Chapter 17 Assessment of Human Vulnerability and Risk of Flood Hazards in Orissa, India

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Abstract Odissa, which is one of the eastern coastal states of India, is affected by frequently recurring flood hazards, many of which have turned out to be disastrous. These floods have often brought large-scale human casualties as well as loss of property for the state. This paper aims to develop and test a set of models to assess the risk of human casualty of the flood hazards at the district level using multivariate linear regression analysis. This method has been used to estimate the human casualty at the district level using the available human casualty and other socioeconomic data from the Government of Odissa, Census of India, and the United Nations Development Programme (UNDP). For this purpose, a number of explanatory variables are used and human casualty has been a response variable. The observed data show that the districts from the coastal regions have high human casualty and population exposure in comparison to other parts of the state. Relative vulnerability is high for the non-coastal districts because the exposed population is less in comparison to human casualties. Model-predicted human casualty shows a nonlinear relationship with recorded human deaths. Results conclude that flood is an extreme event of nature and that its impacts can be predicted with greater accuracy using the models shown in this chapter if the data can be used at microlevel, preferably from the blocks and villages.

Keywords Flood hazard • Human risk • Physical exposure • Relative vulnerability

17.1 Floods: Need for Vulnerability Analysis and Risk Assessment

Orissa is endowed with a large network of rivers with many catchments extending beyond the state. Most of these rivers drain to the Bay of Bengal through an extensive coastal and deltaic terrain flooded by the rivers and their distributaries

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following cyclonic rains during the rainy season (Sinha [1985\)](#page-15-0). There are frequent flash floods in the upper catchments of these rivers. The state has been recurrently affected by flood hazards, many of which have turned into disasters with widespread damage to property and loss of human life. Further, the impacts on livelihood and damage to housing and crops are also major concerns of the people and the state as well (Behera [2002\)](#page-14-0).

This chapter describes some methodological aspects of the application of the Disaster Risk Index (DRI), a concept used in the World Disaster Report 2004 (UNDP [2004\)](#page-15-1) to improve understanding of the relationship between development and disaster risk. The major assumption behind the DRI was that differences of risk levels faced by countries with similar exposures to natural hazards are explained by socioeconomic factors, that is, by population vulnerability. It can allow measurement and comparison of relative levels of risk, exposure to hazards, and vulnerability at different spatial levels. The DRI can also contribute more quantitative evidence for planning and decision making in the field of disaster risk reduction and management (Dao and Peduzzi [2004\)](#page-14-1). The findings of this study can be a useful proposal for development of more effective hazard management policies, programs, and strategies in the state. This chapter aims at the evaluation of the flood hazard risk of Orissa at the district level using data on exposed population, various socioeconomic indicators, and past human casualties.

17.2 Conceptual Framework and Methodology

A statistical analysis was carried out to identify the socioeconomic indicators reflecting human vulnerability to flood hazards. The final output includes a set of indicators for measuring levels of risk, an evaluation of the population exposed, and the identification of socioeconomic parameters for estimating human vulnerability to flood hazards. The study has been taken up in four distinct stages of 'hazard analyses,' 'human impact analysis,' 'relative vulnerability and disaster risk index analyses,' and prediction of human risk' through multiple regression models. The multiple regression analysis has been undertaken identifying impact indicators and development indicators. The major components, data, methodology, and the possible outcome of the study are discussed next.

17.2.1 Risk of a Hazard

Following a definition by the United Nations, risk "refers to the expected losses from a particular hazard to a specified element at risk in a particular future time period. Losses may be estimated in terms of human casualty, or buildings destroyed or in financial terms" (UNDRO [1979;](#page-15-2) Burton et al. [1993](#page-14-2), p. 34). Hazards are extreme events that may create risk and potentially turn into disasters if the exposed elements are vulnerable. The risk can also be measured in terms of loss of livelihood or in economic terms. However, such data are not available from the affected areas, even at the lowest spatial level of villages and blocks.

