Getting the Scale Right: A Comparison of Analytical Methods for Vulnerability Assessment and Household-level Targeting

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This paper introduces broad concepts of vulnerability, food security and famine. It argues that the concepts and theories driving development and implementation of vulnerability assessment tools are related to their utility. The review concludes that socio-geographic scale is a key issue, and challenge. It analyses three vulnerability assessment (VA) methods, using Ethiopia as a case study. Facing the challenges of vulnerability assessment and early warning requires providing accurate information at the required scale, useful for multiple decision-makers within realistic institutional capacities.

Keywords: Ethiopia, vulnerability, food security, famine, assessments, targeting.

Introduction

Since the early 1990s, early warning systems started incorporating more socio-economic data and have followed an inter-disciplinary approach in their analyses of vulnerability to food insecurity. Three notable approaches to vulnerability assessment and targeting food aid are the Food and Agriculture Organisation Global Information and Early Warning System (GIEWS), the Save the Children Fund Household Food Economy approach (HFE) realised in the RiskMap program, and Classification and Regression Tree analysis (CART) (FAO, 1996; SCF-UK, 1997, 2000; Yohannes and Webb, 1999). The GIEWS has a global remit and has been in operation since the 1980s, while the HFE-RiskMap and CART became operational in the 1990s for national or local analyses.

The purpose of vulnerability assessment (VA) is to identify the susceptibility of individuals or larger populations to food insecurity. VA involves two components: first, identification of who is at risk to climatic and environmental perturbations; and second, prioritising needs. Food security assessments evolved after failed famine relief interventions and Sen’s (1981) convincing arguments that famine was the product of broader interactions in societies and economies.

In this paper, we introduce broad concepts of vulnerability, food security and famine. We argue that the concepts and theories driving development and implementation of vulnerability assessment tools are related to their utility. This
review concludes that socio-geographic scale is a key issue, and challenge. We then analyse three VA methods, using Ethiopia as a case example. Facing the challenges of vulnerability assessment and early warning requires providing accurate information at the required scale, useful for multiple decision-makers within realistic institutional capacities.

**Confronting concepts**

Food insecurity is limited access to food. Famine is a food shortage leading to death by starvation. Like food security, famine is brought on by a range of components that include resource constraints, production, prices, consumption, assets and coping mechanisms (Downing, 1991; Downing et al., 1996; Webb et al., 1992). Both are the culmination of environmental and social factors. The aim of a vulnerability assessment is to capture both the natural and socio-economic processes of food insecurity that might lead to famine. Good vulnerability assessments must measure the right things, at the right scale, with suitable conceptual underpinning.

**Measuring vulnerability to food security and famine**

What are appropriate indicators of vulnerability? Food security cannot be measured by single, discrete variables (Yohannes and Webb, 1999). Effective measurements are those that are able to account for the livelihood conditions of target groups (i.e. the rural and urban poor, female-headed households, pastoralists and the unemployed).

Research since the late 1980s reflects a shift away from the macro-economic production focus toward coping mechanisms of farmers (Corbett, 1988; Swift, 1989b), an explicit focus on socio-economic groups and stress indicators that reflect economic and social behaviour (D’Souza, 1989). Current paradigms and monitoring focus on the processes through which people become vulnerable, expanding food security to livelihood security (as in the sustainable livelihood framework of the Department for International Development). Common questions are:

- What are the components of people’s livelihoods in terms of material and social assets?
- Where do they find off-farm income, and which crops do they depend on?
- What is their political context — are they victims of war?
- What are the agricultural and labour market conditions?
- What behaviours, like migration, signal a crisis?

Vulnerability assessments must be methodologically sound and context sensitive. A common misconception is that poverty correlates with political and socio-economic vulnerability and that the poorest people are also the most vulnerable to food insecurity (Jaspars and Shoham, 1999). Socio-economic data may not be good enough to target the people who need them most (on Sudan, see de Waal, 1988), or data on health may lead to false conclusions as to who is vulnerable to food insecurity (Young, 1990). Other methodological shortcomings include selecting appropriate indicators of
household stress, defining data needs and defining the significance of alternative variables (Borton and Shoham, 1991; Hutchinson et al., 1992).

The political and sometimes competitive environment of early warning often creates methodological fragmentation. However, a substantial body of work suggests that better measurement of vulnerability must integrate across methods and disciplines (Campbell, 1990b). Several multi-sectoral models of famine have been suggested. For example, Desai (1986) proposed a model of the sequence of events, which he felt to be crucial in identifying variables at different stages in the process. Following Sen’s entitlement approach (1981), the components should include the nature of the system, food and non-food production systems and the food supply system (see also Guha-Sapir et al., 1986, 1987; Watts, 1987; Shoham and Clay, 1989). Three fundamental points emerge:

- Socio-economic indicators only contribute to one part of an entire information system.
- Integration only comes about where there was a framework for systematising informal subjective information.
- The choice of methods and indicators often reflects the implicit and explicit adoption of famine models and paradigms.

**Geographic targeting and scale**

Two issues relate to scale. The social construction of scale, not as an objective category but as ‘produced’ by socio-political processes (Marston, 2000; LeFevre, 1991) will be discussed later in this section. Here we highlight empirical issues of spatial resolution — whether information about a phenomenon occurring at one scale can be applied to another scale.

It is not always possible to interpret from one scale to another. One reason is that processes appearing homogeneous at an aggregated scale may be heterogeneous at finer scales. For example, dead trees or patches in a coniferous forest infested with pine bark beetle blight might not be visible at a landscape (or global) scale (Lam and Quattrochi, 1992). Or, factors contributing to poverty are often interpreted homogeneously at broad spatial dimensions, as derived from aggregated census data. Rather, the patterns which identify who could be poor (small farmers, single females, etc.) are more visible at smaller scales. Local levels are particularly important when dealing with multivariate and complex problems (Fotheringham, 1997). Fractals in mapping sciences show that most of the real world is not constant at all scales.

