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GEOGRAPHICAL SOCIETY OF THE NORTH EASTERN HILL REGION  
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Prof. H. J. Syiemlieh

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## **Challenges of Waste Management and Rag Pickers: The Case of Guwahati City**

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### **Abstract**

The task of waste-management in large cities is very complex and difficult. This study examines the problem of waste-management in Guwahati, the capital city of Assam with a population of around 1.2 million. It basically focuses on understanding the role of informal waste workers, i.e. rag pickers, of Guwahati city in this respect. This study is an attempt to unravel the socio-economic, political, working and health conditions of these workers and to find out the reasons behind taking up this type of work by them. The study is based largely on primary data and marginally secondary data. Required primary data have been gathered through exhaustive field survey and group discussion conducted in different locations of the city during the year 2024. The study finally reveals recommendations, education and legal recognition in order to successfully integrate them into approved schemes that promote greater occupational security while providing safety environment in the waste-management of Guwahati city.

**Keywords:** Environmental sustainability, rag pickers, role, health, waste-management.

### **Introduction**

In this modern era of globalisation, humankind is facing a world confronting with numerous crises, where each and every country in this world desires to be developed in multiple fronts. During the period of industrialisation and modernisation, this process of development has got accelerated. A rapid growth of population followed by increasing rate of urbanisation has been leading to new socio-economic challenges globally including the serious issue of waste-management. The growing population and the continuing trend of urbanisation, pose unprecedented challenges for municipal solid waste management (SWM) (Chaturvedi et al., 2015). It is a common trend for people to migrate from rural to urban in search of better opportunities and livelihood. But, many people with lack of required skill and formal education do not get suitable job for sustainable livelihood, and some of them are compelled to work in less lucrative job, and rag picking is one of such. The people who are engaged in such works are known by numerous names, such as

ragman, rag-gatherer, junkman, scavenger, canner, binner, recycler, salvager, waste picker, rag picker, etc. However, the First International and Third Latin American Conference of Waste-Pickers held in Bogota, Columbia, organised by the Latin American Network of Waste Pickers (Global\_Rec. 2008), recommended the term waste pickers for those who collect waste from dumpsites and sell it to middlemen or recyclers.

The term “rag picker” denotes anyone who stoops to pick waste of any kind for a living (Taira, 1968). Rag picking is not a new phenomenon. This have been in practice since prehistoric times in Africa, and many ancient civilisations have displayed such traces including Roman, Chinese, Japanese, Mayan, Indian, etc. In medieval Europe during thirteenth to eighteenth centuries, there was very little demand for the rag pickers (Medina, 2000). But, with the expansion of industries and urbanisation during 19th century the demand raised manifolds. It has been estimated that, the developing countries like India alone produces 65 million tonnes of waste every year, which is also supported by more than 4 million rag pickers’ population (Noda, 2022). Ever since plastic has pervaded Indian life during the mid 1990s, Mumbai was said to be using more than 5 million new plastic bags a day by 1996 (Zhang, 2019). However, India’s waste problem is multifaceted and complex (Gerdes & Gunsilius, 2010). It is influenced by many factors revolving around population growth, economic development, uncontrolled consumerism, and social prejudices of caste, gender, class and religion. This process is carried out by the rag pickers under informal sector, where they generally collect and sell the recyclable waste to the scrap dealers and scrap dealers to the recyclers.

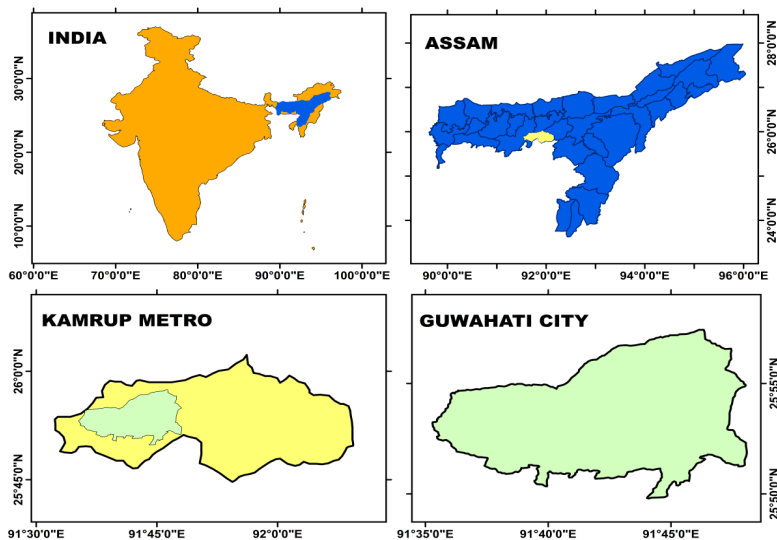
Looking at the developing city like Guwahati, the capital city of Assam as well as the biggest city of North-East India, the problem of waste-management is as such that one can very well identify the complex inter-linkage between waste and the population (Fig. 1). About 550 tonnes of solid wastes are produced daily, of which around 85 per cent is being transported to Boragaon dumping ground (GMC, 2023). Such a huge generation of wastes from people’s daily lives has led to the emergence of rag pickers to play their role in supporting the municipality. This study is an attempt to examine the role of rag pickers in waste management in the city and to explore their day to day experience and challenges while working in the unhygienic condition.

## **Objectives**

The main objectives of the study are:

1. to understand the demographic and socio-economic conditions of the rag pickers;
2. to examine the role of the rag pickers in waste management of the city;
3. to know about the challenges including occupational and environmental health hazards of the rag pickers; and
4. to suggest possible measures and strategies to improve overall quality of their life both at individual and community levels.

Fig. 1: Location map of the study area (Guwahati City), 2024.



### Database and Methodology

The study is based on both primary and secondary data. Necessary primary data have been collected through semi-structured schedule-cum-questionnaire in different locations of the city (Adabari, Ambari, Athgaon, Bamunimaidan, Boragaon, Fancy Bazaar, Fatasil, Jalukbari, Khanapara, Kumarpara, Lankeshwar, Machkhowa, Paltan Bazaar, Pan Bazaar, Pandu, Six Mile and Zoo Road) (Fig. 2). Though the areas where rag pickers generally live are not official or legally demarcated, a number of 40 households have been taken across the city based on snowball as well as purposive sampling technique.

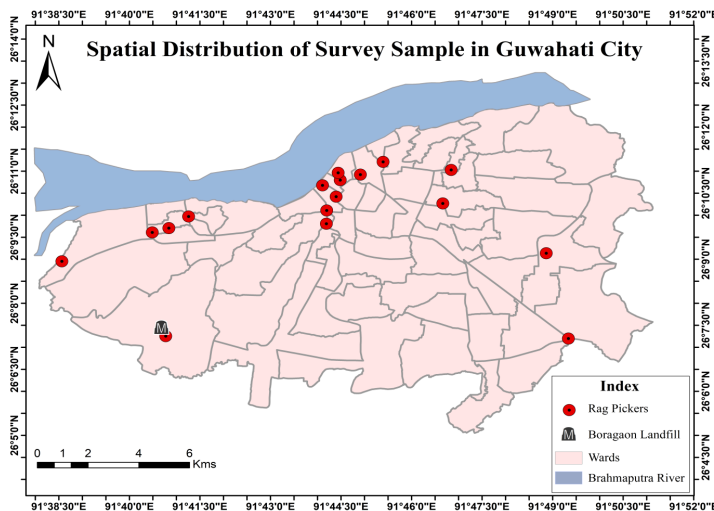


Fig. 2: Spatial distribution of survey sample in Guwahati City, 2024.

Hence, while carrying out the field survey, jurisdiction is being taken to be preconceived, based on personal observation and knowledge. For this, extensive literature review has been carried out to understand various aspects relating to demographic, socio-economic, political, occupational, and environmental and health hazards of rag pickers across different areas. Personal interviews with key stakeholders including NGO and recycling plant called The Midway Journey and Shree Guru Plastic respectively have been conducted to understand their perspectives on the involvement of rag pickers in waste-management in Guwahati. Moreover, some simple and suitable statistical techniques have been used to tabulate and analyse the data. In addition, ethnographic study based on personal observations, informal interviews, content analysis from different journals, newspapers and focused group discussions are made for insightful understanding of the entire issue.

## Results and Discussions

In a populous bustling city like Guwahati, rag pickers play a powerful role in waste-management practices, especially in areas where GMC's waste-management systems are inaccessible as well as insufficient. The life and living of the rag pickers has been full of challenges. This paper mainly tries to examine the demographic, social and economic condition of rag pickers along with their physical and mental health in the city of Guwahati.

### Waste-Management Practices in Guwahati

The waste-management in Guwahati is mainly managed by Guwahati Municipal Corporation (GMC). Municipal solid waste sorting machine which is also known as MSW sorting plant is playing a significant role towards solving the challenges of solid waste disposal in the city. The purpose of such infrastructure is to create waste products into treasure. According to the current waste collection and disposal methods, the solid wastes are collected by the NGOs and waste workers from the households and commercial establishments, after which they usually drop the wastes in secondary collection point such as bins (Table 1). The GMC workers thereafter transport the wastes for disposal at the final dump-site. The state govt. and GMC in collaboration with Geron and Zigma Global Environ Solutions Pvt. Ltd. (Haryana and Chennai based company engaged in Landfill Mining) have been currently operating in the Boragaon dump-site area for recycling and segregation (Plate 1).



Plate 1:Washing and sorting being done to classify the sizes of solid waste at the landfill with the help of Trommel. Photo: Researcher, 2024.

Table 1: List of NGOs working in waste-management sector under GMC

| Sl. No. | Ward No.   | NGO Name                                        | Sl No | Ward             | NGO Name                                     |
|---------|------------|-------------------------------------------------|-------|------------------|----------------------------------------------|
| 1       | 1A, 1C     | Udayan Social Welfare Society                   | 18    | 15B, 17C,<br>19A | Bharati Yuva Shakti NGO                      |
| 2       | 1B         | Brotherhood NGO                                 | 19    | 16A, 17B         | Yuva Prerona                                 |
| 3       | 2A         | Gauri Sevapeeth Mission                         | 20    | 16B, 17A,<br>27B | New Evergreen NGO                            |
| 4       | 2B         | Shikshalaya NGO                                 | 21    | 16C              | Jai Maa Bagala Helping Hand<br>NGO           |
| 5       | 3A         | Bhorosa NGO                                     | 22    | 18A, 18B,<br>18C | Pragati Sangha                               |
| 6       | 3B         | Manab Kalyan Development<br>Social Organization | 23    | 19B              | Guwahati Ladies Club                         |
| 7       | 4A         | Gyanleen NGO                                    | 24    | 19C, 30C         | Pragyan NGO                                  |
| 8       | 4B, 7A, 7B | Sadhana                                         | 25    | 20A, 25A         | Sahajatri                                    |
| 9       | 5A, 5B, 5C | Nava Suraj NGO                                  | 26    | 20B, 20C         | Yatra                                        |
| 10      | 6A, 6B     | Social Development and Beauty<br>Culture        | 27    | 21A              | Poohar NGO                                   |
| 11      | 6C         | Sibanga NGO                                     | 28    | 21B, 21C         | Krishti Welfare Organization                 |
| 12      | 7C         | Ankan                                           | 29    | 22A              | Jana Sevika Atmo Saahayak Got<br>(SHG)       |
| 13      | 8A         | Nabadeep Social Welfare Society                 | 30    | 22B              | Rengoni Atmo Saahayak Got<br>(SHG)           |
| 14      | 8B         | Suryodaya                                       | 31    | 22C              | Nava Nirman Sangskar Sevak                   |
| 15      | 8C         | GaneshguriSuryodaya Sangha                      | 32    | 23A, 23C         | Ashray NGO                                   |
| 16      | 9A, 9B, 9C | Subham Welfare Society                          | 33    | 23B              | Nabarup NGO                                  |
| 17      | 10A        | Jeevan Sathi Welfare Society                    | 34    | 24B, 26C         | North Eastern Society for<br>Human Resources |
| 35      | 10B, 10C   | Shristi NGO                                     | 49    | 24C              | North East Eco Development<br>Society        |
| 36      | 11A, 11B   | Janashakti Welfare Society                      | 50    | 24D              | PatharquaryRodali NGO                        |
| 37      | 12A, 12B   | Bahnishikha Women & Child<br>Welfare Society    | 51    | 25B              | Asthitya NGO                                 |
| 38      | 12C        | Creative NGO                                    | 52    | 25C              | Bhai Bhai Unnayan Samity                     |
| 39      | 13A, 13B   | Kiron Social Welfare Society                    | 53    | 26B, 26D         | Wings Rural Development<br>Society           |

|    |          |                                                 |    |          |                                       |
|----|----------|-------------------------------------------------|----|----------|---------------------------------------|
| 40 | 13C, 24A | Peoples Organization for Social Development NGO | 54 | 27A, 27C | Satabdi NGO                           |
| 41 | 14A, 14B | Suraj NGO                                       | 55 | 28A, 30A | Sunshine NGO                          |
| 42 | 15A      | Kamakhya Environmental Social Welfare           | 56 | 28B      | Unique Society NGO                    |
| 43 | 28C      | Enajori                                         | 57 | 30B, 31C | ShyamkanuSamajikKalyankami Anusthan   |
| 44 | 29A      | Aradhana Area Level Federation                  | 58 | 31A      | No 46 Ward Janakalyan Welfare Society |
| 45 | 29B      | Saptarathi Welfare Society                      | 59 | 31B      | SAKI                                  |
| 46 | 29C      | Orion Society                                   | 60 | 26A      | Uttaran Social Welfare Society        |

*Source: GMC, 2024.*

### Demographic Characteristics of the Rag-pickers

Demographic characteristics reflect the quality of population and level of socio-economic development of any particular area. These include attributes like age composition, sex composition, marital status, etc. (Das, 2013). In this study the rag pickers of all age groups have been considered. It has been observed that the rag picking population of age group 0-14 (8%) and 60+(2%) is too low as compared to the rag picking population in the age group of 15-59 (90%). This is because of huge difficulties in doing this job in the city, the children and aged people witness less participation.

Sex ratio is vital to know about the quality of life of any population in an area and has a profound impact on the demographic structure of any region including growth of population, age at marriage, work force and employment pattern. The overall sex ratio of rag pickers in the city as per the primary data is as low as 333. However, the proportion of married rag-pickers is 68 per cent as against 17.5 per cent of unmarried (Table 2).

Table 2: Marital Status of the Rag Pickers.

| Marital Status  | Percentage (%) |
|-----------------|----------------|
| Married         | 68             |
| Unmarried       | 17.5           |
| Divorced        | 7              |
| Widowed/Widower | 7.5            |

*Source: Primary Survey, 2024.*

### Social Characteristics

Social characteristics of the rag pickers can be studied in terms of a number of attributes including religion, language spoken, literacy and education, family structure, housing condition, place of origin, crime incidence, etc. It has been observed from the study that rag pickers constitute 85 per cent Muslims (non-indigenous origin) and 15 per cent Hindus (both indigenous and non-indigenous origin). So far linguistic composition is concerned, 85 per cent speak Bengali, 12.5

per cent Hindi and 2.5 per cent Assamese. Unexpectedly, the literacy rate among the rag pickers is found to be as high as 67.5 per cent. As regards educational attainment, it is witnessed that there is hardly any rag picker who has crossed the secondary school, and it is more so in the case of female. The female educational attainment is largely confined to primary level (Fig. 4). In view of dominance of joint family system, only 5 and 15 per cent families respectively belong to joint family and extended family type, while 75 per cent have nuclear family structure (Fig. 5).

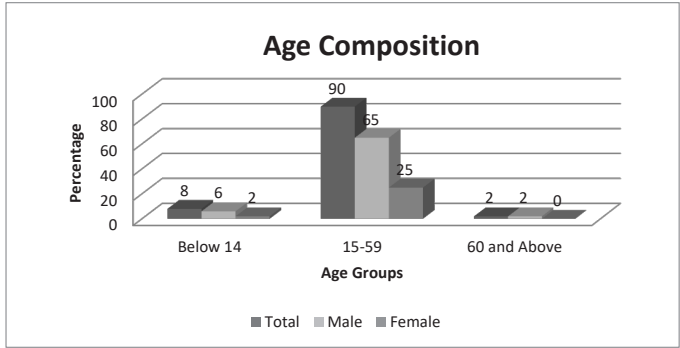


Fig. 3: Age Composition of the Rag Pickers (Primary Survey, 2024).