17.2.2 Study Area and Database

The present study is taken up for the state of Orissa, which comprises 30 districts. The data on flood hazards of the state are collected from the secondary sources of the Government of Orissa. The available data on flood hazard characteristics include the frequency and time of occurrence, affected population, loss of human life, loss of public property, houses collapsed and damaged, loss of crops, and area affected. The study is based on these data of the flood hazards for a period of 10 years from 1998 to 2007 (Government of Orissa [1992](#page-14-3), [1999,](#page-14-4) [2008\)](#page-15-3). These data are considered fairly reliable because of their consistency, collection through the public system, and the utility to support relief operations and their use in the disaster mitigation and management activity of the state. The socioeconomic data at the district level have been collected from the census organization, that is, the office of the Registrar General of India, Bhubaneswar.

17.2.3 The Choice of Risk Indicators

In this study, the choice of risk indicators is made from among the available disaster impacts. Loss of property, loss of crops, loss of domestic animals, area affected, or damage to houses do not reveal the magnitude of total loss of a geographic unit in a flood because of variation in their units of representation. Hence, the number of human casualties is chosen, which is less dependent on subjective evaluations. It is generally accepted that the loss of life is the most critical indicator of a disaster. When the total number of lives lost is considered, certain districts such as Ganjam, Baleswar, Kalahandi, and Cuttack always remain at the top of the list of the areas at risk. Rather, the number of human lives lost per exposed population generally gives a higher rank to the less-exposed and low-density districts. In the DRI, that is, the number of human beings who lost their lives per exposed population represents the relative risk faced by each district, whereas figures on total population killed highlight the districts facing severe impacts, emphasizing the need for disaster mitigation and management.

17.2.4 Modeling Risk of Flood Hazards

According to the UNDRO definition (UNDRO [1979](#page-15-2)), the risk of losses of a hazard results from three components: hazard occurrence, elements at risk, and vulnerability. In case of risk of death, the elements at risk are the exposed population. The hazard occurrence refers to the frequency of a hazard of a return period of a given magnitude, whereas the vulnerability is "the degree of loss to each element should a hazard of a given severity occur." If the hazard frequency or the population vulnerability increases, then risk will be augmented accordingly. Assuming that the risk follows a multiplicative function, the equation for estimation of risk is

$$
R = H * Pop * Val
$$
 (17.1)

where $R = i$ is the risk (measured in terms of people killed/year or property lost/year) $H =$ hazard [characterized by its magnitude and frequency (event/year)] Pop = population living in a given exposed area (population affected/event) Vul = vulnerability depending on socioeconomic factors (no units).

In computing the DRI (Disaster Risk Index), the combination of frequency of a hazard and its exposed population is called physical exposure: this is the average number of people exposed to a hazard per year. Hence, the formula 1 (Eq. [17.1](#page-3-0)) for risk can be simplified as follows:

$$
R = PhExp * Val
$$
 (17.2)

where $R =$ risk of human life lost and Vul = population vulnerability Ph. Exp = average number of people exposed to a flood hazard per year.

Using the foregoing equation, the relative vulnerability can be calculated as follows:

$$
Vul = Risk / PhExp
$$
 (17.3)

17.2.5 Relative Vulnerability and Disaster Risk Index (DRI)

The Disaster Risk Index, which was developed by UNDP, is a mortality-calibrated index that measures the risk of death in a disaster. It is a function of physical exposure and vulnerability to a hazard. People are more or less vulnerable to a hazard depending upon a range of social, economic, cultural, political, and physical variables. The number of deaths is used as a proxy to manifest risk because of nonavailability of other aspects, which can represent the total disaster risk. Using this index, the DRI therefore is able to calculate the relative vulnerability of the districts by dividing the number of deaths by the number exposed. When more people are killed with

respect to the number exposed, the relative vulnerability of a district is higher. Using Eq. [17.3,](#page-3-1) the relative vulnerability of the districts for flood hazards is calculated by using the past data on human casualties and affected population, which represent the physical exposure. The number of deaths of people caused by floods per millions of exposed population is called the DRI (Disaster Risk Index, Eq. [17.3](#page-3-1)©). The spatial pattern of disaster risk reveals that districts such as Mayurbhanj, Gajapati, Nawarangapur, Nawapara, Jharsuguda, and Sundargarh show higher values and come under the high and very high disaster risk index because of low exposed population. The coastal districts, which are traditionally flood prone, show low DRI because of higher number of exposed population in comparison to number of deaths.

