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EDUCATIONAL ATTAINMENT FAVOURABILITY MAPPING WITH THE APPLICATION OF ANALYTICAL HIERARCHY PROCESS (AHP)

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ABSTRACT: *The educational attainment belongs to the core of the educational researches; and, researchers within this domain are attempting to develop the 'tools and techniques' of demarcating the areas having a degree of advancement or backwardness in terms of attainment; as well as effort is being made to examine the internal functions of the interactive variables associated with the process. In the present study we try to apply the algorithm of Analytical Hierarchy Process in mapping the spatial differentiation of the favourability of educational attainment in the district of Purulia, a backward districts in terms of achieved level of human development in India. The output from the model has been validated with the variable of Mean Years of Schooling which is a recognized indicator of the prevailing level of attainment. The spatial mapping of educational favourability is done.*

KEYWORDS: AHP, Developing countries, Multi criteria, Pair wise comparison matrix

INTRODUCTION

The very sensible definition of 'development' by Sen (2001) mentioned that development is about creating freedom for people and removing obstacles to greater freedom. Greater freedom enables people to choose their own destiny. Education may be treated as the 'power' of people to choose the 'destiny' rationally. So, development, when conceptualized as a process of sustainable human well being, cannot be addressed properly without linking it with the parameter of education. Education, occupies a strategic position in India's development policies; and, successive centralized and decentralized development plans as well as Five-Years national development plans have accorded high priority to education development (NUEPA 2014). Alongside, this is also a reality that there is a large variation of enrollment and attainment of education across Indian states since independence as displayed by National Sample Survey database (Filmer and Pritchett 1998) and the same scenario has been revealed at the district as well as sub-district levels in the country by a number of researches done therein. Also, India is not an exception to the very common feature of the developing countries that the educational attainment is increasing but raising average of educational level is often accompanied with increased inequality in education also (Pieters 2009). The 'inequality of opportunity' of educational attainment between castes, communities and genders is considered to be concerned with the low degree of social mobility (Asadullah and Yalonetzky 2010).

The present paper focuses on the analysis of spatial variation of educational attainment which is a multi-dimensional issue; and also, this may be treated as the outcome of the interacting factors on a particular space. However, all these factors possess a very complex interaction between themselves along with many other factors linked with the ambient environment, society, culture, ethnicity and politics. This complex interaction pattern between a varied ranges of factors leads to shape the

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pattern of attainment in education differently over space. Drawing the 'contours' of favourability of educational attainment on the spatial unit through a careful integration of all the factors will be helpful to receive an initial level of knowledge on the educational disparities to address the issue through future planning and policy formulation. The multi criteria based prediction models are gradually making their places in socio-economic sciences as they are capable of mathematizing the complex real-world interacting variables within its theoretical platform and provide output through accepting multiple inputs from the users.

The spatial variation of educational attainment is a multi-dimensional issue; which may be treated as the result of the interacting factors on a particular space. However, all these factors possess a very complex interaction between themselves as well as many other factors linked with the ambient environment, society, culture, ethnicity and politics; and, this complex interaction pattern between a varied ranges of factors results into shaping the pattern of attainment in education differently over space. Drawing the 'contours' of favourability of educational attainment on the spatial unit through a careful integration of all the factors will be helpful to (i) understand the spatial variation of the level of education-friendly socio-economic environment; (ii) assess the spatial differences of the response of contributing or constraining factors on choice of individual toward 'acceptance' or 'refusal' of undergoing an educational level and (iii) to receive an initial level of knowledge on the educational disparities to address the issue through future planning and policy formulation. The multi criteria based prediction models are gradually making their places in socio-economic sciences as they are capable of mathematizing the complex real-world interacting variables within its theoretical platform and provide output through accepting multiple (practically as much as possible) inputs from the users. The present study puts its effort toward Educational Attainment Favourability Mapping with utilizing the algorithm of Analytical Hierarchy Process (AHP).

STUDY AREA:

The district of Purulia, the western most district in the State of West Bengal in India has been selected as the study area. The district is extended between 22.70295^0 N to 23.71335^0 N latitude and 85.82007^0 E to 86.87508^0 E longitude, covering a total area of 6259 sq. Km and accommodates 2,930,115 populations with an average population density of 468 persons per sq. Km. (Census of India, 2011). The district posses a very low level in health, education and GDP – the three basic dimensions of Human Development (West Bengal Human Development Report 2009). The constrains of unfertile soils, extreme climates and lack of irrigation opportunity does not facilitate the district to produce a the agricultural yield beyond the subsistence level. To introduce the level of educational attainment, the rural and urban literacy rate is 62.73 and 76.18 per cent in the district. Moreover, the female literacy rate at the urban areas is 67.15 per cent; and it does not cross 50 per cent (as the presently the rural female literacy rate is 48.06 % only) benchmark yet in the rural areas of the district (District Statistical Handbook 2013). There is a acute disparity of educational status between different social and religion categories, as well as between genders in this districts. Sub-district level database also reveals that the there is also a considerable magnitude of spatial difference, especially rural-urban disparity of literacy and educational attainment within the district. The district is selected as study area for the present work.

DATASETS AND SOFTWARE

Primary Data Collection: The present study uses the primary data collected through household survey with a pre-printed survey schedule. The district of Purulia is constituted with 20 C.D. Blocks and a total of 170 Gram Panchayats (GPs) within the jurisdiction of these Blocks; as well as three urban Municipalities. The required numbers of sample has been collected from each C.D. Blocks in a simple random basis, provided that the sample is distributed at least one census village in each of 170 Gram Panchayats and one Municipal Ward each from three Municipalities of the districts for ensuring a better representativeness of the entire blocks. The coordinates of all the surveyed sites have been recorded for the purpose of utilizing the data representation on a GIS Software platform (*See Fig. 1*).

