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# Crisis Probability Curves (CPCs): A Model for Assessing Vulnerability Thresholds Across Space and Over Time

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## ABSTRACT

*The paper discusses the concept, methods and application of the Crisis Probability Curves (CPCs) to assess vulnerability to droughts in selected regions in India, Portugal, and Russia using published data on susceptibility and water stress indices. The CPCs, which are estimated from regression models and represented in a diagram as contour plots, are a spatiotemporal vulnerability yardstick that estimates vulnerability levels and thresholds to the combined impacts of environmental stress and human susceptibility (or lack of adaptive capacity). As compared to the CPCs for Russia, those for India and Portugal tilt more towards the water stress axis. This implies that the level of vulnerability in the latter countries tends to be more sensitive to the changes in water stress level than socio-economic susceptibility. For a particular water stress level, however, the probability of crisis occurring in India is higher than in Portugal. India has thus the lowest vulnerability threshold. Using pooled and panel regression, the information for three case study regions was combined to develop a common measure of vulnerability thresholds. Building common or generic thresholds will allow comparison of vulnerability across regions, which can be useful for policy in terms of developing priority list for providing adaptation support in vulnerable regions. However, the results revealed that there is a risk of under- or overestimating vulnerability thresholds when comparing regions not only with different level, but also varying sources of vulnerability. Thus, more crucial than developing generic vulnerability thresholds is highlighting differential vulnerability through selection of appropriate susceptibility indicators.*


**Key words**: *Vulnerability, Adaptive Capacity, Drought, Climate Change, Susceptibility, Binary choice model*

## INTRODUCTION

The investigation of human-environment links to understand human adaptation to the impacts of climate change is a challenging task because it requires appropriate concepts and methods that transverse across various disciplines. *Stern et al.* (*1991:6*) explained that "[the] study of human interactions with the global environment poses difficult problems of theory and method that [demands] new links among disciplines, theoretical constructs to deal with the complexities and the large spatial and temporal scales, and careful selection of research methods". In the last two decades, experts from the fields of economics, ecology, geography and sociology have developed a number of concepts and methods for assessing human vulnerability and adaptation including, for example, Social Vulnerability (*Adger 1999*), Double Exposure (*O'Brien and Leichenko 2000*), Vulnerability-Resilience (*Moss et al. 2001*), Risk-Chain (*Heitzmann et al. 2002*), Vulnerability for Sustainability (*Turner et al. 2003*), Eight-Step Approach (*Polsky et al. 2003*), and Intervulnerability (A*costa-Michlik and Rounsevell 2005, 2008; Acosta-Michlik and Espaldon 2008, 2011*). Each of them has its own merits depending on the exposure unit, spatial scale and temporal duration of the analysis.

Most of these previous vulnerability studies have thus far focused on developing vulnerability indices and/or maps to present an overview of vulnerability across regions but without providing practical thresholds for a critical state.

Such thresholds can possibly inform policy where and when adaptation actions should be made. Vulnerability threshold is a useful concept that is applied in related disciplines such as poverty and food security (e.g. *Chaudhuri et al. 2002; Dilley and Boudreau 2001*) as well as environment and ecology (e.g. *Prato 2007; Matzdorf et al. 2008; Lintz et al. 2011*). So far, very little research has been done to investigate vulnerability thresholds to climate change impacts (e.g. *Luers et al. 2003; Luers 2005; Adger 2006*). The assessment of vulnerability to the impacts of climate change (e.g. floods, droughts, etc.) should be able to identify thresholds at which the level of exposure is measurable and the ability of communities to adapt is comparable across space and over time. This paper presents a modeling approach called Crisis Probability Curves (CPCs) to contribute to the assessment of vulnerability thresholds and thus fill an important gap in vulnerability research. The concept of CPCs captures the link between human and its environment and its method enables the empirical estimation of vulnerability thresholds. The empirical application of CPCs focuses here on the vulnerability assessments of different regions to droughts over a long period of time.

The method that we used to estimate the CPCs apply the knowledge on probability. According to frequentist view

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on probability (*Kleindorfer et al. 1993*), the availability of quantifiable albeit limited information allows the estimation of probability of regularly occurring phenomena by their long-run frequencies. Whilst the knowledge to understand the vulnerability concept is limited, quantifiable information that can measure the risks or likelihood of occurrence of damaging events is available. It is thus possible to apply the frequentist approach to estimate the probability of damaging event (e.g. crisis) resulting from vulnerability. The CPCs are estimated from regression functions and represented in a diagram in the form of contour plots. The functions are used to define the relationship of the magnitude of impacts (i.e. crisis) to the level of environmental exposure (e.g. water stress) and socio-economic susceptibility (e.g. income, education, etc.).

The authors define CPCs as a spatiotemporal vulnerability yardstick that estimates crisis thresholds to the combined impacts of environmental stress and human susceptibility. It is a yardstick because the estimated probability curves (or thresholds) represent a well-defined measure generated from observed knowledge of susceptibility and water stress, and validated through various statistical techniques. It is spatiotemporal because it allows comparisons of exposure units at a specified spatial scale (e.g. community, province, region, country) and their levels of vulnerability in a given temporal duration (e.g. monthly, annually). In short, using CPCs one can compare vulnerability levels and thresholds across regions over time.

In this study, the researchers aim to present the concept of the CPCs, propose a method to estimate them empirically and, using the empirical results, to show their potential in measuring and comparing vulnerability thresholds across regions. This article is an extension of a similar article which generated CPCs for only one country (*Acosta-Michlik et al. 2006*). The added value of extending the application of the CPCs to different countries includes regional comparative assessments of vulnerability conditions and development of common vulnerability thresholds. The latter is relevant for testing the practical utility of CPCs for policy, particularly in terms of developing priority list for providing adaptation support in vulnerable regions. It is important to note at this point that we only used available data from previous literature to achieve these research objectives. The researchers chose dataset that are consistent across regions to allow for regional comparison. To test the applicability of the concept and method of CPCs in measuring vulnerability thresholds, we applied them on empirical data in selected case study regions in India (Andhra Pradesh), Portugal (Algarve and Alentejo) and Russia (Volgograd and Saratov) for the period 1970-1995. These countries have distinct social, economic, environmental and institutional systems that are relevant for regional comparative assessments of thresholds. The researchers assessed the vulnerability of the people (the exposure unit) living in these regions (the spatial scale) on an annual basis over 25 years (the temporal duration). Although the CPCs are promising policy tools, this research is more research-oriented, focusing on model verification. Future application of the CPCs for policy analysis should aim not only to use more up-to-date data but also consider the research recommendations. Section 2 deals with the concept underlying CPCs and section 3 the method used to estimate them. Section 4 presents the results of the vulnerability assessment and based on these results, section 5 draws conclusions on the utility of the CPCs for quantifying vulnerability thresholds.

