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Geospatial decision support systems for societal decision making

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ABSTRACT

While science provides reliable information to describe and understand the earth and its natural processes, it can contribute more. There are many important societal issues in which scientific information can play a critical role. Science can add greatly to policy and management decisions to minimize loss of life and property from natural and man-made disasters, to manage water, biological, energy, and mineral resources, and in general, to enhance and protect our quality of life. However, the link between science and decision-making is often complicated and imperfect. Technical language and methods surround scientific research and the dissemination of its results. Scientific investigations often are conducted under different conditions, with different spatial boundaries, and in different timeframes than those needed to support specific policy and societal decisions. Uncertainty is not uniformly reported in scientific investigations. If society does not know that data exist, what the data mean, where to use the data, or how to include uncertainty when a decision has to be made, then science gets left out –or misused– in a decision making process. This paper is about using Geospatial Decision Support Systems (GDSS) for quantitative policy analysis. Integrated natural –social science methods and tools in a Geographic Information System that respond to decision-making needs can be used to close the gap between science and society. The GDSS has been developed so that nonscientists can pose "what if" scenarios to evaluate hypothetical outcomes of policy and management choices. In this approach decision makers can evaluate the financial and geographic distribution of potential policy options and their societal implications. Actions, based on scientific information, can be taken to mitigate hazards, protect our air and water quality, preserve the planet's biodiversity, promote balanced land use planning, and judiciously exploit natural resources. Applications using the GDSS have demonstrated the benefits of utilizing science for policy decisions. Investment in science reduces decision-making uncertainty and reducing that uncertainty has economic value.

Key words: cost-benefit analysis, geologic hazards, GIS-based model

Sistemas geoespaciales de apoyo a la toma de decisiones

RESUMEN

La ciencia, aún suministrando una información rigurosa para describir y comprender la Tierra y sus procesos naturales, podría contribuir más aún ya que existen varios aspectos importantes a nivel socioeconómico en los que la información científica puede jugar un papel crítico. La ciencia puede ayudar de manera muy eficaz a la toma de decisiones reguladoras para minimizar las pérdidas de vidas y propiedades a causa de desastres naturales o tecnológicos, para una mejor gestión de los recursos hídricos, energéticos, minerales y naturales en general y, todo ello, mejorando y protegiendo nuestra calidad de vida. Sin embargo los nexos entre los entornos científicos y los de toma de decisiones son a menudo complejos e imperfectos. El lenguaje excesivamente técnico y el método impregnan la investigación científica y la diseminación de sus resultados. Las investigaciones científicas se llevan a cabo, frecuentemente, en diferentes condiciones, en diferentes ámbitos espaciales y a un ritmo distinto del requerido para dar apoyo a la toma de decisiones políticas y administrativas. Así mismo en este tipo de investigaciones no se informa uniformemente sobre las incertidumbres existentes. Si la sociedad ignora qué datos existen, qué significan esos datos, dónde deben emplearse y cómo tener en cuenta las incertidumbres a la hora de tomar una decisión, no cabe duda que se prescindirá o se utilizarán mal los conocimientos científicos. Se aboga en este trabajo por el empleo de Sistemas geoespaciales de apoyo a la toma de decisiones, para el análisis territorial cuantitativo. Para evitar el vacío existente entre la ciencia y la sociedad pueden utilizarse los métodos y herramientas científicas de las ciencias naturales y sociales integradas en Sistemas de Información Geográfica que respondan a las necesidades de los centros de decisión. Se han desarrollado Sistemas geoespaciales de toma de decisiones para que profesionales no especialistas puedan plantear escenarios para evaluar los hipotéticos resultados de sus decisiones políticas o de gestión. Con este enfoque, los gestores pueden evaluar las consecuencias geográficas, financieras y sociales de sus potenciales opciones. Se exponen casos concretos de uso de estos sistemas geoespaciales, basados en la información científica disponible, para la mitigación de riesgos y la investigación minera, pudiendo ser también utilizados para preservar la calidad del aire o de las aguas, la biodiversidad del planeta y promover una ordenación territorial. Con estos ejemplos se demuestra los beneficios de la utilización del conocimiento científico integrado en los Sistemas geoespaciales para la toma de decisiones políticas y administrativas. Así mismo se muestra cómo la inversión en investigación científica reduce el riesgo en la toma de decisiones y cómo la reducción de la incertidumbre produce un claro beneficio económico.