Secondary Sources of Data: A wide range of reliable sources of secondary from the Census of India, 2011 has been utilized for the present study. The sources of all datasets will be mentioned accordingly at the later part of the paper.

Software used in the data analysis and mapping : The statistical calculations and algorithms were solved using *MS Excel 2010*, *SPSS 17.0* and *MATLAB 7.12*. The mapping has been done with the use of the open source GIS software - *QGIS 2.8.*

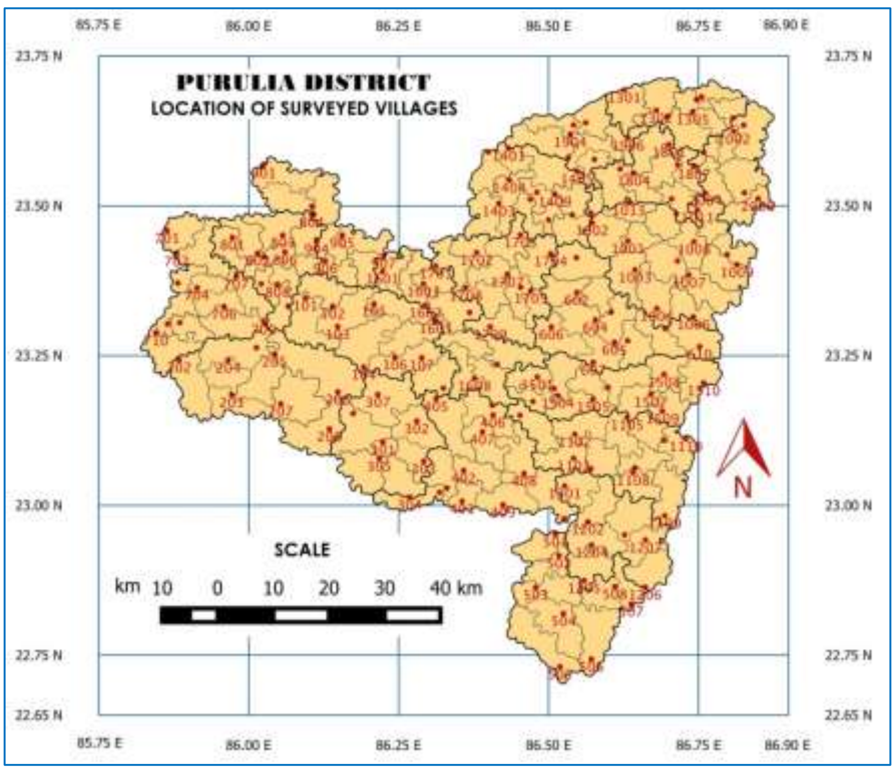

Fig. 1: Map of the Purulia District which has been selected as the study area with indicating the sites of the villages from where the primary data has been collected and used in models

METHODOLOGICAL FRAMEWORK OF THE MODEL

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Input variables: A large volume of literature is available on the relationship between individual characteristics, family background, and education attainment (e.g. Lave, Cole and Sharp 1981; Teachman 1987; Haveman and Wolfe 1995; Glewwe 2002; Lauer 2003). Besides, some other studies have emphasized on parents educational level playing an important role on children's enrollment and attainment (Maitra and Sharma 2010). The renowned work of Smith and Cheung (1986) shows evidences to conclude that there is a stable relationship in the developing countries over long period between the importance of family background and the educational attainment of individuals. Factors like religion and ethnicity also determines individual's educational attainment, with some people from some religious and ethnic backgrounds having a greater statistical likelihood of higher or lower educational attainment than others (Sander 2010). For countries like India, where there is an acute economic backwardness in the wide rural areas, the factor of households' capacity and willingness of investment to children's education plays a vital role in determining the enrollment and attainment level (Tilak 2002). Analysing the primary field data and the relevant literature on the determinants of educational attainment in the study area, the present study examines the role of different factors linked with spatial variation of education-friendly environment and considers a group of ten variables as input variables (*See Table 1*).

Table 1: Factors considered for unequal attainment and corresponding variables used for educational attainment favourability mapping

Factors	Indicator (Variable)		Unit	Data Source
Existing ambient literacy level	FLR	Female literacy rate	*Per cent*	*Primary Census Abstract, Census of India, 2011*
Presence of known marginalized peoples	STP	ST population share to total population	*Per cent*	
Workforce characteristics	MRG	Arithmetic ratio between main and marginal workers	*Decimal*	
Prevailing level of income insecurity	CII	Composite index of income insecurity (see ***Table 2***)	*Decimal*	*Calculated from Primary Field Data, Field Survey 2012*
Availability of pre-school training facilities	PST	Availability of pre-school training within the locality (see ***Table 3***)	*Number*	
Stress due to schools at distance from the residence	MDS	Weighted index of comparative stress due to distance of schools up to Secondary level (see ***Table 4***)	*Decimal*	*Calculated from Directory of Village Amenities, Census of India, 2011*
Access to urban educational goods and services	URB	Weighted index of proximity to nearest urban centers (see ***Table 5***)	*Decimal*	

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Degree of connectivity (*vis-à-vis* isolation)	CON	Weighted index of status of accessibility through roadways (See ***Table 6***)	*Decimal*	
Adequacy of quality human resources	TSR	Average nos. of teachers per thousand students (up to secondary level)	*No. Per thousand*	*Primary Census Abstract, Census of India, 2011*
Household expenditure towards educating children	EDE	Monthly per capita expenditure to education	*Rs.*	*Calculated from Primary Field Data, Field Survey 2012*