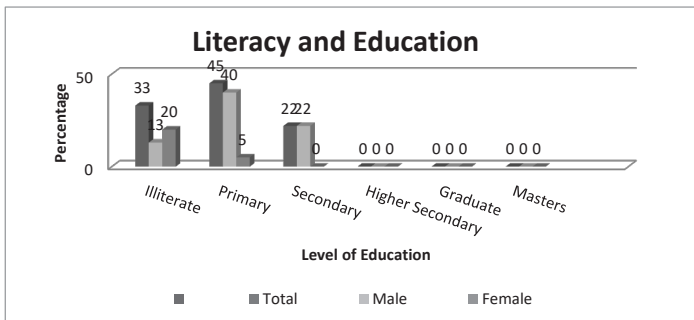


Fig. 4: Literacy and Education Attainment of the Rag Pickers (Primary Survey, 2024).

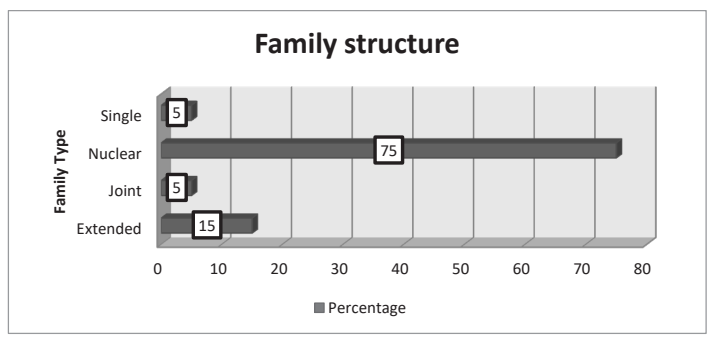


Fig. 5: Family Structure of the Rag Pickers (Primary Survey, 2024).

Housing condition reflects the economic and living standards of the people of an area. Rag pickers in Guwahati city generally live in rented house, public land, and along the railway tracks and roads. They mostly live in a slum environment with poor quality house (made of tin wall and roof, tarpaulin, etc.) without windows and ventilations (Krishna and Chaurasia, 2016). As per the field study it is observed that 22.5 per cent and 12.5 per cent live in tarpaulin and slum house respectively. On the other hand, majority 65 per cent live in rented houses made of roof and wall with tin/asbestos in the city (Plate 2). A large proportion of such people are of migrant origin from neighbouring districts like Dhubri, Barpeta, Morigaon, Goalpara, Bongaigaon, etc in Assam as also from the states of Bihar, Chhattisgarh, Madhya Pradesh, and Uttar Pradesh in search of a livelihood (Salam, 2013).

It has been found that around 10 per cent of the rag picker respondents reportedly have faced physical violence and harassment in their day-to-day work. This is more so among the women (Wittmer, 2021). It has been observed that there has been gradual rise in the number of child rag pickers (5-14 age groups) in the city in recent times. In fact, the prevailing poverty has compelled a large proportion of children trawling through rubbish dump. The rag pickers are forced to live in a deplorable condition without basic amenities including accessibility to safe drinking water. Moreover, of the total respondent households 47 per cent have power supply, 43 per cent with PDS, 32 per cent with government school, and 48 per cent with govt. dispensary.



Plate 2: Housing condition of the rag pickers. Photo: researcher, 2024.

### **Economic Conditions**

The economic conditions of rag pickers are reflected in the workforce, income pattern, financial tools, selling process, etc. The average number of earning members in a family is 2, as there are 94 earning persons in 40 households. Therefore, the total work participation rate is 59.1 per cent.

Again, as per the conservative societal norms, out of the total of 94 workers, the female work participation rate is observed to be only 38 per cent as a whole (Plate 3).



Plate 3: Female and children work participation under informal waste-management in Guwahati. Photo: Researcher, 2024.

It is found that majority of the workers (45%) work between 4 to 6 hours, 27 per cent work 6 to 8 hours, 15 per cent work more than 8 hours, while 12.5 per cent work less than 4 hours in the city (Fig. 6). The daily average income among rag pickers ranges from Rs. 100 to above Rs. 300 based on various conditions like working hours, types of waste they collect, and the marketplace where they sell. While rag pickers often operate in informal and cash-based economic sector, there are few financial tools used by them which vary based on their locations. It is observed that 85 per cent of them usually wear shoes or sleepers, about 57 per cent use metal hooks while working. However, there is absence of wearing masks or cloths on their face, safety hand gloves and use of magnets in the field. Reportedly, the types of plastic waste they collect are quite specific, which include high density, high molecular, low density, polypropylene, etc, among which low density and polypropylene has a higher value in the waste recycling economy. Besides plastics, canned and glass bottles, paper and cardboards, metals including iron and steel scraps are common types of wastes collected by them (Fig.7). Mode of transportation for rag pickers while transporting the wastes from the source to the area of disposal includes walk, bicycles, carts, three-wheelers, etc. On the other hand, for the street rag pickers of Cape Town, trolleys are the best mode of transportation for the collected waste to buy-back centres (Langenhoven and Dyssel, 2007). There is not a single “marketplace” which is solely dedicated to rag pickers, as their work alone involves collecting recyclable or reusable wastes from various sources. However, there are several avenues like scrap dealers, recyclers, middlemen and traders whom the rag pickers sell their wastes. It is found that 70 per cent of the total population in Guwahati city directly sell their

goods to the small scrap dealers, while remaining 22.5 per cent and 7.5 per cent sell it to the big scrap dealers and recycling plants respectively (Fig. 8).

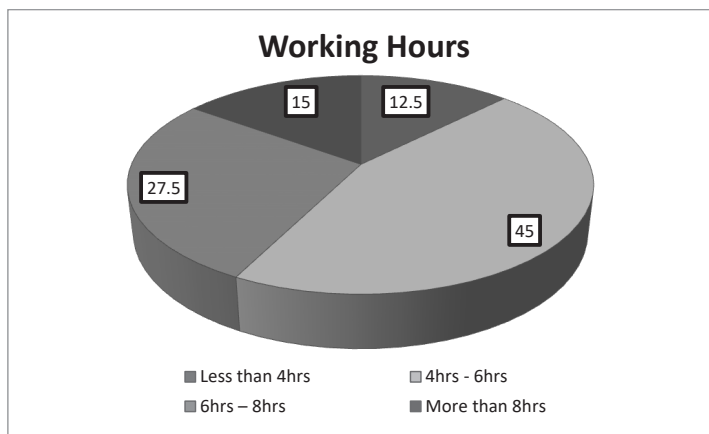


Fig. 6: Working hours of the Rag Pickers (Primary Survey, 2024).

Depending on availability of waste materials, work routine, market demand and personal circumstances, 42.5 per cent of them collect wastes during the day and sell them on the same day or the following morning, some 32.5 per cent prefer to accumulate a significant quantity of waste over a week before selling, while very less proportions of 12 per cent, 8 per cent and 5 per cent of the population adjust their selling patterns on alternate days, fortnightly, and monthly basis respectively. The issue of indebtedness is a complex and multifaceted problem among the rag pickers in Guwahati. Reportedly, 25 per cent of the population have taken loan from the scrap dealers due to lack of access to formal financial services. The fear of falling into debt trap and potential impact on livelihood is the main reason behind lack of interest in taking such loans. Apart from rag picking, it is found that sorting and segregation is the major subsidiary occupation among the rag pickers of the city. Due to independency and flexibility of the work, they prefer not to engage in other occupations, instead continue to work as rag pickers.

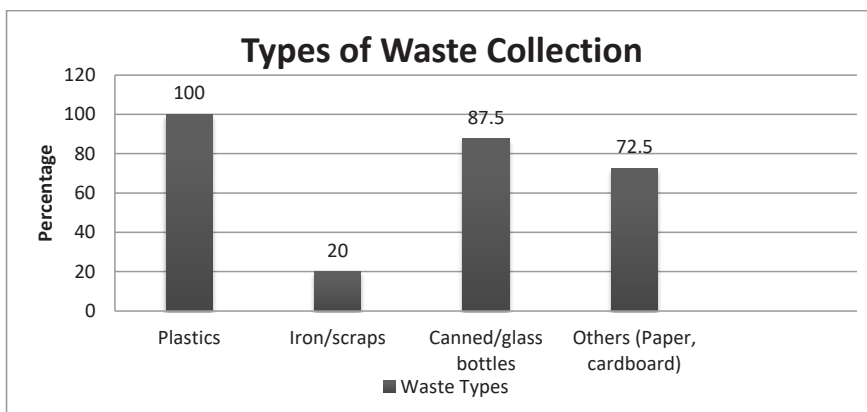


Fig. 7: Types of waste collected by the rag pickers (Primary Survey, 2024).



Fig. 8: Share of market among different stakeholders (Primary Survey, 2024).

### Political Conditions

Being a socially marginalised group, the rag pickers have no representation in politics. They face discrimination and stigmatisation based on their occupation, social status, or belonging to certain community from outside (Furedy, 1984). Over 40 per cent of this population face regular interventions from the local authorities, police and GMC while working in different locations especially at Boragaon landfill. Though there is no such requirement for legal documentations to work as a rag picker, more than 75 per cent of the population holds voter identity card, 64 per cent have ration card, and half of them have their Aadhar card, while only 7.5 per cent have their PAN card. Lack of awareness is still prevalent with 78 per cent who are unaware of NGOs and government welfare schemes.

### Health Conditions

The sanitation and sewerage facilities are not adequate among the rag pickers. Poor sanitation, open defecation, and lack of drainage system cause several water-borne as well as vector-borne diseases including malaria, cholera, high fever, typhoid, hypertension, skin lesions, scabies, unintentional injuries, mental illness, STIs, etc in the city (Gogoi, 2015). The rag pickers have to work under a very unhealthy environment often conditioned by difficult situations. Among the rag pickers in the city, 65 per cent collect wastes from the roadside and railway tracks, 40 per cent from the commercial marketplace, and 17.5 per cent from the dumpsite. It has been recorded that, working in a hazardous environment, i.e., dumpsite or streets with overly crowded traffics cause physical injuries and such injuries happen from the sharp objects, falling heavy materials, accidents, etc. (Vijaya, 2013). It has been observed that 67 per cent have suffered from diverse health issues including injuries due to glass cuts etc, rat and dog and insect bites, headaches, and back pain. Exposure to the extreme weather conditions in the city directly impact on overall health, wellbeing, and performance of the rag pickers in Guwahati city.

### Impacts of Rag pickers on Waste-Management

The rag pickers in the city have both good and bad effects on waste accumulation and landfills. Their activities are mainly directed towards slashing the volume of wastes that keeps coming up every day. They are known to salvage an appreciable quantity of waste by selectively collecting items with recycling value instead of allowing them to be thrown away to the landfill. As such this reduces the overall volume of accumulated waste over time due to lackadaisical attitude of

the GMC authorities and the workers. On the downside, the rag pickers in Guwahati sometimes contribute to landfill overloading and mismanagement. In many cases, unregulated waste picking activities lead to the disturbance of waste disposal sites by creating uncontrolled dumping and littering around the city. However, it is also observed that the rag pickers accumulate waste for a short duration, but in the long-run this leads to overall decrease in waste accumulation (Plate 4). When it comes to recycling and resource recovery, the rag pickers actively collect recyclable waste including certain categories of plastics, paper, cardboard, canned/glass/plastic bottles, metal scraps and other forms of items (Ojha et al., 2014). Several areas in Guwahati city serve as the grounds where they go through to gather such waste products. After this collection process, they sort and separate them. They have their knowledge about how different types of recycled materials can be identified or distinguished by experience. Through sorting and segregation the materials are organized well for purposes of recycling companies' packaging and detailed sorting into packs and divisions. Behind this entire journey the materials further follow several procedures such as cleaning, shredding, melting, or reprocessing to convert them into raw materials which are reused for manufacturing new products. On a positive note, it has great impact on employment generation, offering business opportunities to those having lack of skills and formal education (Morais et al., 2022). On the negative side, lack of formal recognition and support, especially the woman and child rag pickers are vulnerable to exploitation by middlemen and scrap dealers in the city. Another observation reflects the impact of rag pickers on environment in recycling efforts, which helps reduce the amount of wastes that ends up in the landfill, conserve Deepor Beel areas under Boragaon landfill and minimizes environmental pollution interlinked with land-filling.

The formal waste-management systems comprising GMC and Pollution Control Board have certain limitations in reaching out to some inaccessible areas, particularly in densely populated streets, congested areas including Fancy Bazaar, Maligaon slums, Paltan Bazaar railway station, Six Mile, remote localities of Nilachal Pahaar, Chandrapur, Deepor Beel and Silsako Beel. They generally operate at the grass-root level, walking into narrow streets, slums, and informal settlements where formal waste collection is a major challenge (Devi, et al., 2014). Their involvement has expanded the coverage of waste collection ensuring a more comprehensive approach. In fact, they offer a cost-effective solution to waste-management in a city like Guwahati.

Besides these, there are several impacts of rag pickers on society and community in which they live and operate. This work provides them a source or a short cut method to earn livelihood, as compared to that of other similar labour jobs. For keeping the society clean their presence and activities raise considerable awareness among the general people in the society, which leads to a fruitful shift in environmental consciousness and behaviours among the city dwellers. However, majority of the rag picker's population in Guwahati generally face social stigma and discrimination due to their religious identity and nature of their work, as rag picking is associated with a dirty job with low social status, which often pushes these people to marginalisation and exclusion from the mainstream population (Mote, 2016).

#### **Observations Recommendations:**

Apart from the rag picking many of them are involved as segregators. They segregate wastes into various categories and sell them to the middlemen or scrap dealers. This study has surfaced a number of insightful findings associated with the rag pickers of Guwahati city.

Rag pickers, segregators, middlemen and small scrap dealers of all kinds come under informal sectors, whereas the big scrap dealers and recyclers belong to the formal sector. It has been found that the social networks among the rag pickers vary greatly (Prasad et al., 2012). While some rag pickers work completely on their own and only engage in hierarchical economic exchanges with small scrap dealers and other works, and live with families and friends of same community. Being occupied the most marginalised and lower section of the society and occupational network, the social interaction among the rag-pickers is very poor and limited to their community. The study indicates that rag pickers experience differing working times depending on a region's location. For instance, translations have shown that early morning shifts are preferred in peripheral slums such as Dharapur, 'Six mile' and 'Chandrapur' because of lack of waste to be scavenged. Workers in high-stress neighbourhoods like Boragaon, Paltan Bazar, and Fancy Bazar endure harsh working conditions and put forth endless hours of work simply to make ends meet. The rag pickers who tend to spend prolonged periods in a dumpsite are extremely exposed to health risks as well as safety measures. Child rag pickers on the other hand, who are denied the chances to go to school or see a doctor, are very likely to be victims of diseases or road accidents owing to their negligence of trucks and JCBs. Such imbalances show that there is need for tactical approaches that will address the security and productivity of rag pickers in specific areas. The socio cultural context within which rag pickers are situated also provides certain illustrations of issues that such people face in the course of their work. Since 85 % of rag pickers come from ethnically marginalized non-indigenous Muslims embedded within a wider scope of Muslim perspective, discrimination on religious and social grounds prevents them from fulfilling their needs within society. There should be mechanisms that allow the rag pickers to speak directly to the municipality and have equitable representation in the decision-making processes. The earning varies depending upon the nature, quality, and cleanliness of the waste. The rag pickers can earn on an average Rs.15 per kg of mixed materials, while from pre-sorted or individually collected materials they earn Rs. 20 per kg. Moreover, their profit lies more in cane and plastic bottles varying between Rs. 65 and Rs. 27 per kg respectively.

