Operationalising Multidimensional Concepts of Chronic Poverty: An Exploratory Spatial Analysis

by

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I. Introduction

Spatial inequalities exist at all levels of disaggregation – between countries, states, regions, districts, blocks and even within cities, towns and villages. However, the nature and extent of these inequalities varies with choice of indicator and geographical space over which comparisons are made. A given state may perform extremely well on all indicators but there may be districts within that state that are among the most deprived in the country. Or a state may have very high levels of attainment on economic development and health and very low levels of attainment on education and gender parameters.

No single indicator can capture the complexities of development. Therefore, indices are generally estimated by aggregating performance with regard to several indicators. This requires the identification of variables to be included in the index, the range to be used for scaling and weights to be allocated to the different variables. Decisions in this regard tend to be arbitrary and driven by availability of data. Changes in any of these factors can yield very different results. In addition there is the issue of choice of method to be used in estimating the index.

The poor suffer deprivation in multiple ways: low levels of income, illiteracy, relatively high levels of mortality, poor infrastructure, lack of voice and poor access to resources such as credit, land, water, and forests. Human and gender development indices improve on income-based indicators as measures of well being by moving beyond income centered approaches to measuring development and incorporating capabilities such as *being* healthy or literate into the development index.

In this paper we briefly revisit some of the prior research by the authors with regard to the identification of states and regions that suffer high income poverty and multidimensional deprivation and methods of computing indices[1]. We then extend the analysis by using multidimensional indicators to analyse spatial variations in development outcomes for 379 districts in 15 states of India and then to 175 talukas (subdistricts) in the state of Karnataka. The paper tries to

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?? identify areas in chronic poverty at the district level by using multidimensional indicators that could reflect persistent deprivation, such as illiteracy, infant mortality, low levels of agricultural productivity and poor infrastructure.

?? operationalise multidimensional concepts and methods at the district and below level

?? identify patterns of development that can input into policy.

Section 2 identifies the states and regions of India that have experienced greater incidence of long duration or persistent poverty, severe poverty and multidimensional deprivation. Section 3 tries to identify the most deprived districts based on indices of multidimensional poverty using traditionally applied methods and compares the results with alternate more robust methods. Section 4 extends the analysis to the sub district level or Taluka level for the state of Karnataka. Section 5 stresses the importance for planners to decipher "patterns" of development and uses the Kohonen Self-Organizing Map, an artificial intelligence algorithm to do this. We then identify priority areas for state and civil society action and conclude the paper.

II. Spatial distribution of the Chronically, Severely and Multidimensionally Poor: A State level analysis

The incidence of poverty in India has declined continuously from 54.9 percent to reportedly 26 percent of the population and from 321.3 million to reportedly 260.2 million during the period between 1973-74 and 1999-2000 (Table 1).

Table 1: Incidence of Poverty in India – Percentage of Population and Number of People Below the Poverty Line 1973-74 to 1999-2000

Year	Percentage population below the poverty line	Number of poor (millions)
1973-74	54.9	321.3
1977-78	51.3	328.9
1983	44.5	322.9
1987-88	38.9	307.1
1993-94	36	320.3
1999-2000	26.1	260.2

Source: Planning Commission Draft Ninth Five Year Plan (1997-2002) and Government of India, Poverty Estimates for 1999-2000, Press Information Bureau, 22nd February, 2001.

Chronic poverty in the duration, severity and multi dimensionality sense characterises several parts of India. Earlier work shows that pockets of severe poverty exist at the regional level even in the more developed states. The proportion of the poor who suffer long duration and inter-generationally transmitted poverty is likely to be significantly higher in those parts of the country that suffer greater incidence of severe poverty and multidimensional deprivation.

Poverty over time

Those in poverty are unevenly distributed across the country with concentration of poverty in some states. 71.65% of India's poor and half of the population are located in six states. These are Uttar Pradesh (including Uttaranchal), Bihar (including Jharkhand), Madhya Pradesh (including Chhatisgarh), Maharashtra, West Bengal and Orissa. Between 50 to 66 percent of the population of seven states (the six mentioned above and additionally Assam) was living below the poverty line in 1973-74. Twenty years later 35 to 55 percent of their population was still in poverty. In Bihar, Orissa, Madhya Pradesh, Assam and Uttar Pradesh *persistently* high levels of poverty, in excess of 30 percent, have occurred for several decades.(Mehta and Shah, 2003)

Table 2-: Incidence and Concentration of Income Poverty in Selected States of India.

State	State share of India's Poor 1999-2000	State share of India's Population 2001	Percentage of the Population of the state that is in poverty 1973-74	1993-94	1999-2000
Assam	3.63	2.59	51.21	40.86	36.09
Bihar*	16.36	10.69	61.91	54.96	42.6
Madhya Pradesh*	11.47	7.91	61.78	42.52	37.43
Maharashtra	8.76	9.42	53.24	36.86	25.02
Orissa	6.50	3.57	66.18	48.56	47.15
Uttar Pradesh*	20.36	17	57.07	40.85	31.15
West Bengal	8.20	7.81	63.43	35.66	27.02
All India	100.00	100.00	54.88	35.97	26.1

* including the districts in the now newly formed states.

Source: Mehta and Shah (2003) based on Government of India, Poverty Estimates for 1999-2000, Press Information Bureau, 22nd February, 2001 and March 1997 and Government of India, 2001 Provisional Population Tables.

Severe Poverty over time

Of the 260 to 320 million people who are below the poverty line (depending on whether the 1993-94 or 1999-2000 estimates are used) a large subset consists of those who are substantially or severely below the norms identified as necessary for survival. In 1993-94, 15.2% of the rural population and 14.85% of the urban population were estimated to be earning incomes that were less than or equal to three fourths of the poverty line (severely poor). Approximately 134 million people can be considered to be chronically below the poverty line in the severity sense.

The incidence of *severe* rural poverty was higher than average in 5 out of 7 income poverty states - Bihar, Orissa, Uttar Pradesh Madhya Pradesh and Maharashtra. In other words a higher percentage of people in rural areas in these states have a level of income that is less than three fourths of the poverty line than the all India average. (Table 3). Urban poverty was also especially severe in these states and additionally in Andhra, Karnataka and Tamil Nadu.

Table 3-: Estimates of Very Poor and Poor in Rural and Urban Areas in the States:1993-94 (in %)

	Rural		Urban	
State/Regions	**Very Poor**	**Poor**	**Very Poor**	**Poor**
Andhra Pradesh	4.18	15.89	16.78	38.34
Assam	13.12	45.00	1.16	7.74
Bihar	27.67	58.17	14.14	34.65
Gujarat	6.67	22.29	11.18	27.93
Haryana	9.32	28.02	5.02	16.37
Karnataka	11.11	29.89	22.13	40.18
Kerala	9.42	25.68	10.08	24.50
Madhya Pradesh	17.11	40.72	25.69	48.35
Maharashtra	16.17	37.90	18.72	35.08
Orissa	21.77	49.79	22.99	41.72
Punjab	3.12	11.85	2.22	11.40
Rajasthan	8.66	26.48	12.98	30.53
Tamil Nadu	12.67	32.55	18.67	39.78
Uttar Pradesh	19.55	42.31	16.91	35.34
West Bengal	13.62	40.87	7.51	22.38
All India	15.26	37.23	14.85	32.28

Source: K.L. Datta and Savita Sharma, Level of Living in India, Planning Commission, 2000.

Multidimensional Poverty

Comparing state rankings of population below the poverty line and human development index estimated by the Planning Commission for 15 states shows income poverty incidence and performance on human development indicators seem to follow a similar pattern for most of India's 15 large states the exceptions being Andhra, Kerala, Rajasthan, Tamil Nadu and Maharashtra. Low attainments on literacy result in Andhra's rank plummeting from 2 on proportion of population below the poverty line to 9 /10 on HDI and Rajasthan's from 6 to 11/9. Conversely, Maharashtra's rank improves from 10 on poverty to 4 on HDI, Tamil Nadu's from 8 to 3 and Kerala's from 5 to 1 primarily due to high levels of literacy and significant reductions in infant mortality in these states. The HDI ranks for the different states remain fairly stable for most states between 1991 and 2001. 5 out of the 7 high income poverty states- Orissa, Madhya Pradesh, Uttar Pradesh, Assam and Bihar have the lowest five ranks on human development as well. What this reflects therefore is convergence of deprivation in multiple dimensions or *multidimensional* poverty.