Several techniques have been pioneered to address multi-scale phenomena (Fotheringham, 1997; Morris, 1996). For example, geographically weighted regression allows local rather than global parameters to be estimated. Mathematical flow modelling can encompass social processes such as migration, residential choice, retailing and recreational behaviour. Regression models can nest smaller-scale patterns within larger-scales ones (Polsky and Easterling, 2001).

Such techniques have not been widely used in vulnerability assessments. One reason is a policy focus on aggregated information. For example, famine assessment and alleviation strategies that dominated early warning several decades ago relied on national food balance sheets in seeking to target aid at the most vulnerable households.
Geographic targeting works best when the geographic units are relatively small districts as opposed to national states. The geographic or administrative boundary is widely accepted as an indicator of the location of vulnerability, especially as vulnerability is variable across a country, region or even village (Webb et al., 1994; Webb and Harinarayan, 1999; Downing, 1991). In emergency situations, Jaspers and Shoham (1999) advise that targeting needy people should be done on the basis of geography and nutritional status. Often, however, a single targeting method is applied generically to diverse situations. The effect of food insecurity at all scales becomes generalised when data are collapsed into regional and national analyses. Hoddinott (1999) demonstrated that concentrating resources on fewer units, like the district, village or household, could have a large effect on improving food security.

Targeting, even if based on geography, is not always a good thing. There are many examples of communities resisting the notion of household or individual targeting because of traditional practices, hierarchies and beliefs. Current targeting practices force them to prioritise and justify externally derived targeting priorities in ways that may be contrary to their own traditions. Communities sometimes misrepresent themselves, making it difficult to assess the real effects of the problem (Hoddinott, 1999). Community-based representatives may belong to a dominant groups and carry their own biases. Or, the ones who are truly vulnerable are marginalised and therefore have no voice in the targeting exercise (Jaspars and Shoham, 1999).

Ultimately, the appropriate resolution depends on the study’s objectives, the type of environment under consideration and the kind of information desired. Emergency-driven exercises have different constraints and goals than systems designed for developmental assistance.

**The conceptual basis of vulnerability assessment**

The evidence that localised data add value to vulnerability assessments contrasts with the lack of studies on local areas and conditions. The conceptual basis behind vulnerability assessments provides insight into this gap. We focus on the processes whereby ideas regarding famine policy influence methodologies that concentrate on certain socio-geographic scales and policy choices leading to famine interventions.

Early warning is increasingly dependent on technology that handles multi-variant problems, and this trend is connected to the prevailing theories in social sciences during the 1980s and 1990s. The technologies on offer include satellite images of vegetation cover, geographic information systems (GIS), the RiskMap computer program and the Classification and Regression Tree (CART) methodology (a commercial statistical package).

The theoretical bases of these ‘new’ methods and techniques for evaluating vulnerability are the result of post-modern modes of analysis; for example, that space, place and scale are social constructs. The post-modernist geographer argues that human behaviour varies intrinsically across space, and therefore locality frames an intimate picture of behaviour. Many of the underlying assumptions about vulnerability to famine in these models therefore centre on its variable and dynamic nature. In applications, the meta-theories about vulnerable people are taken as given, enhanced by a focus on specific variables like gender inequities in access to food, local trading patterns, ethnicity and seasonality of rainfall. Together, these aspects contribute to an
overall picture of vulnerability and food insecurity. The application of these concepts can be seen in analytical models aimed at interpreting the interacting details of the problem, the socio-economic and environmental patterns that determine vulnerability to famine, and inform the choices of vulnerable people. These models appear to conform to the current view that disaggregation yields a better analysis of famine.

Nevertheless, there is some justification for the critiques of technological approaches to famine assessment. Human geographers have faulted the advocates of quantitative methods for promoting a positivist approach to analysing social phenomenon (Taylor, 1990, 1995; Smith, 1992; Goodchild, 1991). A concurrent movement challenged developers to be more self-critical of digital models. Sheppard (1993), for example, expressed concern that the algorithms in quantitative models privileged a Boolean type of logic and therefore led to reductionist problem solving: sophisticated technologies are inaccessible to many. Mapping itself represents and imposes a certain ‘truth’ (Law, 1994; Pickles, 1997). However, there are advantages and weaknesses of the growing reliance on technological approaches in the social sciences (Clark, 1992; Curry, 1997).

The tenor of these arguments ranges from technological scepticism, dismissive of the value of quantitative approaches, to the philosophical and social theoretical, those who seek greater social responsibility in the use and development of quantitative tools. The latter especially applies to early warning, where various political interests influence the approaches adopted.

Different societies produce different kinds of geographical scale for containing, or enabling, particular forms of social interaction (Smith, 1995; Brenner, 1997). In the Ethiopian early warning system, for example, the spatial analysis of famine at high levels of aggregation has been a tactical measure, exercised by the state and international funding bodies, through both their own organs and non-governmental agencies. It is a policy designed to control the dispersal of scarce resources, but also to preserve the status quo. In an appraisal of Ethiopian famine policy during the 20th century, Wolde-Mariam (1986) demonstrated that government self-interest together with an uninterest in the prospects of the poor led to untimely and insufficient responses. Following the period of Wolde-Mariam’s research, the Ethiopian government moved from a communist regime to a more democratic structure. Despite the formal characteristics of the current political system, it is possible to hypothesise that policies of exclusion have limited the development of technological instruments to only a superficial part of the analysis. The scale at which a technology operates can be seen as a pre-described statement of certain political objectives — scale is not necessarily a pre-designed, hierarchical ordering of the world (Marston, 2000).

Accepting that there are limitations to quantitative approaches to vulnerability analysis but also assuming that they have some value, we argue that a technological analysis of complex social phenomenon that predominantly focuses on higher geographical scales is merely an action through which the discourses within early warning are reproduced.