**The Security Diagrams and CPCs**

The concept underlying the CPCs, which is described in the next section, was drawn from the field of human security. From the traditional issues on military threats, territorial integrity and political independence, research on human security has shifted its focus 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*). *Alcamo and Endejan* (*2002*) have developed Security Diagrams to provide quantitative meaning to earlier studies linking environmental change and human security (*Homer-Dixon 1994, Lietzmann and Vest 1999*), which were mostly qualitative. Using Security Diagrams one can assess the likelihood and degree of an environment-related crisis and identify the locality of the crisis and the affected population. They can also help to develop a broader view of how climate change may affect national, regional and global security. The Security Diagrams framework defines vulnerability to climate change according to three components: environmental stress, state susceptibility, and environmental crisis. The term "state susceptibility" in the original definition of Security Diagrams refers to the inability of a state (i.e. government) to resist and recover from crisis brought about by environmental stress. In assessing susceptibility to droughts from a socio-economic perspective using the framework of Security Diagrams,[1] *Acosta-Michlik et al.* (*2006, 2008a*) redefine these components to make it more relevant and explicit in understanding human vulnerability to water stress:

1. Water stress is the intensity, extent, timing and duration of a change in normal water resource availability that disrupts economic and human activities.
2. Socio-economic susceptibility is the inability of the state and society to protect and support communities from

[1]The methods of the Security Diagrams have also been applied to assess susceptibility to droughts from environmental psychology and political science perspectives (*Alcamo et al. 2008*).

adverse water stress if market mechanisms fail to provide the necessary resources for coping with the stress.

3. Environmental crisis is an unstable or critical economic and human state of affairs caused by the susceptibility of a society to water stress, which has serious adverse consequences on economic development and requires national or international emergency support.

From the above definition, socio-economic susceptibility implies inability to adapt or lack of adaptive capacity. In this paper, we thus consider susceptibility as the inverse of adaptive capacity. Although the climate change research community through the Intergovernmental Panel for Climate Change (IPCC) mostly refers to adaptive capacity as one important component of vulnerability, the researcherd prefer to use the term susceptibility because of its relevance to the method we chose to estimate vulnerability thresholds in this study.

Because the vulnerability thresholds were generated using indices of water stress, socio-economic susceptibility and environmental crisis the CPCs are very consistent with the Security Diagrams, as defined by *Alcamo and Endejan* (*2002*). However, the practical utility of the Security Diagrams framework for assessing vulnerability thresholds across space and over time has been advanced only through systematic integration of the concept of CPCs, as proposed by *Acosta-Michlik et al.* (*2006*) and further developed in this paper.

## Concept behind the CPCs

Following the IPCC definition of vulnerability, the CPCs are derived from a conceptual thinking that vulnerability is "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes" (*IPCC 2001*). Vulnerability and thus the susceptibility of a system to a given climatic stress can be expressed through the following function:

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

Where the dependent variable z is a measure of the level of vulnerability. The independent variables x and y are some measurable indicators of the system's susceptibility and of the environmental stress to which the system is susceptible, respectively (**Figure 1**) [1]. The horizontal dimension represents the two independent (or input) variables x and y, and the vertical dimension represents the outcome z from the combined influence of the input variables. As *Morgan and Henrion* (*1990*) explain, "[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". Imagine z as a smooth surface ascending evenly uphill; we divide this surface into four equal quadrants and choose only the quadrant with positive x and y values (*Figure 1a*). We want both these values to be positive because the surface of the diagram is used to represent the level of vulnerability, which can be zero (or no vulnerability) but, theoretically, never negative. For example, given some scaled values of the input variables x (susceptibility) and y (stress) between 0 and 1, the level of vulnerability is lower the closer the input values are to zero. Referring to **Figure 1a**, some reader may find it counter-intuitive to have the level of vulnerability increasing as one goes up along the vertical z-axis, but it is not. In this paper we assess vulnerability based on the concept of the response surface. If one is to slice the surface of the hill lengthwise (i.e. longitudinal), then the surface at the lower part is larger than at the higher part of the hill. Hence the larger the surface, the higher is the vulnerability. So assuming that the longitudinal slices correspond to points z1, z2, z3 and z4, if one is to plot only the edges of these four slices (represented by the convex contours in Figure 1a) on a two-dimensional diagram of x-axis and y-axis, then the contour plot of z4 is closest (i.e. smallest response surface) and z1 farthest (i.e. largest response surface) to the zero values of the xy axes. Accordingly, the level of vulnerability is lowest at z4 and highest at z1. The contour plots are the bird's-eye view of a finite number of slices of the surface. These contour plots (i.e z1, … z4), which shows lines of constant elevation or height, measures the degree of vulnerability at varying combination of susceptibility x and environmental stress y. In the next section on methods,

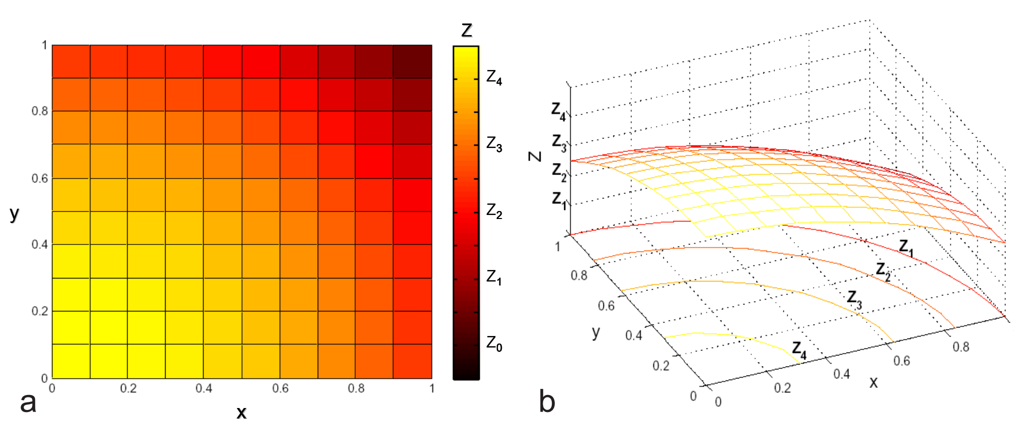


Figure 1. Surface (a) and contour (b) plots of the Security Diagram.

these contour plots can be estimated using observed data of the dependent variable z and independent variables x and y.