17.3 Characteristics of Flood Hazards in Orissa

17.3.1 Frequency of Flooding

Being primarily caused by natural factors and often induced by human activities, Orissa (Odisha) is perpetually affected by flood hazards and disasters. The flood data for the period 1998–2007 indicate there has been no year without floods in Orissa except 2002. The number of flood incidents varied from two to four in a year (Fig. [17.1](#page-4-0)). During 1998–2007, there were more than two flood incidents per year during 1998, 1999, 2003, 2005, and 2007. The coastal and deltaic areas are most vulnerable to flooding because of their dense network of rivers and their distributaries. When the Orissa Coastal Zone is affected by floods, their impacts are felt not only on the economy of the region, but also on the entire state, because it is the "rice bowl of the state" (Panda [1989](#page-15-4)).

Fig. 17.1 Annual distribution of floods, 1998–2007, Orissa

17.3.2 Economic Impact of Flooding

17.3.2.1 Loss of Life and Property

The annual average property loss of the state caused by floods was Rs 7,053 million during 1998–2007. From 1981 to 2000, the state had spent nearly Rs 1, 000 million alone on relief against the tenth finance commission's assessment of the relief expenditure of Rs 140 million. In 1982, the state experienced the highest flood of the century, affecting an area of 34,000 km2 , and the loss of property at 1981–1982 prices was Rs 2,140 million. The state suffers an annual average crop loss of Rs 1,277 million. Annually, $1,720 \text{ km}^2$ of area in the state is affected by floods. During 1998–2007, the number of fully collapsed houses was 83,510. Although most of these houses were made of mud walls and straw thatching, some were built with brick walls and tile roofs. In spite of the prevalence of the hazard, the affinity of the people for the coastal and deltaic tracts and flood plains has continued unabated, partly because of the geographic inertia of settlements growing through peripheral accretion, reasons of socioeconomic compulsion, and as an environment of persistent appeal. The spatial pattern of human casualties in the state caused by floods can be seen from Fig. [17.2.](#page-5-0)

Fig. 17.2 Human deaths from floods, Orissa, 1998–2007

17.3.2.2 Population Affected and Vulnerability Pattern

About 3.5 million people in the state are exposed every year to floods, with a total of 483 deaths for the period 1998–2007. The number of people marooned during this period of 1998–2007 was 2.7 million. Despite massive expenditure on flood control and management, flood losses are continuing to rise (Suri [2000\)](#page-15-5). Nearly 14 % of Orissa is prone to floods as per the Vulnerability Atlas of Orissa (BMTPC [2006](#page-14-5)). The coastal districts are eternally vulnerable to flooding. However, based on the current flood impact data, the vulnerability is spreading toward the western and southern districts of Rayagada, Bolangir, Sonepur, Sambalpur, Kalahandi, and Kendujhar, which are away from the coast (BMTPC [2006\)](#page-14-5). The population affected by floods has varied from 0.6 to 7.6 million from 1998 to 2007. As more and more densely populated and flood-prone areas are coming under the grip of the floods, the number of people affected by floods has increased significantly since 2001 (Fig. [17.3\)](#page-6-0).

Fig. 17.3 Population exposed per year to floods, Orissa, 1998–2007

17.3.3 Causes of Flooding

The floods in Orissa result from heavy cyclonic and monsoon rainfall over the catchments of its rivers (Disaster Management Institute [1988\)](#page-14-6). Because of interlinkage among the rivers in their lower reaches, the flood from one river passes on to the other rivers. When the floods occurring in all the major coastal rivers coincide, the devastation becomes catastrophic (Mahalonobis [1941\)](#page-15-6). The Orissa Coastal Zone experienced such floods in 1982, 2001, and 2003. Flash floods are associated with the sub-montane tracts and the Eastern Ghats region of Orissa. In 1989 the Rushikulya River was flooded by a cyclonic rain of 40 cm in 1 day in its catchments, affecting the Ganjam District. Today these situations are experienced more in the coastal districts where poor drainage outlets create waterlogging and prevent the discharge of rainwater (Fig. [17.4\)](#page-7-0).