Drawing from these theories of scale, we propose that early warning decision-makers conceptualise the spatial dimensions of food security as aggregated because it serves their own agendas. In contrast, peasant farmers necessarily hold to a concept of food security that is more immediate and local. The evidence from research aimed at effective analysis, measurement and targeting strategies, endorses the viewpoint that the farmers’ localised concept of food security is more than self-centred.
Three methods for vulnerability assessment

This section reviews the SCF-UK Household Food Economy Approach and RiskMap (HFE-RiskMap), the Classification and Regression Tree (CART) and an Artificial Neural Network (ANN). We selected the HFE-RiskMap and CART because they have the remit of providing local analysis of household food security. We propose the ANN as an alternative, to evaluate its potential alongside more established systems. We assess each program’s potential given both the policy constraints in early warning systems and the design limitations of the technology. In particular, we show how the models specify the problem of food insecurity, at what scale vulnerability is assumed, and how the models express the variability of vulnerability at the household level. Each approach is discussed from a theoretical and an applied standpoint.

Integrated assessment and mapping: SCF Food Economy Approach/RiskMap

According to the authors, the underlying thrust to their analysis rests on Sen’s (1981) view of famine as entitlement failure. Entitlements refer to the social, political and economic access of affected populations to food, ultimately related to access and power. The HFE methodology aims to provide an understanding of household economy and its relationship to markets and employment opportunities in a baseline or reference year. This information is used to estimate the effect of a ‘shock’ on household income and food supply and the likely ability of the household to compensate for this by implementing the various coping strategies available to it. This helps in constructing an argument about people’s behaviour when their access to food is restricted by environmental and political events (Save the Children Fund-UK/Food Security Unit, 2000). It proposes to do this by examining the ‘entitlement set’ of each household, which is equal to the sum of household income, the exchange value of household labour and other assets (Seaman, 2000: 1). The HFE approach is an attempt to describe the economy of vulnerable households in which a large portion of the household economy centres on food (production and consumption). The RiskMap program is a database system that enables the analysis of household food economies.

Three algorithms have been employed to carry out the assessment of household food deficit based on calculations of normal consumption, food stocks and an estimation of need. The calculations are based on arithmetic calculations and a price model based on a linear relationship between supply and demand. Typically, the program describes income and reserves for three household categories (rich, modal and poor) based on: the normal pattern of employment, specific employment, livestock and other markets used, and the likely distribution of food and other goods between households. Surveys are conducted among experienced field-based and international staff, in collaboration with local ‘informants’, who generally live in the area and follow local market and trading patterns.

A focus on entitlements appears consistent throughout the development process of applying the HFE and the RiskMap program. The program’s output illustrates the features of households that will determine their access to food. The analysis does not focus on specific households, but instead identifies populations with similar characteristics, then describes different types of households within that
The description of typical households is meant to provide insights into the dynamics of rural economies. While the clustering of households can provide a useful profile of vulnerability for a given target area, HFE profiles are sometimes used to describe and classify households in areas for which there are few sample data, and this clustering leads to generalisations. There is always the danger that generalisations will yield misleading results. Further, while in practice the HFE has been used at the level of a village, the RiskMap program has not been capable of assessments at or below the village level. The RiskMap output is expressed in terms of the typical household from defined wealth groups within a specific population, which is usually well above the village boundaries. It incorporates the variation between households within a specific wealth group using data in the form of ranges.

Two striking inconsistencies in the overall program are the absence of variables for labour supply and seasonality, yet these variables are crucial to an analysis whose aim is to anticipate people’s behaviour in response to change. The authors specify the incorporation of the ‘exchange value’ of labour as an aim, yet go on to say that no data on household labour availability are included (Seaman, 2000). In the RiskMap program there is no explicit variable describing the size of the labour supply. Labour supply and demand (or lack of it) are both important indicators of the state of local and regional economies. Labour availability is critical to an analysis of household food security because it affects household income and partly determines how rural households cope with environmental and socio-economic change. Rural agricultural households are highly dependent on their own labour supply to earn income. In addition, it is unclear whether the program has a way of linking demand for labour at one scale, with supply at another. Seasonal climate change is also a strong factor fundamentally affecting household food security. Failed rainy periods jeopardise healthy and sufficient crop growth, which can lead to the employment of coping mechanisms like labour migration. Without these variables the analysis is considerably less robust and an unintended assumption is made that household food security will be static over time.

Finally, Sheppard’s (1995) concern that technology privileges some world-views over others may be evident here. The classification of households into rich and poor categories, for example, is partly acquired through qualitative information using rapid rural appraisal (RRA) methods. RRA methods can be a useful tool for self-targeting in the context of food-distribution programmes and they are also a tool for the qualitative assessment of a wide range of phenomena. However, the methodology sometimes results in some groups being favoured over others (see Jaspars and Shoham, 1999) or a false identification of who is most vulnerable (Young, 1990). The logic of the equations in RiskMap follows the common modes in economic and sociological studies of developing countries. Data on social systems are incorporated along with quantitative price information. Thus, the calculations are as good (or as bad) as those found in current practice.

Classification system: CART analysis

The Classification and Regression Tree (CART) is a statistical approach used in many fields for classifying data. The use of CART in an analysis of food policy and vulnerability in developing countries was based on the International Food Policy Research Institute’s (IFPRIs) ongoing experience in adapting microcomputers in policy.
Table 1  CART outcome for two vulnerable groups

<table>
<thead>
<tr>
<th>Group 2</th>
<th>Group 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average household size ≤4.4</td>
<td>NDVI (estimation of vegetation health)</td>
</tr>
<tr>
<td>Average persons in need = 74%</td>
<td>≤0.05</td>
</tr>
<tr>
<td>Sample size concluding at this node = 3</td>
<td>Average persons in need = 68%</td>
</tr>
<tr>
<td></td>
<td>Sample size concluding at this node = 5</td>
</tr>
</tbody>
</table>


research (see Breiman et al., 1984 for further details of CART methods). CART was used to identify the key variables contributing to household food security in Ethiopia. This was based on their famine research program, which was completed in 1998. The use of CART assumes that vulnerability is multifaceted and multi-variant. The variables in the analysis include household income, food production, prices and consumption, markets and purchasing power. They can be categorical and have continuous variables (Yohannes and Hoddinott, 1999). The CART analysis is used to identify the indicators of a number of outcomes, like vulnerability. It does this by building a statistical picture of vulnerability. The goal is to produce an accurate set of data classifiers through the analytical process, in which the choices of indicators can be based on reliable alternatives.