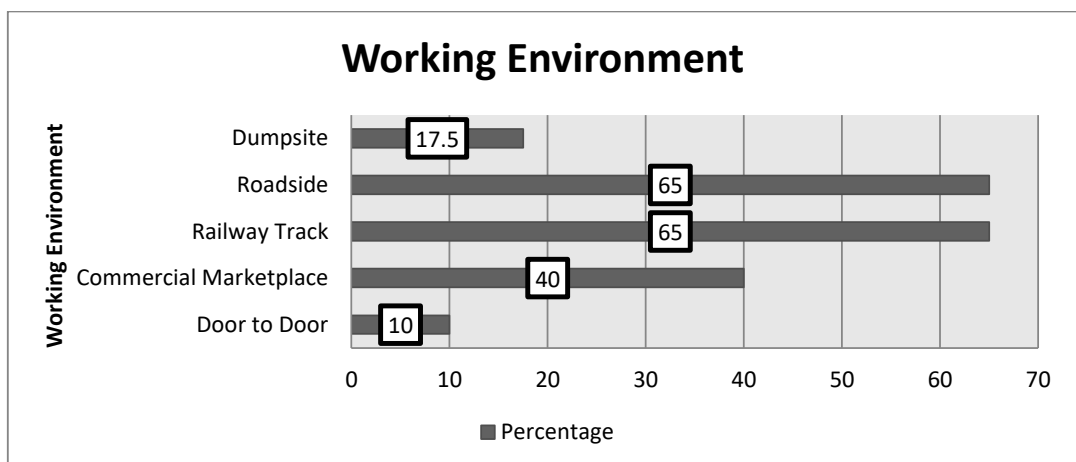


Fig. 9: Working environment of Rag Pickers (Primary Survey, 2024).

The govt. rules and policies for waste-management exclude the informal sector in many ways. The waste-management sector strengthened in the country under Plastic Waste-Management Amendment Rules 2021, prohibiting single use plastic by 2022. As a result of which the rag pickers have been facing a lot of economic constraints. With the introduction of Solid Waste-Management (SWM) Rules in 2016 Integrated Solid Waste-Management (ISWM) is allowed in the city, which has potential to increase competition, reduce the quantity of recyclable waste that rag pickers rely on for their livelihood. Their vulnerabilities are multiple along with low and uncertain income, risks of health and injuries, almost zero access to govt. welfare schemes and social exclusion. Apart from many challenges, on the basis of field observations and findings, few recommendations are proposed so as to uplift the socio-economic, political, and health conditions of the rag pickers involved in waste-management of Guwahati city.

To begin with, it is necessary to provide specific support to address the educational needs of rag pickers. Quite a number of rag pickers in Guwahati have never attained any education above primary school and most children especially girls are out of school. There are areas such as slums of Maligaon, Boragaon and Fancy Bazaar where mobile schools or community learning centers could be established to enable the children to go to school without affecting their work. For instance; a primary school was started close to Gandhi Basti, Guwahati as a result of efforts by the community, local NGOs and funding from the Government. Programs of education should include vocational training and other life skills directed at making rag pickers self-employed and reducing their reliance on waste picking. Also, legal recognition of the rag pickers and their role in waste management as one of the stakeholders is a further necessary step. In SWaCH (Solid Waste Collection and Handling), under the Pune Municipal Corporation, as well as NGOs have been able to provide waste pickers legal recognition through ID cards and bestowing health and education benefits (SWaCH Pune, n.d.). These initiatives would not only regularize their occupation but will also provide them with welfare, health and security insurance. Getting in touch with municipal authority i.e., GMC can help the rag pickers integrate with their communities.

Direct interventions should aim the health and safety of rag pickers. For instance similar kind of examples can be drawn from Delhi, where NGOs like Chintan and Safai Sena disseminated their members with personal protective equipments such as gloves, masks, boots, metal hooks (Chintan Environmental Research and Action Group, 2013). Such initiatives as provision of the basic safety equipments as well as healthcare treatment and immunization drives on regular basis can be implemented and these may be NGO or city Public Health Department supported. Further, healthcare awareness programs particularly focused on women and children can help with the prevalent fear of bureaucracy that often prevents them from utilising existing governmental health schemes.

Plastic Waste Management Amendment Rules (2021), which bans single-use plastics, has decreased the volume of high-value recyclables available recently. Therefore, doing training with rag pickers to identify and sort other recyclables such as e-waste or hazardous waste can expand their income to become more diverse. In Manila, EcoWaste Coalition held workshops for informal waste workers to learn about sorting e-waste and hazardous materials, such as batteries and compact fluorescent lamps (CFLs) (EcoWaste Coalition, 2020). Conclusively, this also needs

to be tied up with fair trade policies that ensure warning signs against middlemen exploitation. There could be building networks of cooperatives or direct-sale systems that would empower rag pickers to sell their collections at better price.



Plate 3: Female and children work participation under informal waste-management in Guwahati. Photo: Researcher, 2024.



Plate 4: Accumulation and segregation process of the wastes.  
Photo: researcher, 2024.

## Conclusion

The foregoing discussion reveals that the role of rag pickers in waste-management of Guwahati is an undeniable fact. From collection, segregation, transportation, and recycling to waste materials, and contributing to overall cleanliness and sustainability of the city, the rag pickers have immense impacts on this urban landscape. However, their conditions and role can be further improved to

ensure their wellbeing and enhance the waste-management system of the city.

The job of a rag picker is quite difficult as it involves risk of getting injured. For some rag picking it is a short cut way to make money, earn alternate livelihood and sometimes better in comparison to other unskilled labour work. Individuals from certain communities prefer this profession, as they get direct cash in hand for which no paper works are needed. Although it is a dirty job, for some it is profitable, because there is absence of pre-requisite capital investment, while for weaker sections including females and children, it is just an unprofitable work.

Though rag picking is identified as a valuable profession for individuals to secure livelihood in urban landscape, social, economic, political, and environmental problems are widespread and differ across the city.

Guwahati can develop a more sustainable waste-management system which is also inclusive by considering the contributions, challenges, effective propositions and implementation of certain steps with respect to the rag pickers' role in waste disposal. This means that it is also important to improve the working conditions of those who collect refuse materials like rags, clothes, or pieces of plastics. The administration should understand that supporting rag pickers will not only help them to lead better lives but will also contribute to a clean and environmentally sustainable city.

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## **Occupational Change and Skill Development among Seasonal Migrants of Kalahandi district, Odisha**

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### **Abstract**

The present paper attempts to understand the importance of occupational change brought about by seasonal migration and the effect of the migration in learning new occupation. It examines this important dimension associated with seasonal migration and empirically investigates the nature and extent of the change among seasonal migrants. It tries to find out the type of occupation the seasonal migrants get engaged in and the diversification of their traditional caste based occupation. It also makes an effort to assess the impact of the newly learned skills in the place of their origin, i.e. their native villages. The objective is to analyse the type of occupation the seasonal migrants engaged in and the skill development and formation of human capital by the migrants. This study finds that people migrate to big cities and other specific destinations in search of livelihoods for a variety of work and engage in a wide range of occupations available in the unskilled sector, mainly as ordinary construction labour. Caste occupation at the villages has no link with the work at the destination. SC seasonal migrants have been more diversified compared to STs and others. It is found that the work pattern is confined to non-agricultural sector and the destination decides the type of work. Raipur is found to be more diverse destination in providing work opportunities compared to all other destinations. Out of total seasonal migrants, more than half acquired Hindi language as a medium of communication while working at the destinations. It is also found that migrants have renovated their houses which brings changing social relations in rural India.

### **Introduction**

The occupational structure is an important parameter for determining seasonal out-migration. Temporary and seasonal migration is mainly a work based movement (Yang and Gup, 1999; Kumar, 2004; Keshri and Bhagat, 2010). Lack of work at

the village is a leading reason behind the high seasonal and temporary migration rate. The working aged people moved in search of work due to lack of work at the village level (Debnath and Ray, 2019). It may be safely assumed that the seasonal migrants move out of their villages to work in other areas, both rural and urban to supplement their meager income in the place of their origin. Evidently they go to nearby rural areas or even to far off destinations where they can engage in works in which they are skilled. Tied to agriculture and associated occupations, they migrate to such locations which offer them to work in those occupations albeit at a higher wage. This is however not always possible as demand for agricultural work in other areas may be highly restricted with increasing mechanization and also for the reason that the wages offered may not be attractive enough for these migrants whose main aim is to maximize their income. Hence, the larger flow of this rural seasonal migration is to the cities and towns that have greater demand for labour in the non-agricultural sectors such as construction work that takes place mainly in the off season. Even in the rural setting, some non-agricultural work such as brick kiln or road construction do provide the seasonal migrants with some demand for labour and offering much better wages than agriculture. In either case, the seasonal labourers will have to engage themselves in occupations other than their traditional occupations in the place of their origin. In ultimate analysis, seasonal migration involves occupational change which may be skilled or unskilled.

The study attempts to understand the importance of occupational change brought about by seasonal migration and the effect of the migration in learning new occupation. It will examine this important dimension associated with seasonal migration and empirically investigate the nature and extent of the change among the seasonal migrants. Are they learning new skills or continue with the traditional, often caste-based skills? Researchers have found that migration inevitably results in informal process of skill development. Migrants learn new skills and knowledge from co-workers and friends at the place of destination (Bhagat, 2013). So with the paucity of literature on micro regional aspects on seasonal out-migration this section tries to find out the type of occupation the seasonal migrants get engaged in and the diversification of their traditional caste based occupation. It also makes an effort to assess the impact of the newly learned skills in the place of their origin, i.e. their native villages.

Specific objective of the research is to analyse the type of occupation the seasonal migrants engaged in and the skill development and formation of human capital by these migrants. There are research questions such as how do acquired skills from migration destination help in changing social and economic conditions of the seasonal migrants? Can seasonal migration change social and economic relations of migrant workers? Despite heavy workloads, and the adverse health conditions, migration is not always a menace. A few researchers have argued that seasonal migration within a single context can simultaneously cause immense suffering and improve social relations from workers' perspective (Lenin, 1964). One way to understand the impact of seasonal migration is to separate professional-category of migrants from blue collar workers. Influence is no doubt positive for the educational professionals, but is it truly negative for the manual labourers and particularly seasonal out-migrants? In spite of their absence from the place of origin or the native villages for a few months and engaging in harsh conditions to eke a livelihood, are they really improving their socio-economic conditions? To address these issues the present research analyses the data collected from the field by interviewing sample migrants and finding out the kind of work they get in other regions/cities and the kind of change that they experience. It must be emphasized here that those who seasonally migrate look for additional income that they need to improve their socio-economic conditions and the fact that most of them are poor, uneducated and largely unskilled. This research looks at various dimensions of these changing social and economic lives of these poor seasonally out-migrants. This is achieved by seeing the changes in occupational structure, caste links to occupations adopted at the place of migration destinations, skill development and formation of human capital among the seasonal migrants and application of those acquired skills.

## **Materials and methods**

Stratified sampling method has been used to select a few villages for the purpose of household survey. The villages have been selected on the basis of their social composition. Villages with social stratification namely Gond's and

Kandha's are mainly STs; Dom and Ghasi's are mainly SCs. Goud, Mali and Teli's are mainly OBCs. All categories have been selected and clubbed together and then they are classified as seasonal migrants and non-migrants. Cross tabulation has been employed for individual categorical variables to see the relationship between them whilst comparing the access and accessibility at household level. We have used size of landholding and index for household durable assets and livestock separately for seasonal migrant and non-migrant groups. For the asset we include household durables and assign a score of 1 if the household possess such assets and 0 if otherwise. We divide the actual score of the households by the maximum score to arrive at the asset index. We also aggregate the livestock of the sampled households for both the groups using the Standard Livestock Index (SLU) into a total livestock index. We use the following conversion factors: cattle= 0.5, bullock and buffalo= 0.5, sheep and goats and sheeps= 0.10, pigs= 0.20 and birds and poultry= 0.01 (Akter et al. 2008).

Higher livestock might be negatively correlated with family migration since there is no family member present at source to look after the household's livestock and also because households with higher livestock will experience economic distress to lesser degree. It is not expected to have any significant impact on migration for income-enhancing or accumulative motives. An adult equivalence scale is defined as the proportionate increase in income per adult necessary to maintain a certain level of household living standard given some change in demographic circumstances (typically, the introduction of children). Equivalisation is a term that describes the measurement of household income by giving differential weight to the members of household. The equivalised income is calculated by dividing the total household income by the total of the weight. For the present work the adult equivalent measure of the family size is computed using the OECD definition of equivalence scale: Adult equivalence of a household =  $1 + (\text{number of adult} - 1) \times 0.7 + 0.5 \times \text{number of children}$  (Chakravorty 2014). Though adults over 65 years of age are going for seasonal migration to far areas, this study excludes those and declares them to be too old to work, along with children below 15 years of age, as dependents.

In order to find out whether the two sample means were significantly different or not, F and t tests were applied. The formula of F and t tests are given below:

$$F = \frac{S_1^2}{S_2^2}$$

Where,

$S_1^2$  = Estimated variance from first sample

$$= \frac{1}{n_1 - 1} \sum (x_1 - \bar{x}_1)^2$$

$S_2^2$  = Estimated variance from second sample

$$= \frac{1}{n_2 - 1} \sum (x_2 - \bar{x}_2)^2$$

$x_1$  = First sample

$x_2$  = Second sample

$n_1$  = Number of observation in first sample

$n_2$  = Number of observation in second sample

$\bar{x}_1$  = Arithmetic mean of observation in first sample

$\bar{x}_2$  = Arithmetic mean of observation in second sample

For this study independent-sample t-test has been used because there are two different experimental conditions and different participants are assigned to each condition namely, seasonal migrants and non-migrants. An independent sample t-test has the following attributes, it has exactly two variables; one variable is categorical with only two levels and it is the independent variable; the other variable is continuous and it is the dependent variable.

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sigma c^2 (1/n_1 + 1/n_2)}$$

Where,

$\sigma_c^2$  = pooled estimate of the sample variance

$$\sigma_c^2 = \frac{\Sigma(x_1 - \bar{x}_1)^2 + \Sigma(x_2 - \bar{x}_2)^2}{(n_1 - 1) + (n_2 - 1)}$$

There are various indicators to measure occupational diversification, like number of occupational sources and their share; Simpson index, Herfindahl index, Ogive index, Entropy index, Modified Entropy index, Composite Entropy index etc. In this study Simpson index is used because of its computational simplicity, robustness and wider applicability. The formula for Simpson index is given below:

$$S.I. = 1 - \sum_{i=1}^N p_i^2$$

Where, n is the total number of income sources and  $p_i$  represents income proportion of the  $i^{th}$  income source. Its value lies between 0 and 1. The value of the index is zero when there is a complete specialization and approaches one as the level of diversification increases.

## Results and Discussion

Before going directly to the occupational change and the skill development the study analyses the socio-economic characteristics of the seasonal migrants by comparing it with those who were non-migrants. We interrogated the data to explore key characteristics of the migrant households by comparing with those who never migrated. The aim is to compare the socio-economic characteristics of the migrants and non-migrants in a drought affected area in Kalahandi district, Odisha. This comparison focuses on the difference between the control group and the experimental or exposed group, whilst avoiding the limitation of why, out of all people placed in the same economic circumstances, some move out while others do not. For the purpose of analysis we have used seasonal migrants as the experimental group and non-migrants

as the control group.

### ***Household characteristics of seasonal migrants and non-migrants***

The household as far as seasonal migrants and non-migrants are concerned spell out variation do exist in terms of their asset holding, livestock wealth, or in terms of average household size, adult equivalence of the households and dependency ratio. There are two aspects, the durable assets and livestock are economic and the remaining three are of demographic. The durable assets like implements and modern gadgets whereas livestock such as cow, bullock, goat, sheep, hen and buffalo are taken into consideration. In a rural setting assets can be extremely varied and households possess several assets of different kind for their livelihood. For the purpose of present analysis we have made distinctions between durable assets and livestock which together constitute the most important assets of the rural livelihood systems. Therefore, for such purposes the classification of livestock have been treated separately because they constitute the most important source of livelihood next only to land and agriculture, a very important source of livelihood for the families when they are in distress. These livestock become secondary and even primary source for sustenance for some of the households who find no other source of income in times of crisis. The migrant and the non-migrant households are compared in terms of the characteristics as for the selected criteria as given in table-1 to get an insight into their role in decision to migrate or not to so.