Heavy rainfall in the interfluves of the Mahanadi delta and coastal backshore zone leads to the ponding of rainwater in depressions and low-lying areas. A high groundwater table also contributes toward this type of flooding. Extensive areas of the lower fluvial plains in the deltaic and coastal region, associated with the meandering channels, tidal creeks, Zora or Pata Lands (low-lying areas), oxbows,

Fig. 17.4 Orissa: Disaster Risk Index for floods

and back swamps, are affected by this type of flooding, which is more prevalent in the districts of Bhadrak, Kendrapara, Jagatsinghpur, and Puri. The Orissa coast is frequently ravaged by the landfall of tropical disturbances. The storm surges push the seawater to a few kilometers inland along the creeks and river mouths, resulting in tidal flooding damaging the crops and contamination of groundwater, and often sweeping away the villages. The spatial spread of this zone varies from 5 to 15 km during depressions and storms, whereas high storm waves in the range of 2 to 3 m sweep inland to a distance from 20 to 25 km during severe storms and cyclones.

17.4 Modeling Human Risk of Flood Hazards

It is now a globally accepted paradigm that the nature of vulnerability and the magnitude of risk are intimately connected to poverty. The poor have been the most vulnerable and their level of risk to natural hazards is relatively high. It is presumed that poverty can contribute to enhancing the disaster risk with lesser capability to recover quickly and recoup the damages inflicted on the people (UNDP [2009](#page-15-7)). Based on the presumption that poverty contributes toward greater disaster risk, the chosen socioeconomic indicators were reflective of poverty and status of development.

17.4.1 Socioeconomic Factors Associated with the Risk of Floods

Orissa is an agrarian state where a large part of the total population lives below the poverty line (49 %). Of the people, 38 % belong to the Scheduled Caste and Scheduled Tribes (SC/ST). The majority of the population is engaged in agriculture, the predominant economy of the state. As per working classification, the population engaged in primary economic activities such as forestry, fishing, hunting, agriculture, and mining comprises nearly 70 % of its people. The level of urbanization is relatively low (16 %) in comparison to the national average, and literacy of the state is 68 % (Director of Census Operations [2005](#page-14-7)). The people living in kutcha houses (houses with mud walls and straw-thatched roofs) vary from 65 to 85 % across the districts. People living in such houses are often the most vulnerable because of the risk of death from the collapse of their homes. Thus, while choosing the independent variables that may configure disaster risk in Orissa, choice is based on the premise that poverty is the overriding factor. Flood hazards are noted for aggravating poverty in two ways: through destruction of food stocks and the meager assets of the poorer households, and through loss of livelihood, making employment opportunities scarce. Poverty is directly linked to the poor household infrastructure, which makes them more vulnerable to flood damages.

In Orissa the people suffer more from wage loss because both farm and non-farm employment opportunities are reduced after a major flood. They own fewer assets to cover the expenditures needed during the disaster and the recovery phases. The poor people depend on borrowing, principally from moneylenders, and face difficulty in buying food because of decreased income and increased prices. They suffer relatively more from diseases and malnutrition. The compounding effect of closely following disaster shocks or concurrent disaster and non-disaster shocks on the poor contributes to increased poverty in the hazard-prone areas. The flood hazards destroy the local food security mechanisms temporarily. The poorer households usually settle on less desirable high-risk marginal land and are unable to afford disaster-proof housing. Consequently, they are compelled to lose their basic investments in housing infrastructure after a disaster. They have lesser access to the social and economic support needed for recovery. The socially marginal groups, such as the Scheduled Tribes (STs) and the Scheduled Castes (SCs), are more adversely affected than the other castes because of their higher incidence of poverty.

Further, people with low income have less command over their resources to handle disasters. Literacy is extremely important for disaster preparation measures. Hence, lower literacy levels are reflected through higher vulnerability to disasters. In the Indian situation, when income (at the district, state, and national level) does not translate into poverty alleviation, achievements in human development are extremely important in improving access to various opportunities in life and thereby reducing poverty and vulnerability. Hence, the Human Development Index (HDI) can represent poverty and vulnerability more than income ($P \& C$ Department [2006\)](#page-15-8). The higher the HDI values, the higher is the ability to face disasters successfully. Pucca houses (burnt brick and concrete) provide greater protection during floods and also present the possibility of saving lives during submergence. Kutcha houses, made of mud walls with wooden support and straw thatching, provide little or no protection. Pucca houses provide the possibility of overcoming disaster impacts much faster and can withstand flood hazards, but kutcha houses enhance vulnerability and risk. Keeping all these factors in mind, the following independent variables were chosen, at the district level, to explain disaster risk: the Human Development Index (HDI), percentage of BPL (below poverty line) population, population density, percentage of SC and ST population, literacy, percentage of population under primary economic activities, and percentage of households living in kutcha houses.

