatory variables is augmented by a non-linear term (i.e. the square of the linear relation) indexed by a single parameter. The purpose of this is to check the non-linearity of the regression function. An alternative procedure would have been to raise each parameter by a power of two, which is not appropriate in this case because of the limited sample size (only *26* observations). Assigning a square to each parameter would have led to a substantial loss in degrees of freedom and thus in statistical relevance of the estimation. The estimation results for equation [7] is as follows:

[9] $$Y_t = -22.26 + 35.84WSI_t + 9.09SSI_t + 0.07\left(-22.26 + 35.84WSI_t + 9.09SSI_t\right)^2$$

with a maximum log-likelihood of *-8.116*. The standard errors of the parameters are: 13.50 for β_0, 20.33 for β_1, 15.60 for β_2, and 0.03 for δ. The parameter δ, which measures the weight of the nonlinear term, does not only have a small value but also have a low standard error. We thus tested the statistical significance of parameter δ using the likelihood ratio (LR). The maximum log-likelihood for the restricted model (the restriction being $\delta = 0$) was -*8.503*, which means that eliminating the linear component does not lead to a great loss in explanatory power of the regression function. Moreover, the p-value of the LR test for the null hypothesis *H0:* $\delta = 0$ is only 0.379, confirming the supposition that the non-linear component in equation [9] is not significant considering the insufficient data points. In terms of the Security Diagram, this means that the crisis probability curves on the basis of the 26 observations from 1970 to 1995 are not convex but straight lines.

After dropping the non-linear term in the regression of the latent variable in equation [7], the model reduces to the following functions:

[10] $$Y_t = \beta_0 + \beta_1 WSI_t + \beta_2 SSI_t + ut$$

[11] $$P\left(CRI_t = 1\right) = F\left(Y_t\right)$$

Note that the equation for estimating the probability of an occurrence of crisis (equation [11]) remains the same.

The estimation results for equation [10] for the logit model is as follows:

[12] $$Y_t = -18.20 + 25.53WSI_t + 10.03SSI_t$$

with a maximum log-likelihood of *-8.503*. The standard errors of the parameters are: 9.93 for β_0, 11.35 for β_1, and 10.48 for β_2. The LR tests of zero slopes (*H0:* $\beta_0 = 0$, $\beta_1 = 0$, $\beta_2 = 0$) led to a clear rejection of the null hypothesis, which proves the statistical significance of all the regressors. The overall predictive power of equation [12] is quite high, with water stress and socio-economic susceptibility explaining 88% of the occurrence of crises. Both the constant and the water stress coefficient (β_1) are statistically significant. In particular, the coefficient β_1 *1* has a positive sign, reflecting the positive dependence to water stress levels of the occurrence of a crisis. The negative sign of the constant means that very low levels of both water stress and susceptibility translate in a low probability of a crisis occurrence, which is theoretically correct. The socio-economic susceptibility coefficient (β_2) possesses the desired positive sign, but turned out to be statistically insignificant. The p-value of the t-test for the null hypothesis *H0:* $\beta_2 = 0$ is high at *0.33*, rejecting the hypothesis that socio-economic susceptibility is an important explanatory variable.

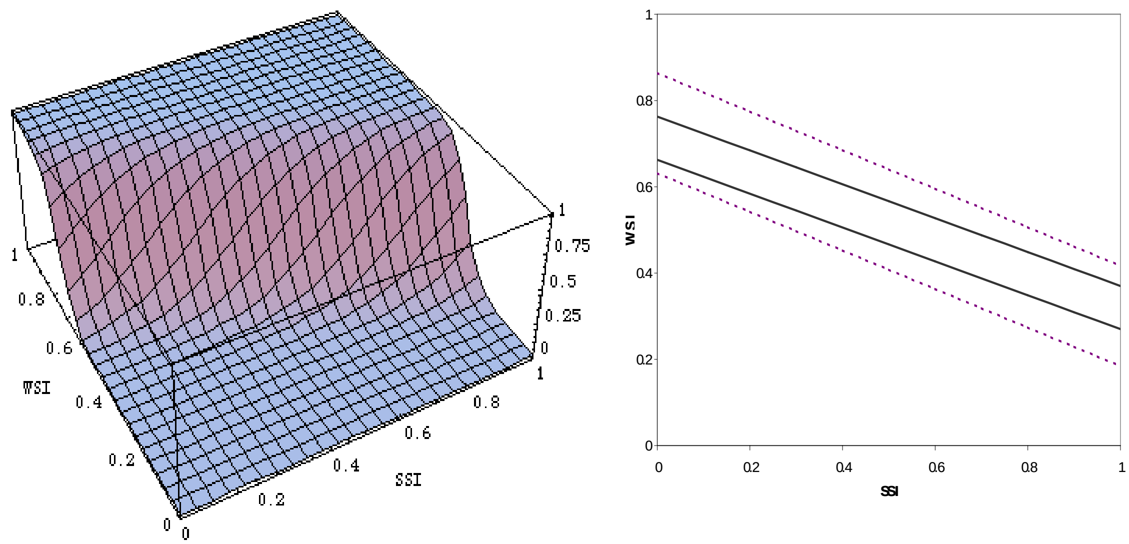
The reduced function in equation [10] was also applied to specify the probit model, yielding the following results:

$$[13] \qquad Y_t = -10.58 + 14.15WSI_t + 6.32SSI_t$$

The maximum log-likelihood is -8.565, whilst the standard errors of the parameters are: 5.43 for β_0, 5.68 for β_1, and 5.81 for β_2. There is thus a slight improvement in the statistical significance as compared to the logit model. The standard error of the parameter β_2 remained relatively large, but the p-value for the t-test of significance at 0.276 has at least improved as compared to that of the logit model. Moreover, the proportion of correct predictions is slightly better than in the logit estimation, increasing from 88% to 92%.

The overall poor performance of parameter β_2 in both models could be explained by several factors, more importantly, the convergence of values of the socio-economic indicators in the process of aggregation resulting in loss of information, the omission of other socio-economic indicators due to unavailability of time-series data, and the limited sample size. Worth noting is that the maximum likelihood t-test can only find an asymptotic justification because the small sample distribution of the t-statistic is not known, which means that the reliability of such a testing procedure in small sample is reduced. Such a small sample size should allow for significance levels of more than 5% for any testing. This implies that the t-test at 5% confidence cannot strongly confirm the statistical insignificance of the socio-economic susceptibility as an explanatory variable. A more practical reason to justify the inclusion of *SSI* in the set of regressors can be found by visually inspecting a plot of the data. Whilst the observations on water stress index (*WSI*) have a rather high variance (their range goes from *0.20* to *0.74*), the observed social susceptibility (*SSI*) does not vary too much, with a minimum of *0.56* and a maximum of *0.75*, thus limiting the scope for the analysis of its explanatory power. A more articulated data set, with a richer range of observations for the socio-economic susceptibility, could probably yield quite different results in terms of the significance of this index. This is currently being explored in another paper (Acosta-Michlik and Galli, in preparation). Nevertheless, the estimated equation [11] can be applied for the development of a Security Diagram because the results of the inference to test the goodness-of-fit of the estimated model with WSI and SSI as explanatory variables, yielded good results for both logit and probit models. The inference procedures include McFadden R-square[5], pseudo-R-square[6], and autocorrelation test[7]. Because the estimation and inference results for the probit is better than the logit model, the former provides better estimates for the Security Diagram.

Figure 9. 3D and 2D representations of the estimated functions



The three-dimensional (3D) and two-dimensional (2D) view of the estimated function is presented in Figure 1. In the 2D diagram, the estimated function refers to the low and high probability curves in the Security Diagram. The broken lines refer to results of the logit model, whilst the solid lines are the estimates of the probit model. These lines were derived by computing the probabilities of the estimated functions in equations [12] and [13] (Acosta-Michlik and Galli, in preparation). Although both lines are plotted using the same confidence interval (i.e. 5% and 95% for the lower and higher curves, respectively), the estimates of the logit model gives a much wider gap between the two probability curves. Because a wider gap