Table 4:- State Rankings: HDI and Population below the Poverty Line

Rank	Ranks of states based on Population below poverty line in 1993-94	Ranks estimated for HDI in 1991	Ranks estimated for HDI in 2001	Difference in HDI Rank between 1991 and 2001
1	Punjab	Kerala	Kerala	0
2	Andhra Pradesh	Punjab	Punjab	0
3	Gujarat	Tamil Nadu	Tamil Nadu	0
4	Haryana	Maharashtra	Maharashtra	0
5	Kerala	Haryana	Haryana	0
6	Rajasthan	Gujarat	Gujarat	0
7	Karnataka	Karnataka	Karnataka	0
8	Tamil Nadu	West Bengal	West Bengal	0
9	West Bengal	Andhra	Rajasthan	+2
10	Maharashtra	Assam	Andhra	-1
11	Uttar Pradesh	Rajasthan	Orissa	+1
12	Assam	Orissa	MadhyaPradesh	+1
13	Madhya Pradesh	MadhyaPradesh	Uttar Pradesh	+1
14	Orissa	Uttar Pradesh	Assam	-4
15	Bihar	Bihar	Bihar	0

Source: Planning Commission Press Release, March, 1997 and Planning Commission, National Human Development Report, (2002)

Estimates of human and gender development indices at the state level on the basis of the HDI, GDI, GEM and HPI indices have been estimated by researchers in India (see CPRC working paper 7). Kerala, has the highest rank on all four indices, Maharashtra also performs well. Punjab and Haryana have high scores on human development but perform poorly on gender indicators. 5 out of the 7 high income poverty states - Orissa, Uttar Pradesh, Bihar, Madhya Pradesh and Assam – have the lowest ranks or perform equally poorly on HDI, GDI, GEM and HPI. Rajasthan ranks better on income poverty but performs dismally on all four multidimensional indicators.

Spatial distribution of the Chronically, Severely and Multidimensionally Poor: A Regional level analysis

Disaggregating to the regional level shows that while chronic poverty in the duration, severity and multi dimensionality sense characterises several parts of India, pockets of severe poverty exist at the regional level even in the more developed states.

Poverty related estimates for 59 regions in 16 large states show that between 20% and 43% of the population living in rural areas of 12 regions and urban areas of 21 regions suffer severe poverty (income 75% or less than the poverty line). The 12 rural regions are southern, (now Jharkhand) northern and central Bihar, central, southern and south western, Madhya Pradesh, inland central and inland eastern Maharashtra, southern Orissa and central, eastern and southern Uttar Pradesh. Approximately half to more than two thirds of the population of the rural areas of these regions was below the poverty line (the exact estimates are 46% to 69%). Further, variables reflecting multidimensional deprivation, such as incidence of child mortality, literacy, access to infrastructure such as electricity, toilet facilities and postal and telegraphic communications show that in these regions, child mortality is 1.7 times to 3.7 times, female literacy one tenth to half, total literacy one fourth to two thirds of the estimates for the best performing region. Similarly, access to public provisioning of infrastructure such as electricity, toilet facilities and post and telegraph are as low as 5%, 6% and 9% of those in the best performing region.

The 21 urban regions with 20% to 43% of their population in severe poverty include inland southern and southwestern Andhra, northern Bihar, inland eastern and inland northern Karnataka, central, northern, southern and southwestern Madhya Pradesh as also Malwa, Vindhya and Chattisgarh, (now one of the newly formed states) regions of Madhya Pradesh, eastern, inland central, inland eastern and inland northern Maharashtra, coastal and southern Orissa, coastal and southern Orissa and southern Uttar Pradesh. 16 out of the 21 regions had 45% to 72% of their population below the poverty line. (see table 5). Estimates of access to education, health and infrastructure for the urban areas of these regions also reflect values that are well below those for the best performing region. It is therefore possible to conclude that those vulnerable to severe and long duration poverty tend to suffer deprivation in multiple and mutually reinforcing ways.

Table 5:- Deprivation at the Regional Level: Different Dimensions

Rural		**% severely poor**	**% poor**	**Child mortality**	**Female literacy**	**Total literacy**	**Electricity**	**Toilet facility**	**P & T**
State	Region								
Bihar	Central	24.66	54.03	72.28	22.53	39.77	6.53	7.74	18.12
Bihar	Northern	27.62	58.68	76.05	15.71	30.39	3.88	3.98	22.68
Bihar	Southern	31.57	62.44	69.8	16.31	32.66	7.65	3.65	9.17
MP	Central	21.78	50.13	127.77	21.33	38.65	37.1	4.45	11.14
MP	South	22.37	46.36	123	27.27	42.24	36.73	3.5	13.02
MP	S Western	42.24	68.2	133.21	21.96	35.77	48.07	5.41	14.72
Maharashtra	Inl Central	28.91	50.02	60.23	27.5	45.74	48.63	2.85	25.51
Maharashtra	Inl Eastern	20.06	49.08	93.38	47.17	59.86	57.31	7.87	23.46
Orissa	Southern	34.08	69.02	123.25	11.01	23.56	6.64	2.77	11.83
Uttar P.	Central	26.79	50.2	98.43	18.95	34.92	5.74	3.42	17.82
Uttar P.	Eastern	23.2	48.6	92.33	15.12	35.33	10.32	3.26	13.98
Uttar P.	Southern	39.7	66.74	101.54	16.63	36.34	7.47	3.71	23.83
Max		1.67	7.55	35.39	87.96	91.06	85.88	48.69	99.11
Min		42.24	69.02	135.66	9.37	23.56	3.88	2.11	9.17

Urban		**% severely poor**	**% poor**	**Child mortalit y**	**Female literacy**	**Total literacy**	**Electrici ty**	**Toilet facility**	**P & T**
AP	InlSouthern	22.75	45.44	53.40	29.18	43.44	51.34	5.42	60.21

AP	SWestern	20.29	40.93	68.98	20.00	34.83	44.54	4.11	76.42
Bihar	Northern	21.68	49.37	76.05	15.71	30.39	3.88	3.98	22.68
Karnat	Inl Eastern	20.15	36.29	61.04	44.73	55.95	46.67	9.56	68.15
Karnat	InlNorthern	36.49	57.63	63.87	28.25	43.02	36.47	3.63	44.08
MP	Central	32.93	53.68	127.77	21.33	38.65	37.1	4.45	11.14
MP	Chattisgarh	21.88	44.2	109.06	20.98	35.22	25.26	3.31	13.11
MP	Malwa	21.85	45.53	92.93	14.45	31.49	43.96	4.92	12.51
MP	Northern	23.54	44.72	113.98	14.70	36.40	39.73	2.73	15.32
MP	South	27.9	51.23	123	27.27	42.24	36.73	3.5	13.02
MP	S Western	36.6	57.14	133.21	21.96	35.77	48.07	5.41	14.72
MP	Vindhya	24.32	50.45	135.66	15.80	32.03	24.71	2.11	12.76
Maharashtr	Eastern	21.02	52.02	91.24	40.75	54.95	74.36	11.28	15.98
Maharashtr	Inl Central	42.62	60.13	60.23	27.5	45.74	48.63	2.85	25.51
Maharashtr	Inl Eastern	38.99	59.32	93.38	47.17	59.86	57.31	7.87	23.46
Maharashtr	InlNorthern	32.28	56.94	74.89	38.74	52.96	64.83	5.20	35.05
Orissa	Coastal	26.54	48.42	127.52	41.29	55.92	23.50	4.51	20.20
Orissa	Southern	33.53	45.64	123.25	11.01	23.56	6.64	2.77	11.83
T. Nadu	Coastal	20.31	42.11	50.11	44.46	57.66	37.5	7.06	61.12
T.Nadu	Southern	24.82	48.13	55.63	48.68	63.53	44.56	9.03	56.33
UP	Southern	37.54	72.52	101.54	16.63	36.34	7.47	3.71	23.83
Max		72.52	<1	35.39	87.96	91.06	85.88	48.69	99.11
Min		3.86	42.62	135.66	9.37	23.56	3.88	2.11	9.17

Source: Planning Commission, June, 2000 and NIRD, India Rural Development Report, 1999

III. Methodological Issues

As pointed out in the introduction, no single indicator can capture the complexities of development. Therefore, indices are generally estimated by aggregating performance with regard to several indicators. This requires the identification of variables to be included in the index, the range to be used for scaling and weights to be allocated to the different variables. Decisions in this regard tend to be arbitrary and driven by availability of data. Changes in any of these factors can yield very different results. In addition there is the issue of choice of method to be used in estimating the index. Among the criticisms leveled against use of composite indices is the argument that in the process of averaging indicator index values to yield a composite index, information is lost or wasted (Ravallion 1996).