Table 2: Structure of Composite Index of Income Insecurity (CII)

Parameter 1: Magnitude of Income inconsistency			Parameter 2: Likelihood of loss of present job			Parameter 3: Difficulty of re-employment			Parameter 4: Alternative source of income		Income insecurity index
Deviation between minimum & maximum monthly income	Severity scale	Score for Income Deviation	Chance of loss of present job	Severity scale	Score for Job loss Possibility	How easy to be re-employed to a job as good as current	Severity scale	Score for Difficulty of re-employment	Incoming person have secondary sources of income	Score for Alternative source of income	
	S_i	c_1		S_i	c_2		S_i	c_3		c_4	$\tilde{I}=(c_1+c_2+c_3+c_4)$
<20%	1	1.0	No chance	1	0.5	Very easy	0	0	Yes	0	
20-39%	2	2.0	Very unlikely	2	1.0	Quite easy	1	0.5	No	1.0	
40-59%	3	3.0	Quite unlikely	3	1.5	Quite difficult	2	1.0			$0 \le \tilde{I} \le 10$
60-79%	4	4.0	Evens	4	2.0	Very difficult	3	1.5			
>80%	5	5.0	Quite likely	5	2.5						

Table 3:Structure of indicator of availability of pre-school training within locality (PST)

Type of availability of PST	Level	Indicator value
No PST facility available	Nil	0
Only private PST facilities available	Moderate	1
Only Government PST facilities available	Good	2
Both private and Government PST facilities	Fair	3

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Table 4: Structure of the indicator of Weighted index of comparative stress due to distance of schools up to Secondary level (MDS)

Level of attainment *(x)*	Distance range in km *(d_x)*				Distance range in				Calculation of MDS
	0[#]	1 to 5	6 to 10	>10	0[#]	1 to 5	6 to	>10	
	Assumed stress level due to				Score assigned *(s_x)*				
Primary schools	Nil	Very	Very	Very	0	1	1	1	$MDS = \frac{1}{3.5}(s_{PS} + s_{MS} + s_{SS} + s_{HS})$ *...Eqn. (1)*
Middle schools	Nil	High	Very	Very	0	0.5	1	1	
Secondary schools	Nil	Moderate	High	Very	0	0.25	0.5	1	
Senior secondary	Nil	Nil	Moderate	High	0	0	0.25	0.5	

[#]0 indicates the school is available within the own village

Table 5: Structure of the weighted index of proximity to urban centers (URB)

Distance from *(x)*	Distance range in km *(d_x)*						Calculation of URB
	< 10	10-20	20-40	40-80	80-100	>100	
	Score *(s_x)*						
District Head Quarter *(DHQ)*	1	1	1/2	1/4	1/8	1/16	$URB = (s_{DHQ} + s_{OST} + s_{SDT})$ *Eqn. (2)*
Nearest Other Statutory Towns *(OST)*	1/2	1/4	1/8	1/16	1/32	1/64	
Sub-districts HQ / Notified Township / C.T. *(SDT)*	1/4	1/8	1/16	1/32	1/64	1/128	

Table 6: Structure of weighted index of accessibility through roadways

Site located at a distance from *(x)*	Distance range in km *(d_x)*			Calculation of CON
	0	1-5	> 5	
	Score assigned *(s_x)*			
National Highway *(NH)*	1	1/2	1/4	$CON = (s_{NH} + s_{SH} + s_{MDR} + s_{ODR} + s_{OCR})$ *Eqn. (3)*
State Highway *(SH)*	1/2	1/4	1/8	
Major District Roads *(MDR)*	1/4	1/8	1/16	
Other District Roads *(ODR)*	1/8	1/16	1/32	
Other Concretized Roads *(OCR)*	1/16	1/32	1/64	

Output variable: The output of the Analytical Hierarchy Process (AHP) model will be considered as the Index of Favourability to Educational Attainment (ϑ_{AHP}) which indicates the level of favourability of a spatial unit toward educational attainment of the population depending on the set of variables (predictors) considered for the present work. The standardized value of this index (ϑ_{std}) will be used for mapping the spatial pattern of favourability in the study area.

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BUILDING AHP MODEL:

The AHP model building process has been started with the normalization of the dataset. Let, $v_{i.j}$ is the value of i^{th} variable in j^{th} sample site, influencing the educational attainment favourability ($c_{attainment}$); and this have been normalized ($x_{i,j}$) between the value of 0 and 1 with reference to the standard range specified for the present model bounded by the maximum and minimum value of v_i as $v_{i[max]}$ and $v_{i[min]}$ accordingly. The rule of normalization can be expresses as:

$$x_{i,j} = \frac{(v_{i,j} - v_{i[min]})}{(v_{i[max]} - v_{i[min]})} \quad \text{when, } v_{i,j} \propto c_{attainment}$$

Eqn. (4)

$$x_{i,j} = \frac{(v_{i[max]} - v_{i,j})}{(v_{i[max]} - v_{i[min]})} \quad \text{when, } v_{i,j} \propto \frac{1}{c_{attainment}}$$

Eqn. (5)

Now, the normalization of the dataset of *m* numbers of variables for *n* numbers of sample sites results into the formation of a *m*x*n* asymmetrical matrix $M_{m\times n}$.

$$M_{m\times n} = \begin{pmatrix} x_{1,1} & x_{2,1} & x_{3,1} \cdots & x_{m,1} \\ x_{1,2} & x_{2,2} & x_{3,2} \cdots & x_{m,2} \\ x_{1,3} & x_{2,3} & x_{3,3} \cdots & x_{m,3} \\ \cdots & \cdots & \cdots & \cdots \\ x_{1,n} & x_{2,n} & x_{3,n} \cdots & x_{m,n} \end{pmatrix}$$