The application of CART to an assessment in Ethiopia was aimed at understanding which indicators of vulnerability best explained the reported numbers of ‘people in need’ across geographic regions. Based on extensive time-series survey data, households were placed into two broad classes: vulnerable and not vulnerable. The original sample was split repeatedly based on a series of questions to which households could be classified as ‘yes’ or ‘no’. The first question was whether the households were in an area of ‘green’ vegetation cover (as indicated by NDVI measurements). Another question was whether annual income was less than or equal to 2,000 Ethiopian birr (about $240). The outcome or result of this ‘sample splitting’ was a number of ‘terminal nodes’ that consisted of groups of sample households which shared some characteristics of vulnerability (see Table 1 for an example of two groups).

The average percentage of needy people at each terminal node (or group) adds to the total at the district level. The average district in Ethiopia covered 11,314 square kilometres. In this example, there were 10 groups, the total sample at the district level was 462 households and the average number of people in need was estimated at 11 per cent. At each stage in the process, sub-samples were created and each step represented a branch in the tree. Statistical classification rules enabled the prediction of vulnerable versus non-vulnerable.

The scale of operation was set at the district level, although it could also have been set for smaller geographic areas. The analysis was useful for identifying and understanding the interaction among variables as well as the characteristics of affected households. For the most part, it is an objective tool, but there are subjective elements that could enter the process during the development and administration of surveys on which the program relies. Another aspect is that the program produces different trees based on transformations of the data. The program allows different trees to be cross-validated, but ultimately the choice of the ‘best’ tree will depend on the user’s goals and choice.

A limitation of CART is that no probability is associated with the outcomes. There is no confidence interval associated with predictions that could help classify a new set of data in a reliable manner (Yohannes and Webb, 1999). Thus, a question
Pattern recognition in an Artificial Neural Network

Artificial Neural Networks (ANNs) are designed to solve problems for which there is no known algorithm or defining set of logical rules. They are computer systems that can ‘learn’ outcomes from pre-selected data. Learning means the process through which neural networks process the information and the structure inherent to input data from which they then yield classifications of that data set (Kohonen et al., 1991). ANNs have been widely used in the physical and chemical sciences, but have only recently been applied to environmental and social problems (Pearson et al., 2000; Kropp, 1998). The ANN approach employs a wide range of input variables that can be derived from various methods. We used the neural network for food security analysis. The underlying basis was that vulnerability is a multivariate entity and its assessment must consider the whole set of its potential indicators, which include exogenous political and environmental stress and the capability of individual households to cope with food crises. Thus, the analysis must consider the range of variables at a local scale. A further aim of the analysis was to identify other inherent processes of household vulnerability.

An ANN can model two types of learning processes: supervised and unsupervised (Kohonen et al., 1991). A supervised neural network is one that requires prior knowledge of the values of the dependent variable (for example, a variable discriminating between vulnerable and non-vulnerable households). In this way, the number and kinds of potential categorical outcomes of the dependent variable are known a priori and entered into the calculation. Unsupervised network outcomes are entirely data driven. In the beginning, no targets are established that would influence the identification of the final classification of cases into functional groups. Unsupervised learning performs a similar function to cluster analysis, where variables or data are classified according to their similarities (Tabachnick and Fidell, 1996). The unsupervised learning process operates by generating a self-organising map (SOM) of the input data. This means that the program autonomously finds patterns within the data.

An example of an unsupervised network used data from World Bank studies to develop a ‘poverty map’ of countries grouped by their wealth (Kohonen, 1980). Kropp (1998) showed that it is possible to identify places (and households) that are susceptible to perturbations in human–environment interactions, including those that possibly lead to a disaster. In this post-hoc way, the learning algorithms were also able to calculate ‘fuzziness’ and uncertainty in the data in order to produce a distinct, logical outcome. The self-organising map uses specific algorithms to cluster data (see the annex for a mathematical description of the SOM).

We evaluated the possibility of applying a neural network to analysing complex, socio-economic problems, as in cases of food insecurity. This approach was based on the understanding that vulnerability is variable at the household level and that
capturing this variability is important for a thorough vulnerability assessment and response.

Using data from Ethiopia, we trained a supervised neural network to identify the vulnerability of 189 households. Selected data from a 1998 food security survey (Stephen, 1999; unpublished data) were used as inputs. The surveyed population was a statistically representative proportion of the total households within the Delanta sub-area. The raw data were first processed and analysed statistically to identify vulnerability variables. We used the US Agency for International Development (USAID) vulnerability assessment indicator system, first, to code each family’s socio-economic group, then to identify four vulnerability classes: extremely food insecure, highly food insecure, moderately food insecure and food insecure (see Annex 2). In order for the ANN program to identify existing and potential patterns of vulnerability to food insecurity, it was trained on one-third of the households in the data set. The remaining two-thirds of the households were used to test the validity of the ANN’s predictions. The ANN accommodated quantitative and qualitative data. For example, the data were both environmental and social, such as soil type (not specified categorically) and variables related to socio-economic entitlements (for example, total household expenditure, land size, number of oxen owned, number of labourers). All values were normalised to range between -1.0 and +1.0. We examined populations within peasant associations, villages and households.

The network was trained until the output values and the input values could be closely matched. We ran a three-layered, back-propagation network with the following structure (see Figure 1). The three layers are the arena in which the data are first fed forward from the input layer and then are propagated backward from the output layer. The first layer, the input layer, was the storage point for the variables and households (one-third for training). There were 20 nodes (or storage points) in the input layer. The second layer was a hidden layer, part of whose function was to process the data. The hidden layer consisted of 41 nodes. The third layer was the output layer that contained the four vulnerability classes, represented by four nodes. The values in the input layer are weighted then passed through connecting links to the hidden layer. The nodes in the hidden layer then produce outputs that are based on the sum of the weighted values passed to them. ANNs are designed to adjust repeatedly the weighted links connecting each layer, as the model learns to match the patterns in the input layer to the categories in the output layer. The training algorithms for this process are given in Annex 1.