For the purpose of this study, the researchers are only interested in the contour plots that correspond to the vulnerability levels where the probabilities of crisis to occur are high. These particular contour plots are what we call "crisis probability curves" because they represent the thresholds at which the levels of vulnerability could lead to a crisis due to inability of the system to adapt to the impacts of the stress without any emergency support. Within the context of the Security Diagrams, the researchers estimated two of these curves, which refer to as low crisis probability curve ($CPC_L$) and high crisis probability curve ($CPC_H$). The $CPC_L$ and $CPC_H$ may correspond, for example, to contour plots $z_2$ and $z_1$ in **Figure 1b**, respectively. The importance of these curves is shown in the two-dimensional conceptual representation of the Security Diagrams in **Figure 2**. As in **Figure 1b**, the *x*-axis represents the index of socio-economic susceptibility (SSI) and the *y*-axis represents the index of water stress (WSI). The use of aggregated indices that are scaled or normalized not only provides equal units for the axes, but also allows representation of a set of relevant socio-economic susceptibility and water stress indicators. Since the spatial scale of this study is regional and the temporal interval is annual, the scattered boxes in the diagram represent the levels of the socio-economic susceptibility index and water stress index of the region in a given year. The boxes are thus a measure of vulnerability levels and the CPCs provide the vulnerability thresholds at which crisis are likely to occur. When climate change impacts such as droughts reach an unprecedented level beyond the capacity of the people to adapt and recover, crisis could occur. The probability of crisis occurrence is higher the further the boxes are from the origin and the closer they are to the $CPC_H$, as represented by the grey boxes.

The probability curves are a convenient yardstick for measuring the degree of vulnerability of a region over time. However, to make these yardsticks more policy relevant, they should be generated from robust models that can be submitted to some validity tests and empirical estimations. Among others, the statistical test and estimation of the $CPC_L$ and $CPC_H$ are necessary for the following reasons:

1. The distance between the two crisis probability curves, i.e. low probability curve ($CPC_L$) and high probability curve ($CPC_H$), defines the critical zone where a region 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 because many regions will tend to be located within the critical area.
2. The distance of the curves from the intersection tells a lot about the predictive capability of the diagram. If the curves are farther away from the intersection or lower left corner of the diagram, crisis occurrence is less frequent as it gives ample space for crisis-free zone.
3. The shape of the curves influences the frequency of crisis events. For example, crisis probability curves with straight contours increase the number of crisis occurrence as compared to those with convex contours.

To elaborate argument (3) above, the $CPC_L$ and $CPC_H$ are presented in the form of straight lines in **Figure 2b**. Straight crisis probability curves increase the number of events (if the assessment is done for one region) or number of regions (if regional assessment is carried out) falling within the crisis zone, as exemplified by the black boxes in the diagram. In contrast, these boxes are below the critical levels when the $CPC_L$ and $CPC_H$ are convex. Consequently, it is important to investigate whether or not the crisis probability curves follow a straight line. To sum up, the predictive power of the Security Diagram depends on the precision of the estimated $CPC_L$ and $CPC_H$, which in turn is dependent not only on the indicators chosen to measure the level of susceptibility and water stress, but also on the crisis data.

## METHODS

### Estimation of CPC Function

The vulnerability function in equation [1] was used as

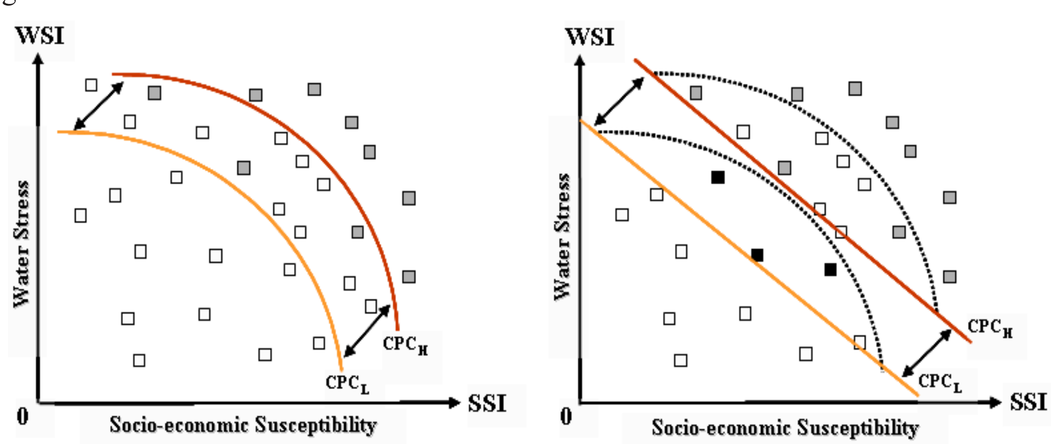


Figure 2. Convex (left) and Straight (right) Crisis Probability Curves.

a basis for estimating the CPCs for the following regions: Andhra Pradesh in India, Algarve and Alentejo in Portugal, and Volgograd and Saratov in Russia. The dependent variable *z* in equation [1] is a set of discrete values, taking the value of 1 to indicate the presence and 0 to indicate the absence of a crisis in these regions. Such a binary type of dependent variable renders the use of conventional regression methods inappropriate because it would result in conceptual problems such as the need to impose unrealistic hypotheses on the distribution of the errors and in statistical problems such as heteroskedasticity (*Greene 1993*). The binary choice model is a better statistical tool for estimating the CPCs. This model was applied in this paper to identify the shape of the crisis probability curves and to determine the relative position of these curves in the Security Diagrams. In the binary choice framework, the 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. The latent variable representing the unobservable indicator (i.e. the chance that the binary event will take place) is linearly regressed on the explanatory variables. The probability of crisis event (*P(CRI=1)*) is computed by evaluating the latent variable with values ranging from 0 to 1. The regression function to estimate the latent variable is given in equation [2] and the probability of the event is given in equation [3]:

$$Y_{it} = \beta_0 + \beta_1 WSI_{it} + \beta_2 SSI_{it} + ut_i \quad [2]$$

$$P(CRI_{it} = 1) = F(Y_{it}) \quad [3]$$

where $WSI_{it}$ refers to the water stress index in region *i* at time *t*, $SSI_{it}$ the socio-economic susceptibility index in region i at time t, and $CRI_{it}$ occurrence of crisis in region i at time t. In econometrics literature, there are two common choices for the function  : the standard logistic distribution function (logit model) and the standard normal distribution function (probit model). Both models were estimated to determine which of them better represent the probability of drought-related crisis in the case study regions. The parameter estimates from both models can be interpreted as predicted or forecasts probabilities given a set of values in the explanatory variables (*Liao 1994*). Thus, the estimates from $P(CRI_{it} = 1)$ are predicted probabilities of crisis event, and these estimates were used to generate the CPCs. Because the logit and probit models are generalized linear models expressing the linear relationship of the probabilities of crisis to the indices of water stress and socio-economic susceptibility, the estimated CPCs in this paper are presented in straight lines.[2]

Different model specifications to estimate equation [2] including simple, pooled, and panel regressions were used for the linear part of the model, but the link function $F(Y_{it})$ remained the same for all the case study regions. Control dummies were included in all regression models to consider the breaks in the observations resulting from structural changes. For example, for Portugal, the intercept was given two different values corresponding to "before" and "after" the year 1986, when Portugal joined European Union. In the case of Russia, a different constant is allowed before and after 1991, which was the year of the dissolution of the Soviet Union. The $CPC_L$ and $CPC_H$ correspond to the estimates from equation [2] at 5 % and 95 % confidence interval, respectively. We chose these intervals to provide a reasonable distance between the CPCs. Not only the distance between, but also the shape of the CPCs will change depending on the relationship between socio-economic susceptibility and water stress over a long period of time. The CPCs are thus not static because they take into account the long-term development in the levels of vulnerability indicators.