Table 1: Migrants and the non-migrants: economic and demographic background

| Types                              | Index Value      |             |            |
|------------------------------------|------------------|-------------|------------|
|                                    | Seasonal migrant | Non-migrant | Difference |
| Durable Assets                     | 0.20             | 0.27        | -0.07      |
| Livestock                          | 0.09             | 0.14        | -0.05      |
| Average household size             | 3.63             | 3.52        | 0.11       |
| Adult equivalence of the household | 2.98             | 3.11        | -0.13      |
| Dependency ratio                   | 1.25             | 1.33        | -0.08      |

Table 1 reveals that the average migrant household owns fewer assets in general and livestock in particular as compared to their non-migrants counterparts on an average. Evidently more livestock with households indicates their better economic status as well as their ability to cope with difficult situation in times of food crisis and food insecurity and hence will experience economic distress to a lesser degree. Though the difference among the seasonal migrants and non-migrants in assets and livestock is not substantial, yet it does have a significant impact on the process of migration for income enhancement. It was expected that higher livestock might be negatively correlated with family migration since there is no family member present at source to look after the household's livestock and also because households with higher livestock will experience economic distress to lesser degree. On the other hand the average household size is higher among the migrant households. It is clear that larger size of the households and households with lesser number of adults and dependents are more likely to migrate. The index of adult equivalence is lesser among the migrant households compared with the non-migrant households which emerge as an important differential characteristic with the migrant households. The extent of dependency too appears to be slightly less in the case of migrant households. This is rather intriguing though not entirely impossible. The differences in adult equivalence and dependency ratio are 13 and 8 between the seasonal migrants to non-migrants. Even though there may be more earners in the non-migrant group of people their adult equivalence is high compared to seasonal migrants due to which their dependency ratio is also high.

Table 2: Land ownership by different farm size groups of seasonal migrants and non-migrants

| Farm size | Seasonal migrants |       |                       | Non-migrants |       |                        |
|-----------|-------------------|-------|-----------------------|--------------|-------|------------------------|
|           | HHs               | %     | Av.holding<br>(acres) | HHs          | %     | Av. holding<br>(acres) |
| Landless  | 120               | 24.48 | 0                     | 46           | 9.38  | 0                      |
| Marginal  | 365               | 74.49 | 1.09                  | 426          | 86.93 | 1.12                   |
| Small     | 5                 | 1.03  | 3.41                  | 18           | 3.67  | 4.15                   |
| Total     | 490               | 100   | 0.85                  | 490          | 100   | 1.32                   |

Size of the land holding is an important component of socio-economic profile which has considerable impact on the households' compulsion to migrate or otherwise. Existing literature suggests that landholding should be negatively correlated with propensity to migrate (Deshingkar and Start 2003; Keshri and Bhagat 2012). Mosse et al. (2002) suggest that land constraint may be significant for families migrating out of distress. It may not be significant for migration for income-enhancing or accumulative purposes. Size of agricultural land is also a component of socio-economic profile which is a key factor in influencing the seasonal migration from the study area. The agricultural land owned or operated by the seasonal migrants is far less compared to the non-migrant households as seen in table 2. A quarter of the former is landless and the remaining are marginal land holders unlike the non-migrant category which has better access to land resources. Far fewer households in the latter are landless though most of them are marginal farmers. Greater incidence of landlessness among the migrant households seems to be an important determinant in pushing such households to seek seasonal employment outside their villages. Concentration of seasonal migrants in marginal and landless size groups is perhaps due to the fact that those with marginal size of land had to supplement their meagre income from agriculture in order to meet the expenditure of the family while for landless seasonal migrants; it is the case of eking-out livelihood in case they are not in a position to permanently migrate. It may further be observed from the table that only 1.03 percent of seasonal migrants have a small holding which is proportionately lower than those households who are landless and with marginal holdings. The average size of holding of the seasonal migrants is 0.85 acres whereas it is 1.32 acres for the non-migrants.

Table 2 also shows that majority (86.93 percent) of the non-migrants belong to marginal farm size category followed by landless category at 9.38 percent and small holders at 3.67 percent. 86 percent of the non-migrants are marginal farmers who have a meagre amount of land of their own. During interview it got clear that the non-migrant households had access to employment outside agriculture. Many of them

are held on to their traditional caste occupation who practice their age old profession. A few of the non-migrating households had some sort of business at the village or in the nearby market, while a few also worked as permanent and temporary teachers in various schools. The average size of land holding of marginal farmers in the category of non-migrant is 1.12 acres which is higher than their migrant counterpart (1.09 acres). In the category of small farmers among seasonal migrants the average size of holding is 3.41 acres and the small farmers had 4.15 acres as the average among the non-migrants. The average landholding for the non-migrants it is 1.32 acres which is significantly more than seasonal migrants. Lack of access to adequate land appears to be a major push factor to out migrate at least seasonally.

### ***Occupational distribution in the village***

Occupation is closely related with the economic status as well as the living standard of the household. Moreover, it is hypothesized that seasonal migration takes place mainly from agricultural households. In order to examine this assumption an analysis is carried out and the findings have been placed in Table 3.

Table 3: Occupation at village of seasonal migrants

| Farm size | Number and percentage of seasonal migrants |              |             |
|-----------|--------------------------------------------|--------------|-------------|
|           | Cultivator                                 | Wage earning | Total       |
| Landless  | 22 (18.33)                                 | 98 (81.66)   | 120 (24.48) |
| Marginal  | 354 (96.98)                                | 11 (3.01)    | 365 (74.48) |
| Small     | 5 (100.00)                                 | 0            | 5 (1.02)    |
|           | 381 (77.75)                                | 109 (22.24)  | 490         |

It may be observed from the table 3 that majority (77.75 percent) of the seasonal migrant households in their usual place of residence in the village depend on agriculture as their primary occupation followed by wage earning (22.24 percent) undertaken as an exclusive occupation. Occupational diversity is minimal as no household reported occupations other than these two. Exclusive dependence on agriculture and wage work in or outside agriculture does reveal limited work

opportunity in the villages and little diversification of the economy of the drought affected villages. Needless to re-emphasise that agriculture in the region has been handicapped and is dependent on the vagaries of nature which results in frequent crop failures and lack of employment in this sector compelling the most vulnerable to permanently migrate elsewhere in order to supplement their low income from agriculture and others to seek seasonal employment to tide over financial crisis arising out of lack of employment, lower wages and repayment of loans taken. The table 3 further reveals that 18.33 percent of the landless households are cultivators. This may sound contradictory as the segment does not own land and hence cannot be cultivators. However, it was revealed in the fieldwork that some of the landless households have reclaimed parts of forest land and practice agriculture there or are share croppers in the village by leasing in some amount of land from the landowning households who do not cultivate their land due to a variety of reasons. An overwhelming 82 percent of the landless households are however agricultural wage earners who get some work in the village during cropping season mostly confined to three or four months in a year. As expected, a majority of the marginal landholders and all of the small landowning migrant households are owner cultivators. Very few (1.02 percent) marginal landholders work as wage earners. Out of total wage earners 81.66 percent are landless and 3.01 percent have marginal farm size. Lack of irrigation facilities and irregularity of rainfall creates conditions forcing them to do the wage earning in village for their sustenance.

The occupation of the non-migrant households is studied with a view to compare and contrast with that of the seasonal migrant households and the findings are presented in Table 4.

Table 4: Occupation at village of non-migrants

| Farm size | Number of non-migrants |           |           |             |
|-----------|------------------------|-----------|-----------|-------------|
|           | Farming                | Business  | Service   | Total       |
| Landless  | 35 (76.59)             | 7 (14.89) | 4 (8.51)  | 46 (9.59)   |
| Marginal  | 420 (98.58)            | 0         | 6 (1.41)  | 426 (86.73) |
| Small     | 18 (100.00)            | 0         | 0         | 18 (3.67)   |
|           | 473 (96.53)            | 7 (1.42)  | 10 (2.04) | 490         |

It may be observed from the table 4 that agriculture is the primary occupation of the majority (96.53 percent) of the non-migrant households which is followed by negligible 2.04 percent employed in service and 1.42 percent in business adopting these activities as the source of their livelihood. It is interesting to note that wage earning activity is missing as an occupation among the non-migrants even for those who are landless who actually work as cultivators in leased in land. Around 8 percent landless households have members who are employed in service sector. Nearly 77 percent landless non-migrant households are engaged in farming activity in their leased in land while some 15 percent households do some petty business to sustain themselves. Among the marginal landholding non-migrant households, nearly all of them are owner cultivators while a handful of them (1.41 percent) are engaged in services. All non-migrant households with greater access to land are owner cultivators. The economic activities in which the non-migrant households are engaged are slightly more diversified compared to those opting for seasonal employment. A few of them do get employed in service sector including business (shop owners etc.) and salaried employment in government sector as school teachers etc.

### ***Indebtedness***

It is construed that poverty is rampant in the study area which compels the people of the area to migrate to more developed parts so that they could increase their income and meet their household requirements. At times, particularly in years of crop failure, one has to resort to borrowing money from others for meeting certain compelling needs. An attempt has been made to examine the extent of indebtedness, the source, and reasons for indebtedness of the seasonal migrant households compared with the non-migrant households. The findings have been placed at Table 5.

Table 5: Incidence of indebtedness among seasonal migrants and non-migrants

| Amount of loan  | Seasonal migrants |         | Non-migrants |         |
|-----------------|-------------------|---------|--------------|---------|
|                 | HHs               | Percent | HHs          | Percent |
| No loan         | 415               | 84.7    | 444          | 90.61   |
| < 5000          | 16                | 3.3     | 5            | 1.02    |
| 5000-10000      | 37                | 7.6     | 20           | 4.08    |
| 10000-15000     | 12                | 2.4     | 17           | 3.47    |
| 15000-20000     | 8                 | 1.6     | 4            | 0.81    |
| 20000 and above | 2                 | 0.4     | 0            | 0       |

Table 5 reveals that 75 out of 490 (15 percent) of the seasonal migrant households are indebted and the rest 415 (84.7 percent) have not taken any loan. Among the indebted households, 3.3 percent had debt less than Rs. 5000, 7.6 percent had debt Rs. 5000 to Rs. 10000, 2.4 percent households had debt Rs. 10000-15000, and 1.6 percent households had debt Rs. 15000 to Rs. 20000 and 0.4 percent households had debt in excess of Rs. 20000. The non-migrant households too are indebted though relatively less in proportion and quantum of loan taken. Over 90 percent of the non-migrant households reportedly did not take loan. A small proportion of little over 1 percent non-migrant households took loan of small amount often below Rs. 5000. However around 8 percent of the non-migrant households availed loan to the tune of Rs. 5000 to 15000 in the preceding year. Less than one percent of the non-migrant households took loan for an amount in excess of Rs. 15000. Thus it is evident that the seasonal migrant households are more indebted than those who are not migrants and this provides one of the reasons why the former has greater propensity to migrate seasonally.

Table 6: Source and purpose of loan among seasonal migrants and non-migrants

| Source and purpose of loan | Seasonal migrants |         | Non-migrants |         |
|----------------------------|-------------------|---------|--------------|---------|
|                            | Frequency         | Percent | Frequency    | Percent |
| <b>Source of loan</b>      |                   |         |              |         |
| Neighbours                 | 10                | 13.33   | 4            | 8.69    |
| Moneylenders               | 29                | 38.66   | 3            | 6.52    |
| Anchalik Bank              | 32                | 42.67   | 29           | 63.04   |
| Co-operative society       | 4                 | 5.34    | 10           | 21.73   |
| <b>Purpose of loan</b>     |                   |         |              |         |
| To meet basic necessities  | 46                | 61.33   | 0            | 0       |
| For farm investment        | 27                | 36.0    | 29           | 63.04   |
| For marriage               | 2                 | 2.67    | 10           | 21.74   |
| For children's education   | 0                 | 0       | 7            | 15.22   |

The sources and purposes of loans are not only diverse but also play a crucial role in shaping the motivations behind seasonal migration. It is clear from

Table 6 that non-institution borrowing as a source is more frequent among the seasonal migrants compared to the non-migrants. As many as 75 migrant households who are indebted 13.33 percent have taken the loan from immediate neighbours, 38.66 percent households from local money lenders while 42.67 percent of them have taken loans from Anchalik Bank and 5.34 percent from Co-operative society. An enquiry revealed that the rate of interest charged by the local money lenders on the loan amount was exorbitant, ranging from 4 to 6 percent per month. Most of the indebted households have been in debt for 3-4 years, and almost half of them had not paid the principal amount at the time of the survey. It is also observed from the Table 6 that 61.33 percent of the seasonal migrant households sought loan to meet basic necessities. Other important reasons for purpose of loan are farm investment (36.0 percent) and marriage (2.67 percent). On the other hand, fewer non-migrant households are in debt and the amount taken as loan by them is also smaller compared to their migrant counterparts. Moreover, a very high (85 percent) proportion of the non-migrant households have received loan from formal lending institutions consisting of the rural banks and cooperatives which extend loan at far lower interest rate. Only 15 percent of such households have depended on their friends and neighbours for seeking loan.

An investigation into the reasons of indebtedness of non-migrant households reveals that farm investment was the most important reason for their indebtedness. About 15 percent of the non-migrant indebted households reported that meeting educational expenses of their children was the reason for their indebtedness. Expenses incurred on meeting social obligations and on marriage of their sisters/daughters were other important reasons for indebtedness of these households. Two independent variables namely agricultural land owned and debt has been studied scientifically to see the significant difference between seasonal migrants and non-migrants. The results have been explained in the following table.

Table 7: Independent sample t-test (Agricultural land and amount of loan)

| Statistics                    | Agricultural land (in acres) |             | Amount of loan (in Rs.) |             |
|-------------------------------|------------------------------|-------------|-------------------------|-------------|
|                               | Seasonal migrant             | Non-migrant | Seasonal migrant        | Non-migrant |
| Mean                          | 0.86                         | 1.13        | 1529.60                 | 921.43      |
| Standard Deviation            | 0.77                         | 0.74        | 4586.32                 | 3120.19     |
| SEM                           | 0.04                         | 0.03        | 207.19                  | 140.96      |
| N                             | 490                          | 490         | 490                     | 490         |
| <i>F</i>                      | 15.93                        |             | 19.66                   |             |
| <i>p</i> value                | 0.000                        |             | 0.000                   |             |
| Mean Difference (SM-NM)       | -0.28                        |             | 608.16                  |             |
| <i>t</i> (Independent sample) | 5.73                         |             | -2.42                   |             |
| <i>p</i> (2-tailed)           | <b>.000</b>                  |             | <b>.015</b>             |             |
| <i>Df</i>                     | 976.29                       |             | 861.79                  |             |

*Source: Computed from field survey data*

The comparison between seasonal migrants and non-migrants in agricultural land ownership reveals that there is a statistically significant difference ( $t = 5.73$ ,  $df = 976.29$ ,  $p < 0.0001$ ) between the groups (Table 7). The magnitude of the difference between them (Eta squared/Mean difference = -0.28) is not very low. 28 percent variance in agricultural land holding of the seasonal migration process is explained in the *t*-test. Thus, our data shows that agricultural land has a significant impact on seasonal migration form the study area.