Palabras clave: análisis coste-beneficio, modelos SIG, riesgos geológicos

Introduction

People frequently regard the landscape as part of a static system studied by geologists and other scientists. The mountains and rivers that cross the landscape, and the bedrock that supports the surface, change little during the course of a lifetime. However, through our use of land and resources, society can alter the landscape very quickly and affect the occurrence and impact of specific environmental events (Bernknopf *et al.*, 1997). For example, changes in land use can induce changes in the impacts of: sedimentation on water clarity and quality, splintered natural habitats on biodiversity, and earthquakes on built environments. With the increased complexity of societal decisions, need has arisen for a user-friendly decision support tool to analyze environmental policy issues. Fortunately, an abundance of natural scientific and socioeconomic information, and the number of stakeholders with conflicting interests, now makes this possible.

This paper outlines an approach to and provides an example of a quantitative policy and risk analysis in a Geographic Information System (GIS). The Geospatial Decision Support System (GDSS) is a map-based descriptive model founded on the principles of microeconomics and statistical decision theory. Its goals are to characterize the nature of adverse or beneficial effects of an environmental change at regional scale and to produce quantitative estimates of: (1) the probability of an environmental change, (2) the expected consequences to individuals, communities, and/or industries, i.e., the hazard risk, and (3) the uncertainty associated with hypothetical scenarios, i.e., the decision risk. The GDSS relies on expertise from a mixture of disciplines including: earth and other natural sciences, ecology, economics and other social sciences, geography, and statistics.

A Geospatial Decision Support System as a Decision Framework

There is considerable scientific uncertainty about natural processes in space and time, such as a natural disaster striking a community or the discovery and extraction of mineral deposits. Scientific uncertainty impacts both economic and social decisions. That is, scientific uncertainties affect our ability to implement the "best" policies and programs to reduce the severity of disasters or to minimize the environmental impacts of land-use decisions. Thus, individuals, communities, and industries must make decisions in an uncertain economic and social environment based on their perceptions of the outcome of a hazardous event, exploitation of a resource, or land management choice.

The GDSS approach to policy and risk analysis is an application of the expected utility framework and assumes that choice is based on the notion that society favors some positive level of return on investment. It has been developed to evaluate the societal impacts of specific, yet hypothetical, policy and management choices that impact communities. The GDSS approach consists of the following parts:

(1) Estimate a physically based stochastic model - the probability of the occurrence of an event is estimated with scientific variables along with the uncertainty inherent in these estimates. The earth science input of an environmental change is:

$$p = p(s|t) \cdot p(t) \tag{1}$$

where p is the probability of an environmental change, $p(s|t)$ is the conditional probability of the geographic distribution of an environmental change, and $p(t)$ is the probability of recurrence of an environmental change.

(2) Develop a map-based linkage of the human-physical environmental interface - the outcome for a parcel of land depends on site specific and regional factors that are used to assign probabilities for an environmental change. The probabilities are combined with information on the built and natural environment in the GIS. With the scientific data quantified, the policy application can proceed.