Maximum likelihood was used to estimate both the link function $F(Y_t)$ and linear specification. However, it is well known that in a time series framework (i.e. annual data could display a high degree of temporal dependency) particular attention must be devoted to verify the presence of stationary variables or cointegrated system to avoid spurious results caused by the correlation between the stochastic trends. Thus, prior to model specification and estimation, a stationarity test of the time series has been performed on all the variables to check for eventual unit roots and any ensuing spurious regression. The data series of WSI and SSI for India, Portugal and Russia were tested for the presence of a unit root using the standard tool of augmented Dickey-Fuller (ADF) test.

**The Case Study Regions**

The case study regions that were selected to test the practical utility of CPCs for regional comparative assessments include Andhra Pradesh in India, Algarve and Alentejo in Portugal and, Volgograd and Saratov in Russia (**Figure 3**). There are two important reasons for selecting them: They have distinct social, economic, environmental and institutional systems, which are useful for model verification; and time-series data for the estimation of CPCs are available from previous studies (i.e. *Acosta-Michlik et al. 2008a; Alcamo et al. 2008; Tänzler et al. 2008*).

Covering an area of about 275,000 km$^2$, Andhra Pradesh is the fifth largest state in India and the fourth most populous. Out of the 76 M population in 2009, nearly three quarters live in rural areas. The state has areas rich in water resources, but also semi-arid regions where agriculture is mainly rainfed. Although agriculture's share to GDP has significantly declined, the sector continues to play a vital

[2] The researchers applied both linear and non-linear models to identify the more appropriate regression function. The results of the linear models yielded better results hence only the linear regression function is presented here.

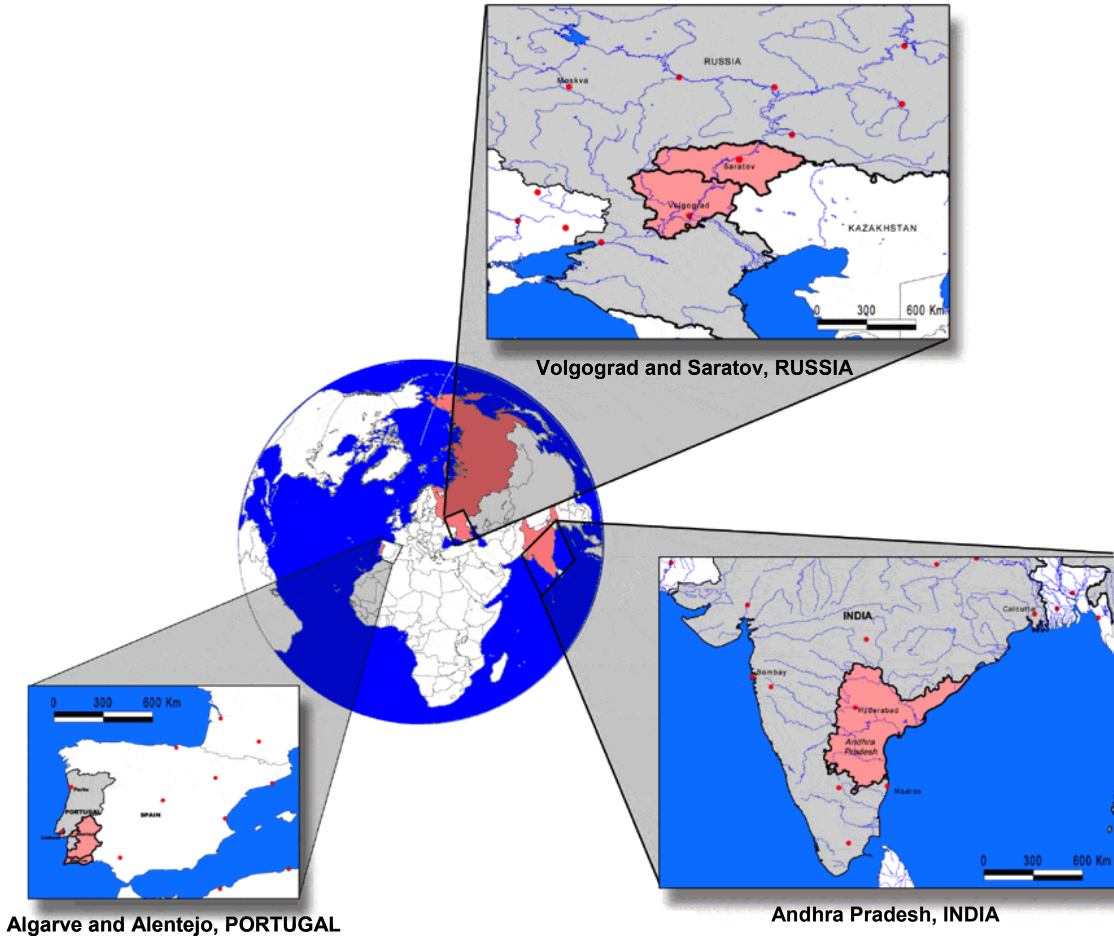


Figure 3. Map of case study regions.

Source: Security Diagrams Project, http://www.usf.uni-kassel.de/secdiag/frame01e.html

role in the state's economy, contributing over a third of the state's GDP as well as providing a livelihood for over 70 % of the population and employment to over 80 % of the labour force. Almost 60 % of the gross cropped area lacks stable irrigation and is categorized as "rainfed drylands". Since 1960 droughts have frequently affected many districts in Andhra Pradesh often causing shortage of drinking water, loss of agriculture livelihoods, migration of families, cumulative indebtedness, and in recent years, even suicides of farmers.

Because of their relatively warm and dry climate Algarve and Alentejo are the regions in Portugal that frequently suffer from droughts, affecting the economy's tourism and agriculture. Portugal's economy is very diverse so that wealth remains rather unevenly distributed. Whilst the areas around the capital Lisbon have per capita income that is close to European average, those in the Alentejo region remain very poor. With an area of 26,000 km$^2$, the Alentejo region covers a quarter of the Portugal's land area. However, it is home to only 5 % of the country's over 10 M people in 2009. The region is predominantly agriculture with very low contribution to the country's GDP because many areas are marginal. The Algarve region has a land area of 5,411 km$^2$ extending along the coastal lines. As compared to Alentejo, many people here capitalize on tourism. Nevertheless, both regions are among the poorest in the country and thus receive structural support from the European Commission.