A multiple correlation between DRI and the aforementioned variables was carried out taking their log-normal values (Chow [1964](#page-14-8)). The conversion of data to the log-normal form was to reduce their variations. The multiple correlations reveal that DRI shows a positive correlation with BPL population, primary workers, SC and ST population, and percentage of kutcha houses. However, the '*r* value' is only significant for the SC and ST population at a 99 % confidence limit. There is negative correlation with affected population, literacy, population density, and HDI, of which the first three are significant at a 99 % confidence limit. The affected population, population density, and literacy show negative correlation because the DRI is high in the districts where deaths reported for floods have occurred with a very low exposed population.

17.4.2 The Multiple Regression Model

Multiple logarithmic regression models are used with district-level data to study the human risk of flood hazards and disasters against a grouping of socioeconomic attributes that define disaster risk. The socioeconomic variables as discussed earlier, that is, the Human Development Index (HDI), percentage of BPL population, population density, percentage of population belonging to SC and ST, percentage of literates, percentage of population under primary workers, and percentage of households living in kutcha houses, are taken as a set of independent variables and DRI as the dependent variable. To reduce diversity in the variance of different independent variables and change over time, their log values have been considered and the following general model is used:

$$
R = A_1 X_1 + A_2 X_2 + A_3 X_3 + \dots + A_n X_n + C \qquad (Model 17.1)
$$

where *is the dependent variable*

 $X_1, X_2, X_3, \ldots X_n$ are the independent variables

 $A_1, A_2, A_3, \ldots, An$ are the multiple regression coefficients

'*C*' is the residual that follows normal distribution with mean 0 and variance 1.

The output of the models is assessed based on the value of $R²$. To work out the different models, stepwise regression has been considered eliminating the least significant variables at each step of the analysis. The eight different models based on this step are given in Table [17.1](#page-10-0) along with the values of *R* and *R*² .

17.4.3 Analysis of Results

The first model uses eight independent variables to predict the DRI. The value of *R*² is 0.56; that is, the model with all eight variables explains 56 $\%$ of total variability for human risk. There seems to be high multicollinearity among the independent

Method	Model	R	R^2	Adjusted R^2	Standard error
Enter/remove/backward		0.75	0.56	0.39	0.67
Backward	2	0.75	0.56	0.42	0.65
Backward	3	0.75	0.56	0.44	0.64
Backward	$\overline{4}$	0.74	0.55	0.46	0.63
Backward	5	0.73	0.53	0.46	0.63
Backward	6	0.72	0.51	0.46	0.63
Backward	7	0.69	0.47	0.43	0.65
Backward	8	0.65	0.43	0.40	0.66

Table 17.1 The different multiple logarithmic models and their corresponding values of R , R^2 , adjusted R^2 , and the standard error of the estimate

variables, which suggests either looking for other appropriate variables or removing some of the variables in subsequent models. In the second model, the backward regression method is applied with seven variables, removing literacy, which was least correlated (Table [17.2\)](#page-12-0). Although the values of *R* and *R*² are the same, adjusted *R*2 improves, which suggests that literacy does not have any significant role in predicting human risk. The third model is similar to the second except that six variables are used, removing HDI. It is observed that the value of $R²$ remains unchanged, but the adjusted R^2 improves to 0.44. In the fourth model, five variables were used, taking out primary workers; the value of R^2 is 55 % compared with 56 % in model 3, but adjusted R^2 improves. In all the other four models, the values of R and R^2 decrease. The foregoing models show the importance of different independent variables in explaining the variability in human risk based on the value of R^2 , which varies from 56 % to a low of 43 %.

A review of the regression coefficients in the first model reveals that human casualty increases with increase in affected population, which is significant at the 99 % level of confidence (Table [17.2\)](#page-12-0). Although not significant, the higher the illiteracy, the greater is human death. A negative relationship exists between human death and the log of HDI, meaning that human deaths decrease with improvement in the HDI of the districts. As expected, human casualty is positively associated with the log of the density of population; the effect is significant at the 87 % level. When log of BPL population and log of kutcha houses are higher, human risk is decreased, showing significance at 33 % and 76 %, respectively, which reveals a contradictory situation, because a greater BPL population and more kutcha houses are likely to increase human risk in a flood.