(3) Apply a model for decision making under uncertainty - the probability of environmental change is input to a decision framework for a risk assessment. The probability can be used to communicate regional-scale risk. The expected utility hypothesis is assumed to represent behavioral preferences. The expected utility hypothesis states that people choose among alternative actions to maximize the probability-weighted sum of utilities under each of the possible contingencies (Weimer and Vining, 1992). The specific expected utility model that is applied approximates risk as an expected economic value and its standard deviation (Sinn, 1983):

$$U = U(\mu, \sigma) \tag{2}$$

where U is utility or level of satisfaction that an individual derives from a specific economic outcome, μ is the expected value of an economic outcome or $E(V_i)$, $i = 0, \ldots, I$ alternative policies, and σ is the standard deviation of an outcome or its decision risk $\sigma(V_i)$. The economic outcome or wealth, V, is assumed to be equal to the program investment plus the land-use values at risk in the community. The investment budget available could come from several sources, including the individuals, taxes, loans, or other external income transfers (such as grants from public programs).

(4) Incorporate a management model to represent tradeoffs in the economic analysis. Investment choice requires a decision rule as a preference for one outcome over another as a guide. The GDSS uses the rule:

$$\begin{gathered} A \text{ policy is preferred if}: \\ p(V_1) > p(V_0) \text{ and } \sigma(V_1) < \sigma(V_0) \end{gathered} \tag{3}$$

Economic theory states that a decision maker can use the expected value and standard deviation to select which policy is most preferred (Sharpe, 1970). Even though investors may have different risk attitudes, it is generally agreed upon that an outcome with a higher expected value is a positive attribute, while a greater standard deviation (decision risk) is a negative attribute.

Policy and Risk Analysis

The world is a complex system and decision makers can expect to make errors. Our theories about human behavior are not powerful enough for us to have great confidence in most of our scientific and socio-economic predictions. Changing economic, social, and political conditions can make even initially accurate predictions about the consequences of adopted policies become highly uncertain as time elapses. Most issues arise from decisions concerning:

- *The built environment and economic efficiency:* For example, what motivates a community to develop a risk assessment to minimize the impacts of a disaster? How many existing institutions, such as markets, can be used to provide the most efficient allocation of the risks associated with geologic processes? How do we prepare for disaster and deal with the fallout of disaster? What types of markets would work best when risks are connected and collective? Who and how much is society willing to pay for the uncertain payoff of loss avoidance? How will governments coordinate preparedness, disaster mitigation, and recovery?
- *The distributive impacts and societal equity:* Different segments of the population are affected in dissimilar ways. There is considerable disparity of the effects of a policy decision on local communities. For example, should mitigation and emergency preparedness vary depending on how much is contributed to the tax base by an individual, or should society be blind to which income group receives assistance? Where and how much emergency services should be provided to the homeless? What types of emergency assistance should be provided by the public sector?

Decisions regarding natural hazards policy and management issues involve all of the above questions.

Evaluating Regional Hazard Mitigation Management Policies in Watsonville, California

The study area for the quantitative policy analysis is Watsonville, California, a small, coastal town shown in Figure 1. Watsonville is located approximately six kilometers from the San Andreas fault system and is subject to multiple earthquake-related hazards including strong ground shaking, landslides, and liquefaction. Although a relatively minor hazard in terms of the total economic losses caused by the 1989 Loma Prieta earthquake (M 6.9) in this coastal region, there were 360 lateral spread failures documented and mapped locations documented (field validated (Lunetta *et al.*, 1991) and mapped (all data collected is at one scale and by accepted scientific protocols) by USGS geologists of, a type of ground liquefaction, in the region surrounding Watsonville. This area was chosen as a case study because of the availability of information related to the Loma Prieta event. This example is adopted from Bernknopf *et al.* (2006).

Hazard Characterization

Different interpretive methods of classifying locations by their susceptibility to lateral spread, namely an expert (earth scientist), a statistical model (rank order probit statistical regression), and an artificial intelligence model (probabilistic neural network), result in distinct hazard-zone patterns (Figure 2). These patterns reflect predicted locations of site failure for three frequencies of hazard zones, where higher hazard zone classifications suggest a greater risk of ground failure. This classification of predicted site failures for each hazard zone, in turn, results in different conditional probabilities of failure for each hazard class relative to the actual failures that occurred in the area during the 1989 Loma Prieta earthquake.