The two case study regions in Russia are Volgograd and Saratov, which are located in the south of Volga reservoir. Volgograd has a land area of 113,900 km$^2$ with about 3 M population, and Saratov has a land area of 380 km$^2$ with less than 1 M population in 2009. The Volgograd region has 190 rivers and two big dams that support the water supply for both industry and agriculture. Nevertheless, droughts have significant effect on agriculture not only because the temperature can become very high in summer (34 – 45 °C), but also because two thirds of the annual rain falls in summer when evaporation is very high. Saratov is in the heart of the economic centre of Volga. With its 180 small rivers and the milder summer temperature, the region has better water supply than Volgograd. The region is very suitable for agriculture, but it is also rich in mineral resources. Consequently, machine and electric industries, petroleum and chemical industries, and food processing companies are important in the Saratov region. The political reforms and ensuing crisis between 1991 and 1998 had severe impacts on many small industries as well as middle- and low-income families in both regions (*Shleifer and Treisman 2001*).

Among the three case study areas, the region of Andhra Pradesh in India had the highest socio-economic susceptibility index (SSI) throughout the period 1970-1995 (**Figure 4**). Its susceptibility index steadily declined at a rate faster than that of Russia from 1980 to 1995. The fall in GDP per capita in Andhra Pradesh due to the adverse impacts of global economic crisis caused the socio-economic susceptibility to increase in 1991 (*Acosta-Michlik et al. 2008a*). Socio-economic susceptibility in the Volgograd and Saratov regions in Russia was low, particularly in the late 1980s and early 1990s. However, the combined effects of a global economic crisis and domestic structural adjustment (i.e. decentralization of Soviet power) in the early 1990s have contributed to the increase in socio-economic susceptibility in Russia. The Portuguese regions of Algarve and Alentejo had the second highest level of socio-economic susceptibility from 1970 to 1979. The drastic decline in susceptibility from 1980 can be attributed to the impacts of the structural reforms following the fall of the dictatorship regime in 1974. Another significant drop in the level of socio-economic susceptibility was experienced in the Portuguese regions from 1989, which can be traced from the structural changes following Portugal's accession to the European Community in 1986. From 1989 to 1995 the Portuguese case study regions recorded the lowest level of socio-economic susceptibility due to significant economic development.

The indices for water stress (WSI) showed very erratic trend for all the case study regions from 1970 to 1995, with the Portuguese regions showing the largest mean deviation (**Figure 4**). The water stress indices were very high at over 0.8 in 1981 and 1992. Whilst the EM-DAT database did not report any occurrence of crisis in both years, the results of the media content analysis conducted by *Tänzler et al* (*2008*) reported a crisis (**Table 1**). The highest level of water stress index in the case study region in India was recorded for the year 1971. Although the level of water stress approached the average mean level in 1972 and 1973, crises were reported in these years. These crisis events could be explained not only by the delayed and extended impacts of the water stress in 1971, but also by the absence of drought adaptation measures prior to this year. Andhra Pradesh experienced the next highest levels of water stress in 1984 and 1986. Again, no records of crisis were found in the EM-DAT, but the media content analysis revealed the presence of crises in these years. The Russian regions of Volgograd and Saratov

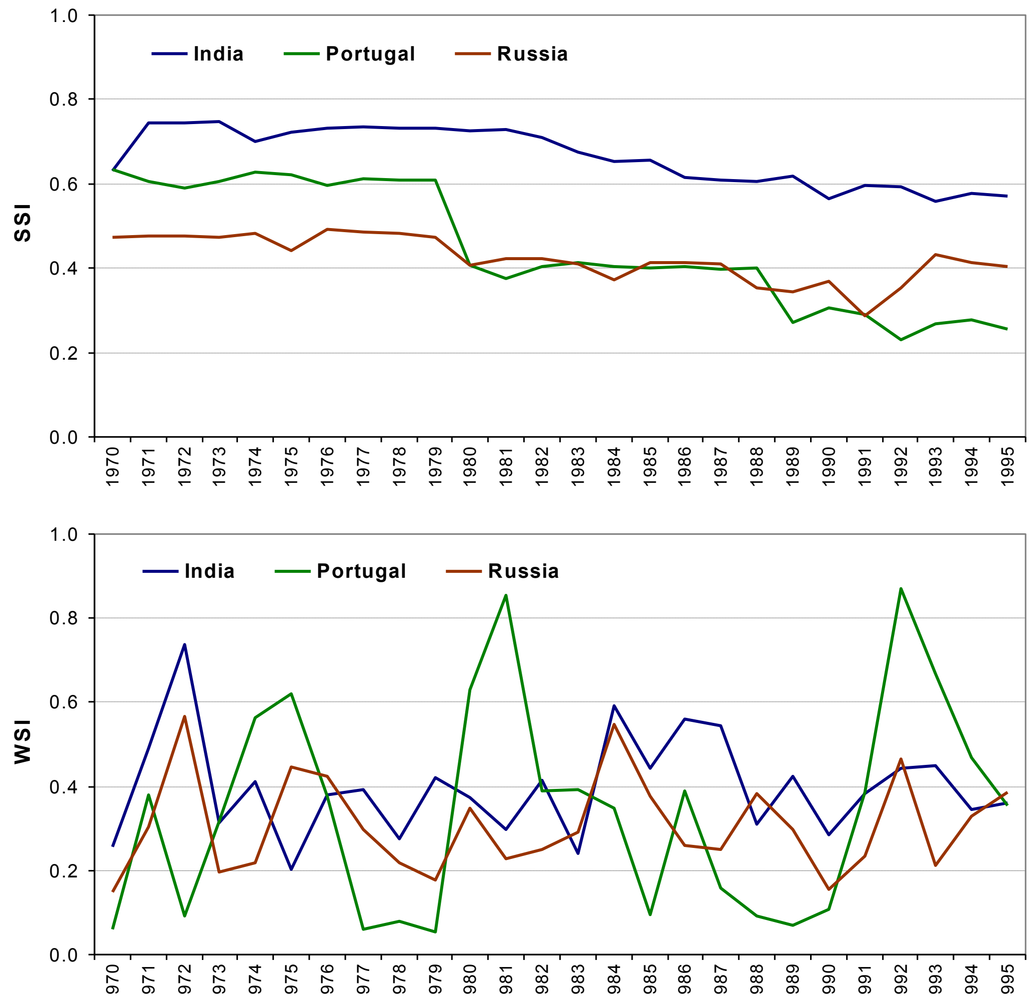


Figure 4. Trends in socio-economic susceptibility and water stress, 1970-1995.
Source: Alcamo et al. 2008, Acosta-Michlik et al. 2008a.

Table 1. Occurrences of drought-related crisis in the case study areas, 1970-1995.

| | 1970 | 1971 | 1972 | 1973 | 1974 | 1975 | 1976 | 1977 | 1978 | 1979 | 1980 | 1981 | 1982 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| India | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| Portugal | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| Russia | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | **1983** | **1984** | **1985** | **1986** | **1987** | **1988** | **1989** | **1990** | **1991** | **1992** | **1993** | **1994** | **1995** |
| India | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| Portugal | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 |
| Russia | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |

Note: 1 = presence of crisis, 0 = absence of crisis
Sources: EM-DAT, (Tänzler, Feil, Krömker, & Eierdanz, 2008), Golubev and Dronin (2004).

recorded the highest indices of water stress in 1972 and 1984, during which crises were also reported. *Golubev and Dronin* (*2004*) reported other major droughts in Central and Southern Russia in 1975, 1979 and 1981.