The comparison between seasonal migrants and non-migrants in debt position reveals that there is a statistically significant difference ( $t = -2.42$ ,  $df = 861.79$ ,  $p = 0.015$ ) between the groups (Table 7). The magnitude of the difference between them (Mean difference = 608.16) is not very high. Thus, our data shows that amount of loan taken by the seasonal migrants is Rs. 608 higher than the non-migrants and the results have a significant effect on seasonal migration process from the study area

## ***Occupational Change***

Seasonal migration has changed in the recent past. A sharp shift in working behaviour and destination of migrants has emerged across places. In the past the majority of migrants usually moved towards agriculturally prosperous regions as agricultural labour. However, recently these migrants turned towards urban areas across the country, particularly in western and southern states as shown in the previous chapter. Consequently, a shift in their working behaviour has been observed from agricultural to non-agricultural type. Such change in destination and type of work is also directly associated with economic benefits, primarily manifested in earning higher wage resulting in better income, which migrants are deprived of in the native villages (Debnath, 2020). The occupational category at the village explained clearly shows that there is a strong correlation between the occupation and the propensity of migration in the study area. Migration among the landless is found to be the highest, and gradually declines with increasing access to the land ownership.

This section specifically examines the nature of work pursued by the seasonal migrants at the place of their destination and how it is changing the social relations in acquiring new skills and adoption of those skills benefitting at the native locations. There is a clear differentiation in the work pattern of the migrants working locally at in the village and those migrating out seasonally. More than ninety percent of the seasonal migrants work locally as farmers and the rest as wage earners to earn a livelihood available at the native village. While reaching at respective destination they are changing their traditional occupation and engaging in works related to construction workers, brick-kiln workers, rickshaw pullers, auto-rickshaw drivers, waiters and earth workers- most of which come under unskilled work. From the Table 8 it is clear that the highest proportion of the seasonal workers get absorbed in construction industry, followed by brick-kilns. These two activities together represent nearly ninety percent of the seasonal migrant workers occupation at the destinations. Astonishingly, rickshaw pulling is the third ranking activity, engaging 8.16 percent of total seasonal migrants followed by auto-rickshaw driving at 1.63 percent, working

as waiter at 1.02 percent and earth workers at 0.41 percent. It is evident that the occupational diversity in the destination is highly restricted as the seasonal migrants, mostly consisting of illiterate or semi-literate young people lack skills of other kind and find only two sectors that require seasonal labour.

Table 8: Occupational change among the seasonal migrants

|                                                     | Social Group |       |        |       |
|-----------------------------------------------------|--------------|-------|--------|-------|
|                                                     | SC           | ST    | Others | Total |
| <b><i>Composition of workers at destination</i></b> |              |       |        |       |
| Construction worker                                 | 47.09        | 57.05 | 62.96  | 55.51 |
| Brick-kiln worker                                   | 21.51        | 42.95 | 36.42  | 33.27 |
| Rickshaw puller                                     | 22.67        | 0     | 0.62   | 8.16  |
| Auto-rickshaw driver                                | 4.65         | 0     | 0      | 1.63  |
| Waiter                                              | 2.91         | 0     | 0      | 1.02  |
| Earth worker                                        | 1.16         | 0     | 0      | 0.41  |

There are however important variations to this pattern when viewed for the three categories of seasonal migrants, i.e. the SCs, the STs and the others. As depicted in the Table 8, over 47 percent SC migrants find themselves working in construction activities which are lower than the proportion among the STs (57.05 percent) and others (62.96 percent). The occupational diversity among the SCs is the highest in the destinations as they are found distributed in all the five occupations listed in the table unlike the other two groups who are mostly confined to two of the five occupations. Brick-kiln workers in STs Category are 42.94 percent, and among others it is 36.42 percent followed by SCs (21.51 percent). A significant 22.67 percent of the SC migrants to the towns and cities work as rickshaw pullers. The rest work pattern as auto-rickshaw drivers, waiters and earth workers is confined to SCs only, and not a single migrant work from STs and others for these three type of work are found to be adopted at destinations. The calculated value from Table 9 i.e. occupational diversification index states that the occupation is diversified as moderate to high (0.57). It is high among the SCs (0.67) as compared to STs (0.49) and others (0.47). SCs are found to be working in multifarious activities. This is largely due to lack of social stigma in SCs who have always worked in menial works, polluted activities in their native villages, which are not performed by high caste people included under

Others category. Therefore, they are more eager to earn and learn, willingness to accept any kind of jobs coming their way and not pre-decided or selective, and thus find seasonal migration as an important means to improve their living even if it means working under extreme trying conditions. The STs find construction and Brick kiln occupations as the only two options. A very large proportion of the ‘Others’ tend to be employed in the construction sector.

In a developing country like India, 600 million live in a place other than the one that they originally belong to. For oppressed castes, migration offers a chance at economic mobility because 450 million individuals work in the unorganized sector and overwhelming majority belong to oppressed castes. The NSSO survey placed the proportion of daily wage labourers highest in SCs at 63 percent. UNDP’s multidimensional Poverty Index (2021), categorically states that 5 out of 6 multidimensionally poor belong to the marginalized caste groups in India. The statistics here are not merely numbers or a coincidence- social identity is one of the biggest factors of forced migration. It is the impact of globalization on villages. Globalization has facilitated greater mobility and faster connectivity mainly because of faster means of transport and communication. This has contributed to rapid migration to nearby and distant places in search of better employment.

Table 9: Occupational diversification index of the seasonal migrants

| Types of occupation  | SC               | ST     | Others | Total  | SC                              | ST     | Others  | Total   | SC                          | ST     | Others | Total |
|----------------------|------------------|--------|--------|--------|---------------------------------|--------|---------|---------|-----------------------------|--------|--------|-------|
|                      | Percentage share |        |        |        | Square of each percentage share |        |         |         | Diversification index value |        |        |       |
| Construction worker  | 0.4709           | 0.5705 | 0.6296 | 0.5551 | 0.2217                          | 0.3254 | 0.3963  | 0.3081  |                             |        |        |       |
| Brick-kiln worker    | 0.2151           | 0.4294 | 0.3641 | 0.336  | 0.0462                          | 0.1843 | 0.1325  | 0.1128  |                             |        |        |       |
| Rickshaw Puller      | 0.2267           | 0      | 0.0061 | 0.0816 | 0.0513                          | 0      | 0.00003 | 0.0066  |                             |        |        |       |
| Auto-rickshaw Driver | 0.0465           | 0      | 0      | 0.0163 | 0.0021                          | 0      | 0       | 0.0002  |                             |        |        |       |
| Waiter               | 0.0291           | 0      | 0      | 0.0102 | 0.0008                          | 0      | 0       | 0.0001  |                             |        |        |       |
| Earth worker         | 0.0116           | 0      | 0      | 0.004  | 0.0001                          | 0      | 0       | 0.00001 |                             |        |        |       |
|                      | 1                | 1      | 1      | 1      | 0.3225                          | 0.5098 | 0.529   | 0.428   | 0.6775                      | 0.4902 | 0.471  | 0.572 |

Table 10 Composition of workers at migrant's last destination in percentage

| Migration destination | Construction worker | Brick-kiln worker | Rickshaw Puller | Auto-rickshaw Driver | Waiter | Earth worker | Total |
|-----------------------|---------------------|-------------------|-----------------|----------------------|--------|--------------|-------|
| Raipur                | 54.46               | 21.95             | 12.19           | 5.69                 | 4.06   | 1.63         | 25.10 |
| Hyderabad             | 53.34               | 43.38             | 0.00            | 0.00                 | 3.34   | 0.00         | 12.24 |
| Mumbai                | 62.87               | 32.97             | 4.14            | 0.00                 | 0.00   | 0.00         | 19.80 |
| Bangalore             | 60.01               | 39.98             | 0.00            | 0.00                 | 0.00   | 0.00         | 16.33 |
| Goa                   | 66.62               | 33.31             | 0.00            | 0.00                 | 0.00   | 0.00         | 15.31 |
| Chennai               | 71.13               | 28.86             | 0.00            | 0.00                 | 0.00   | 0.00         | 9.18  |
| Bargarh               | 67.21               | 0.00              | 0.00            | 32.78                | 0.00   | 0.00         | 0.61  |
| Thiruvananthapuram    | 51.21               | 48.79             | 0.00            | 0.00                 | 0.00   | 0.00         | 0.41  |
| Rajahmundry           | 40.19               | 59.80             | 0.00            | 0.00                 | 0.00   | 0.00         | 1.02  |

As observed from the Table 10, majority of the seasonal migrants, almost ninety percent are employed as construction workers (55.51 percent), followed by brick-kiln workers (33.6 percent). Of the rest, they engage themselves as Rickshaw pullers (8.16 percent), auto-rickshaw drivers (1.63 percent), waiters (1.02 percent) and earth workers (0.4 percent). One fourth of the sampled migrants migrated seasonally to Raipur, followed by destinations like Mumbai (19.80 percent), Bangalore (16.33 percent), Goa (15.33 percent), Hyderabad (12.24 percent), Chennai (9.18 percent). Of the rest, 1.02 percent migrated to Rajahmundry, within the state destinations like Bargarh (0.61 percent), and 0.41 percent to Thiruvananthapuram. The lack of other opportunities of employment has compelled the migrants and their families to situate at construction sites, brick making sites and work as other allied unskilled activities. Migrants frequently change their occupations in search of higher wages.

This study finds that people migrate to big cities and other specific destinations in search of livelihoods for a variety of work and engage in a wide range of occupations available in the unskilled sector, mainly as ordinary construction labour. More than 54 percent people migrate to Raipur city and work in construction sector, followed by brick-kiln worker 21.95 percent, rickshaw pullers 12.19 percent, auto-rickshaw drivers (5.69 percent), waiters (4.06 percent) and earth workers (1.63 percent). Among the migrants in Hyderabad, the composition of workers is distributed as construction workers (53.34 percent), brick-kiln workers (43.38 percent) and waiters (3.34 percent).

The composition of workers in Mumbai is construction workers (62.87 percent), brick-kiln workers (32.97 percent) and surprisingly rickshaw pullers (4.14 percent). The composition of workers at the rest of the destinations is confined to construction and brick-kiln sector only. They work as construction workers in Bangalore (60.01 percent), Chennai (71.13 percent), Goa (66.62 percent), Bargarh (67.21 percent) and Rajahmundry (0.41 percent), and Thiruvananthapuram (0.20 percent). Similarly, they work as brick-kiln workers in Bangalore (6.53 percent), Chennai (2.65 percent), Goa (5.10 percent), Thiruvananthapuram (51.21 percent) and Rajahmundry (40.19 percent).

It is found that the composition of workers is confined to non-agricultural sector and the destination decides the type of work. Raipur is found to be more diverse destination in providing work opportunities compared to all other destinations. This is may be because of migrant's nearest destination and their social kith and kin having migrated before, and thus having a history in the city. Working in construction sector in far off cities may be because they are attached to specific labour contractors and they keep on working wherever they are sent to work. The picture of brick-kiln industry is different, because the migrants mostly are found working as bonded labour, and in return they take money in advance. Majority of seasonal migrants choosing these two types of work and flocking together may be because of the work availability, high wage rate and personal interest. It has also been remarked that many educated and semi-skilled persons in absence of better employment opportunities at the villages, readily accept unskilled and menial jobs after reaching the destination sites.

### ***Skill development and occupational changes***

Caste occupation of the seasonal migrants is as follows; SCs (Dom) are experts in collecting and processing skin and hides (tanners), and are traditional Drummers, sweepers and leather workers; STs (Gond and Kandha) are expert food gatherers, NTFP collectors and Hunters; and among the Others, the Gouds are traditionally Milkmen; Khaparaa Mali or the gardeners as well as expert in making puffed rice (*Muri & Khoi*) and flat rice (*Chira*); Sagbaria Mali cultivate vegetables and flowers, and Telis are experts in pressing of oil seeds. Sundhi do business, Paikas are Cultivators and Brahmins are priests. This study found that there is no relation of caste links to occupations adopted at migration destinations but caste occupation has its role in the villages. Seasonal migration has consequences for social and

economic relations at migrant's household level. Despite problems at the destination sites, seasonal migration is not always the 'menace' it is made out to be within and between migrant's households. Though there is no uniform definition of skills, in many countries 'skills' are defined in terms of occupational skills and/or educational attainment levels. Similarly, there is no single methodology for skill needs analysis. However, what has proved to be useful in the experience of major destinations, is a holistic approach: a combination of qualitative analysis as well as quantitative data (ILO). For the present study, we have taken acquired language skills from the destination, and the time interval they have renovated their houses been analysed as the social changes after adopting seasonal migration as a livelihood strategy. Whereas new skills learnt at destination, adoption of skills at village and benefits of adoption are counted as consequences to those acquired skills.

Table 11: Skill development and occupational changes among seasonal migrants

|                                                     | Social Group |       |        |       |
|-----------------------------------------------------|--------------|-------|--------|-------|
|                                                     | SC           | ST    | Others | Avg.  |
| <b><i>Acquired and improved language skills</i></b> |              |       |        |       |
| Hindi                                               | 40.78        | 28.46 | 31.26  | 54.49 |
| Telugu                                              | 4.89         | 73.11 | 21.98  | 8.37  |
| Kannada                                             | 13.85        | 31.08 | 55.07  | 5.92  |
| Konkani                                             | 0            | 36.30 | 63.69  | 4.49  |
| <b><i>New skills learnt at destination</i></b>      |              |       |        |       |
| Mason                                               | 24.42        | 37.18 | 39.51  | 33.70 |
| Driver                                              | 4.65         | 0     | 0      | 1.55  |
| Waiter                                              | 2.91         | 0     | 0      | 0.97  |
| <b><i>Adoption of skills at village</i></b>         |              |       |        |       |
| Yes                                                 | 6.98         | 4.49  | 14.20  | 8.55  |
| <b><i>Benefits of adoption</i></b>                  |              |       |        |       |
| Structural change in houses                         | 5.23         | 3.85  | 2.47   | 3.85  |
| <b><i>Renovated their house</i></b>                 |              |       |        |       |
| Last year                                           | 20.91        | 35.29 | 43.78  | 31.22 |
| Last to last year                                   | 3.79         | 79.84 | 15.80  | 34.29 |
| A long ago                                          | 39.05        | 26.56 | 34.37  | 13.06 |

From table 11 it has been observed that out of the total seasonal migrants, more than half i.e. 54.49 percent acquired Hindi language as a medium of communication while working at the destination sites. The rest learnt Telugu (8.37 percent), Kannada (5.92 percent) and Konkani (4.49 percent) as they moved to different linguistic regions. More SCs have acquired Hindi language as compared to the STs and others. Similarly, STs are good in acquiring Telugu and others are good in acquiring Kannada and Konkani language. Skill of acquiring new language is not so easy, but it is made so by the seasonal migrants as a form of social capital which is a symbol of change in their sphere of life. It is the *intrinsic motivation* to learn the new language which must have a learning strategy at individual learning differences. This *paired-associate learning* develops group solidarity among them.

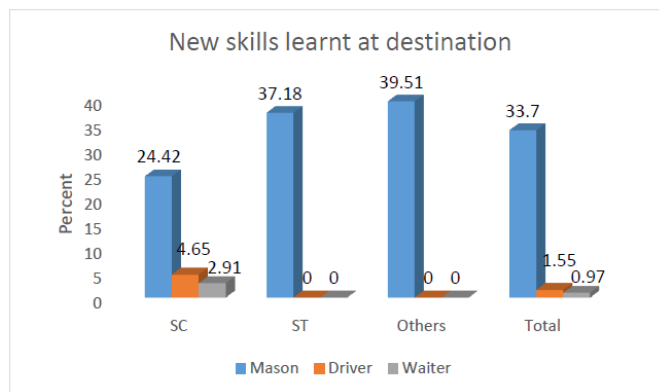


Fig 1: New skills learnt at destination by seasonal migrants

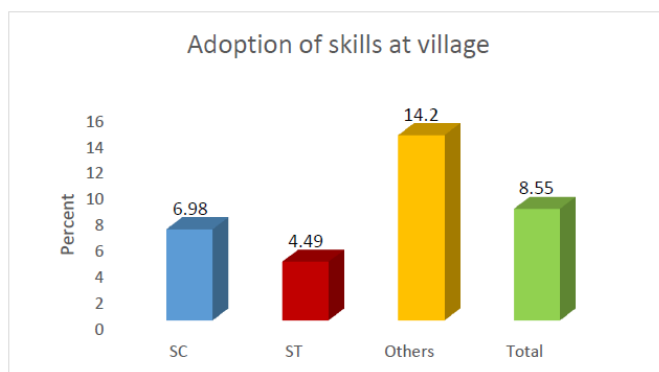


Fig 2: Adoption of new skills learnt at village by seasonal migrants

While working in construction sector, 33.47 percent are found to be skilled as masons, and the rest 1.63 percent skilled as drivers and 1.02 percent skilled as waiters from the total seasonal migrants surveyed. The share of skilled workers in construction sector is higher among the others category, as compared to SCs and STs. In driving and hotel work (waiter) the contribution is only from SCs and it is absent among the STs and others. A majority of them engage as unskilled workers, as expected, because if they were skilled then they would not prefer to go as seasonal migrant to earn a livelihood for the family. As they are manual labourers, the type of work they engage in also implies that there is very little chance for them acquiring skills whilst engaging in labour at the time. The skilled workers among females were negligible. Table 11 also reveals the fact that from the total seasonal migrants 8.57 percent adopt learnt skills at the native village and 5.92 percent among those report the benefits of adoption as external architectural development i.e. structural change in house construction. As far as the caste-wise comparison is concerned, SCs (6.98 percent), STs (4.49 percent) and others (14.20 percent) learnt new skills from destination and adopted them at villages.