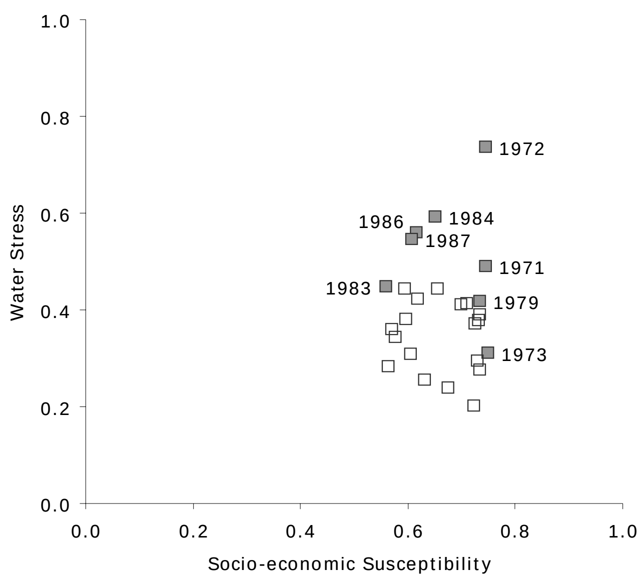
[5] The McFadden R-squared is based on the comparison of the maximum log-likelihood in the estimated model (*l1*) and the one in a model where all the explanatory variables have been eliminated, except the constant (*l0*). The expression for this indicator is the following: *McFadden R2 = 1 – l1/l0*. The computed McFadden R-square is *0.47*, which is a very good result, given that usually goodness-of-fit is fairly low for discrete choice models.
[6] The pseudo-R-square is computed as 1 minus the ratio between the wrong predicted outcomes in the full model and in the one with the constant only as a regressor. The pseudo-R-square of *0.62* is also good, which confirms the good predictive power of the combined explanatory variables *SSI* and *WSI*.
[7] Given that the data employed are a time series, the residuals have been tested for the presence of autocorrelation. None of the *12* lags considered have a significant Q-statistic, which means rejection of the null hypothesis of the presence of autocorrelation. The test conducted on the squares of residuals, which assesses the possible presence of an ARCH style dynamics in the errors, also showed an absence of autocorrelation.

makes the application of the Security Diagram less robust, this further confirmed the suitability of the probit model in the construction of the Security Diagram for India.

5. Vulnerability assessment using the Security Diagram

The socio-economic susceptibility indices generated from fuzzy logic method and the water stress indices validated using statistical tests are presented in a scatter plot in Figure 10. The boxes tend to draw together towards the lower right-hand side of the diagram. This implies that the indices for socio-economic susceptibility indices are relatively higher that those for water stress in Andhra Pradesh from 1970 to 1995. As mentioned earlier, the water stress indices have a rather high variance than the social susceptibility indices. The grey boxes, which represent the years when drought-related crisis occurred, are generally located on the outer part of the diagram. This supports the assumption of the Security Diagram that the probability of the occurrence of crisis is higher when the socio-economic and water stress indices are high.

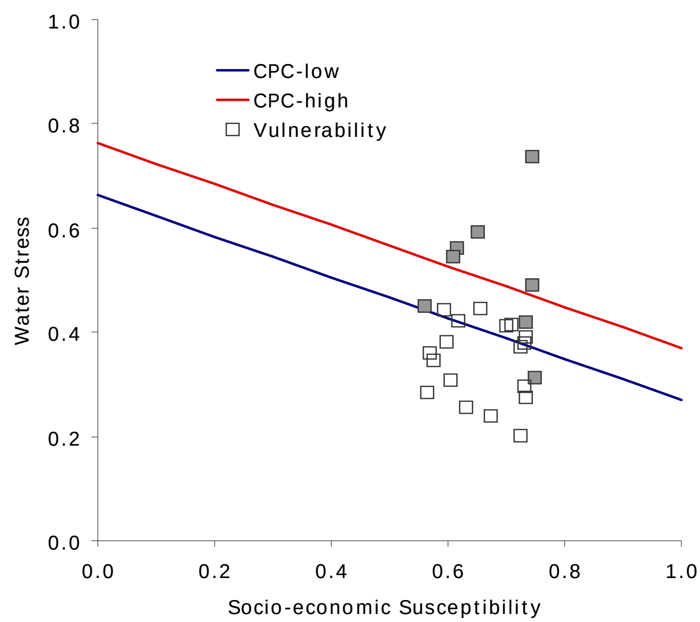
Figure 10. Scatter plot of water stress and socio-economic susceptibility indices



The grey box corresponding to the year 1973 appears however to be an outlier because water stress index is relatively low at 0.312. But then in this year, Andhra Pradesh has experienced one of the highest level of socio-economic susceptibility. Moreover, it is important to note that the state has experienced crisis for three consecutive years ending in 1973. This implies that vulnerability to drought intensifies with the increase in the frequency of crisis and that the state would require a higher level of adaptive capacity (i.e. lower level of susceptibility) to cope with even a low level of stress. In this case, it is important to implement planned adaptation measures so as to avoid ensuing crisis. Moreover, considering that climate change will increase the frequency of climate extremes such as droughts, it is necessary to increase the current level of adaptive capacity (or lower the level of socio-economic susceptibility) of the state to avoid the occurrence of drought-related crisis in the future. An important question is, however, what type of actions should be done to reduce their level of vulnerability.