## Data description

The main focus of this paper is the discussion of CPCs as a model for assessing vulnerability thresholds, hence this section only briefly describes the methods for deriving the three input variables for estimating the CPCs. Detailed discussion on the methods used to derive these variables are published elsewhere: *Acosta-Michlik et al.* (*2006*) and *Acosta-Michlik et al.* (*2008a*) for socio-economic susceptibility; *Alcamo et al.* (*2008*) for water stress; and *Tänzler et al.* (*2008*) for drought-related crisis.

The susceptibility index in **Figure 4** was generated from combining socio-economic indicators that are relevant for improving the adaptive capacity of communities in the agricultural sector (*Acosta-Michlik et al. 2008a*). These indicators include financial resources, agriculture dependency, infrastructure development, health condition, educational attainment, and gender inequality. Using fuzzy logic approach, a stepwise aggregation of the indicators was applied to develop indices ranging from 0 to 1. An index of one (1) implies a very high level of susceptibility, and an index of zero (0) indicates an absence or negligible level of susceptibility. (*Eierdanz et al. 2008*) discuss in detail the three components of fuzzy logic – fuzzification, fuzzy inference and defuzzification – and how they applied them to the concept of susceptibility.

To compute the water stress index (**Figure 4**), this paper considered three water stress indicators that were generated from the WaterGAP model (*Alcamo et al. 2003a, b*). These indicators are: the withdrawal to availability ratio; the deviation of water availability from its long term (climate-normal) average; and the percentage of area with high water stress (defined as water withdrawal to availability ratio of 0.4 or higher) (*Alcamo et al. 2008*). Although the WaterGAP model generated a wide range of indicators, only these three were chosen because indicator (1) covers regions where water use accounts for a large fraction of the total available water resources; indicator (2) represents events where a short term but sharp decrease in water availability affects a region; and indicator (3) includes situations in which there is an uneven spatial distribution of water resources across a region. *Alcamo et al.* (*2008*) applied the "MaxIndex" approach, which takes the maximum value of the indicators that are considered in the analysis, to generate water stress indices for the period 1970-1995.

The identification of relevant indicators for crisis was a challenge because of the lack of not only information on drought-related crisis, but also a clear concept and standard indicators of environmental crisis from different sources and for different countries. In the international disaster database (EM-DAT), an event is reported as disaster in the database if it defines at least one of the following criteria: 10 or more people reported killed; 100 people reported affected; declaration of a state of emergency; and call for international assistance. Using information from online news database issued by Factiva (information service by Reuters & Dow Jones) and newspapers with a specific regional focus, *Tänzler et al.* (*2008*) applied media content analysis and impact reports from local surveys to both validate and complement the EM-DAT database. The media content analysis combines quantitative and qualitative coding to determine a 'crisis': the number of hits were noted and then the articles were screened to both verify the relevance of the article and to identify in what context the term 'drought' was mentioned. The assessment was based on the ''attributes'' of the crisis as reported by the media, for example, 'significant cutbacks in hydroelectric production', 'curtailment of drinking supply', 'the distribution of aid', 'the adoption of emergency plans', 'prayers for rain', 'demonstrations' and even incidence of 'people committing suicide' (*Tänzler et al. 2008*). Due to the dearth in regional data for Russia in both EM-DAT and Factiva databases, we carried out additional literature review to improve the crisis data. To create a better database on drought-related crisis (**Table 1**), we thus combined the data from EM-DAT, *Tänzler et al.* (*2008*) and *Golubev and Dronin* (*2004*). It is important to emphasize at this point that the poor quality of crisis data in terms of consistency and completeness may have affected the statistical fit of the estimated CPC functions.

The next section discusses the vulnerability thresholds that were estimated from the socio-economic susceptibility and water stress indices as well as crisis data for the selected regions in India, Portugal and Russia.

## RESULTS AND DISCUSSION

### Estimated CPC Functions

Three model specifications were tested including simple, pooled and panel regressions. The results of the logit estimation for these different models are as follows:[3]

MODEL 1 (simple)

For India: $Y_t = -18.18 + 25.50\ WSI_t + 10.02\ SSI_t$

For Portugal: $Y_t = -7.53 + 11.00\ WSI_t + 3.13\ SSI_t$

For Russia: $Y_t = -8.13 + 9.17\ WSI_t + 9.37\ SSI_t$

MODEL 2 (pooled)

For all countries: $Y_t = -7.73 + 12.04\ WSI_t + 3.02\ SSI_t$

MODEL 3 (panel)

For all countries: $Y_t = -9.82(\text{India}) -9.65(\text{Portugal}) -8.01(\text{Russia}) + 12.60\ WSI_t + 5.70\ SSI_t$

The signs of the intercept and coefficients are consistent for all the countries in Model 1. Moreover, the regression intercepts turned out to be statistically significant for all the countries. Generally, the coefficients for WSI display rather high levels of significance not only in Model 1 but also in the other two models. The likelihood ratio (LR) tests show that the null hypothesis on the significance of WSI as explanatory variable for the probability of crisis cannot be rejected given the very low P-Values ranging from only 0.0001 to 0.09. In contrast, the statistical significance of the SSI coefficients in Model 1 is rather low with P-Values for LR test ranging from as high as 0.30 to 0.67. However, these results do not necessarily mean that SSI is not a relevant variable to explain the probability of crisis. The possible presence of a unit root in the SSI time series data may have affected the precision of the susceptibility estimators. It is worth noting that unit-root tests such as Dickey-Fuller are characterized by having low power. That is, they tend to be often prone to the type II error of accepting the null hypothesis when in fact it is not true. This is particularly true in cases where sample size is limited, like the models in this paper with only 25 observations. Improving the models by using longer time series will most likely give better results in terms of stationarity. As for the results of Model 2, again here, whilst the intercept and WSI coefficient (in both cases the P-Values of LR tests are smaller than 0.01) have very high statistical significance, the SSI coefficient is less statistically significant displaying a P-value of 0.36. However, like in Model 2 the statistical significance of the SSI coefficient in Model 3 has slightly improved with a P-value of 0.27. The three models show that the statistical significance of the SSI coefficients improves as the number of observations in the model estimation increases.

As a summary, the estimation for the three model specifications show that: the coefficients of both WSI and SSI are generally of positive sign, which is consistent with the theory that water stress and socio-economic susceptibility have direct relationship with the probability of water crisis; and Whilst the coefficients of WSI are always highly significant, the statistical significance of the SSI coefficients is rather low. There are reasons however not to totally dismissed the importance of SSI in explaining the occurrence of crisis.

- The first reason relates to the quantity of data and is thus a purely technical issue. Considering the small size of the dataset, the asymptotic nature of the results has to be considered carefully. The suspicion that unit roots are present in the regressors suggests some flexibility in doing inference based on asymptotic normal distributions. Moreover, the correct sign of the coefficients suggests that a larger dataset (either based on longer time series, or more countries as shown in Model 3) could improve the significance of SSI explanatory variable.