In spite of these drawbacks, measuring inequalities could be important for some purposes. For instance, in the disbursement of non-specific equalization grants and budgetary allocations, or for advocacy purposes[2] (Lok-Dessallien - www), it is useful for government organizations, NGO funding organizations and NGOs to have a ranking of regions based on a composite index, at least as a first step. Single indicator based development indices and maps also provide important information for targeting of plans policies and projects (PPPs).

It is argued that the range depends only on two extreme values and changes in these values can change the ranks given to different countries/states/regions/districts/talukas. We therefore calculate an Adjusted value of each index so that the values obtained are not sensitive to changes in the ranks with changes in the minimum – maximum limits used. The method for calculating the AHDI is modified on the basis of Panigrahi and Sivaramakrishna, 2002. [3]

The method proposed to calculate the AHDI first scales down each indicator index value proportionately so as to equalize the spread for all indicator index values to that of the minimum spread in indicator index values. This scaling down of indicator index values will mean that aHDIj ? HDI_j. For instance, suppose country j has reached index values of 1for all three indicators. Then if, say, 1 < e and 1 <g, the $aHDI_j$ will not be equal to 1. The closer 1, e and g are in value, the smaller will be the difference between HDIj and $aHDI_j$. However, since the $aHDI_j$ values can be lowered significantly compared with HDI_j values, we then scale up the $aHDI_j$ to $AHDI_j$ by the constant, v. This makes the AHDI values comparable with the HDI values. Unlike HDI-based rankings, AHDI-based rankings are invariant to change in limits. At the same time, unlike the Borda Count method, the AHDI meets the objectives of HDI.

It is also argued that in the construction of a composite index, the process of averaging indicator values leads to wastage of information; in particular information that maybe of specific use to development organizations. As pointed out by Ravallion (1996),

> "aggregation wastes information; it can be important to know that region A is doing well in the income space, but not in basic health and schooling, while in region B it is the reverse".

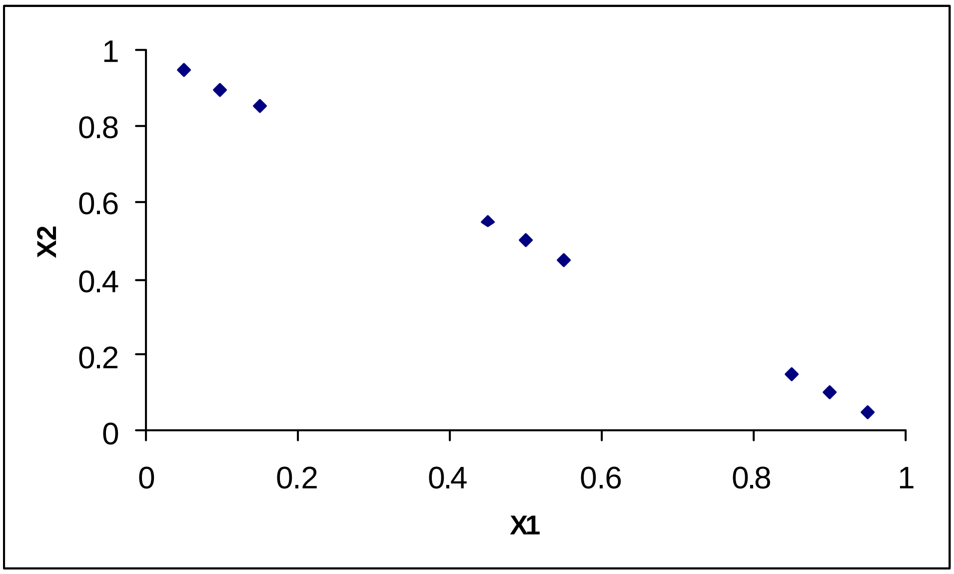
We use a contrived data set (Table 6) for nine regions (R_1, R_2, …, R_9) and two indicators, X_1 and X_2, given equal weights to illustrate this. The corresponding composite index, I, is given by $(X_1 + X_2)/2$ – similar to the method adopted by HDI. In the next column, the Borda score, B[4], is calculated and presented. Using either of the two methods, we find that **on average**, all nine regions are equally developed. This may be important information to development organizations. However, there is another piece of information so easily apparent in Figure 1 (plot of data in Table 6) but not extracted by the composite indices or Borda count, namely, the existence of three clusters of homogeneous regions. In other words, using composite indices we lose information on *similar* regions within a cluster and *differences* between clusters.

Table 6: A Contrived Data Set, Composite Index Value (I), Borda Score (B) and Rank

Regions	X1	X2	Composite	Borda	Rank
			Index Value	Score	
R1	0.05	0.95	0.5	10	1
R2	0.1	0.9	0.5	10	1
R3	0.15	0.85	0.5	10	1
R4	0.55	0.45	0.5	10	1
R5	0.5	0.5	0.5	10	1
R6	0.45	0.55	0.5	10	1

R7	0.85	0.15	0.5	10	1
R8	0.9	0.1	0.5	10	1
R9	0.95	0.05	0.5	10	1

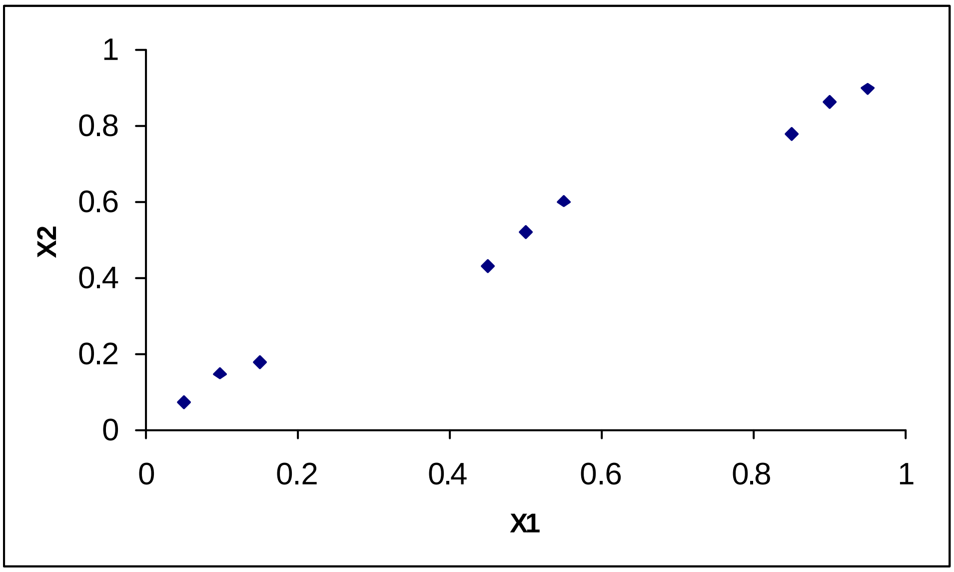
Figure 1: Scatter Plot of X1 and X2 from Table 1



A case in point here is that of Kerala and Punjab States in India where the composite indices of development are almost equal: 0.775 for Kerala and 0.744 for Punjab based on 1991 data (Krishnan 2000). However, what remains concealed in this index is the fact that per capita State domestic product of Kerala is less than half that of Punjab (Indian Rupees 4618 and 9643 respectively in 1991-92). On the other hand, female literacy and infant mortality rates in Kerala are 86.9% and 17 respectively whereas in Punjab they are at 49.7% and 61 respectively (Krishnan 2000). These wide differences in development variables are not captured by the composite index; instead, they get averaged out. Capturing the regional differences between Kerala and Punjab States could be useful and important information to development organizations for more efficient and effective Plan, Policies and Projects (PPPs). For instance, a health project could have a different impact in Kerala and Punjab due to the differences in education levels in the two states.

It is important to point out that the process of averaging does not distort or conceal information where data is distributed as in Figure 2[5]; where regions are usually more developed than others for all indicators.

Figure 2: Scatter Plot of X1 and X2 for a Positively Correlated Distribution



On the other hand, the methods used to explore regional *patterns* of development, like factor analysis, require more specialized skills. This fact has limited its appeal amongst a larger audience. Artificial intelligence, in particular the Kohonen Self-Organizing Map (K-SOM), as we will see, is not only a proficient tool to decipher patterns in development but its user-friendliness could promote its acceptance amongst policy makers and development practitioners in targeting PPPs.