Whenever primary workers and SC and ST population variables are higher, human risk is also high. These results are statistically significant at the 63 % and 92 % level of significance, respectively, possibly because they are a lower income group of people who normally dwell in vulnerable locations with greater risk of death and damage. Similar situations are found in the second and third models, taking out literacy and HDI. In order of their decreasing significance to explain human casualties, the variables are literacy, HDI, BPL population, primary workers, kutcha houses, population density, and SC and ST population. However, in the sixth model, which best explains the predictability of human casualties, these variables are affected population, population density, and SC and ST population. Using these models, human casualties as estimated for the districts are presented in Table [17.3](#page-13-0).

Of all eight models tested, adjusted R^2 is maximum in the fourth, fifth, and sixth (Table [17.1\)](#page-10-0) with 63 % of the standard error. The variables selected by the statistical analysis in this model are physical exposure, population density, and percentage of SC and ST population. The equation for the estimation of risk is as follows:

$$
\ln(R) = 0.50 \ln(Popln, Exp) + 0.46 \ln(Popln, Density) + 0.90 \ln(SC & ST Popln,) - 11
$$

		Unstandardized		Standardized coefficients		
		coefficients Standard error Beta				
	Model Variables			Beta	\boldsymbol{t}	Significance
$\mathbf{1}$	(Constant)	-6.79	10.23		-0.66	0.51
	Affected population	0.47	0.16	0.71	2.92	0.01
	Literacy	0.03	1.03	0.01	0.03	0.98
	HDI	-0.42	1.15	-0.09	-0.37	0.72
	Population density	0.66	0.42	0.49	1.58	0.13
	BPL population	-0.51	1.16	-0.09	-0.44	0.67
	Primary workers	0.94	1.02	0.24	0.92	0.37
	SC and ST population	1.06	0.59	0.58	1.81	0.08
	Kutcha houses	-1.14	0.95	-0.26	-1.21	0.24
$\overline{2}$	(Constant)	-6.72	9.69	$\overline{}$	-0.69	0.50
	Affected population	0.47	0.15	0.71	3.05	0.01
	HDI	-0.40	0.94	-0.08	-0.43	0.67
	Population density	0.66	0.40	0.49	1.63	0.12
	BPL population	-0.51	1.12	-0.09	-0.46	0.65
	Primary workers	0.93	0.94	0.24	0.98	0.34
	SC and ST population	1.05	0.50	0.58	2.10	0.05
	Kutcha houses	-1.14	0.89	-0.26	-1.27	0.22
\mathfrak{Z}	(Constant)	-10.08	5.61		-1.80	0.09
	Affected population	0.49	0.15	0.74	3.31	0.00
	Population density	0.63	0.39	0.47	1.61	0.12
	BPL population	-0.50	1.10	-0.09	-0.45	0.66
	Primary workers	1.02	0.90	0.26	1.13	0.27
	SC and ST population	1.12	0.47	0.61	2.40	0.03
	Kutcha houses	-1.12	0.88	-0.25	-1.28	0.21
$\overline{4}$	(Constant)	-11.59	4.43		-2.62	$0.02\,$
	Affected population	0.48	0.14	0.73	3.34	$0.00\,$
	Population density	0.68	0.37	0.51	1.82	0.08
	Primary workers	0.93	0.86	0.24	1.08	0.29
	SC and ST population	1.11	0.46	0.61	2.42	0.02
	Kutcha houses	-1.20	0.85	-0.27	-1.42	0.17
5	(Constant)	-9.01	3.74		-2.41	0.02
	Affected population	0.52	0.14	0.79	3.77	0.00
	Population density	0.46	0.31	0.34	1.46	0.16
	SC and ST population	1.08	0.46	0.59	2.35	0.03
	Kutcha houses	-0.69	0.70	-0.16	-0.98	0.34
6	(Constant)	-11.00	3.15	$\overline{}$	-3.50	0.00
	Affected population	0.50	0.14	0.75	3.65	0.00
	Population density	0.46	0.31	0.34	1.48	0.15
	SC and ST population	0.90	0.42	0.49	2.13	0.04
τ	(Constant)	-8.06	2.49	$\overline{}$	-3.23	0.00
	Affected population	0.57	0.13	0.86	4.42	0.00
	SC and ST population	0.55	0.36	0.30	1.54	0.13
8	(Constant)	-4.54	1.04		-4.38	0.00
	Affected population	0.43	0.09	0.65	4.55	0.00