- The second reason relates to the quality of the data. Important socio-economic indicators, which significantly influence the occurrence of crisis, may have been excluded from the aggregated index of socio-economic susceptibility. It is important to mention here that in an attempt to create a consistent dataset for different regions, *Acosta-Michlik et al.* (*2008a*) used not only the same number but also the same type of indicators to compute the socio-economic susceptibility index. As a result, some susceptibility indicators that better explain the variation in crisis may have been neglected in the model.

Although the quantity and quality of the data that we used to apply the concept and methods of the CPCs affected the precision of the estimated SSI coefficients, the results of the estimations are on the whole sufficient to illustrate the utility of the modeling approach for assessing vulnerability pattern and thresholds.

[3] The results of the probit estimation are very similar so they are not presented here. Moreover, the statistical significance of the coefficients from the probit model is lower than the logit model.

## Vulnerability pattern and thresholds

The boxes representing the levels of vulnerability for the selected regions in India, Portugal and Russia show different distribution patterns (**Figure 5**). For India these boxes tend to gather together very close in the middle, right hand side of the diagram, which implies that the case study region in this country requires a higher level of adaptive capacity to overcome the impacts of water stress. The distribution of the boxes for Russia shows almost a similar crowding pattern, but the boxes tend to group together in the lower part of the diagram. Generally, Russia thus tends to experience lower levels of vulnerability than India. The distribution of the boxes for Portugal is quite dispersed, which makes it difficult to discern any particular pattern of vulnerability. The grey boxes represent the vulnerability levels where water crises have occurred. In **Figure 5**, the researchers superimposed the CPCs, which were estimated from Model 1 (simple regression), on the scattered boxes. Most grey boxes are located close to the CPCs, which is theoretically consistent. However, few boxes that do not show any occurrence of crisis (i.e. not grey) are also located between the low and high probability curves. The absence of crisis may be explained by the presence of adaptation measures taken by governments to prevent the possible occurrence of crisis. If such measures were taken into consideration, these boxes should have been outside the critical zone because the level of susceptibility would have been lower. However, the socio-economic susceptibility indices, which we adopted from *Acosta-Michlik et al.* (*2008a*), do not include such information. Future application of CPCs should thus explicitly consider adaptation policies and programs in different regions in model estimations.

The estimated CPCs for the different regions vary significantly in terms of inclination and position in the diagram space (**Figure 5**). The CPCs for India and Portugal tilt more towards the water stress axis, implying that the level of vulnerability tends to be more sensitive to the changes in water stress level than socio-economic susceptibility. The position of the intercept of the high crisis probability curve (CPCH) is a bit lower for India than Portugal, which means that for given water stress level, the probability of crisis occurring in the former is higher than the latter country. In other words, India has lower vulnerability threshold than Portugal. India was indeed most vulnerable to water stress in the past as evident from the reports that farmers were committing suicide due to crop failures and inability to pay their debts (*Newman 2007; Gruère 2008*). The lack of stable irrigation contributes to high vulnerability in many parts of India. Moreover, unlike in Portugal where the farmers in marginal areas receive significant income support from the government through the Common Agricultural Policy (CAP), the farmers in India are mostly left alone to deal with the adverse consequences of droughts. The plot of the CPCs

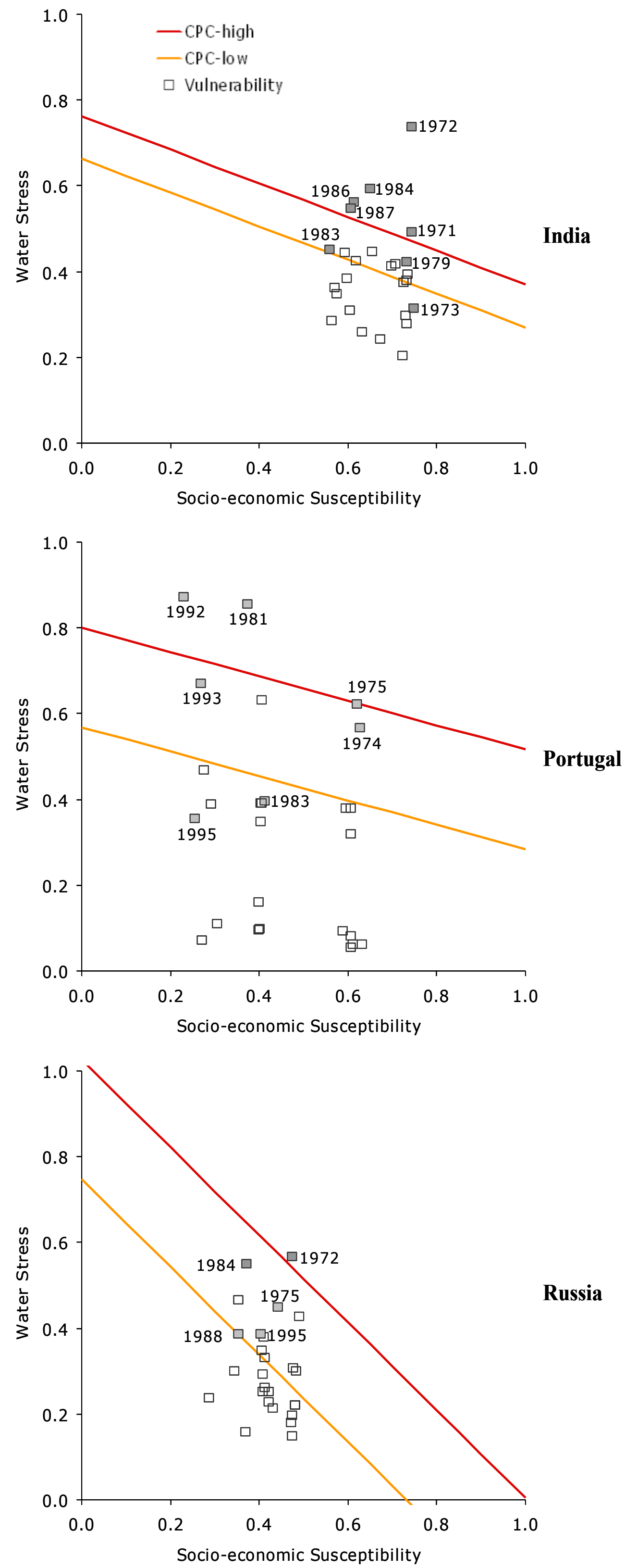


Figure 5. CPCs and vulnerability thresholds for different case studies, 1970-1995.

for the regions in Russia is very different from India and Portugal. The probability curves are almost equally inclined to both water stress and socio-economic susceptibility, which implies that both variables have similar influence on the probability of the occurrence of crisis. The distances between the CPCs differ for the different regions (**Figure 5**). We used the same confidence intervals for the CPCH (5 %) and CPCH (95 %) for all the case study regions. Nonetheless, the distances between the CPCs vary across regions depending on the values of the regression estimates. The distance between the $CPC_L$ and $CPC_H$ is much wider for the regions in Portugal and Russia than for India. The power for predicting the probability of crisis in the former regions is thus weaker because it provides more room for crisis to occur resulting to less precise prediction. One reason for this is perhaps the indicators chosen to estimate CPCs, particularly with respect to socio-economic susceptibility, may be less relevant for crisis occurrence in these regions. These results thus reveal the limitations of comparing vulnerability thresholds using the same set of indicators across regions with different economic development, social structure and institutional system. An indicator that is important in one country may not necessarily be relevant for another. Consequently, adaptation measures for the same type and level of water stress will be different for different economic, social and institutional settings.