IV. Deprivation at the District Level: Identifying the 50 most deprived districts in India

Extending the analysis to the district level, we estimate multidimensional indicators for about 379 districts in 15 large states of India based on data for the early 1990s. The attempt is to use variables for which data is available at the district level and that may reflect long duration deprivation. For example, persistent spatial variations in the infant mortality rate could be considered to be a reflection of persistent deprivation to the means of accessing good health or an outcome indicator of chronic poverty. This could be due to inability to get medical care due to lack of income or lack of available health care facilities in the vicinity or poor quality of drinking water resulting in water borne diseases that cause mortality or lack of roads and public transport that enable quick transportation to hospitals in case of emergency or all of the above. Similarly, illiteracy could be considered to be a persistent denial of access to information, knowledge and voice. Low levels of agricultural productivity may reflect poor resource base, low yields due to lack of access to irrigation and other inputs, poor quality of soil resulting from erosion or lack of access to resources for investment because of lack of collateral or adverse climatic or market conditions. Poor quality of infrastructure reflects persistent denial of opportunities for income generation and growth.

We therefore use multidimensional indicators at the district level that could reflect persistent deprivation, such as illiteracy, infant mortality, low levels of agricultural productivity and poor infrastructure to help sharpen the identification of areas in chronic poverty and map these spatially.

Three groups of indices are computed.

1) An average of three indicators representing education, health and income, with equal weights of one third each assigned to each. These are:
    a. An average of female literacy and percent population in the age group 11-13 years attending school
    b. Infant mortality rate
    c. Agricultural productivity
2) An average of four indicators representing education, health, income and development of infrastructure with equal weights of one fourth each assigned to each. These are:
    a. An average of female literacy and percent population in the age group 11-13 years attending school
    b. Infant mortality rate
    c. Agricultural productivity
    d. Infrastructure development
3) An average of four indicators representing education, health, income and development of infrastructure with equal weights of one fourth each assigned to each. These are:
    a. An average of literacy and percent population in the age group 11-13 years attending school
    b. Infant mortality rate
    c. Agricultural productivity
    d. Infrastructure development

Each of these sets of three indices are computed on the basis of three different methods with a view to determining robustness of the results. The three methods are:

1) the method used by the UNDP with the minimum-maximum range given below:
    a. For literacy, female literacy and percent population in the age group 11-13 years attending school – 0 to 100 in each case
    b. Infant mortality rate - 0 to 200
    c. Agricultural productivity – 0 to 30
    d. Infrastructure development – 0 to 500

2) calculating an Adjusted value of each index so that the values obtained are not sensitive to changes in the ranks with changes in the minimum – maximum limits used. The method for calculating the AHDI is given in a footnote below (to do) The minimum-maximum used is the same as in the UNDP method in (1) above.

3) calculating an Adjusted value of each index so that the values obtained are not sensitive to changes in the ranks with changes in the minimum – maximum limits used.

The minimum-maximum used are the actual minimum and maximum for each of the variables.
The 9 sets of results were then sorted to identify the most deprived districts.

The seven most deprived districts computed on the basis of the 9 sets of indices have been identified as Bahraich and Budaun in UP, Barmer in Rajasthan, Damoh and Shahdol in MP, Kishanganj in Bihar and Kalahandi in Orissa (see table 7). Additionally in the case of index 2, 3 and 5 due to clustering of districts around a given value the cut off had to include an additional district, Rajgarh in the case of index 2, Koraput in the case of index 3 and both these districts in the case of index 5. The results clearly show stability across all 9 indices with regard to the identification of the most deprived districts.

Table 7:-Seven Most Deprived Districts in India on all 9 Indices.

	3 variables	4 variables	4 variables	3 variables	4 variables	4 variables	3 variables	4 variables	4 variable
	Felit &sch	Felit &sch	Lit & sch	Felit &sch	Felit &sch	Lit & sch	Felit &sch	Felit &sch	Lit & sch
	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlp
		infrastr	infrastr		Infrastr	infrastr		infrastr	infrastr
Index	ADJ HDI1	ADJ HDI2	ADJ HDI3	HDI1	HDI2	HDI3	ADJ HDI1	ADJ HDI2	ADJ HDI
Scale	UN	UN	UN	Original	Original	Original	Actual	Actual	Actual
Range	0.09-0.10	0.09-0.10	0.08-0.09	0.24-0.25	0.21-0.23	0.23-0.24	0.03-0.04	0.03	0.(
Index	1	2	3	4	5	6	7	8	9
UP	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich
Rajasthan	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer
UP	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun
MP	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh
Orissa	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahand
Bihar	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanga
MP	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol
MP		Rajgarh			Rajgarh				
Orissa			Koraput		Koraput				

Comparing the districts identified as most deprived based on multidimensional indicators with the regions that are identified as having the largest percentage of their population below the poverty line and in severe poverty, shows that (see tables 7 and 8):

?? Kalahandi and Koraput in Orissa are the most deprived regardless of how we measure poverty. Both districts are in the 7 most multidimensionally deprived as also belong to the poorest region in the country.

?? All the regions of Bihar have relatively high levels of poverty. However, Kishanganj in Northern Bihar is additionally one of the 7 most multidimensionally deprived districts.

?? Districts in South west Madhya Pradesh have the largest proportion of their population in poverty and severe poverty but do not get included among the 7 most multidimensionally deprived. However, Damoh in Central MP and Shahdol in Vindhya as also Rajgarh in Malwa are among the most multidimensionally deprived districts in India

?? Rajasthan does relatively well in income poverty terms and less well on multidimensional criteria. However, Barmer in Western Rajasthan is one of the 7 most multidimensionally deprived districts.

?? Southern UP is among the poorest regions in the country. However none of the districts in Southern UP gets included in the 7 most multidimensionally deprived districts in India while Bahraich in Eastern and Budaun in Western UP are in this group of districts.

Table8a: -Percentage of population below the poverty line and in severe poverty in rural and urban regions from which 7 districts have been identified as most multidimensionally deprived.

			Rural	Rural	Urban	Urban
STATE	REGION		%population poor	% population severely poor	%population poor	% population severely poor
Orissa	Southern	Kalahandi	69.02	34.08	45.64	33.53
Orissa	Southern	Koraput	69.02	34.08	45.64	33.53
Bihar	Northern	Kishanganj	58.68	27.62	49.37	21.68
Madhya Pradesh	Central	Damoh	50.13	21.78	53.68	32.93
Madhya Pradesh	Vindhya	Shahdol	36.71	13.8	50.45	24.32
Madhya Pradesh	Malwa	Rajgarh	27.39	9.97	45.53	21.85
Uttar Pradesh	Eastern	Bahraich	48.6	23.2	38.6	18.48
Uttar Pradesh	Western	Budaun	29.59	10.24	31.03	14.37
Rajasthan	Western	Barmer	25.48	5.84	23.68	7.43

Table8b:- Seven Regions with the largest percentage of population in poverty and severe poverty

Rural		Poor			Very Poor
Orissa	Southern	69.02	Madhya Pradesh	South Western	42.24
Madhya Pradesh	South Western	68.2	Uttar Pradesh	Southern	39.7
Uttar Pradesh	Southern	66.74	Orissa	Southern	34.08
Bihar	Southern	62.44	Bihar	Southern	31.57
West Bengal	Himalayan	58.73	Maharashtra	Inland Central	28.91
Bihar	Northern	58.68	Bihar	BIHAR	27.67
Bihar	Central	54.03	Uttar Pradesh	Central	26.79
Urban		Poor			Very Poor
Uttar Pradesh	Southern	72.52	Maharashtra	Inland Central	42.62
Maharashtra	Inland Central	60.13	Maharashtra	Inland Eastern	38.99
Maharashtra	Inland Eastern	59.32	Uttar Pradesh	Southern	37.54
Karnataka	Inland Northern	57.63	Madhya Pradesh	South Western	36.6
Madhya Pradesh	South Western	57.14	Karnataka	Inland Northern	36.49

Maharashtra	Inland Northern	56.94	Orissa	Southern	33.53
Madhya Pradesh	Central	53.68	Madhya Pradesh	Central	32.93

Similarly computations based on the 9 indices listed above show that the 52 to 60 most deprived districts out of 379 districts in 15 large states of India can be identified as 1 district in Assam, between 5 to 8 districts in Bihar, 11 to 12 districts in Rajasthan, 21 to 26 districts in Madhya Pradesh, 4 districts in Orissa, and 6 to 10 districts in UP. Again what clearly emerges is the constancy of districts regardless of indicators used and method of computation. The same 52 to 60 districts are identified as the most deprived in almost all 9 cases listed below. Identification of districts that reflect chronic deprivation in multidimensional parameters is the first step in determining strategies to correct such imbalances.

Table 9:- Most deprived 50 or so districts.