Eqn. (6)

The AHP algorithm determine the weight of each elements of the data matrix, deriving from the pair wise inter-variable (or, inter-column) comparison matrix as well as pair wise inter-class (or, inter-row) comparison matrix through utilizing the set of relative preferences assigned by the users. The ultimate result of the AHP modeling is the calculation of a favourability index 'using a weighted linear sum procedure' (Voogd 1983). Consequently the Weighted Linear Index of Favourability to Educational Attainment for site *j* ($\vartheta_{AHP,j}$) derived by the Analytical Hierarchy Process can be expressed as:

$$\vartheta_{AHP,j} = \sum_{i=1}^{m} \left(w[AHP]_i \times w[AHP]_j \times x_{i.j} \right)$$

Eqn. (7)

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Where, $w[AHP]_i$ denotes the weight assigned by inter-variable comparison and $w[AHP]_j$ is the weight assigned by inter-class comparison. The comparison between a pair of factors with reference to their relative effectiveness towards attainment has been done following Satty's scale of comparison which is mentioned in *Table 7* below:

Table 7: Scale of preference between two parameters in AHP (After Saaty 2000)

Scale	Degree of preference	Explanation
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favor one activity over another
5	Strongly	Experience and judgment strongly or essentially favor one activity over another
7	Very strongly	An activity is strongly favored over another and its dominance is showed in practice
9	Extremely	The evidence of favoring one activity over another is of the highest degree possible of an affirmation
2, 4, 6, 8	Intermediate values	Used to represent compromises between the preferences in weights 1, 3, 5, 7, and 9
Reciprocals	Opposites	Used for inverse comparison

The pair wise comparison of preferences between fifteen variables is given in *Table 8*. The principal eigenvalue derived from the matrix is 10.154. The *Consistency Ratio (CR)* has been calculated as 0.011 (i.e. <0.1) which indicates a reasonable level of consistency in the pair-wise comparison that is good enough to recognize the class weights. The class wise comparison within each variable is comparatively more complex task. As, the data has been normalized at the beginning of the AHP analysis, so values of all variables have been bounded between *0* and *1*; and, as the normalization has considered the effect of variables on the favourability to attainment, owing to an increase of each variable from *0* toward *1* tends to indicate a higher degree of favourability of the corresponding region, then the class wise comparison within variables requires careful allocation of relative preferences. The normalized values of each variables are categorized into four classes S_1, S_2, S_3 and S_4 using the Jenk's Natural Break Optimization algorithm (*Table 9*) for the purpose of allocating intra-variable preferences within the data matrix (see *Table 10*).

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Table 8: The inter-variable pair-wise comparison matrix and determination of consistency level

	FLR	STP	MRG	CII	PST	MDS	URB	CON	TSR	EDE	λ_{max}	CI	CR	$w[AHP]_i$
FLR	1	3	3	0.5	2	1	4	4	2	0.5	*10.154*	*0.017*	*0.011*	0.131
STP	0.333	1	1	0.25	0.5	0.333	2	2	0.5	0.25				0.05
MRG	0.333	4	1	0.25	0.5	0.333	2	2	0.5	0.25				0.05
CII	2	4	4	1	3	2	5	5	3	1				0.208
PST	0.5	2	2	0.333	1	0.5	3	3	1	0.333				0.08
MDS	1	3	3	0.5	2	1	4	4	2	0.5				0.131
URB	0.25	0.5	0.5	0.2	0.333	0.25	1	1	0.333	0.2				0.031
CON	0.25	0.5	0.5	0.2	0.333	0.25	1	1	0.333	0.2				0.031
TSR	0.5	2	2	0.333	1	0.5	3	3	1	0.333				0.08
EDE	2	4	4	1	3	2	5	5	3	1				0.208

Table 9: Result of Jenk's natural break optimization algorithm run on the variables for classification of values into different intra-variable favourability classes

Variable	Favourability class	Lower limit	Upper limit	Count		Variable	Favourability class	Lower limit	Upper limit	Count
FLR	S1	0.000	0.149	22		MDS	S1	0.000	0.272	13
	S2	0.157	0.252	72			S2	0.363	0.545	42
	S3	0.255	0.404	76			S3	0.636	0.818	62
	S4	0.830	1.000	3			S4	0.909	1.000	56
STP	S1	0.000	0.200	17		URB	S1	0.000	0.244	69
	S2	0.235	0.525	20			S2	0.265	0.428	76
	S3	0.549	0.811	31			S3	0.510	0.673	25
	S4	0.827	1.000	105			S4	0.877	1.000	3
MRG	S1	0.000	0.138	147		CON	S1	0.000	0.177	114
	S2	0.143	0.321	22			S2	0.193	0.419	40
	S3	0.552	0.552	1			S3	0.467	0.725	15
	S4	0.890	1.000	3			S4	0.806	1.000	4
CII	S1	0.000	0.243	59		TSR	S1	0.000	0.220	59
	S2	0.269	0.496	37			S2	0.261	0.522	45
	S3	0.510	0.742	44			S3	0.534	0.770	62
	S4	0.753	1.000	33			S4	1.000	1.000	7
MDS	S1	0.000	0.272	13		EDE	S1	0.000	0.126	67
	S2	0.363	0.545	42			S2	0.128	0.238	69
	S3	0.636	0.818	62			S3	0.244	0.587	34
	S4	0.909	1.000	56			S4	0.906	1.000	3

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Table 10: Intra variable fovourability classes, pair-wise comparison and consistency level of the matrix