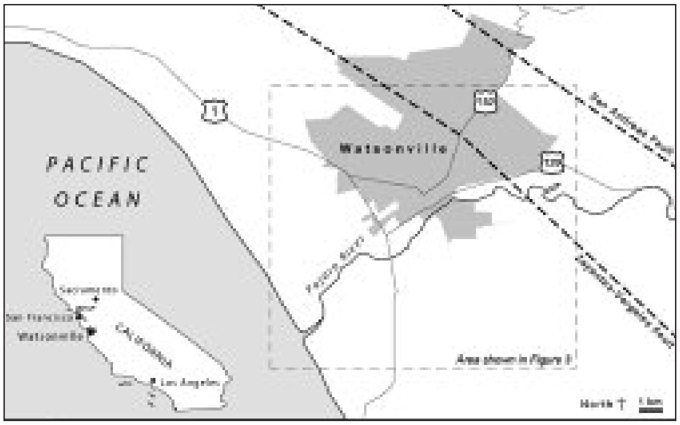

Fig. 1. Study area map of *Watsonville, California. The dashed box delineates the area of analysis in Figure 2*
Fig. 1. Mapa de la zona de estudio en Watsonville, California, con indicación del área de estudio de la figura 2 (recuadro de línea discontinua)

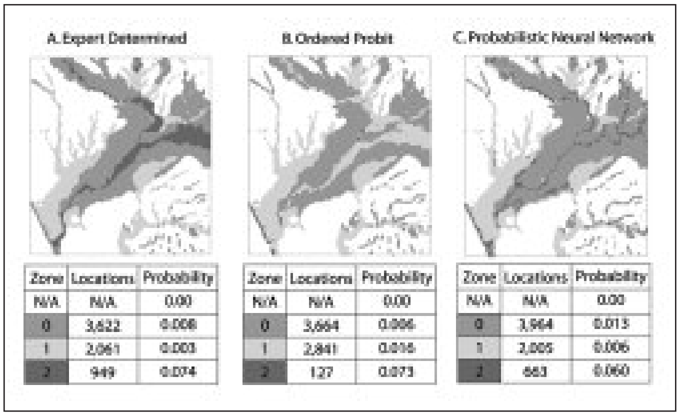

Fig. 2. Three approaches for classifying susceptibility to lateral-spread ground failure near Watsonville, California
Fig. 2. Tres aproximaciones de clasificación del terreno según su susceptibilidad a la propagación lateral de rotura del suelo cerca de Watsonville, California

Given that we cannot contrast the three hazard susceptibility maps currently developed to the true site failures that will occur from some future earthquake, we compare both of the numerical hazard susceptibility approaches to the map based on expert judgment to assess which method best reproduces the expert's assessment, which for the purposes of this comparison is assumed to be the most correct. In general, the maps suggest that differences between the probabilistic neural network and the expert were greatest at the extremes of hazard zone classification, meaning the greatest amount of dissention occurred where one method assigned a location to hazard zone 0 (lowest risk) while the other classified it as zone 2 (highest risk). Dissention was also evident between the rank order probit statistical regression and the expert, but was greatest between the classification of hazard zones 1 (moderate risk) and 2 (high risk).

A Cramer's V test, a measure of association for nominal data, was applied to compare the hazard classifications of the three methods. This statistic is roughly analogous to a correlation coefficient, with 0.0 being no association and 1.0 being a perfect match. For the data in the Watsonville case study, the rank order probit statistical regression had a V = 0.68, while the probabilistic neural network had a V = 0.59. Therefore, the rank-order probit statistical regression was more closely associated to the expert analysis.

Policy Analysis

After showing that the three different lateral spread susceptibility approaches produce three distinct hazard patterns in the GIS, the next step is to evaluate the impact of these hazard model variations on the assessment of three hypothetical mitigation policies. The three policies include: (1) a no mitigation decision rule, i.e., the status quo where there is no publicly funded mitigation, (2) mitigation of all locations in the highest hazard zone, and (3) mitigation of all residential land use locations. Using the GDSS, estimates were calculated for total investment cost, number of locations mitigated, mean and standard deviation of expected post-event total community wealth, and total expected loss under each policy using each of the three available hazard inputs (Table 1).