After training the model to identify vulnerability, we ran the validation data set (the remaining two-thirds of the data) through the network and achieved a vulnerability score for each household. The validation data set was used to test how well the network trained, and this testing occurred every 100 cycles. When the program had run through 10,000 cycles, we stopped the validation process. At that point, the minimum mean standard error was .00025. Beyond this error value, the network began ‘over-training’, which meant that it started simply to memorise the patterns presented in the training data (one-third of data set) and was not generalising well with the new patterns in the validation set. When examined, the scores produced by the network made sense matched to the initial USAID vulnerability code assigned to each household.

Using a supervised network we obtained a vulnerability score for each household derived from a series of algorithms within the program. Households were classified in hierarchical, ordinal sets (such as rich, middle income and poor). As shown in Table 2, 65 per cent of the households classified as highly to extremely food insecure by the model were also below the average income for the study area.
This ANN analysis was useful as it provided a basis for observing the variability between households in the sample. This was supported by a cluster analysis of the data, which also showed a high differentiation between households (Stephen, 2001; unpublished data.). By using three different scales, we observed that the identification of vulnerable households could be extrapolated from the smaller (households) to larger (peasant association) scales.

The program trained on static information, which can serve as a baseline for predicting future household vulnerability. It established profiles of vulnerable households in the form of ranges of numbers representing different levels of need. The added value in having a score for each household is that one household could be distinguished from another. Consequently, if there were a drought in the study area this year, an analyst would be able to make a preliminary target of vulnerable households based on their individual scores. This estimate could then be a supplement to other targeting mechanisms, like individual self-targeting. There are, of course, practical and economic constraints of distributing relief to individual households which must be taken into consideration when selecting appropriate targeting instruments.

An important limitation of the ANN is that it does not provide insight to the

Table 2 ANN analysis of household food security compared to household income

<table>
<thead>
<tr>
<th></th>
<th>Food insecure households</th>
<th>Food secure households</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income &gt; birr 1,716</td>
<td>28</td>
<td>42</td>
<td>70</td>
</tr>
<tr>
<td>Income &lt; birr 1,716</td>
<td>53</td>
<td>32</td>
<td>85</td>
</tr>
<tr>
<td>Totals</td>
<td>81</td>
<td>74</td>
<td>155</td>
</tr>
</tbody>
</table>

Percentage with income below average 65% 43%

Source: Data from Delanta, Ethiopia household survey, 1998.
processes by which people become vulnerable. The ANN equations can handle time-series data, which can be a basis for predicting change. However, given the dynamic nature of vulnerability, the model better serves as a tool for targeting rather than as a fully comprehensive analytical system.

The ANN may have additional potential as a tool for vulnerability assessment, which we have not demonstrated so far. In the future, we plan to test the supervised ANN (trained on Delanta data) on a different region and with new data. This can be accomplished by using the new data as inputs and then observing how closely they match the Delanta outputs. That will be a way to prove the robustness of our methods for selecting the variables, for establishing the vulnerability codes used for the output, and the capability of the program to learn patterns of vulnerability.

We also plan to train an unsupervised neural network, as this method has been proven to illustrate inherent patterns in the data set without the need of prior assessment. The unsupervised approach lessens the bias that may result from using pre-analysed and subjective data, such as that derived from the USAID process. To test the influence of subjective ideas, we would like to apply vulnerability classes derived from different methods to the supervised ANN. Finally, we would also like to incorporate the nutritional status of household members, the numbers of people receiving external assistance and seasonal forecasts. Each of these variables is important in calculating vulnerability (see Hoddinott, 1999).

**Facing the challenges of early warning**

In addition to the conceptual challenges of measuring food security and scaling, any analytical approach needs to perform amid the practical challenges facing institutions in early warning systems. A brief discussion of each program in the context of the political, technical and administrative constraints is presented below.

**Vulnerability assessments in multi-agency settings**

When the RiskMap program was first introduced to governmental and non-governmental institutions in early warning, it was dismissed for having a ‘black box’ approach and for not being widely tested (FAO, 1996; Stephen, 2001; unpublished data). The underlying rationale to the program’s analysis was not transparent and the authors were unwilling to explain the algorithms in which some of the assumptions were imbedded. Today, there is a growing interest in RiskMap, which can mainly be attributed to more openness on the part of the authors to explain its operations. Its calculations are more transparent. Some of the initial ‘bugs’ in the software program have been eliminated so that it can be proposed for testing in various settings. Another reason for interest in the program is the rationale of its methodology, which is based on the household economy approach (HFE). Save the Children-UK and a wide range of agencies (FAO, WFP) and national governments are increasingly using HFE in countries that are most under threat from food insecurity and humanitarian crises (SCF/FSU, 2000; Seaman, 2000; pers. comm.). More than that, HFE-RiskMap can now be seen to offer a comprehensive analysis of famine processes, using a transparent methodology that is applied to levels of aggregation at which administrations are comfortable basing their decisions.
CART has not been extensively adopted by any early warning system as a mechanism for analysis, despite several published manuals and software programs. Experienced and trained personnel can understand the program, but the difficulty lies in the time it takes for the initial set up. Given the time constraints of early warning staff, there would need to be adequate support and justification for the CART approach, before resources could be allocated towards it. It would therefore require some consensus on the conclusions drawn from the input data. Perhaps for these reasons, the CART is only available through commercial sale and remains a marketed tool for analysis. In addition, because the CART analysis has not been widely tested, it has not been well proven as an effective system to use for vulnerability analysis.