Favourability class		S1	S2	S3	S4	λ_{max}	CI	CR	$w[AHP]_j$
Highly favourable	S1	1	2	3	4	4.033	0.011	0.012	0.466
Moderately favourable	S2	0.5	1	2	3				0.277
Marginally favourable	S3	0.333	0.5	1	2				0.161
Almost un-favourable	S4	0.25	0.333	0.5	1				0.096

VALIDATION OF THE MODEL:

The variable of Mean Years of Schooling (MYS) is a well recognized indicator of the educational attainment achieved in a region. The value of MYS for all the sites have been calculated (following the UIS Scheme, 2012 as mentioned in *Table 11*) for the population in the age group 25-65 years ($MYS_{25\text{-}65Y}$) using the formula below:

$$MYS_{25-65Y} = \sum_{l} [HS_l]_{25Y}^{65Y} \times [YS_l]_{25Y}^{65Y}$$

Eqn. (8)

Where, HS_l is the portion of the population (25 -65 years) attained up to the 'l' level of education and YS_l is the official duration of level 'l' of attainment.

Table 11: Different levels of educational attainment as proposed by UNESCO Institute of Statistics (UIS, 2012) and syncing the scheme with Indian standard levels along with official durations for each

Attainment level	Status (HS_l)	Synced with	Official duration	Years of
ISCED 01	No schooling	Illiterates	0	0
ISCED 02	No schooling	Literates	1#	1
ISCED 03	Some primary	Class I - III	2#	2
ISCED 1	Completed	Class IV	4	4
ISCED 2	Completed	Class X	6	10
ISCED 3	Completed	Class XII	2	12
ISCED 4	Completed post-	Class XII+	1#	13
ISCED 5	Completed	Diploma	2#	14
ISCED 6	Completed	Graduation	3	15
ISCED 7	Completed	Post Graduation	2	17
ISCED 8	Completed	Research degree	8#	25

Duration assumed for intermediate/ unrestricted levels

The variable $MYS_{25\text{-}65Y}$ is plotted along y-axis as dependent variable against the variable of ϑ_{std} along x-axis (see *Fig. 2a*). For the purpose of comparison, the Multiple Regression

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is also done with all the ten variables used in AHP model as dependent variables and $MYS_{25\text{-}65Y}$ as independent variable in SPSS software. The estimated MYS ($MYS'_{25\text{-}65Y}$) from Multiple Regression Analysis is standardized similarly and plotted along y-axis against observed MYS ($MYS_{25\text{-}65Y}$) along x-axis (*Fig. 2b*).

Table 12: Summary of regression analysis

Case	X	Y	Trend line	R	R^2	Std. Err.
I	ϑ_{std}	$MYS_{25\text{-}65Y}$	y = 5.4133x + 1.9299	0.931	0.867	0.57106727
II	$MYS'_{25\text{-}65Y}$ (std)	$MYS_{25\text{-}65Y}$	y = 4.9124x + 2.0569	0.901	0.811	0.68057092

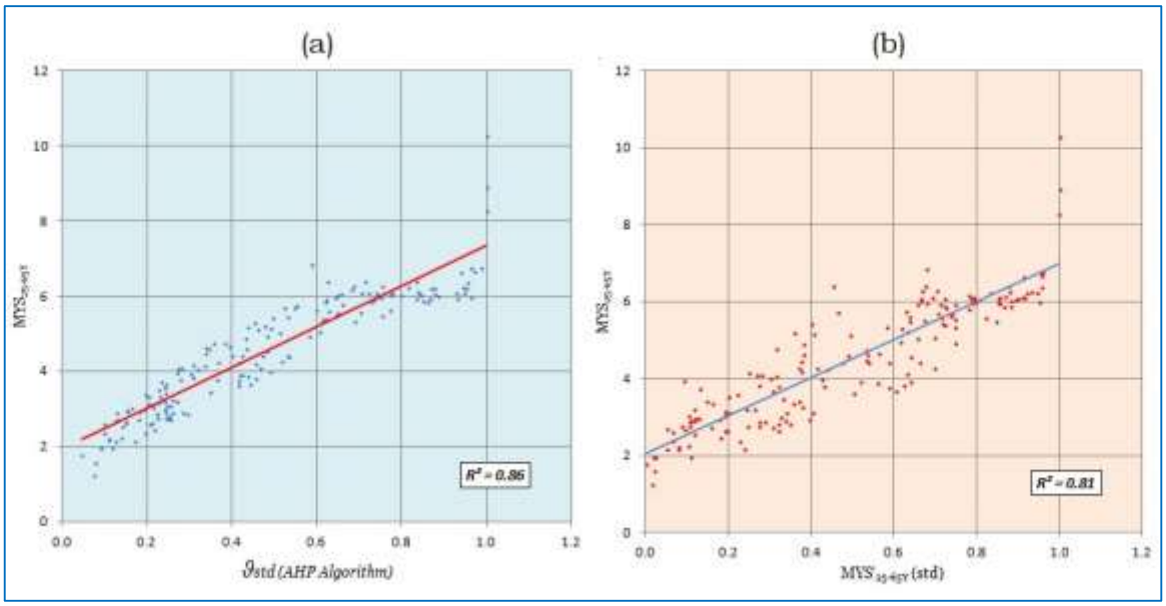

Fig. 2: The scatter diagram showing the trend of relationship of the observed values of Mean Years of Schooling ($MYS_{25\text{-}65Y}$) with (a) the standardized output of AHP model (ϑ_{std}) and (b) the estimated values of Mean Years of Schooling ($MYS'_{25\text{-}65Y}$) calculated by Multiple Regression Analysis.