	3 variables	4 variables	4 variables	3 variables	4 variables	4 variables	3 variables	4 variables	4 variab
	Felit &sch	Felit &sch	Lit & sch	Felit &sch	Felit &sch	Lit & sch	Felit &sch	Felit &sch	Lit & scl
	imr, agrlpro	imr, agrlpro	imr, agrlpro	Imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpro	imr, agrlpr	imr, agr
		infrastr	infrastr		Infrastr	Infrastr		infrastr	infrastr
	ADJ HDI1	ADJ HDI2	ADJ HDI3	HDI1	HDI2	HDI3	ADJ HDI1	ADJ HDI2	ADJ HD
	UN min-max	UN min-max	UN min-max	UN min-max	UN min-max	UN min-max	Actual min-max	Actual min-max	Actual r
Range	0.09-0.16	0.09-0.15	0.08-0.14	0.24-0.32	0.21-0.28	0.23-0.30	0.03-0.09	0.03-0.07	0.03-0.(
No. of districts	56	54	60	56	55	55	52	52	59
Index	1	2	3	4	5	6	7	8	9
State									
Assam	Dhubri	Dhubri	Dhubri	Dhubri	Dhubri	Dhubri	Dhubri	Dhubri	Dhubri
Bihar	Araria	Araria	Araria	Araria	Araria	Araria	Araria	Araria	Araria
Bihar		Deoghar			Deoghar	Deoghar	Kishanganj	Deoghar	Deogha
Bihar									Katihar
Bihar	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj	Kishanganj		Kishanganj	Kishang
Bihar	Palamu	Palamu	Palamu	Palamu	Palamu	Palamu	Palamu	Palamu	Palamu
Bihar	Purnia			Purnia			Purnia		Purnia
Bihar		Sahibganj	Sahibganj		Sahibganj	Sahibganj		Sahibganj	Sahibga
Bihar	Sitamarhi	Sitamarhi	Sitamarhi	Sitamarhi	Sitamarhi	Sitamarhi	Sitamarhi	Sitamarhi	Sitamar
MP	Bastar	Bastar	Bastar	Bastar	Bastar	Bastar	Bastar	Bastar	Bastar
MP	Betul	Betul	Betul	Betul	Betul	Betul	Betul	Betul	Betul
MP	Chhattarpur	Chhattarpur	Chhattarpur	Chhattarpur	Chhattarpur	Chhattarpur	Chhattarpur	Chhattarpur	Chhatta
MP	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh	Damoh
MP	Datia			Datia			Datia		
MP									Dhar
MP	East Nimar	East Nimar	East Nimar	East Nimar	East Nimar	East Nimar	East Nimar	East Nimar	East Nir
MP	Guna	Guna	Guna	Guna	Guna	Guna	Guna	Guna	Guna
MP	Jhabua	Jhabua	Jhabua	Jhabua	Jhabua	Jhabua	Jhabua	Jhabua	Jhabua
MP	Mandla	Mandla	Mandla	Mandla	Mandla	Mandla	Mandla	Mandla	Mandla

MP	Panna	Panna	Panna	Panna	Panna	Panna	Panna	Panna	Panna
MP	Raisen	Raisen	Raisen	Raisen	Raisen	Raisen	Raisen	Raisen	Raisen
MP	Rajgarh	Rajgarh	Rajgarh	Rajgarh	Rajgarh	Rajgarh	Rajgarh	Rajgarh	Rajgarh
MP		Rajnandgaon			Rajnandgaon	Rajnandgaon		Rajnandgaon	Rajnand
MP	Ratlam	Ratlam	Ratlam	Ratlam	Ratlam	Ratlam	Ratlam	Ratlam	Ratlam
MP	Rewa	Rewa	Rewa	Rewa	Rewa	Rewa	Rewa	Rewa	Rewa
MP	Sagar	Sagar	Sagar	Sagar	Sagar	Sagar	Sagar	Sagar	Sagar
MP	Satna	Satna	Satna	Satna	Satna	Satna	Satna	Satna	Satna
MP	Sehore	Sehore	Sehore	Sehore	Sehore	Sehore	Sehore	Sehore	Sehore
									Seoni
MP	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdol	Shahdo
MP	Shajapur	Shajapur		Shajapur	Shajapur				
MP	Shivpuri	Shivpuri	Shivpuri	Shivpuri	Shivpuri	Shivpuri	Shivpuri	Shivpuri	Shivpuri
MP	Sidhi	Sidhi	Sidhi	Sidhi	Sidhi	Sidhi	Sidhi	Sidhi	Sidhi
MP	Surguja	Surguja	Surguja	Surguja	Surguja	Surguja	Surguja	Surguja	Surguja
MP	Tikamgarh	Tikamgarh	Tikamgarh	Tikamgarh	Tikamgarh	Tikamgarh	Tikamgarh	Tikamgarh	Tikamga
MP	West Nimar	West Nimar	West Nimar	West Nimar	West Nimar	West Nimar	West Nimar	West Nimar	West Ni
Orissa	Ganjam	Ganjam	Ganjam	Ganjam	Ganjam	Ganjam	Ganjam	Ganjam	Ganjam
Orissa	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahandi	Kalahan
Orissa	Koraput	Koraput	Koraput	Koraput	Koraput	Koraput	Koraput	Koraput	Koraput
Orissa	Phulbani	Phulbani	Phulbani	Phulbani	Phulbani	Phulbani	Phulbani	Phulbani	Phulban
Rajasthan	Banswara	Banswara	Banswara	Banswara	Banswara	Banswara	Banswara	Banswara	Banswa
Rajasthan	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer	Barmer
Rajasthan	Bhilwara	Bhilwara	Bhilwara	Bhilwara	Bhilwara	Bhilwara	Bhilwara	Bhilwara	Bhilwar
Rajasthan	Dholpur			Dholpur					
Rajasthan	Dungarpur	Dungarpur	Dungarpur	Dungarpur	Dungarpur	Dungarpur	Dungarpur	Dungarpur	Dungar
Rajasthan	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalmer	Jaisalm
Rajasthan	Jalor	Jalor	Jalor	Jalor	Jalor	Jalor	Jalor	Jalor	Jalor
Rajasthan	Jhalawar	Jhalawar	Jhalawar	Jhalawar	Jhalawar	Jhalawar	Jhalawar	Jhalawar	Jhalawa
Rajasthan	Nagaur	Nagaur		Nagaur	Nagaur	Nagaur	Nagaur	Nagaur	Nagaur
Rajasthan	Pali	Pali	Pali	Pali	Pali	Pali	Pali	Pali	Pali
Rajasthan	Sirohi	Sirohi	Sirohi	Sirohi	Sirohi	Sirohi	Sirohi	Sirohi	Sirohi
Rajasthan	Tonk	Tonk	Tonk	Tonk	Tonk	Tonk	Tonk	Tonk	Tonk
UP	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraich	Bahraic
UP	Banda	Banda	Banda	Banda	Banda	Banda	Banda	Banda	Banda
UP	Basti	Basti	Basti	Basti	Basti	Basti	Basti	Basti	Basti
UP	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun	Budaun
UP	Gonda	Gonda	Gonda	Gonda	Gonda	Gonda	Gonda	Gonda	Gonda
UP	Hardoi	Hardoi	Hardoi	Hardoi	Hardoi	Hardoi	Hardoi	Hardoi	Hardoi
UP	Lalitpur	Lalitpur		Lalitpur	Lalitpur	Lalitpur	Lalitpur	Lalitpur	Lalitpur
UP	Shahjahanpur			Shahjahanpur		Shahjahanpur	Shahjahanpur		Shahjah
UP	Siddrathnagar			Siddrathnagar	Siddrathnagar	Siddrathnagar			Siddrath
UP	Sitapur	Sitapur		Sitapur	Sitapur	Sitapur			Sitapur

V. Deprivation at Below District Level: A Taluka level analysis for the state of Karnataka.

Unevenness of development becomes more and more prominent as we move to smaller spaces. Section V extends the analysis to even smaller spaces i.e. the taluka or below district level for the state of Karnataka in India. We first apply the UNDP procedure to explore the inequalities in development for Karnataka and identify the poorest talukas of the state and then point out the limitations of this procedure and suggesting use of the K-SOM technique to analyse the pattern of regional development at the taluka level using the same database and same number of variables for determining spatial inequality of development in the state.