Under Policy 1, expected losses from lateral-spread in the Watsonville community in another Loma Prieta-like event are estimated to range from \$3.65 to \$4.98 million (US), depending on the hazard model used for the analysis (Table 1). The example points out a critical finding of the comparison: not only does the number of locations in each zone differ but the exact locations differ, and this difference will impact assessment of any policy that uses hazard zones to target mitigation.

Because Policy 2 proposes to mitigate the highest hazard areas (Zone 2) and therefore uses the hazard maps in its strategic design, the availability of the three different science models has the effect of making the estimate of the total cost and number of locations impacted less certain. The cost of Policy 2 is estimated to range from \$3.12 million to \$8.69 million (US) and the number of locations which would be protected varies from 99 to 562, depending on which hazard model is applied. Deciding upon which hazard model is not clear-cut, as the rank order probit statistical regression suggests the lowest number of mitigated locations but the expert's model yields the lowest expected losses.

Policy 3 targets mitigation of only residential land uses. Results suggest that such an approach would involve mitigating an estimated 722 locations at a cost of $55.54 million, regardless of the hazard method applied (Table 1). An additional factor associated with this policy is the relatively lower uncertainty in expected wealth.

In addition to differences in number of mitigated locations and expected wealth, the different science interpretations also create uncertainty in the estimates of the reduction in expected loss that is achieved by each policy. Figure 3 depicts the post-event total community wealth statistics by policy and hazard classification, without consideration of policy cost. From inspection of Figure 3 and Table 1, either mitigation policy is preferable to the status quo according to the mean-variance choice framework. Based on these and other factors listed in Table 1, the risk-benefit argument could be made that the most efficient decision, regardless of investment cost, is to implement the land use decision rule (Policy 3) that employs the rank-order probit statistical regression. This choice identifies the maximum expected post-event total community wealth of $979.6 million and smallest standard deviation of community wealth of $2.28 million. However, there is enough of an overlap between policies 2 and 3 to create a choice ambiguity among the multiple methods available to determine the preferred policy.

When policy investment budgets are considered, the policy preference ranking is clearer. Policy 3 costs significantly more (approximately 6 to 18 times more) and yet mitigates only 1.2 to 7 times the number of locations. Taking into account the mitigation investments, the hazard zone decision rule (Policy 2) is preferred over all other policies having expected net post-event total community wealth between $969.09 million and $975.69 million. Policy 2 eliminates expected losses more cost-effectively. This is evident in a comparison of the dollars spent per percent of predicted loss eliminated shown in Table 1. Clearly other, less economic policy-making priorities

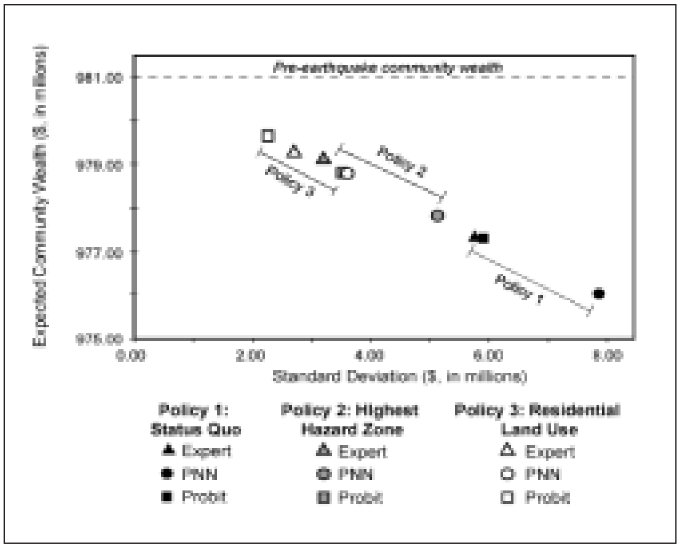

Fig. 3. Expected Community Wealth and Standard Deviation by Policy and Hazard Classification Method
Fig. 3. Riqueza comunitaria esperada y desviación estándar por el método de clasificación política y de riesgo natural