The above validation effort concludes to: (i) There is significantly strong positive relationship between ϑ_{std} and $MYS_{25\text{-}65Y}$ which indicates that the Favourability Level explained by the AHP model is in strong similarity with the observed level of Educational Attainment in the study area; (ii) The result obtained from AHP model when compared with the Linear Regression model, it is found that, the correlation is high for both the cases (R>0.9), but the AHP model output are in better agreement (R^2=0.867) than the other (R^2=0.811) and (iii) The lower level of Standard Error of Estimate for the regression between ϑ_{std} and $MYS_{25\text{-}65Y}$ indicates a better precision of the estimation made by the AHP model than that of Multiple Regression Analysis (see *Table 12*).

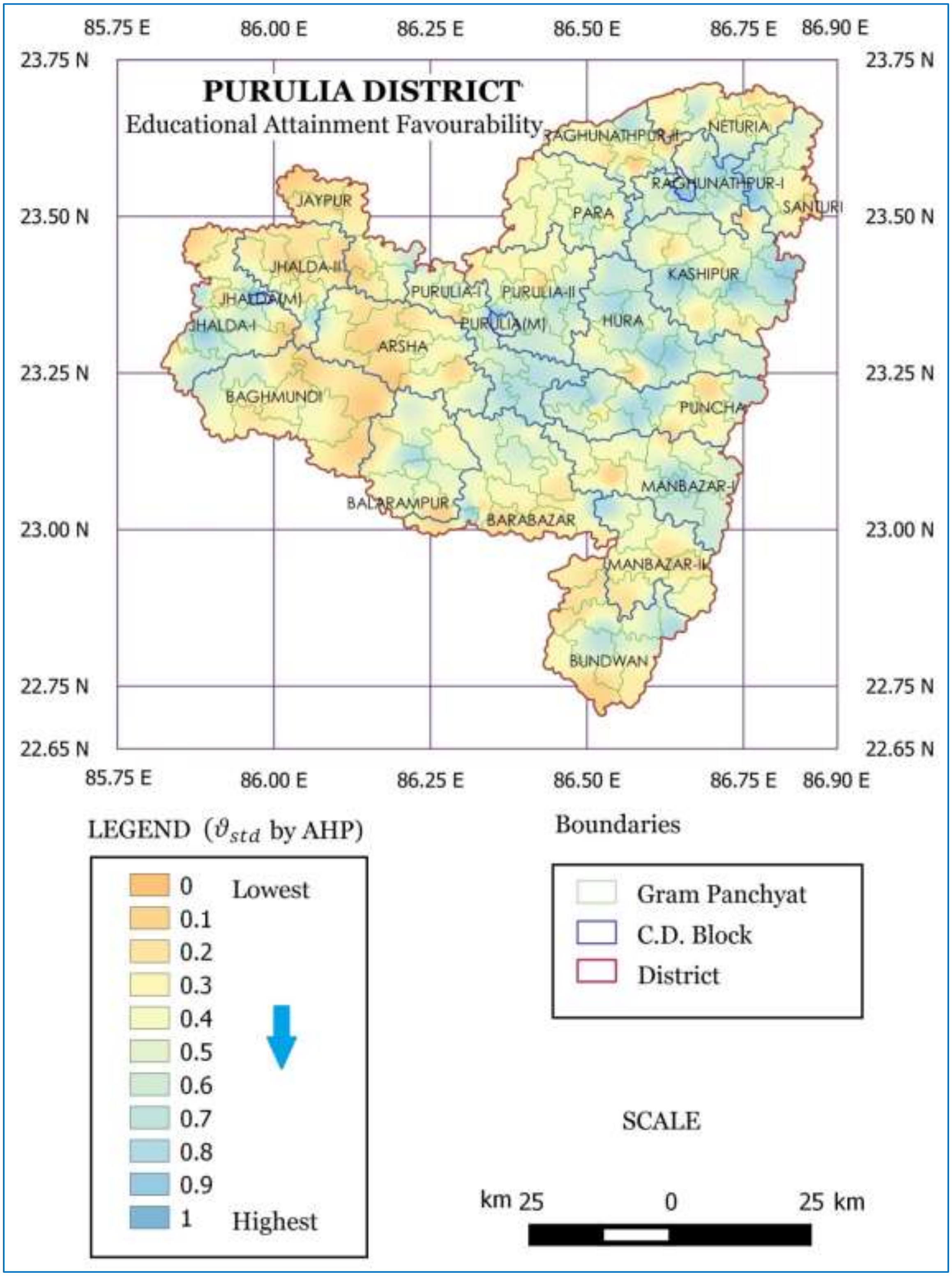

Fig. 3: Educational Attainment Favourability Map of Purulia (prepared with the application of the Analytical Hierarchy Model (AHP) algorithm)

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MAPPING, INTERPRETATION AND CONCLUSION:

The result of the AHP algorithm on the dataset is the point wise output of ϑ_j which is then standardized to ϑ_{std}. The coordinates of all the points have been collected during the field survey which enable point wise plotting of ϑ_{std} on their respective location on the study area. A total of 170 such points over the total area of the district of 6259 km^2 (i.e. averagely 36.8 km^2 per point or likelihood of getting one point for each 6.0666 x 6.06666 km grid) is intensive enough to express the spatial differentiation of attainment favourability fairly. All the points with respective attributes have been fed to QGIS 2.8 Software and the map of spatial variation of favourability of educational attainment has been generated (see *Fig. 3*).