Table 17.2 The different multiple regression models, beta coefficients, and their level of significance

HDI Human Development Index, *BPL* below poverty level

	Estimated human risk through different models									Observed
Sl. no.	District	M1	M ₂	M ₃	M ₄	M ₅	M6	M7	M8	human risk
$\mathbf{1}$	Anugul	0.69	0.69	0.66	0.68	0.72	0.67	0.79	0.98	1.70
2	Baleswar	5.06	5.04	4.70	5.46	4.87	4.71	4.18	3.41	4.60
3	Baragarh	1.32	1.32	1.26	1.25	1.24	1.44	1.47	1.38	0.70
$\overline{4}$	Bhadrak	2.64	2.64	2.54	2.80	2.52	2.77	2.52	2.55	5.10
5	Bolangir	1.78	1.79	1.70	1.68	1.87	2.11	2.46	2.06	1.60
6	Boudh	0.28	0.28	0.26	0.29	0.30	0.38	0.48	0.63	0.20
7	Cuttack	3.02	3.03	2.85	3.00	3.31	2.80	2.48	2.60	2.10
8	Deogarh	0.62	0.61	0.63	0.72	0.64	0.55	0.71	0.72	0.90
9	Dhenkanal	0.87	0.86	0.80	0.84	0.90	0.95	1.01	1.17	0.70
10	Gajapati	1.19	1.19	1.04	1.04	0.91	0.80	0.87	0.79	2.40
11	Ganjam	3.05	3.05	2.70	2.81	2.10	1.60	1.68	1.96	1.60
12	Jagatsinghpur	1.59	1.59	1.37	1.40	1.35	1.47	1.14	1.42	0.90
13	Jaipur	3.51	3.50	3.13	3.34	3.51	3.60	2.93	2.56	4.10
14	Jharsuguda	0.53	0.53	0.51	0.50	0.58	0.56	0.42	0.49	0.60
15	Kalahandi	1.15	1.16	1.15	1.16	1.00	0.98	1.02	0.97	1.10
16	Kandhamal	0.99	0.98	0.84	0.92	1.10	1.05	1.33	1.00	1.10
17	Kendrapada	2.26	2.26	2.14	2.21	2.18	2.62	2.63	2.79	3.40
18	Kendujhar	1.30	1.29	1.21	1.36	1.40	1.43	1.35	1.10	1.00
19	Khordha	1.01	1.01	0.91	1.07	1.46	1.26	1.01	1.39	0.90
20	Koraput	0.75	0.75	0.65	0.77	0.74	0.73	0.69	0.63	1.30
21	Malkangiri	0.89	0.89	0.76	0.84	0.87	0.91	1.05	0.79	0.50
22	Mayurbhanj	0.96	0.96	0.97	1.10	1.16	1.26	1.02	0.84	2.30
23	Nawarangpur	0.69	0.69	0.60	0.65	0.53	0.59	0.43	0.42	1.30
24	Nayagarh	0.70	0.70	0.63	0.70	0.72	0.71	1.01	1.37	1.10
25	Nuapada	0.88	0.89	0.87	1.02	0.99	1.02	1.15	1.04	0.20
26	Puri	1.84	1.84	1.74	2.00	1.92	1.95	2.08	2.40	3.80
27	Rayagada	1.36	1.37	1.23	1.31	1.36	1.31	1.41	1.04	1.70
28	Sambalpur	0.74	0.74	0.70	0.71	0.88	0.81	0.85	0.80	0.70
29	Sonepur	0.58	0.58	0.53	0.59	0.50	0.58	0.56	0.72	0.30
30	Sundargarh	0.84	0.84	0.84	0.91	0.89	0.78	0.65	0.62	0.40

Table 17.3 Estimation of risk of human casualty caused by floods using multiple regression models (M)

The regression shows that exposed population (*Popln.Exp*), SC and ST population (SC&ST Popln), and high population density (Popln.Density) areas are more subject to suffering casualties from floods. The estimated risk of death from floods as shown in Table [17.3](#page-13-0) indicates that the districts showing high risk are Baleswar, Bhadrak, Cuttack, Jaipur, Kendrapada, and Bolangir; the medium-risk districts are Bargarh, Ganjam, Jagatsinghpur, Kondhamal, Kendujhar, Khurda, Mayurbhanj, Nuapada, Puri, and Rayagada; and the districts showing low risk are Anugul, Deogarh, Dhenkanal, Gajapati, Jharsuguda, Kalahandi, Koraput, Malkangiri, Nayagarh, Nawarangpur, Sambalpur, Sonepur, Sundargarh, and Boudh.