ANNs are being introduced in this paper as a potential alternative to other methods for vulnerability analysis and targeting, and have never been used in early warning settings. However, it is possible to hypothesise about their place in early warning. Designers and policymakers may use their own data, which are likely to be analysed and agreed before being put into the program. Obviously, data taken from different sources may produce a ‘nonsense’ output, and, therefore, the pre-analysis must be initially ‘ground truthed’ against real situations. Once this is done, however, the network can be trained on 10 to 30 per cent of the data set, validated on the remainder, and tested on new data sets using the same categories of variables (for example, income, land size, nutritional status) and at the same scale. There is the possibility that supervised ANNs, in this context, will learn the biases of institutions, therefore an unsupervised network is recommended. The process through which the program’s algorithms derive the outcome could be questioned, as they were with RiskMap. For this there is an abundance of published material explaining the calculations, which could also be explained by a technician. But we would suggest that the calculations become a secondary concern, once the output is found to be accurate after a few trials and validation.

**Capability of meeting goals of vulnerability assessments and measuring vulnerability to food insecurity**

Table 3 shows that each program exhibits a medium capability of addressing the dual processes of vulnerability: environmental and non-environmental (social/economic/political). In each program, the process of selecting indicators and measurements of vulnerability requires collaboration and careful pre-analysis. Variables tend to come from both quantitative and qualitative surveys, which can contain their own biases. Of the three, the CART and the unsupervised ANN are the most philosophically versatile and objective, meaning that it would be more difficult to impose subjective viewpoints into CART or the unsupervised ANN. However, the quantitative operations of ANNs in general (supervised and unsupervised) provide one reason why they are limited as a tool for a comprehensive vulnerability assessment. They can incorporate qualitative and quantitative data, but they do not analyse the data qualitatively, and thus are not able to provide sufficient insight to the processes leading to vulnerability. In contrast, the RiskMap aims to follow a pre-determined theory of famine, Sen’s entitlement theory, and in doing so presents some of the underlying logic to vulnerability processes. RiskMap loses effectiveness not so much because of an in-built ‘subjectivity’, as because it omits key food security variables.
Table 3a  Comparison of ANN and other methods from a conceptual basis

<table>
<thead>
<tr>
<th></th>
<th>ANN</th>
<th>CART</th>
<th>HFE/RISKMAP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accounts for dual processes of vulnerability:</strong> environmental and social/political/economic</td>
<td>Medium to low: incorporates qualitative and quantitative data representing socio-economic and environmental processes, but the interaction of these variables is analysed mechanically through algorithms and does not necessarily follow the logic of real situations.</td>
<td>Medium: follows a logical process in which environmental and social factors influence the final outcome.</td>
<td>Medium to high: illustrates the dynamism and interaction of the two processes in context and explores a range of possible outcomes. Limited by lack of variables for labour supply and seasonal forecasts.</td>
</tr>
<tr>
<td>Facilitates a range of variables and key indicators</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td><strong>Accuracy at household level</strong></td>
<td>High</td>
<td>High: Targets at HH level but is designed to identify key variables not key vulnerable households.</td>
<td>Medium to low: Lowest level targets for HFE are village levels. RiskMap targets typical household expressed at ‘community’ scale, usually above the village level.</td>
</tr>
</tbody>
</table>

Table 3b  Comparison of ANN and other methods from a theoretical basis

<table>
<thead>
<tr>
<th></th>
<th>ANN</th>
<th>CART</th>
<th>HFE/RISKMAP</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Theoretical basis</strong></td>
<td>The high variability of vulnerability: employs algorithms whose purposes are to calculate the interaction of variables and classify the ‘patterns’ found in the data set.</td>
<td>Food security variables are diverse: classification and regression analysis used to refine the process of identifying key outcome indicators.</td>
<td>Entitlement theory: household vulnerability to food security is determined by their ‘set’ of entitlements (assets, availability, utilisation).</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Levels of dis-aggregation (scale)

The scale of the analysis in each program is dependent on their design capabilities (see Table 4). Each program employs techniques for integrating data from different scales. In the case of RiskMap, the programme was not well developed to analyse below a certain level of aggregation. Instead, the RiskMap adapts the principles of mathematical flow modelling, in which the peoples’ choices and behaviours are the focus of the model given their differing alternatives and assets. The CART program relies on a set of ‘sample splitting’ rules to create both classification and regression trees and to disaggregate the data. Ultimately, the households are disaggregated according to various characteristics of food insecurity and this could also be applied to their individual levels of food insecurity. The neural network can also differentiate levels of need between households, using various equations to calculate ranges of difference in the data.

Costs and skills needed

The initial costs of the neural network are moderate to low in comparison with the other programs considered in this paper. Some neural network programs (including that discussed in this paper) are available free from the Internet, which makes it inexpensive as compared to any standard GIS and as compared to CART or RiskMap (see Table 3). As the RiskMap and CART are more expensive, institutional funding restrictions could make their functions more accessible to the needs of early warning personnel. The time involved in pre- and post-analyses, and the levels of skill required, are comparable among the three approaches. Each requires some experience and training.

Conclusion

In this paper we have argued that practical challenges and conceptual frameworks carry equal weight in the delivery of effective famine early warning. Among the impediments to good practice, the most detrimental is the politics of negotiation amongst institutions, and its effect on decision making, choice of methods and effective targeting. A conceptual analysis has helped in framing discussions about the measure-
Table 4 Comparison of ANN and other methods in terms of costs, time, skill level and advantages