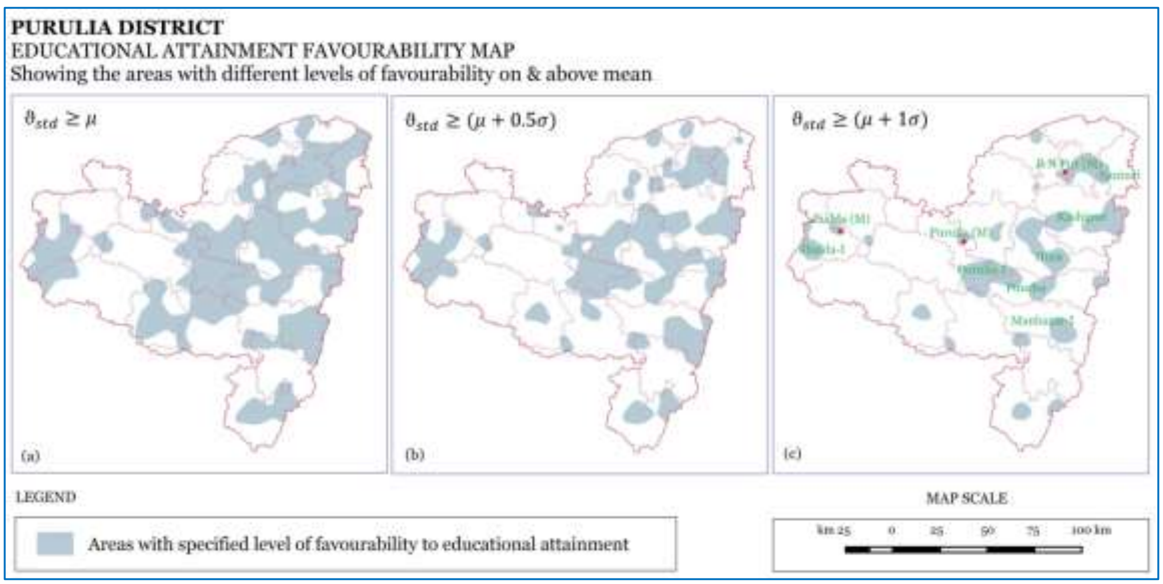

Fig. 4: The map demarcating the areas in the district of Purulia with the level of favourability to attainment on and above the average

A careful observation on *Fig. 3* reveals the spatial extension of the favourable socio-economic environment for a greater attainment as well as demarcates the zones with low degree of favourability, represented by a very low value of the attainment favourability index. However, the specific identifications of the regions with their tendency of favouring or hindering the attainment requires preparation of maps with more specific demarcation of the zones. In connection with this objectives, the whole district can be broadly categorized into two parts: (i) Areas with the level of favourability to attainment is on and above the average (see *Fig. 4*) and (ii) areas with below-average level of favourability condition prevails (*Fig. 5*).

ISSN: 2052-6377(Print), ISSN: 2052-6385(Online)

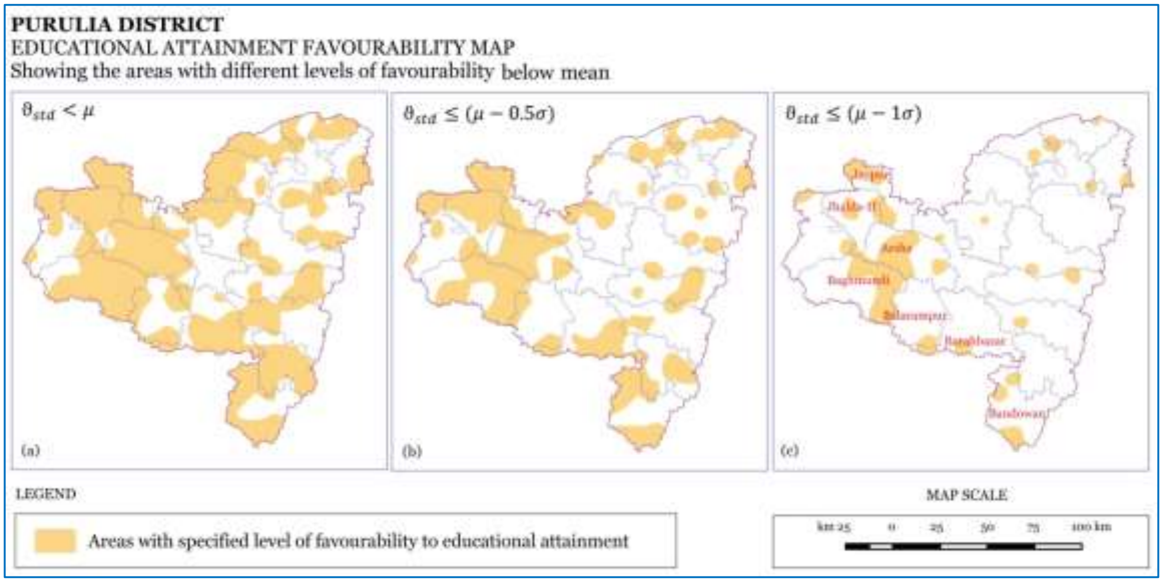

Fig. 5: The map demarcating the areas in the district of Purulia with the level of favourability to attainment below the average.

The areas with the criteria of $\vartheta_{std} \geq \mu$, when demarcated, shows that most of the eastern and middle part of the district along with some isolated pockets at other part exhibits the favourability toward attainment with the level above average in the districts. But as the level of favourability criteria is increased to $\vartheta_{std} \geq (\mu + 0.5\sigma)$, it shows a greater concentration toward eastern part of the district and finally the more higher level i.e. $\vartheta_{std} \geq (\mu + 1\sigma)$ becomes restricted around the three urban centers of the district (see Fig. 4c). Besides, a wider part of the district – mainly the western and southern blocks shows the levels of favourability to attainment as below the average. The very low level of favourability (may be said as almost unfavourable) scenario to attainment (i.e. $\vartheta_{std} < (\mu - 1\sigma)$ is found in the blocks of Baghmundi, Balarampur, Bandowan, Barbazar, Arsha, Jhalda-II and Jaypur (Fig. 5c). All these blocks have some common characteristics – firstly, all these blocks are located at the western edge of the district as well as the state, making inter-state boundary with neighbouring state of Jharkhand; secondly, they have the higher share of ST population in comparison to other blocks; thirdly, these blocks have greater share of forest covered area to total geographical area and lastly, these block show the comparatively lower rate of female literacy than other blocks within the district. These demarcation will help in further investigation of the causes of spatial variation of educational attainment in this district also.