The plots of the CPCs estimated from Model 2 (pooled regression) as well as the occurrences of crisis for the different case study regions are presented in **Figure 6**. The boxes, which represent the crisis occurrences, tend to gather around the CPCs. These results are desirable conceptually. However, the researchers noticed that the distinct characteristics of the CPCs for each case study region in terms of inclination, distance and position are concealed by pooling together the information. The vulnerability thresholds appear to replicate those of Portugal, which can be ascribed to the rather dispersed pattern of its boxes (**Figure 5**). Whilst building common thresholds, such as those presented in **Figure 6**, would allow a direct comparison of vulnerability across regions, there is a risk of under- or overestimating vulnerability thresholds if the regions have significantly different economic development, social structure and institutional system. The results of the different models for estimating CPCs convey an important knowledge. That is, differential vulnerability is evident not only at the community level (*Acosta-Michlik 2005; Acosta-Michlik et al. 2008b; Acosta-Michlik and Espaldon 2008; Acosta-Michlik and Rounsevell 2008*), but also at a higher administrative level. Highlighting the differential vulnerability through selection of appropriate indicators of susceptibility is crucial for estimating reliable vulnerability thresholds.

The intercepts and regional dummy coefficients of the estimated CPCs from Model 3 (panel regression) are almost similar to those from Model 2. It is thus not necessary to plot the former because the CPCs are almost identical to **Figure 6**.

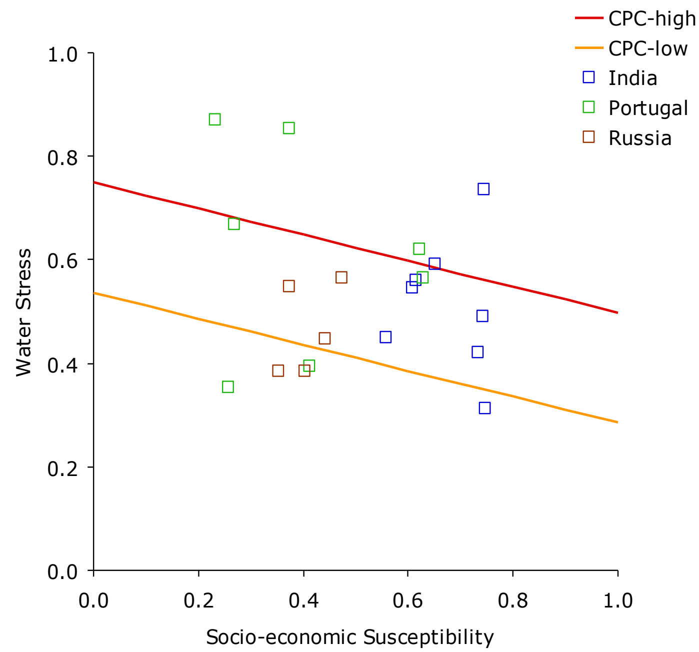


Figure 6. Crisis occurrence and vulnerability thresholds for different case studies, 1970-1995.

## CONCLUSIONS

The paper discusses the concept, methods and application of CPCs to assess vulnerability in selected regions in India (Andhra Pradesh), Portugal (Algarve and Alentejo) and Russia (Volgograd and Saratov) using published data on susceptibility and water stress indices for the period 1970-1995. The CPCs are vulnerability thresholds, which are estimated from regression functions and represented in a diagram as contour plots with constant elevation. The functions define the relationship of the magnitude of impacts (i.e. crisis) to the water stress and socio-economic susceptibility indices. Similar indices are used in many studies to assess vulnerability. However, although the vulnerability indices from previous studies are generated using some quantitative methods (e.g. indiscriminate aggregation, fuzzy logic, and weighted indicators, etc.), the assessment of vulnerability is not purely based on some explicit empirical criteria. The indices are at best compared, combined or mapped to derive some qualitative indication of the level of vulnerability. Moreover, there is a dearth in research on the empirical estimation linking susceptibility (or lack of adaptive capacity) and water stress indices to human impacts over time and across regions. In this paper, the novel approach on CPCs were developed to compare these indices to some empirically derived thresholds, offering statistically tested and estimated criteria for regional comparative assessments of vulnerability.

Different regression models were used to estimate the functions of CPCs including simple, pooled and panel. Estimating the CPCs for each case study region using simple regression model revealed that the characteristics of vulnerability thresholds, as depicted in the intercept and slope of the contour plots, are very diverse for regions with different economic, social and institutional conditions. Using pooled and panel regression, the information for the three case study regions was combined to develop a common measure of vulnerability thresholds. Building common or generic thresholds will allow comparison of vulnerability across regions or countries, which can be useful for policy in terms of developing priority list for providing adaptation support in vulnerable regions. However, the results revealed that there is a risk of under- or overestimating vulnerability thresholds when comparing regions not only with different level, but also varying sources of vulnerability. Thus, more crucial than developing generic vulnerability thresholds is highlighting differential vulnerability through selection of appropriate susceptibility indicators, which should not necessarily be the same for different regions. Moreover, regional comparisons of vulnerability thresholds using CPCs will be more appropriate for group of countries with similar or common attributes. For example, whilst contribution of agriculture to GDP remains high in least developed and developing countries, this is not the case in developed and industrial countries. Susceptibility of agriculture to drought due to lack of irrigation and/or crop insurance will be very relevant when comparing countries within Asia, but not so much between Asian and European countries like India and Portugal.

An important contribution of this paper to vulnerability research is the development of vulnerability thresholds that are based on empirical methods and subject to statistical validation. Following the discussion of the model results, we recommend that future application of the CPCs for vulnerability assessments should be able to: identify most relevant susceptibility indicators for different regions to capture differential vulnerability; include the effects of adaptation measures to explain the non-occurrence of crisis even at a higher level of water stress and susceptibility; increase the number of observations to improve the statistical significance of the regression coefficients, in particular of the socio-economic susceptibility; and create a comprehensive database of vulnerability impacts that adequately covers the crisis situations in different regions. Addressing these issues will make CPCs a practical tool for assessing not only vulnerability conditions but also adaptation measures. The latter is very relevant for further advancing CPCs as tools for designing adaptation policies and monitoring policy impacts.

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