	Policy 1 Status Quo			Policy 2 Highest Hazard Zone			Policy 3 Residential Land Use		
	Expert	**Probit**	**PNN**	**Expert**	**Probit**	**PNN**	**Expert**	**Probit**	**PNN**
Mitigation Investment Budget ($, millions)	0	0	0	$ 8.65	$ 3.12	$8.69	$ 55.54	$ 55.54	$ 55.54
Locations Mitigated	0	0	0	562	99	431	722	722	722
Expected Wealth ($, millions)	$977.30	$977.30	$976.00	$979.04	$978.81	$977.78	$979.30	$979.60	$978.78
Wealth Std. Dev. ($, millions)	$5.84	$5.86	$7.88	$3.23	$3.53	$5.16	$2.71	$2.28	$3.57
Total Expected Loss ($, millions)	$3.66	$3.65	$4.98	$1.93	$2.17	$3.20	$1.68	$1.38	$2.19
Mean Expected Loss Per Location	$950	$948	$1,293	$588	$577	$935	$535	$442	$701
Standard Deviation of Loss Per Location	$2,572	$3,318	$2,877	$934	$763	$1,532	$1,537	$1,256	$1,928
Percent of Expected Loss Eliminated	0	0	0	47%	40%	35%	54%	62%	55%
Dollars Spent Per Percent of Loss Eliminated (mil)	0	0	0	$ 0.18	$ 0.08	$ 0.25	$ 1.03	$ 0.90	$ 1.01

Table 1. Outcome statistics for three policies and three interpretations of scientific information for a regional mitigation portfolio
Tabla 1. Resultados estadísticos de tres políticas y tres interpretaciones de información científica para un plan de mitigación regional

such as protection of human safety may make the direct comparison of the net benefits of these policies more difficult, but this kind of assessment can provide decision makers with important alternate ways to compare their alternatives.

Conclusion

A quantitative and visual policy analysis was conducted with the Geospatial Decision Support System for two hypothetical mitigation policies for Watsonville, CA. Specific policy and management programs were selected and compared with the case of taking no public actions to prevent damage from lateral spread ground failure associated with a future earthquake. This policy comparison was conducted three times with different interpretations of the scientific data to assess the influence of variations in GIS-based hazard susceptibility mapping. Results presented here show that the three methods of classifying locations into hazard zones affect the hypothetical policy outcomes and influence which policy would be most preferred. Three implications emerge from this analysis: (1) a mitigation policy to reduce earthquake losses would be preferred to the status quo, (2) the type of earth science interpretation significantly influences regional risk assessments and subsequent mitigation analysis, and (3) a mitigation policy investment budget can alter the preferred choice in the risk assessment.

Given the way in which society considers risky choices, there now is a way to communicate both spatial and temporal information so that we can compare and evaluate the efficiency and equity of potential policy and management strategies. The objective of the GDSS is to characterize the nature of the effects of societal decisions on the natural and built environments to examine alternative policy and management measures in a community context. It provides stakeholders with a decision framework to examine different policies and projects and to help identify feasible and cost-effective regional solutions. The GDSS is an objective way to analyze spatially specific investment opportunities in a community.

Analytical applications of GIS can be useful in regional risk assessments, as they can accommodate and assess several types of uncertainty at the same time, both about the spatial distribution of an environmental change in a community and the distribution of potential benefits from spatially specific investments. By addressing the concept of uncertainty in policy analysis -how likely a payoff is to occur- the model presented here provides the decision maker with an important additional metric when comparing alternative risk allocation rules and strategies.

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