<table>
<thead>
<tr>
<th></th>
<th>Neural Network</th>
<th>CART</th>
<th>HFE/RiskMap</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Initial costs</strong></td>
<td>Free download or US$30.</td>
<td>US$600–$1000.</td>
<td>US$50 (includes VAT).</td>
</tr>
<tr>
<td><strong>Time required for data analysis</strong></td>
<td>1 day</td>
<td>Labour intensive. Initial data acquisition and set-up ½ day.</td>
<td>1 day</td>
</tr>
<tr>
<td><strong>Skill level required</strong></td>
<td>Requires basic training.</td>
<td>Requires training and knowledge of statistics.</td>
<td>Requires basic training.</td>
</tr>
<tr>
<td><strong>Advantages</strong></td>
<td>Finer level of detail. Classifies varying degrees of vulnerability. Policy neutral — can incorporate various concepts of vulnerability.</td>
<td>Quick analysis. Copes well with large data sets. Data can be categorical or continuous. Exploratory analytical tool.</td>
<td>Captures regional determinants of HH food insecurity (i.e. price changes). Helps create good hypotheses of behaviour.</td>
</tr>
<tr>
<td><strong>Disadvantages</strong></td>
<td>Provides a static picture while famine situations are dynamic.</td>
<td>No probability. Accuracy of results depends on a tree’s historical accuracy.</td>
<td>Excludes important variables (i.e. labour supply, seasonality of income, economic activities and rainfall.</td>
</tr>
</tbody>
</table>

ment, targeting and scale of vulnerability. It has also helped elaborate the processes shaping and constituting the practices of early warning, the end result of which is that decision-makers generalise about the spatial dimensions of vulnerability and thereby minimise its complexity and variability.

In famine early warning systems, there is chronic resource scarcity, and where that exists there will sometimes be competition, prioritisation and exclusion. Individuals and institutions will actively aim to resolve their differences as well as to bring their cases forward in various settings. Thus, at the beginning of the 21st century, political discourse remains the backdrop to improvements and impediments to early warning.

Further, a lack of institutionally standardised approaches can create practical difficulties, which complicate vulnerability assessments by producing divergent methods that often fail to target the poorest. The purpose of the vulnerability assessment is to target vulnerable people, who are best examined in data disaggregated to the household level. Some of the current approaches to vulnerability assessment miss this mark because of how they conceptualise the scale of the problem. The methods and measurement instruments used reflect some inconsistencies. While all three approaches discussed in this paper integrate both the environmental and social processes of vulnerability, the HFE-RiskMap contained the most clear and comprehensive analysis of the dynamics of vulnerability. However, the CART and the
Methods for Vulnerability Assessment and Household-level Targeting

ANN were able to target at the household level, while it is clear from its application and outputs that the HFE-RiskMap was not designed to reach household level as such. Its objective is to establish arguments about behaviour in the face of crisis. A further limitation of RiskMap was present when it was initially introduced to early warning systems as a famine assessment tool. At that time, the program’s underlying assumptions and quantitative manipulations were not made clear, and therefore contention arose when the application was proffered in the context of early warning. The underlying principles became the focus of discussion and were used to disqualify the value of the methods and those who developed them. As such, unclear agendas embedded in methods and techniques reinforce the conflict and competition over scarce resources that are prevalent within early warning systems. The ANN as an alternative method for targeting has the advantage of being able to incorporate different viewpoints while targeting to the lowest level. In each case, the quality of the outcome will always be dependent on the quality and accuracy of the data used.

The key to understanding the inconsistency between the location of vulnerable people and assessment methodologies is to study the politics of early warning and of the construction of scale. The inconsistencies are not a threat to theorising, but to effective early warning. Indeed the failure to target well is evidence to the effect that the theories are right, it is the formal and informal analytical systems and their implementation that are limited. The assumptions underlying famine assessment technologies are consistent with current knowledge and theories of famine. With the exception of CART, these analytical approaches are more affordable and therefore more accessible today than they were a decade ago when they were first developed. When tested, they gave an output that was accurate within the parameters the designers set for them. The weaknesses in their design are caused by the way institutions conceptualise the problem and choose to respond to it. The stated purpose of the HFE/RiskMap is to assess household-level vulnerability, yet the software is designed to describe vulnerability at scales that are inconsistent with the best knowledge of where vulnerability should be measured. The ANN will be less robust if it is only trained in a supervised way, where the outcome values are derived using only qualitative methods. Its effectiveness is also limited because it does not clearly show the processes leading to vulnerability. Finally, the CART lacks the probability statistics that could lend credibility to the approach.

Acknowledgements

We thank the 1998 Oxfam Delanta team (Demmelesh Getachew, Kebede Molla, Samuel Molla, Abraham Wolde-Giorgis, Kessaye Mezmur, Mohammed Yimer, the drivers and social promoters) with whose support we have been able to gather the Ethiopian household data presented in this article. Thanks also to Fabrizio Sergio, for detailed comments on earlier drafts; to Terry Dawson, Richard Pearson and Wen for technical discussions on the application of Neural Networks; to Gina Ziervogel for her willing legwork in the final stages; and to Patricia Daley for general guidance.

Notes

2. The post-modern analysis of food security shifts focus from macro-economic indicators like GDP/GNP towards micro-economies and the dynamics of local places. See Maxwell (1994). See the compilation of Foucault’s writings (1980), in which he articulates a post-modernist view on the social construction of knowledge, such as the influence of gender and culture on our interpretation of events. See also Derrida (1976) for application of ‘deconstruction’, a post-modern form of text analysis.

3. NDVI is the normalised difference vegetation index, which measures vegetation ‘greenness’ detected by remote sensing. The range of possible values is -1 to 1.0, where -1 is not green and 0.6 to 1.0 is green. See www.infocarta.es/new.htm for elaboration.

4. The district refers to the Awaraja, which was a sub-regional designation until the early 1990s. The average size was calculated based on an approximation of the total square kilometres of Ethiopia.

5. The cases must reflect the whole range of possible values for each variable, in order for ANNs to calculate changes in data over time.