Due to non-availability of data on variables such as GDP per capita at the taluka level we use multiple input surrogates for each indicator of development – income, health, education and social equality. The surrogates are listed below:

Income

1. Percentage of Urban Population to Total Population
2. Percentage of Workers to Total Population
3. Percentage of Agricultural Workers to Total Workforce
4. Percentage of Total Cropped Area to Net Area Sown
5. Percentage of Gross Irrigated Area to Gross Cropped Area
6. Population per Registered Factory
7. Population per Banks
8. Population per Cooperative Societies
9. Total Road Length per 100 Sq Km.
10. TRMV per Lakh (One hundred thousand) Population
11. Population per Post Office
12. Telephones per Lakh (One hundred thousand) Population

Health

13. Population per Medical Institutions
14. Bed per lakh Population

Education

15. Literacy Rates

Social Equality

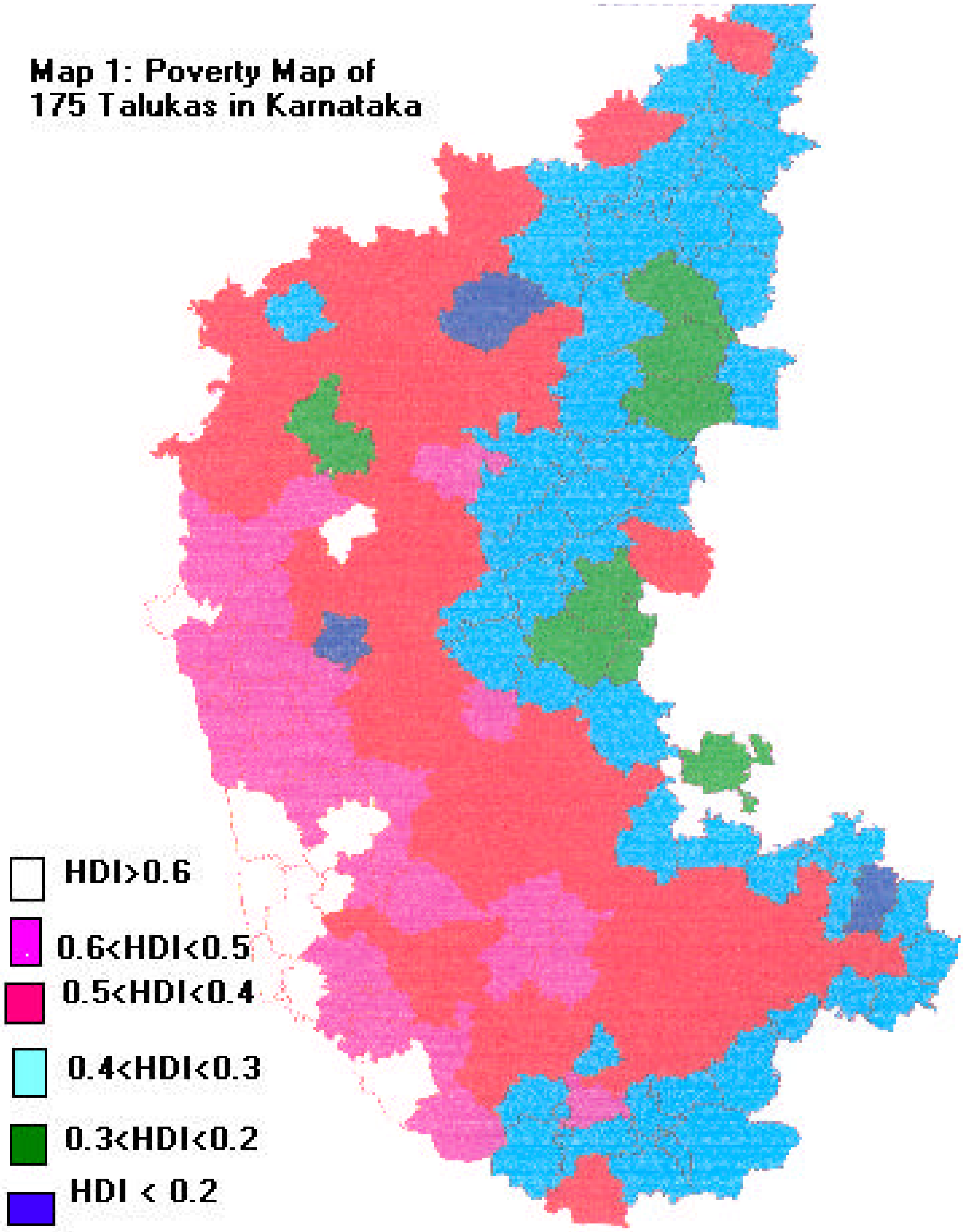
16. Percentage of SC & ST Population to Total Population
17. Sex Ratio

Each surrogate for income has been assigned a weight of (0.25)/(12) = 0.02. For health, each indicator is assigned a weight of (0.25)/(2) = 0.125. In the case of education, we have assigned weight of 0.25 to literacy rates since that is the only indicator to represent

Education index. For Social equality each indicator is again assigned a weight of (0.25)/(2) = 0.125. All variables chosen have a definite bearing on development, either positive or negative.

We first construct the development (inequality) map presented in Map 1 where the talukas have been assigned six levels of development: very high, high, high-middle, middle, low-middle and low. However, the cut-off points to define these levels of development are arbitrary(as is the usual practice of UNDP type of studies that rely on composite indices)and are stated in the key to Map 1[6].

Map 1: Poverty (Inequality) Map of 175 Talukas of Karnataka State of India


Map 1: Poverty Map of
175 Talukas in Karnataka
HDI>0.6
0.6<HDI<0.5
0.5<HDI<0.4
0.4<HDI<0.3
0.3<HDI<0.2
HDI < 0.2

The inequality map provides information of average or overall development of each taluka, but does not delineate homogeneous regions. We can conclude that the talukas of coastal Karnataka have very high development and as we move towards inland, the level of development decreases which are represented by the HDI values. Though certain talukas have similar HDI values, the individual indicator va lues are significantly different from each other and in the process of constructing the composite index such loss of information occurs as the importance of each indicator values get averaged out.

Constructing composite indices from several indicators of development, especially for small spaces, like districts or *talukas*, are more likely to face problems from averaging and render rankings quite irrelevant to PPPs (Lok-Dessallien - www). Concentrating only on single indicators of development is important but does not "reduce" data – the very purpose of constructing a composite index. With reference to our example in Table 1, disaggregating information would mean mapping X_1 and X_2 separately using arbitrary cut-off index values to cluster regions into different levels of development. We need a technique to reduce the data set into three clusters; each cluster containing regions with similar combinations of X_1 and X_2 and at the same time, segregating different clusters. However, before discussing techniques and methods, we must understand the nature of information that we are trying to extract from the data set. The notion of development *patterns* is introduced for this reason.

<u>Regional *Patterns* in Development</u>:

Patterns in development neither rank regions nor measure their levels of development, only that regions with similar combinations of development indicators are extracted from the data. In other words we need to construct a summary map that relates data to locations, provides a truly geographical representation of information and identifies or illustrates spatial patterns and relationships (Cowlard 1998).

Development planners and practitioners are often concerned not only with development or poverty indicators but also their interrelationship with a region's social, demographic, cultural and physical attributes; attributes which cannot always be categorically classified as good or bad, better or worse, more or less developed. In other words, they cannot be ranked. Unlike in the study of inequalities, these are easily brought into a study of regional patterns of development since we are not intent on measuring development or poverty or ranking regions in terms of their level of development; we are only interested in identifying relationships between the variables across regions.

Exploring multivariate data could reveal certain interesting and useful underlying patterns in the spatial distribution of development. Consider, for instance, a children's health project. Its effectiveness will benefit from knowledge of regional patterns in demography, education, health, income, gender, urbanization, women's occupational structure, child labor and social (caste/tribe) parameters. Areas with high incomes, but low education and women's status, may require a different program design and implementation strategy as compared to a region where education levels and status of women are better, but incomes low. Policy design requires not only identification of the poorest or least developed regions but also those that are most likely to benefit from interventions thereby making them efficient and effective. The study of development patterns is essential to such efforts.

What we then often look for is a reduction in data, *keeping intact* information on regional *differences* – without these differences getting averaged out. As we have shown above, composite indices and single indicator mapping fail in identifying patterns in development. In fact, patterns in data are concealed, wasted or ignored by the methods used to identify regional inequalities. In the context of Table 1, the three distinct clusters in the data set must be identified, i.e. neither reduced to a single index value in the process of averaging (composite index) nor ignored (single indicator mapping).