Variance 1.15 1.14 0.97 1.21 1.04 1.01 0.78 0.64 1.77

17.5 Conclusion

This study has two main findings: the calculation of the average risk of death per district, and a set of indicators that point out the districts that are most at risk, vulnerable, and exposed to floods. Another important feature of the DRI is that it is based on the datasets with district-level resolution. The method used in this statistical analysis proved to be appropriate, and of the correlations observed among the data variables, physical exposure appeared to be the most significant factor leading to risk. In a sense this also validates the methodology developed for estimating the number of people exposed to flood hazards. The research has highlighted a relationship between higher level of development, higher literacy, and low casualties. This relationship can be understood in both ways: lower development may lead to higher casualties, or higher development may lead to lower casualties, but high hazard occurrence may also lead to lower economic development because it destroys infrastructures and crops.

Such models should not be used as predictive models when the precision of the data sources is not sufficient. A database with block-level resolution and risk defined in terms of monetary loss can be better substitutes for this exercise. The study indicates a need to improve the socioeconomic impacts of floods in terms of precision and completeness. There is also a need to improve data on hazard characteristics and exposure in addition to inclusion of indicators on disaster risk management and reduction. In the present study, DRI only measures the levels of risk and their associated factors, but not the actions taken to reduce risk. This study underlines the usefulness of continuing the improvement of data collection for a better identification of populations at risk.

References

- Behera A (2002) Creating sustainable and disaster resistant communities. J Gopabandhu Acad 1(1):32–34, Bhubaneswar
- Building Material and Technology Promotion Council (BMTPC) (2006) Vulnerability Atlas of India, first revision. Ministry of Housing and Urban Poverty Alleviation, Government of India, New Delhi
- Burton I, Kates RW, White GF (1993) The environment as hazard. Guildford Press, London
- Chow VT (1964) Hand book of applied hydrology: a compendium of water resources technology. Tata McGraw Hill Book Company, New York
- Dao H, Peduzzi P (2004) Global evaluation of human risk and vulnerability to natural hazards. Enviroinfo, Sharing, Editions du Tricorne, Genève
- Director of Census (2005) General population and housing table. Bhubaneswar
- Disaster Management Institute (1988) Flood control and management proceedings volume. Paryavaran Parisar, Bhopal
- Government of Orissa (1992) Cyclone advance preparation in Cuttack District. Unpublished report. Collectorate, Control Room, Cuttack
- Government of Orissa (1999) Flood and cyclone advance preparations in Jagatsinghpur District. Control Room, Collectorate, Jagatsinghpur
- Government of Orissa (2008) Annual reports of the Department of Revenue and Disaster Management. Bhubaneswar
- Mahalonobis PC (1941) Rainstorms and river floods in Orissa. I. & P. Department of Orissa, Bhubaneswar
- Panda GK (1989) Drainage and flood problems of coastal plain: a study in applied geomorphology. Ph.D. dissertation. Department of Geography, Utkal University, Bhubaneswar
- Planning and Coordination Dept. (P & C Dept.) (2006) Orissa human development report. Government of Orissa, Bhubaneswar
- Sinha BN (1985) Geography of Orissa. NBT Publications, New Delhi
- Suri S (2000) Orissa disaster, agony of the living. Jawahar Park, Laxmi Nagar, Hyderabad
- UNDP/BCPR (2004) Reducing disaster risk: a challenge for development. UNDP/Bureau for Crisis Prevention and Recovery, New York. <http://www.undp.org/bcpr/disred/rdr.htm>
- UNDP (2009) Preliminary presentations on world disaster report. Bahrain
- UNDRO (United Nations Disaster Relief Coordinator) (1979) Natural disasters and vulnerability analysis in report of expert group meeting (9–12 July 1979). UNDRO, Geneva