The Security Diagram, which was constructed by overlaying the estimated probabilities of the probit equation [13] to the scatter plot, provides a very interesting answer to this question (Figure 11). The crisis probability curves tend to tilt towards the water stress axis, which implies that the level of vulnerability tends to be more sensitive to the changes in the level of water stress. A water stress index of around 0.7 already yields a very high probability of crisis and requires a very low level of susceptibility (or high level of adaptive capacity) to avoid the occurrence of crisis. Considering the very low financial capacity of the Indian government to support a large number of affected population, it may be difficult to lower down substantially the socio-economic susceptibility of Andhra Pradesh. A more effective planned adaptation measure is thus to invest in infrastructure or technologies that could help hinder the intensity of drought. These include, for example, adequate water reservoirs and appropriate irrigation system.

Figure 11. Security Diagram for Andhra Pradesh for the period 1970-1995



The widespread practice of boring wells for irrigation is contributing to the intensification of drought problems in India because this practice dramatically decreases the level of groundwater (Ainger 2003). The *Drought-Prone Areas Programme* (DPAP), which became exclusively a watershed development programme focusing on soil conservation, water harvesting, pasture development, and afforestation in the late 1980s, is good start to tackling this problem. In recent years, the state of Andhra Pradesh is in the forefront as far as implementation of watershed development programme is concerned. Of the 23 districts of Andhra Pradesh the DPAP is being implemented in 17 districts. In recent years the state has received one of the highest levels of central funding for the watershed development programme (Appendix 2). Strengthening this programme and ensuring its sustainable implementation through guaranteed allocation of appropriate budget would reduce the vulnerability of the state to drought.

All the gray boxes, which indicate the occurrence of crisis, gathered around or above the crisis probability curves with only one exception. The diagram has thus captured a rather good representation of the vulnerability condition in the state of Andhra Pradesh from 1970 to 1995 despite the poor statistical significance of the socio-economic susceptibility parameter. These probability curves are useful not only a useful yardstick for assessing vulnerability in the past, as in Figure 11, but also in evaluating the critical level of water stress and socio-economic susceptibility that could results in high probability of crisis in the future. In the latter case, the Security Diagram becomes a useful tool for developing scenarios of vulnerability, which is very important for assessing impacts of dynamic global processes like climate change and globalisation. This is of course based on the premises that the estimated functions are statistically robust and all the explanatory variables are statistically significant.

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Appendix 1: Droughts in Andhra Pradesh (1960 – 1999)

District	No. of years with		Total (%)
	Moderate drought	Severe drought	
Adilabad	8	-	8 (20%)
Anantapur	8	-	8 (20%)
Chittor	4	-	4 (10%)
Cuddapah	7	1	8 (20%)
East Godavari	6	-	6 (15%)
Guntur	6	1	7 (18%)
Hyderabad	8	1	9 (23%)
Karimnagar	10	-	10 (25%)
Khammam	7	-	7 (18%)
Krishna	5	-	5 (13%)
Kurnool	9	-	9 (23%)
Mahaboobnagar	9	1	10 (25%)
Medak	11	1	12 (30%)
Nalgonda	7	-	7 (18%)
Nellore	8	2	10 (25%)
Nizamabad	9	2	11 (28%)
Prakasam	6	-	6 (15%)
Rangareddi	3	-	3 (8%)
Srikakulam	4	-	4 (10%)
Visakhapatnam	5	-	5 (13%)
Vizianagarm	1	-	1 (3%)
West Godavari	6	-	6 (15%)
Warangal	7	-	7 (18%)

Source:

Appendix 2. Funds released by the government under the DPAP

	1995-1996	1996-97	1998-99	1999-00	2000-01
Andhra Pradesh	17.71	23.83	25.26	28.12	23.99
Bihar	6.09	0.27	1.27	2.42	8.51
Gujarat	8.52	6.65	5.82	9.25	7.19
Himachal Pradesh	0.56	1.76	0.77	0.95	1.25
Jammu & Kashmir	2.19	1.80	1.25	2.32	1.86
Karnataka	9.74	4.49	8.66	8.44	7.19
Madhya Pradesh	16.30	19.27	9.84	14.76	16.01
Mahrashtra	14.47	11.47	21.88	6.79	9.78
Orissa	3.40	2.68	0.71	0.48	3.16
Rajasthan	5.41	1.38	4.62	4.06	4.89
Tamil Nadu	4.47	11.13	7.79	8.71	4.58
Uttar Pradesh	9.19	15.01	9.28	11.51	10.90
West Bengal	1.93	0.25	2.86	2.20	0.68

Source: (DLR/MRD 2001)