The Kohonen Self-Organizing Map:
Though artificial intelligence, in particular neural network techniques, has found widespread application in the sciences and engineering, it's use has remained rather limited in economics and confined to specific areas like finance (Skapura 1995, Deboeck 1998, Deboeck and Kohonen 1998, Shumsky and Yarovoy 1998). An in-depth introduction to artificial intelligence and neural networks is beyond the scope of this paper and can be found elsewhere[7] (Ginsberg 1993, Aleksander and Morton 1995, Skapura 1995, Nilsson 1998). The artificial intelligence technique chosen for our study here is the Kohonen Self-Organizing Map (K-SOM). The K-SOM is an unsupervised learning technique that clusters data based on a distance function without any *a priori* information on the number of clusters. The (artificial) intelligence of the algorithm is that it discerns something similar to what the human brain sees in the data set. In the present context, the algorithm is able to group or cluster regions with similar combinations of indicators based on information within the data set itself. Once again, a technical understanding of the Kohonen Self-Organizing Map algorithm is beyond the scope of this paper. Interested readers may refer to Beale and Jackson (1990), Kohonen (1990), Aleksander and Morton (1995), Kaski and Kohonen (1996), Beveridge (1996), Frohlich (1999), Germano (1999), Deboeck (2000).

Applying the K-SOM technique to the data set in Table 5[8] clusters the data into 3 distinct sets, namely, (R_1, R_2, R_3), (R_4, R_5, R_6), and (R_7, R_8, R_9), which can be readily transformed into a development map.

It is important to reiterate here that the number of clusters was not specified *a priori* as in the K-means algorithm. Moreover, the difficulty encountered by non-specialists in using and interpreting the results of factor analysis is absent. The development practitioner can take a "black-box" approach to obtain the clusters of homogeneous regions – a vital input for their PPPs.

In our contrived example, a composite index (I or B) makes possible ranking of regions (equal rank of 1). The K-SOM, on the other hand, neither measures development nor ranks regions; it only identifies the spatial pattern of development. However, average indicator values for each cluster, could provide information on the general level of development of regions in the cluster. The K-SOM algorithm, by extracting information on regional differences in development from the data set, could be a useful tool[9] in PPP formulation and intervention.

A Taluka-Level Analysis for Karnataka

The K-SOM technique has been used in the study of country-level development by Kohonen and Kaski (1996) and Deboeck (2000). However, as we have stated above, the data distribution of country-level indicators is likely to follow a pattern as in Figure 2. This would mean that results obtained using a composite index and the K-SOM are quite similar. Moreover, these country-level studies do not articulate the essential difference between inequalities and patterns of development, the latter forming the *raison d'etre* of using the K-SOM technique.

We use the K-SOM technique for a study of regional disparities at a level of relatively smaller spaces using data from official source i.e. Directorate of Economics and Statistics, Bangalore, Karnataka. In this study we have taken into consideration all 175 talukas in the State.

Map 2 is a poverty (pattern) map constructed using the K-SOM technique, with the same indicators and weights as taken above in the construction of composite indices so as to compare the results from the two methods. The K-SOM algorithm, without any *a priori* information on the number of clusters, identified nine distinct groups of regions. Table 3 shows the average values for the variables in each cluster. It is clear that Cluster 1 has a higher development level than most others clusters, but when we look at Clusters 2 and 3 no definitive ranking is possible. Cluster 2 is better off for some indicators whereas Cluster 3 is better off for others. A ranking of clusters with a Borda count of average values of indicators could be performed to indicate regional levels of development.

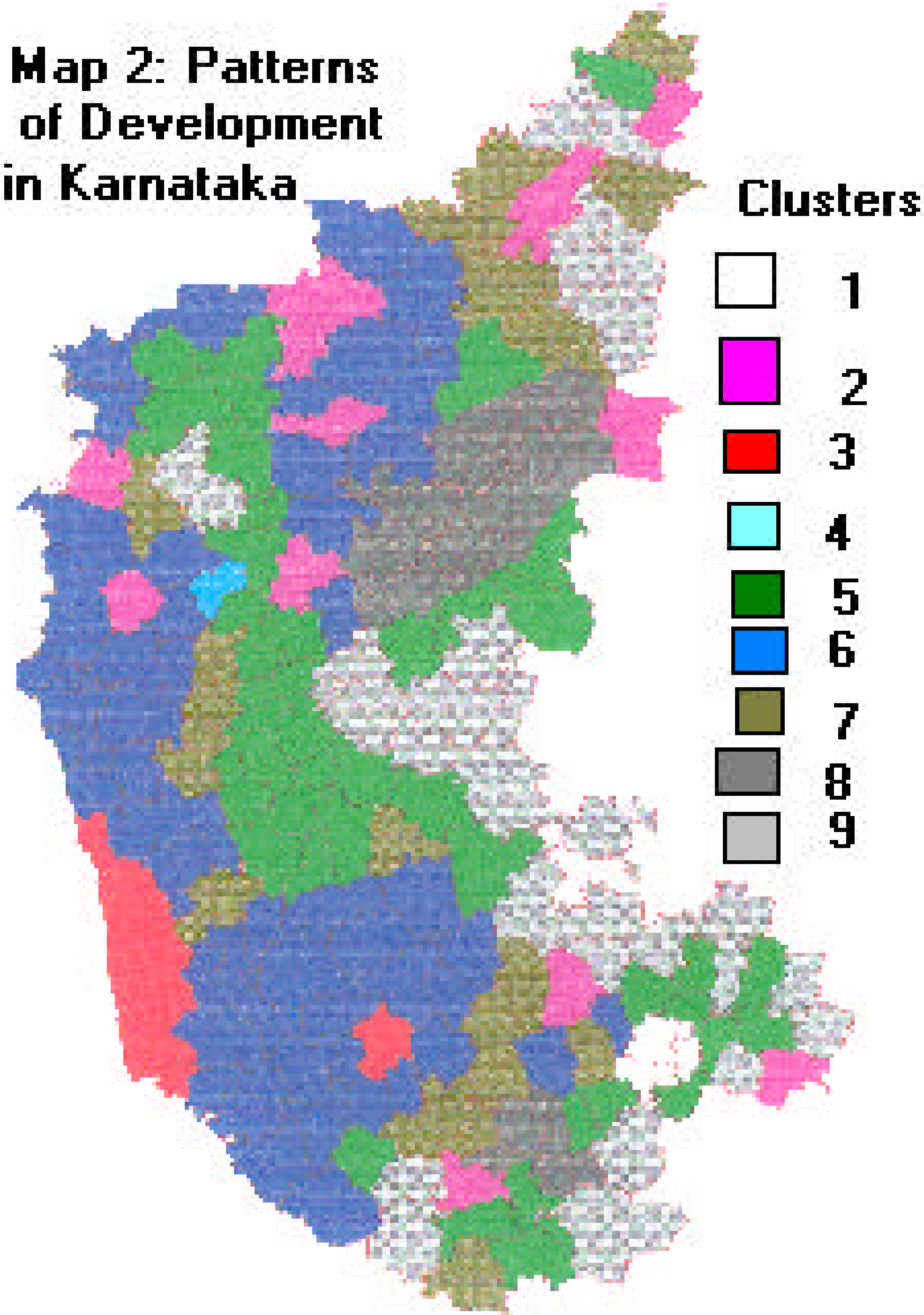

Map 2: Patterns of Development in Karnataka
Clusters
1
2
3
4
5
6
7
8
9

Table 10: Cluster-Wise Average Value for Each Indicator

Indicators	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5	Cl.6	Cl.7	Cl.8	Cl.9
UP to TP	70.02	48.1	29.31	0.62	21.62	13.99	15.13	14.23	8.74
W to TP	35.46	37.38	47.69	69.42	43.33	44.57	45.09	45.52	45.74
AW to TW	21.69	51.25	33.79	53.54	67.98	58.09	75.29	73.22	74.01
TCA to NAS	110.4	112	138.7	132.5	124.7	110.8	120.2	110.8	114.1
GIA to GCA	24.44	18.27	30.18	5.64	35.37	20.60	37.25	20.28	24.11
P per RF	1971	5943	9038	516	19835	14295	19546	32744	124286
P per CB	8355	13281	7995	1907	15019	10433	24545	17135	20488
P per CS	3827	1808	3610	147	1794	2064	3128	2461	2309
TRL	125.5	86.9	79.9	79.5	83.3	67.7	233.7	56.8	76.2
TRMV	12581	4390	4376	36781	2026	2169	1379	1138	1006
P per PO	16314	5979	4066	1460	5620	3437	4959	4888	4132
T per LP	3344	1026	1966	12061	467	735	477	334	282
P per MI	32170	37282	19480	9244	20493	14941	24661	18222	14362
Bed per LP	160.4	92.1	89.2	704.2	50.1	72	38.8	41.6	44.6
Lit Rates	68.04	58.03	72.06	54.63	49.95	59.41	36.08	41.19	47.32
SCST to TP	17.85	20.4	10.54	8.99	23.77	16.35	22.03	32.54	19.78
Sex Ratio	905	938	1064	936	950	978	973	956	976