Similarly, external architectural development (structural change in house) as the benefits of adoption among SCs was 5.23 percent, among STs (3.85 percent) and 2.47 percent among the others. Skills acquired by seasonal migrants at destination are however negligible. This is so because the seasonal migrants spend a limited time at the places of destination and have no long term interests vested in the places where they go to work. It is important for them to spend a few months working for an earning that they so desperately need as an additional income when none is available at the native places of their usual residence, particularly in the off-season. This is different for those who migrate out for much longer period involving a change of residence. They completely give up their traditional occupations heralding a shift in occupation at the destination. But still the situation may be because of majority, almost ninety percent are pursuing farming as the sole occupation at the village. However, they have learnt new skills and become experts of the occupation adopted and it stands at 35 percent.

Through the process of *Sanskritisation*, economic and political empowerment, caste system does not remain static. A virtually occupation-free caste system has developed where caste and occupation are now almost delinked. The type of available work in the cities is different from any traditional caste occupation. It is developed because of modernization, industrialization and urbanization which has no link with the upper caste or lower caste occupation. It's a juncture developed through the time which shows the complete deviation from any traditional India's caste occupation. Seasonal migration here is acting as agents of *social change* in this age of high degree of modernization, both cultural and technological. In terms of other social changes brought by these migrants, it is observed from the field that 31.22 percent from the total migrants renovated their house last year, 34.29 percent last to last year and only 13.06 percent renovated their house a long ago.

## **Conclusion**

It can be concluded that occupation at the migration destinations are totally different from the native villages. SC seasonal migrants have been more mobile compared to STs and Others. Among skilled migrants it is again the SCs who are found more in number. Raipur and Hyderabad are the important two destinations where seasonal migrants are heading. This may be because these two are the nearest cities from the origin villages and they have a close relation to the work place as their kith and kins have worked there before. Moreover, closer the destination it is easier to manage both family and seasonal work opted. The composition of workers is confined to non-agricultural sector and most of them engage themselves as construction sector and brick-kiln activities. Caste occupation at the villages has no link with the work at the destinations. They mainly work depending on the wage rate at the destination. However, it can be understood that change in economic or social sphere has not come on a single day or season. Since long time these people are migrating seasonally in search of livelihood to far off areas, living in different conditions. The seasonal migration is helping them in eradicating absolute poverty from the household and creating a zone of hope for the children in a long run to come out of all odds. Caste as an institution

remains strong in the rural areas affecting almost all aspects of seasonal migrant's life. Caste has little relevance in the urban society for these sections and it is associated with rural, traditional societies and not with urban, modern societies. The seasonal migrant is seen to leave the rural to become a part of urban setting. The temporary separation of spaces of operation gives the impression that caste and migration have nothing to do with each other (Vartak, 2016). Caste only as a part of identity or social profile and in the interplay of caste and migration it has been observed that caste is not seen as dynamic in migration. The kinds of skills is new which they have learnt and they don't have the scope to acquire these in the origin villages because they are from rural areas and the skills are interlinked with the agriculture and cultivation type of activities in the villages they live. The composition of workers distribution among social group is seen as diversified from their caste occupation. The kind of occupation at destination has nothing to deal with the occupation they were previously engaged in. Thus, in essence, seasonal migration underscores a transition influenced primarily by economic necessity and opportunity, rather than by traditional caste identity.

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# Spatio-Temporal Analysis and Prediction of Land Use and Land Cover Changes in Samaspur Wetland, Uttar Pradesh (1988 – 2050) Using Geospatial Techniques

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### Abstract:

Recognized for its high productivity and biodiversity, the Samaspur Wetland, a Ramsar site in Uttar Pradesh, India, was designated as a bird sanctuary in 1987 and acknowledged for its global ecological significance in 2019. This study examines the Land Use and Land Cover (LULC) changes in the Samaspur Wetland, Uttar Pradesh, from 1988 to 2050. The study aims to understand the impact of anthropogenic activities, climate change, and natural processes on the wetland ecosystem over time. Significant changes were observed, including a reduction in wetland coverage and an increase in agricultural land and built-up areas, indicating a shift towards urbanization and agricultural expansion. Comparative analysis revealed significant changes over the study period, with agricultural land showing a net increase of 4%, Open land decreasing by 87%, built-up areas increasing by 626%, vegetation rising by 257%, and water bodies expanding by 123%. These changes have impacted the wetland's biodiversity and hydrology, threatening its ecological stability. To forecast future LULC scenarios, the study applies the Cellular Automata (CA)-Markov Chain model, predicting a substantial further reduction of wetland areas by 2050, with the highest expansion in agricultural areas. These projected changes could exacerbate biodiversity loss, disrupt migratory bird patterns, and affect local community dependent on the wetland for livelihood. The study underscores the dynamic nature of Samaspur Wetland, highlighting the need for effective conservation strategies.

**Keywords:** Wetland Mapping and monitoring, Samaspur wetland, Landsat data, land use/land cover, Land transformation

### Introduction

Wetlands are transitional zones between aquatic and terrestrial ecosystems and are considered among the most productive ecosystems, comparable to rainforests and coral reefs (Balwan & Kour, 2021). These ecosystems include swamps, peatlands, sloughs, marshes, bogs, and fens,

and they play a critical role in supporting biodiversity, providing water resources, enabling agriculture, regulating climate, recharging groundwater, protecting coasts from floods, and offering opportunities for recreation, tourism, and livelihoods (Kumar & Singh, 2020). According to the National Wetland Inventory and Assessment (NWIA, 2011), India's wetlands cover approximately 15.26 million hectares, accounting for 4.63% of the country's geographical area. Lakshadweep stands out with nearly all of its land, over 96% classified as wetland, making it the clear leader in wetland coverage relative to total area. It's followed by the Andaman and Nicobar Islands (18.52%), Daman and Diu (18.46%), and Gujarat (11.56%) as regions with the next highest wetland proportions while other places with notable wetland coverage include Puducherry (13%), West Bengal (12.5%), Assam (9.74%), Tamil Nadu (6.92%), Goa (5.76%), Andhra Pradesh (5.26%), and Uttar Pradesh (5.16%) while the states like Mizoram, Haryana, Delhi, Sikkim, Nagaland, and Meghalaya have far less than 2% of their area categorized as wetlands, highlighting significant regional differences in wetland distribution across India (National Wetland Atlas, 2011; Gupta, 2021). However, many of these wetlands are under threat due to human activities, including agricultural expansion and weed infestation, leading to their gradual disappearance (Pattanaik et al., 2008). Designating these wetlands as Ramsar sites is part of global conservation efforts. Ramsar sites are wetlands of international importance, as they are home to diverse ecosystems, including freshwater lakes, marshes, mangroves, and high-altitude lakes. These sites are critical for biodiversity, providing habitat for numerous species of flora and fauna (Ramsar Convention on Wetlands, 2018). India, with the highest number of Ramsar sites in South Asia, has 85 such sites as of August 2024, covering 1,358,067.757 hectares across 18 states, where Tamil Nadu has the highest number of Ramsar wetlands in India, with a total of 18 sites, followed by Uttar Pradesh, which has 10 (MoEFCC, 2024).

Uttar Pradesh wetlands cover an area of approximately 1,242,530 hectares, representing 5.16% of its geographical area and key wetlands, including Nawabganj Bird Sanctuary, Parvati Bird Sanctuary, and Samaspur Bird Sanctuary, play vital roles in preserving wetland ecosystems and avian diversity (Garg, 2018; Rajamani et al., 2015). Among them, Samaspur Bird Sanctuary is especially important for its contribution to protecting a rich variety of bird species. Covering nearly 800 hectares, it serves as a crucial stopover for migratory birds traveling thousands of kilometers from Europe and Central Asia (Ramsar Information Sheet, 2020). Designated as a bird sanctuary in 1987, Samaspur supports essential ecological processes like groundwater recharge, flood mitigation, and nutrient cycling. Historically, Samaspur Wetland was characterized by dense natural vegetation and marshlands, providing ideal conditions for diverse species. However, land use and land cover (LULC) changes have drastically transformed ecosystems in recent decades, especially impacting wetlands and biodiversity (Alam et al., 2021). Agricultural expansion, primarily for crops like rice, wheat, and sugarcane, has contributed to habitat loss and degradation due to the intensification of farming practices associated with the Green Revolution (Behera et al., 2011). This expansion has led to the encroachment of critical habitats, diminishing natural wetland areas and disrupting local ecosystems (Gokhale, 2009; Madugundu, 2009). The impact extends to nearby flora and water systems due to the widespread use of agrochemicals, which degrade native vegetation and cause water pollution, contributing to eutrophication and

biodiversity loss. Additionally, urban growth has significantly reduced wetland areas, reshaping landscapes and eliminating habitats essential for migratory bird species such as the northern pintail, gadwall, and common teal (Rajpar et al., 2022). Fish populations have also declined due to deteriorating water quality and altered vegetation. This decline impacts local communities relying on fishing for their livelihoods. Agricultural runoff, rich in fertilizers and pesticides, has further exacerbated eutrophication, promoting algal blooms, lowering oxygen levels, and negatively impacting aquatic biodiversity (Behera et al., 2011).

Given these challenges, the study aims to examine the spatiotemporal changes in land use and land cover in the Samaspur Wetland from 1988 to 2024 and to predict future LULC changes by 2050.

### **Study area**

The present study considers Samaspur wetland, located in the Rae Bareilly district of Uttar Pradesh, spanning an area of 7.99 km<sup>2</sup> between the latitudes 25° 57' 49" to 26° 01' 05" N and longitudes 81° 21' 34" to 81° 25' 11" E. This S-shaped wetland consists of five interconnected lakes Samaspur, Mamani, Gorwa-Hasanpur, Hakganj, and Rohnia with a sixth nearby lake, Bissaiya, that is not connected to the main water body but also forms part of the sanctuary (Wildlife Conservation Organization, Uttar Pradesh, 2010). These wetlands are officially recognized under the National Wetland Conservation Program administered by the Ministry of Environment and Forests (MoEF), Government of India (Behera et al., 2011). The sanctuary is a rich center of biodiversity, home to 149 species of higher plants, at least 46 species of fish, and over 250 species of resident and migratory birds, several invertebrates such as mollusks, butterflies, both terrestrial and water snakes, turtles, frogs and higher vertebrates such as the blue bull (Ramsar, 2002; Gokhle, 2009). This sanctuary serves as a vital wintering ground for countless migratory birds that travel here during the colder months, with the wetland complex hosting more than 75,000 water birds annually (Kanauiya, 2015; Samaspur Bird Sanctuary, Ramsar Sites Information Service, 2020).

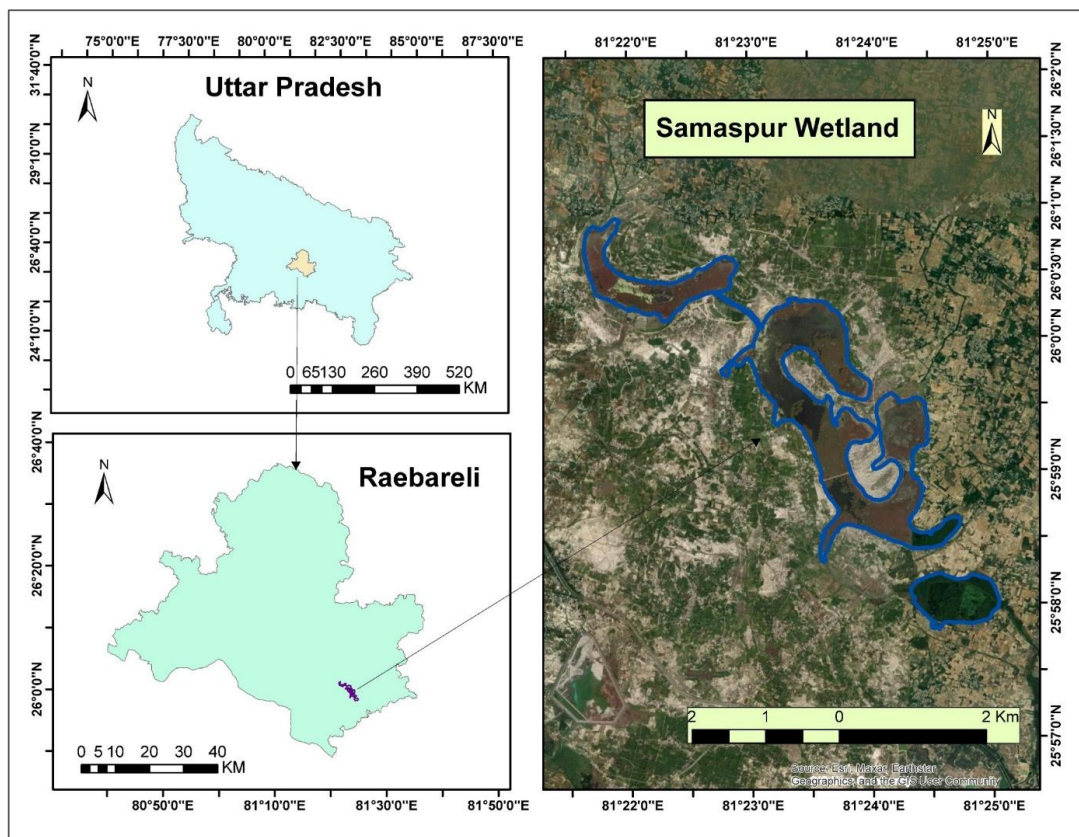


Figure 1: Location Map of the study area

## Data and Methodology

The Landsat data for 1988, 1995, 2003, and 2024 are acquired from USGS. All the data are processed and projected to the Universal Transverse Mercator (UTM) projection system. A list of data is provided in Table 1.

Table 1: Details of Satellite Images (Sources: United States Geological Survey)

| Satellite | Sensor     | Data sources | Spatial-resolution<br>(Meter) | Date of acquisition |
|-----------|------------|--------------|-------------------------------|---------------------|
| Landsat-9 | OLI-2/TRIS | USGS         | 30                            | 27-03-2024          |
| Landsat-7 | ETM+       | USGS         | 30                            | 18-03-2003          |
| Landsat-5 | TM         | USGS         | 30                            | 17-12-1995          |
| Landsat-5 | TM         | USGS         | 30                            | 11-12-1988          |

For further processing of the image and study of LULC change in the Samaspur wetland, five classes of LULC are prepared (Table 2).