References


Accessed: November 2000)


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Annex 1 Artificial Neural Network algorithms

<table>
<thead>
<tr>
<th>Type of network</th>
<th>Error calculation</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supervised (feed-forward, back propagation)</td>
<td>Quadratic (mean squared error): ( E(t) = \frac{1}{2} \sum \sum (d_j(t) - y_j(t))^2 )</td>
<td>Connection weights adjusted using the delta rule: ( \Delta w_{ij}(t+1) = \eta \delta_j o_i + \mu \Delta w_{ij}(t) )</td>
</tr>
<tr>
<td></td>
<td>( \delta_j = (f_j (net_j) + c) (t_j - o_j) ) if unit j is an output unit</td>
<td>( \delta_j = (f_j (net_j) + c) \sum k \delta_k w_{jk} ) if unit j is a hidden unit</td>
</tr>
<tr>
<td></td>
<td>( e(t) = ) global error function at discrete time t, ( y_j(t) = ) predicted network output at t, ( d_j(t) = ) the desired network output at t.</td>
<td>( \eta = ) learning parameter (a constant — typically in the range 0.1 to 1.0)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \delta_j = ) error (difference between the real output and the teaching input) of unit j</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( t_j = ) teaching input of unit j</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( o_i = ) output of the preceding unit i</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( i = ) index of a predecessor to the current unit j with link ( w_{ij} ) from i to j</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( j = ) index of the current unit</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( k = ) index of a successor to the current unit j with link ( w_{jk} ) from j to k.</td>
</tr>
</tbody>
</table>

Unsupervised (self-organising map) | Quantisation (mapping) error: \( D(x,m_i) = \min \{d(x,m_i)\} \) \( x = \) input vector, \( m_i = \) reference vectors, \( d(x,m_i) = \) generalised distance function of \( x \) and \( m_i \), \( c = \) index of closest reference vector to \( x \) in the space of input signals. | Euclidean distance to all nodes: \( \| x - m_i \| \leq \min \{ d(x,m_i) \} \) \( x \) is presented to the network where all nodes compete to represent the input pattern. Output node \( i \) is selected to represent \( x \). Modify weights of closest matching ‘winner’ node: \( m_i(t+1) = m_i(t) + e(t) \bullet h_b \bullet [x(t) - m_i(t)] \) \( e(t) = \) a decreasing learning parameter and \( h_b = \) a time-dependent neighbourhood function, which defines the vicinity of the mesh in which other nodes learn from the same input stimulus. |

Sources: \(^1\)Kohonen (1980: 118–21); \(^2\)Kropp (1998: 84–5); \(^3\)Pearson et al. (2000); \(^4\)Stuttgart Neural Network Simulator (1995).
Annex 2  USAID famine early warning system ‘modified’ current vulnerability assessment: socio-economic groups and vulnerability classes

<table>
<thead>
<tr>
<th>CVA process</th>
<th>CVA applied to Delanta, Ethiopia</th>
<th>Rationale</th>
<th>Description</th>
<th>ANN code</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Define socio-economic groups.</td>
<td></td>
<td>Adapted Kenya CVA, as could not find documentation of an Ethiopian CVA.</td>
<td>Cereal and vegetable crop farmers</td>
<td>F1</td>
</tr>
<tr>
<td></td>
<td>Farmer 1</td>
<td></td>
<td>Mixed vegetable and dairy farmer</td>
<td>F2</td>
</tr>
<tr>
<td></td>
<td>Farmer 2</td>
<td></td>
<td>Dairy farmer</td>
<td>F3</td>
</tr>
<tr>
<td></td>
<td>Farmer 3</td>
<td></td>
<td>Labourer in town</td>
<td>NFU</td>
</tr>
<tr>
<td></td>
<td>Non-farmer</td>
<td></td>
<td>Non-farm labourers and other</td>
<td>NF</td>
</tr>
<tr>
<td>3. Determine whether population has sufficient access to food.</td>
<td>XX% of households have direct and indirect access.</td>
<td>Access in terms of: 1. income strategies 2. coping strategies 3. assets</td>
<td>Woreda is chronically food insecure.</td>
<td></td>
</tr>
<tr>
<td>4. Determine whether population faces important challenges to using food healthfully.</td>
<td>XX% of households face challenges to healthy diet.</td>
<td>We assumed that consumption needs could only be partially met if HH had insufficient food availability, access, and utilisation.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Determine if access and utilisation permit population to meet consumption requirements.</td>
<td>Not determined</td>
<td>No full nutritional survey data for Delanta.</td>
<td>We assumed that consumption needs could only be partially met if HH had insufficient food availability, access, and utilisation.</td>
<td></td>
</tr>
<tr>
<td>6. Assess whether XX% of population</td>
<td>Assets include: land, crops, oxen, other</td>
<td>Crops, oxen, livestock and labour are</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Methods for Vulnerability Assessment and Household-level Targeting

<table>
<thead>
<tr>
<th>CVA process</th>
<th>CVA applied to Delanta, Ethiopia</th>
<th>Rationale</th>
<th>Description</th>
<th>ANN code</th>
</tr>
</thead>
<tbody>
<tr>
<td>population can protect its asset base.</td>
<td>livestock, labour.</td>
<td>all vulnerable to a drought and ensuing food shortage. Land portions are assigned at the discretion of local administrations.</td>
<td>0</td>
<td></td>
</tr>
</tbody>
</table>

7. Assign population to food security category.

- XX% of HH extremely food insecure.
  - XX% of HH highly food insecure.
    - XX% of HH moderately food insecure.
      - XX% of HH food secure.

- HHs had insufficient local food available, insufficient food access, insufficient utilisation, out-migrated.
- HHs had insufficient local food available, insufficient food access, insufficient utilisation, disposed of productive assets.
- HHs had sufficient local food available, sufficient food access, sufficient utilisation, recourse to adaptive coping strategies.
- HHs had sufficient local food available, sufficient food access, sufficient utilisation, normal income-generating patterns.

| XX% of HH extremely food insecure. | HHs had insufficient local food available, insufficient food access, insufficient utilisation, out-migrated. | 0 |
| XX% of HH highly food insecure. | HHs had insufficient local food available, insufficient food access, insufficient utilisation, disposed of productive assets. | 0.5 |
| XX% of HH moderately food insecure. | HHs had sufficient local food available, sufficient food access, sufficient utilisation, recourse to adaptive coping strategies. | 0.75 |
| XX% of HH food secure. | HHs had sufficient local food available, sufficient food access, sufficient utilisation, normal income-generating patterns. | 1.0 |