Key:

UP to TP: Percentage of Urban Population to Total Population
W to TP: Percentage of Workers to Total Population
AW to TW: Percentages of Agricultural Workers to Total Workers
TCA to NAS: Total Cropped Area to Net Area Sown
GIA to GCA: Gross Irrigated Area to Gross Cropped Area
P per RF: Population per Registered Factory
P per CB: Population per Commercial Banks
P per CS: Population per Co-operative Society
TRL: Total Road Length per 100 Sq. Kilometers
TRMV:
P per PO: Population per Post Office
T per LP: Telephone lines per *Lakh* (One hundred thousand) Population
P per MI: Population per Medical Institution
Bed per LP: Hospital Beds per *Lakh* population
Lit Rates: Literacy Rates
SCST to TP: Percentages of SC and ST Population to Total Population

Sex Ratio: Sex Ratio

We can make good judgment of the K-SOM algorithm from the results of our present study of 175 talukas of Karnataka state. Consider the following:

- ?? The K-SOM based map has been able to identify two talukas viz. Bangalore North and Bangalore South of Bangalore city. Hubli taluka has been identified as one unique cluster (i.e. cluster number 4) because of its unique value for the number of hospital beds.

- ?? Another interesting result in Map 2 is that, most of the district headquarters are grouped in cluster 2. However, rest of the district headquarters are falling in other clusters due to the similarity of indicator values of specific talukas.

- ?? From the *patterns* map 2, we can identify the talukas with similar development without losing any information on each of the indicators especially in the context of specific PPPs.

This application illustrates the difference in results obtained when we consider development inequalities and development patterns. In practice, development planners and practitioners often have to work with smaller spaces with several development variables as well as socio-cultural, environmental, physical and other indicators relevant to a specific PPP. As Rao and Babu (1996) argue:

> One type consists of those which are resource poor and do not possess adequate development potential. The other type consists of those which have rich natural resources … but owing to historical and political factors could not exploit the resources for development purposes and, therefore, remained backward. These differences in the nature of the sub-regions are important while formulating a regional plan …"

The flexibility offered by considering patterns of development, allows for PPPs to take into account variables that could be of relevance to them.

Plans, policies and projects to reduce regional imbalances need to study *both*, inequalities in and patterns of development. The composite index has become an attractive tool to development practitioners to study inequalities. On the other hand, the complexity in the techniques to study patterns of development has limited application in PPP formulation. The K-SOM artificial intelligence algorithm is a user-friendly tool that could provide insights into development patterns, an invaluable input for optimal targeting of PPPs.

VI. Conclusions

Spatial estimates at various levels of disaggregation reflect convergence of deprivation in multiple dimensions or *multidimensional* poverty. Those in poverty are unevenly distributed across India with concentration of poverty in some states. 5 out of the 7 high income poverty states- Orissa, Madhya Pradesh, Uttar Pradesh, Assam and Bihar have the lowest five ranks on multidimensional indicators as well. Poverty related estimates for 59 regions in 16 large states show that between 20% and 43% of the population living in rural areas of 12 regions and urban areas of 21 regions suffer severe poverty. Variables reflecting multidimensional deprivation, such as incidence of child mortality, literacy, access to infrastructure such as electricity, toilet facilities and postal and telegraphic communications are estimated to be several times worse in these regions relative to those in the best performing region.

Measuring inequalities is important for many purposes. No single indicator can capture the complexities of development. Therefore, indices are generally estimated by aggregating performance with regard to several indicators. This requires the identification of variables to be included in the index, the range to be used for scaling and weights to be allocated to the different variables. Decisions in this regard tend to be arbitrary and driven by availability of data. Changes in any of these factors can yield very different results. In addition there is the issue of choice of method to be used in estimating the index.

In estimating indices at the district level, we use multidimensional indicators that may reflect persistent deprivation, such as illiteracy, infant mortality, low levels of agricultural productivity and poor infrastructure to help sharpen the identification of areas in chronic poverty. We calculate an adjusted value of each index so that the values obtained are not sensitive to changes in the ranks with changes in the minimum – maximum limits used. The 9 sets of results are then sorted to identify the most deprived districts.

The seven most deprived districts computed on the basis of the 9 sets of multidimensional indices reflecting deprivation are Bahraich and Budaun in UP, Barmer in Rajasthan, Damoh and Shahdol in MP, Kishanganj in Bihar and Kalahandi in Orissa. While Kalahandi in Southern Orissa is one of the most income poor regions in the country, Bahraich and Budaun in Eastern and Western UP are not among the poorest regions of India. Therefore, the districts identified as poorest on income criteria are not always the same as the districts identified as poorest in multidimensional terms.

Similarly computations based on the 9 indices listed above show that the 52 to 60 most deprived districts out of 379 districts in 15 large states of India are distributed as follows: 1 district in Assam, between 5 to 8 districts in Bihar, 11 to 12 districts in Rajasthan, 21 to 26 districts in Madhya Pradesh, 4 districts in Orissa, and 6 to 10 districts in UP. While it is true that some districts in Rajasthan and one in Assam get averaged out in the regional and state level analysis, the fact that districts in MP, Bihar, Orissa and UP are among the most deprived is no surprise. What clearly emerges is the constancy of districts regardless of indicators used and method of computation. Identification of districts that reflect chronic deprivation in multidimensional parameters is the first step in determining strategies to correct such imbalances.

Unevenness of development becomes more and more prominent as we move to smaller spaces. We first apply the UNDP procedure to identify the poorest talukas (below district level) for the state of Karnataka in India and then point out the limitations of this procedure and suggest use of the K-SOM technique to analyse the pattern of regional development to determine spatial inequality of development in the state. We find that the talukas of coastal Karnataka have very high development and as we move towards inland, the level of development decreases. Though certain talukas have similar HDI values, the individual indicator values are significantly different from each other and in the process of constructing the composite index such loss of information occurs as the importance of each indicator values get averaged out.

Since plans, policies and projects to reduce regional imbalances need to study *both*, inequalities in and patterns of development use of the K-SOM artificial intelligence algorithm can be an invaluable tool to provide insights into development patterns and optimal targeting of PPPs.

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[1] See for example,
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[2] An example of such advocacy could be State reorganization within a country.

[3] 1. In the case of the UNDP three indicator (life expectancy at birth, education and income) based calculations:
i). let
$l = L_b – L_k$, where L_b is the maximum actual LEB index value, say, of country b, and L_k is the minimum actual LEB index value, say, of country k
$e = E_m – E_n$, where E_m is the maximum actual EDN index value, say, of country m, and E_n is the minimum actual EDN index value, say, of country n
$g= G_p – G_q$ where G_p is the maximum actual GDP index value, say, of country p, and G_q is the minimum actual GDP index value, say, of country q.
ii). Take the minimum of (1,e and g). Let us suppose that 1 <e and 1<g (i.e. 1 is the minimum or least value among 1,e and g).
iii). Then let $e^* = 1/e$ and $g^* = 1/g$.
iv). Adjust L_j, E_j and G_j as follows.
Since 1 is minimum, let:
$aL_j = L_j$ for all j
$aEj = e^* E_j$ for all j
$aGj = g^* G_j$ for all j
v). $aHDI_j = (aL_j + aE_j + aG_j)/3$
vi).Choose max_j $(aHDI_j)$ and HDI_j)
vii). Let $v= (HDI_j)/max_j(aHDI_j)$
viii). Let $AHDI_j = v(aHDI_j)$
ix). Rank countries according to AHDI with higher values getting a better rank.

[4] The Borda Score or Borda Count of a region is the sum of its ranks for each indicator; higher the score lower the rank of a region in terms of overall development.

[5] Here R_i+1 is “better than” R_i (for all i) with respect to all indicators X_j (in this case, X_1 and X_2).

[6] talukas referred in the text have been marked on Map 1 only.

[7] Several interesting and informative articles are also available on the Internet.

[8] The VISCOVERY® SOMine Standard Edition package was used for the K-SOM analysis. We are grateful to Chemols Infotech Private Limited for the data analysis. .

[9] The specialized VISCOVERY® SOMine package gives users scope for exploratory data analysis like, for example, “nearest” regions in development levels, component maps, and so on. These could be of practical use to development agencies.