The factors causing spatial difference of educational attainment are multidimensional in nature; and, admittedly, all of the social-economic phenomena do not lend themselves to easy explanations which makes the task of explaining the cause more challenging. The present study is framed with ten basic variables for the attainment favourability mapping; however, more refinement of the data structure and the utilization of more relevant variables may add more precision in the demarcation of advanced or vulnerable zones as

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well as provide meaningful insight toward addressing the causes of such distribution. Besides finding relevant environmental-socio-political variables with finer resolution, the '*mathematization*' of human behavior and cognition are becoming a very challenging issue for the socio-economic scientists, planners and researchers; and, this is becoming obvious for achieving the accuracy level of the output of such prediction models to a desired 'benchmark' in the domain of socio-economic sciences.

REFERENCES

Asadullah, M. N. and Yalonetzky, G. (2010). Inequality of Educational Opportunity in India: Changes over Time and across States, IZA, DP No. 5146.

Barro, R.J. (1991), Economic growth in a cross-section of countries, Quarterly Journal of Economics, 106(2): 407–443.

Bhaumik, S.K. and Chakrabarty, M. (2009), Is education the panacea for economic deprivation of Muslims? Evidence from wage earners in India, 1987–2004. Journal of Asian Economics, 20(2): 137–149.

Census of India (2011), Govt. of India.

District Statistical Handbook (2013), Govt. of India

Filmer, D. and Pritchett, L. (1998), Educational Enrollment and Attainment in India:Household Wealth, Gender, Village, and State Effects, World Bank

Glewwe, Paul. 2002. "Schools and Skills in Developing Countries: Education Policies and Socioeconomic Outcomes." Journal of Economic Literature, 40(2): 436-482.

Haveman, R. and Wolfe, B. (1995). The Determinants of Children's Attainments: A Review of Methods and Findings. Journal of Economic Literature . Vol. 33, No. 4 (Dec., 1995), pp. 1829-1878

Krueger, A.B. and Lindahl, M. (2001), Education and growth: Why and for whom? Journal of Economic Literature, 39: 1101–1136.)

Lauer, C. (2003), Family background, cohort and education: A French-German comparison based on a multivariate ordered probit model of educational attainment, Labour Economics, 10(2): 231–251.

Lave, C., Cole, M. and Sharp, D. (1981), Determinants of education achievement, Economics of Education Review, 1(2): 253–262.

Maitra, P. and Sharma, A. (2010), Parents and children: Education across generations in India, Mimeo, Monash University, Melbourne, Australia.

Malczewski, J. (1999), GIS and multi-criteria decision analysis, Wiley, New York, p 392.

Mankiw, N.G., Romer, D. and Weil, D.N. (1992), A contribution to empirics of economic growth, Quarterly Journal of Economics, 107(2): 407–437.

NUEPA (2014), Education for all: Towards quality with equity, MHRD, Govt. of India

OECD. (2008), Statistics, Knowledge and Policy 2007: measuring and fostering the progress of societies (ISBN 9264043233), General Economics & Future Studies, 6, 1–567.

Pieters, J. (2009). Education and Inequality in India: A Microeconometric Decomposition Analysis, http://www.ecineq.org/ecineq_ba/papers/pieters.pdf

ISSN: 2052-6377(Print), ISSN: 2052-6385(Online)

Pulselli, F.M., Ciampalini, F., Tiezzi, E., Zappia, C. (2006), The index of sustainable economic welfare (ISEW) for a local authority: a case study in Italy, Ecological Economics, 60 (1), 181–271.

Ranst, E.V., Tang, H. (1996), Application of fuzzy logic to land suitability for rubber production in peninsular Thailand, Geoderma, 70: 1 - 19

Saaty T.L., Vargas L.G. (2001), Models, methods, concepts and applications of the analytic hierarchy process, Kluwer, Dordrecht.

Saaty T.L., Vargas L.G. (2001), Models, methods, concepts and applications of the analytic hierarchy process, Kluwer, Dordrecht.

Saaty, T.L. (1980), The analytical hierarchy process, McGraw-Hill, New York

Saaty, T.L. (2000), Decision making for leaders: the analytical hierarchy process for decisions in a complex world, RWS Publications, Pittsburgh.

Sander, W. (2010), Religious background and educational attainment: The effects of Buddhism, Islam and Judaism, Economics of Education Review, 29(3)

Sen, A. (2001), Development as Freedom, Oxford University Press

Smith, H.L. and Cheung, P.P.L. (1986), Trends in the effect of family background on educational attainment in the Philippines, American Journal of Sociology, 91(6): 1387–1408.

Teachman, J.D. (1987), Family background, educational resources and educational attainment, American Sociological Review, 52(4): 548–557.

Tilak, J.B.G. (2002). Determinants of Household Expenditure on Education in Rural India. National Council of Applied Economic Research, Working Paper No. 88, New Delhi

UIS (2012), UIS Methodology for Estimation of Mean Years of Schooling, UNESCO

ISSN: 2052-6377(Print), ISSN: 2052-6385(Online)