Table 2: LULC classification

| S. No. | Class name  | Description                                                                                                        |
|--------|-------------|--------------------------------------------------------------------------------------------------------------------|
| 1      | Water-body  | Area covered by water with natural drainage systems like rivers, man-made features, lakes, waterlogged ponds, etc. |
| 2      | Barren land | Area of land where plant growth is unsuitable                                                                      |
| 3      | Built up    | Road, residential area, etc.                                                                                       |
| 4      | Vegetation  | Land which is under the natural plantation, tree cover, scrub etc.                                                 |
| 5      | Agriculture | The area used for the cropping                                                                                     |

The next step is Accuracy Assessment which is an important step in evaluating the quality and reliability of a land use/land cover. It involves comparing the classified data against reference data collected by ground truth or survey method to determine the classification correctness. Accuracy assessment aims to measure the precision or effectiveness of pixel sampling in a classified LULC map, assessed and quantified by error matrix (Jamal, S., & Ahmad, W. S. 2020). Thus, the accuracy assessment is used to create a confusion matrix and calculate the area of the LULC for the years 1988, 1995, 2003, and 2024.

The producer accuracy was done, which indicates the probability of a reference sample being correctly classified using the following formula.

$$\text{Producer's Accuracy} = \frac{\text{Total Number of Reference Samples in that Class}}{\text{Number of Correctly Classified Samples in a Class}}$$

The User's accuracy indicates the probability that a sample classified into a given category represents that category on the actual ground.

$$\text{User's Accuracy} = \frac{\text{Total Number of Samples Classified into that Class}}{\text{Number of Correctly Classified Samples in a Class}}$$

The Overall Accuracy is the ratio of correct classified samples to the total number of samples. It provides a general measure of the classification accuracy

$$\text{Overall Accuracy} = \frac{\sum (\text{Correctly Classified Sample})}{\text{Total No. of Sample}}$$

Kappa Coefficient: A statistical measure accounts for the possibility of agreement occurring by chance. A higher kappa coefficient indicates better agreement between the classified map and the reference data.

$$K = \frac{n \sum_{i=1}^r X_{ii} - n \sum_{i=1}^r (X_{i+} - X_{+i})}{n^2 = \sum_{i=1}^r (X_{i+})(X_{+i})}$$

where  $r$  = number of rows in the matrix

$x_{ii}$  = number of observations in row  $i$  and column  $i$ .

$x_{i+}$  and  $x_{+i}$  = marginal totals of row  $i$  and column  $i$ , respectively, and

$n$  = total number of observations. (Jamal, S., & Ahmad, W. S. 2020)

The change matrix also known as the confusion matrix, the following formulae are used:

Class-wise Change:

$$\text{Change Rate } ij = \frac{\text{Number of pixel change from class } i \text{ to class } j}{\text{total number of pixel in class } i}$$

Overall Change:

$$\text{Overall Change} = \frac{\sum \text{Diagonal Elements}}{\sum \text{Total Pixels}}$$

**Trends Analysis:** Land use land cover trends analysis involves examining changes in LULC over multiple time periods to identify patterns, rates, and direction of change. Trends analysis is essential for understanding long-term environmental change, agriculture expansion, and other dynamic processes affecting the LULC. Trends analysis over the time 1987 to 2024 and after the process, find the change according to linear regression, which shows the rate of change of each class. Here, a low value of regression presents low variation around the mean, and a high value shows high variation around the mean.

The Markov chain is employed to predict the future Land Use Land Cover. This helps to predict land use and cover and assume the probability of transition between different LULC classes over time. Markov chain believes that the likelihood of future land cover state depends only on the current state, not necessarily on the entire history. The study-based year is 2024, and prediction is carried out for 2050 using the following rating criteria of the kappa statistics.

## Results and Discussions

### *Land Use Land Cover of Samaspur Wetland (1988 to 2024)*

Land Use and Land Cover (LULC) is classified into five categories: Built-up, Water Bodies, Agriculture, Vegetation, and Barren Land, covering a total area of 58.46 km<sup>2</sup> (Figure 2). In 1988, agricultural land occupied 31.32 km<sup>2</sup>, Barren land covered 19.13 km<sup>2</sup>, water bodies spanned 4.90 km<sup>2</sup>, vegetation accounted for 2.711 km<sup>2</sup>, and 0.402 km<sup>2</sup> was built-up area. At that time, over 45% of the land was used for agricultural activities, followed by barren land as the second-largest category. By 1995, agricultural land had expanded significantly, mainly due to the conversion of barren land. Out of the total 58.46 km<sup>2</sup> study area, 41.05 km<sup>2</sup> was agricultural land, 5.91 km<sup>2</sup> was water bodies, 5.83 km<sup>2</sup> was barren land, 5.22 km<sup>2</sup> was vegetation, and 0.44 km<sup>2</sup> was built-up area. The most notable changes were the reduction of barren land and the expansion of the agricultural regions. In 2003, the LULC showed that agricultural land had decreased to 35.88 km<sup>2</sup>, barren land was reduced to 5.16 km<sup>2</sup>, the built-up area grew to 0.53 km<sup>2</sup>, vegetation increased to 6.15 km<sup>2</sup>, and water bodies expanded to 10.83 km<sup>2</sup>. Compared to 1995, agricultural land decreased by approximately 5 km<sup>2</sup>, while water bodies increased by the same amount. In 2024, the agricultural land further decreased by 3.33 km<sup>2</sup>, and barren land declined by 2.77 km<sup>2</sup>. The built-up area, however, experienced a growth of around 300%. The LULC study shows that 32.55 km<sup>2</sup> is agricultural land, 2.39 km<sup>2</sup> is barren land, 2.92 km<sup>2</sup> is built-up, 9.68 km<sup>2</sup> is covered by vegetation, and water bodies occupy 10.91 km<sup>2</sup> (Figure 2). Significant land-use changes include the transformation of barren land into agricultural land.

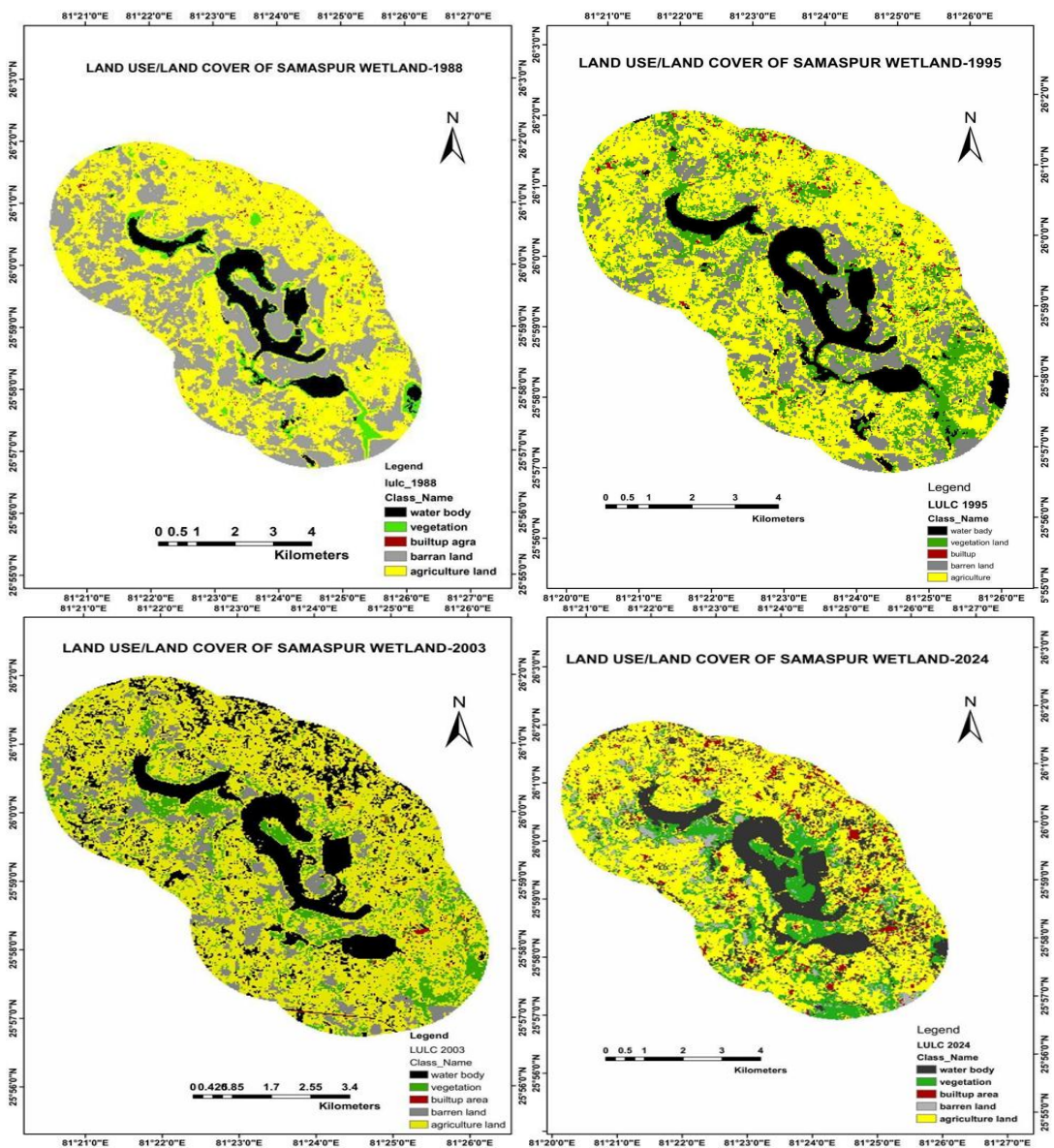


Figure 2: LULC map of Samaspur wetland 1988,1995, 2003, 2024

The accuracy assessment for 1988, 1995, 2003, and 2024 had a kappa of 0.62, 0.71, 0.71, and 0.74, respectively (Table 4)

Table 4: Accuracy matrix of LULC map of Samaspur wetland (1988, 1995, 2003, and 2024)

| 1988         |           |            |             |             |              |       |      |       |
|--------------|-----------|------------|-------------|-------------|--------------|-------|------|-------|
| Classes name | Waterbody | Vegetation | Built-up    | Barren land | Agriculture  | Total | UA   | Kappa |
| Water body   | 16        | 0          | 0           | 0           | 1            | 17    | 0.94 | 0     |
| Vegetation   | 0         | 42         | 12          | 0           | 12           | 66    | 0.63 | 0     |
| Built-up     | 1         | 0          | 9           | 0           | 0            | 10    | 0.9  | 0     |
| Barren land  | 0         | 0          | 1           | 2           | 2            | 5     | 0.4  | 0     |
| Agriculture  | 3         | 6          | 10          | 4           | 99           | 122   | 0.81 | 0     |
| Total        | 20        | 48         | 32          | 6           | 144          | 220   | 0    | 0     |
| PA           | 0.8       | 0.87       | 0.28        | 0.33        | 0.86         | 0     | 0.76 | 0     |
| Kappa        | 0         | 0          | 0           | 0           | 0            | 0     | 0    | 0.626 |
| 1995         |           |            |             |             |              |       |      |       |
| Classes name | Waterbody | Vegetation | Barren land | Agriculture | Built up     | Total | UA   | Kappa |
| Waterbody    | 16        | 0          | 0           | 0           | 0            | 16    | 1    | 0     |
| Vegetation   | 0         | 16         | 3           | 0           | 0            | 19    | 0.84 | 0     |
| Barren land  | 1         | 0          | 17          | 0           | 1            | 21    | 0.81 | 0     |
| Agriculture  | 1         | 4          | 12          | 120         | 4            | 141   | 0.85 | 0     |
| Built-up     | 0         | 0          | 0           | 2           | 1            | 3     | 0.33 | 0     |
| Total        | 18        | 20         | 32          | 124         | 6            | 200   | 0    | 0     |
| PA           | 0.89      | 0.8        | 0.53        | 0.97        | 0.17         | 0     | 0.85 | 0     |
| Kappa        | 0         | 0          | 0           | 0           | 0            | 0     | 0    | 0.716 |
| 2003         |           |            |             |             |              |       |      |       |
| Classes name | Waterbody | Vegetation | Barren land | Built up    | Agricultural | Total | UA   | Kappa |
| Waterbody    | 10        | 1          | 0           | 0           | 5            | 16    | 0.62 | 0     |
| Vegetation   | 0         | 14         | 0           | 1           | 1            | 16    | 0.87 | 0     |
| Barren land  | 0         | 0          | 14          | 0           | 0            | 14    | 1    | 0     |
| Built up     | 0         | 0          | 0           | 0           | 0            | 0     | 0    | 0     |
| Agriculture  | 0         | 4          | 2           | 5           | 43           | 54    | 0.79 | 0     |
| Total        | 10        | 19         | 16          | 6           | 49           | 100   | 0    | 0     |
| PA           | 1         | 0.74       | 0.88        | 0           | 0.88         | 0     | .81  | 0     |
| Kappa        | 0         | 0          | 0           | 0           | 0            | 0     | 0    | 0.714 |
| 2024         |           |            |             |             |              |       |      |       |
| Classes name | Waterbody | Vegetation | Barren land | Built up    | Agriculture  | Total | UA   | Kappa |
| Waterbody    | 12        | 1          | 0           | 0           | 5            | 18    | 0.66 | 0     |
| Vegetation   | 0         | 11         | 2           | 2           | 2            | 17    | 0.65 | 0     |
| Barren land  | 0         | 1          | 5           | 0           | 1            | 7     | 0.71 | 0     |
| Built up     | 0         | 0          | 0           | 7           | 1            | 8     | 0.87 | 0     |
| Agriculture  | 0         | 1          | 0           | 0           | 48           | 50    | 0.96 | 0     |
| Total        | 12        | 14         | 7           | 9           | 57           | 100   | 0    | 0     |
| PA           | 1         | 0.78       | 0.71        | 0.78        | 0.84         | 0     | 0.86 | 0     |
| Kappa        | 0         | 0          | 0           | 0           | 0            | 0     | 0    | 0.741 |

### Change Percentage of LULC of Samaspur Wetland (1988 to 2024)

The LULC change analysis of Samaspur Wetland reveals significant shifts in the landscape from 1988 to 2024. In 1988, agricultural land covered 31.33 km<sup>2</sup>, increasing slightly to 32.55 km<sup>2</sup> by 2024, marking a net change of 3.89%. This modest growth suggests relatively stable agricultural use, though it experienced fluctuations peaking at 41.06 km<sup>2</sup> in 1995 and then reducing to 35.88 km<sup>2</sup> by 2003 (Figure 3). Barren land, by contrast, has consistently decreased. In 1988, it accounted for 19.13 km<sup>2</sup> but declined sharply to 5.83 km<sup>2</sup> in 1995, further decreasing to 5.17 km<sup>2</sup> in 2003, and ultimately shrinking to 2.40 km<sup>2</sup> in 2024. This represents a significant net reduction of 87%.

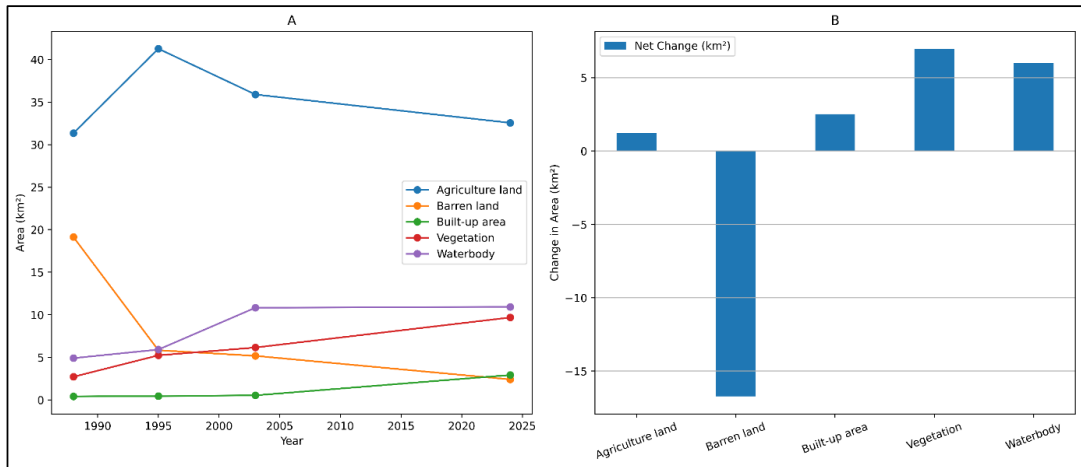


Figure 3: A- Year-wise LULC change, B- Net LULC Change (1988-2024)

The built-up area has expanded substantially from 0.4 km<sup>2</sup> in 1988 to 2.92 km<sup>2</sup> in 2024, registering a net increase of 630%, reflecting a high rate of built-up area development. Vegetation cover, on the other hand, has risen markedly with a 257% change, suggesting successful reforestation efforts. Water bodies fluctuated notably between 1995 and 2003, although showing a net increase of 122.6 % from 1988 to 2024 (Figure 3B).

Table 5: LULC changes and percentage of change from 1988 to 2024

| LULC Class       | Area (km <sup>2</sup> ) |       |       |       | Area Change (km <sup>2</sup> ) |           |           | Net Change (1988-2024)  |          |
|------------------|-------------------------|-------|-------|-------|--------------------------------|-----------|-----------|-------------------------|----------|
|                  | 1988                    | 1995  | 2003  | 2024  | 1988-1995                      | 1995-2003 | 2003-2024 | Area (km <sup>2</sup> ) | Area (%) |
| Agriculture land | 31.33                   | 41.26 | 35.88 | 32.55 | 9.93                           | -5.38     | -3.33     | 1.22                    | 3.89     |
| Barren land      | 19.13                   | 5.83  | 5.17  | 2.4   | -13.3                          | -0.66     | -2.77     | -16.73                  | -87.45   |
| Built-up area    | 0.4                     | 0.44  | 0.53  | 2.92  | 0.04                           | 0.09      | 2.39      | 2.52                    | 630.00   |
| Vegetation       | 2.71                    | 5.23  | 6.15  | 9.68  | 2.52                           | 0.92      | 3.53      | 6.97                    | 257.20   |
| Waterbody        | 4.9                     | 5.91  | 10.83 | 10.92 | 1.01                           | 4.92      | 0.09      | 6.02                    | 122.86   |

### *LULC Change Matrix of Samaspur Wetland (1988 to 2024)*

The transformation matrix in Table 6, covering 1988 to 2024, illustrates how land-use classes within the Samaspur wetland have shifted over time. 0.60 km<sup>2</sup> of agricultural land transitioned into barren land, 2.17 km<sup>2</sup> were developed into built-up areas, 4.62 km<sup>2</sup> became vegetated, and 4.20 km<sup>2</sup> were taken over by water bodies. Barren land also experienced significant transitions: 1.32 km<sup>2</sup> shifted to agricultural use, 0.15 km<sup>2</sup> was built over, 2.12 km<sup>2</sup> converted to vegetation, and 0.05 km<sup>2</sup> transformed into water bodies. Notably, no other class encroached upon built-up areas, indicating stability in this category. Vegetation, however, saw 2.53 km<sup>2</sup> become agricultural land, 0.24 km<sup>2</sup> turn to barren land, 0.34 km<sup>2</sup> developed as built-up areas, and 6.13 km<sup>2</sup> occupied by expanding water bodies. Water bodies themselves shifted, with 4.19 km<sup>2</sup> turning to agricultural use, 0.03 km<sup>2</sup> to barren land, 0.12 km<sup>2</sup> to built-up areas, and 0.29 km<sup>2</sup> transitioning to vegetation. These findings underscore a dynamic landscape with significant exchanges among land-use classes, especially in vegetation and water bodies.

Table 6: Transformation matrix of Samaspur Wetland, (1988 to 2024) in Km<sup>2</sup>

| Classes     | Agriculture | Barren land | Built-up | Vegetation | Waterbody | Total |
|-------------|-------------|-------------|----------|------------|-----------|-------|
| Agriculture | 24.31       | 1.32        | 0.00     | 2.53       | 4.19      | 32.34 |
| Barren land | 0.60        | 1.52        | 0.00     | 0.24       | 0.03      | 2.39  |
| Built-up    | 2.17        | 0.15        | 0.34     | 0.34       | 0.00      | 2.91  |
| Vegetation  | 4.62        | 2.12        | 0.00     | 2.59       | 0.29      | 9.61  |
| Waterbody   | 4.20        | 0.05        | 0.00     | 0.43       | 6.19      | 10.87 |
| Total       | 35.90       | 5.16        | 0.34     | 6.13       | 10.81     | 58.34 |

### *Trends analysis of Samaspur wetland (1988 to 2024)*

Trends analysis of LULC quantifying the change areas for each cover class between the historical and recent maps. LULC trends are structured continuously as the man-environment changes. For analyzing the trends of LULC change in Samaspur, a linear regression model is used to assess the rate of change.

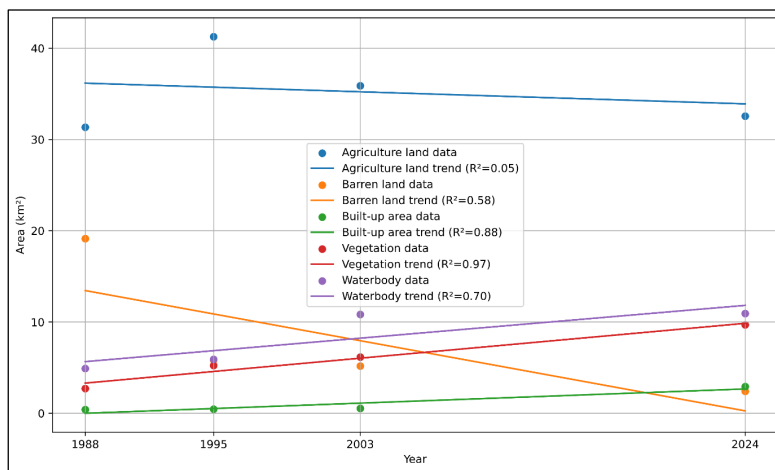


Figure 4: Trend Analysis of LULC Classes (1988-2024)

Figure 4 highlights that the most dramatic change is seen in built-up areas, which show a very strong and clear increasing trend. This is confirmed by its very high  $R^2$  value of 0.88, meaning the trend line is an almost perfect fit for the data, indicating rapid urbanization. Similarly, vegetation shows an extremely strong and clear trend, with an  $R^2$  value of 0.97. This near-perfect score means its increase over time is very consistent and predictable. Barren land and waterbodies also show noticeable trends. Barren land has a moderately strong trend ( $R^2=0.58$ ), suggesting a general pattern of increase or decrease, while waterbodies have a relatively strong trend ( $R^2=0.70$ ), indicating a reliable pattern of change. In contrast, agricultural land shows almost no clear pattern over time. Its very low  $R^2$  value of 0.05 means the trend line is a very poor fit for the data, indicating that changes in farmland have been unpredictable and inconsistent.

#### *Samaspur wetland LULC 2050 prediction using Markov chain*

In this study, the Samaspur wetland LULC maps of 1988 and 2024 were used to predict the land use land cover of Samaspur wetland in 2050. The probability matrix shows the probability of a specific land cover class changing to another class between two points in time.

Table 7: Transition probability matrix of Samaspur Wetland LULC 1998 to 2024

| Transition Probability Model (Area in Km <sup>2</sup> ) |            |            |             |          |             |
|---------------------------------------------------------|------------|------------|-------------|----------|-------------|
| Class Name                                              | Water Body | Vegetation | Barren Land | Built-Up | Agriculture |
| Water Body                                              | 0.57       | 0.05       | 0           | 0        | 0.05        |
| Vegetation                                              | 0.1        | 0.12       | 0.02        | 0.06     | 0.68        |
| Barren Land                                             | 0.02       | 0.42       | 0.17        | 0.04     | 0.33        |
| Built Up                                                | 0.15       | 0.17       | 0.02        | 0.05     | 0.05        |
| Agriculture                                             | 0.19       | 0.04       | 0           | 0.11     | 0.65        |

As seen in Table 7, the water body class converted into only vegetation and agricultural land, not Barren land or built-up areas. Vegetation areas mainly change into agricultural land after the water body. Barren land converts into vegetation and agricultural classes. The built-up area has no specific change, and the farmland is converted into water body and built-up area.

Table 8: Predicted Area of Samaspur, 2050

| Class name    | Area in km <sup>2</sup> | Percentage |
|---------------|-------------------------|------------|
| Waterbody     | 8.021                   | 13.71      |
| Vegetation    | 5.498                   | 9.43       |
| Barren land   | 0.951                   | 1.62       |
| Built-up area | 4.591                   | 7.85       |
| Agriculture   | 39.407                  | 67.39      |
| Total         | 58.469                  | 100        |

Based on Markov chain analysis, the land use and land cover in the Samaspur wetland for the year 2050 are predicted and presented in Table 8. Agricultural land is expected to increase by 21%, and will be the dominant landscape with nearly 67.4% of the total area in 2050. Built-up area will also expand notably by 57%, making up 7.85% of the area. In contrast, barren land will decline sharply by 60%, representing just 1.63% of the total. Vegetation is projected to decrease

significantly, losing 43% and accounting for only 9.4% of the area, while waterbodies will shrink by 27%, making up 13.7% of the total highlighted in Table 8. Overall, the results highlight a future trend of expanding agriculture and built-up areas at the cost of natural vegetation, barren land, and waterbodies.

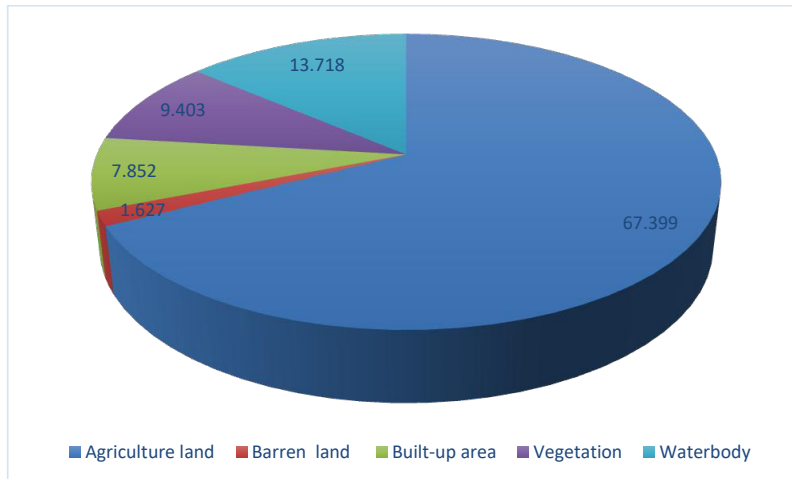


Figure 5: Samaspur wetland LULC area in 2050

## Conclusion

This study maps the profound transformation of Samaspur Wetland from 1988 to 2024. The analysis reveals a landscape dramatically reshaped, marked by two powerful, opposing trends. On one hand, we observed the near-disappearance of barren land and a vigorous expansion of vegetation, suggesting a greening of the area. Water bodies also showed a significant net increase. On the other hand, these positive changes were countered by an explosive growth in built-up areas and the consistent dominance of agricultural land, which remains the largest cover type. The projection to 2050 forecasts a tipping point, where the historical gains in natural covers are reversed, and agriculture and built-up become overwhelmingly dominant.

Effective conservation strategies and sustainable management are crucial to preserving this vital wetland area's ecological integrity and multifunctional benefits. Some suggestions can be incorporated into Samaspur Wetland a development towards sustainable management and ensure its ecological health and participatory community engagement, like establishing long-term monitoring programs, promoting Eco-tourism, raising awareness, conserving and restoring habitat, and developing a Land Use management program.

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# Landslide Susceptibility Analysis in Jaintia Hill Districts, Meghalaya by Fuzzy based Analytical Hierarchy Process (FAHP)

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### Abstract

One of the most frequent geohazards in the hilly areas of all of northeastern India, particularly Meghalaya, is landslides, which can result in significant loss of life and property. The primary goal is to assess the region's natural landslide susceptibility using an inventory and zonation process. The present work employs a GIS-coupled fuzzy based Analytical Hierarchy Process Multi-Criteria Decision Making (MCDM) technique to assess the areas in the Jaintia Hill regions of Meghalaya that are susceptible to landslides. Ten causal factors: slope, relative relief, TWI, soil, geology, land use/cover, distance to roadways, drainage density, lineament density, and rainfall—were subjected to the Fuzzy-Analytical Hierarchy Process (F-AHP) method in order to determine the weights. These landslide influencing variables were delineated and fuzzy numbers were used to specify their relative weights. The landslide susceptibility spatial matrix was generated after the fuzzy numbers were gone through pairwise comparison in the Analytical hierarchy process (AHP) system to provide standardised causative component weights and the normalised weights for the theme layers. The F-AHP model classifies over 53% of the research region as a highly sensitive zone. The outcome was confirmed by the earlier instances of the incident. The location of popular tourist destinations and vulnerable water routes were shown to be connected with the identification of such risk zones. The project's output will help with emergency decision-making and the prioritisation of activities targeted at reducing and minimising the danger of future landslides in addition to providing knowledge about current landslides and their causes.

**Keywords:** landslide susceptibility, fuzzy based Analytical Hierarchy Process, causal factors, pairwise comparison, sensitive zone, decision-making.

### Introduction:

A large-scale landmass instability results in the collapse of hundreds of homes and other infrastructures, as well as the loss of life and natural resources. According to Cruden (1991), landslides can be caused by rainfall, earthquakes, volcanic eruptions, river-induced slope erosion,

and human operations like excavation and slope-cutting. This kind of natural disaster mostly occurs in rocky environment of Himalayan terrain, North-East Indian hilly tract and peninsular Indian Ghats. To minimise the disastrous impacts, identification of landslide risk zones also known as Landslide Susceptibility Mapping (LSM) plays an important role. Recent studies on this Landslide Susceptibility Mapping and subsequent prevention planning are showing the effective use of geospatial platform and dataset.

Several landslide-influencing factor data are overlayed with their weighted contribution or contribution ratio in the spatial decision-making process within the GIS platform in order to get a final result. Different approaches exist worldwide for determining the relative importance of individual contributing elements. Different techniques, including qualitative and quantitative approaches, have been developed today to predict the locations in the literature that are likely to experience landslides (Dai and Lee, 2002). In practical terms, qualitative or knowledge-based procedures are expert-based approaches that rely on responsible expert judgements to develop a knowledge-based model (Lazzari and Danese, 2015; Akgun, 2012; Osna et al., 2014; Bourenane et al., 2015; Bahrami et al., 2019). Since knowledge-based strategies combine years of experience with a theoretical understanding of events, their results are highly renowned in overcoming issues in a number of fields (Luger, 2005). This is most likely the reason knowledge-based techniques have been employed for mapping the susceptibility to landslides for a long time.

In order to minimise subjectivity and prevent prejudices when determining the significance of criteria, quantitative or data-driven approaches have been developed (Kanungo et al., 2006). When it comes to landslide issues, data-driven approaches use a scientific model to forecast the likelihood of a landslide occurring, with assistance from the spatial distribution of a number of elements that can cause landslides in landslide-prone locations (Wu et al., 2013).

Among the knowledge-based approaches, Satty's Analytical Hierarchical Process (AHP) is used extensively for several spatial decision-making with or without a questionnaire survey among the experts and local inhabitants. AHP method for mapping landslide susceptibility has been applied by various researchers in their studies: Barredo et al. (2000) in the Tirajana basin, Spain; Ayalew et al., (2005) in Sado Island, Japan; Gorsevski et al., (2006) in the Clear Water National Forest, Idaho, USA; Akgun and Türk (2010) in Ayvalik, Turkey; Rozos et al., (2011) in the Peloponnesus, Greece; Hasekiogullari and Ercanoglu (2012) in Karabuk, Turkey; Mondal and Maiti (2012) in the Shiv-Khola watershed, Darjiling, India and many more. Individual pairs of parametric classes and their sub-classes were compared in these investigations.

Some researchers integrated logical simulation like Fuzzy with AHP knowledge-based method. Feizizadeh et al. (2014) mapped landslide susceptibility using two techniques: fuzzy and AHP. Since this method covered 53% of the prior landslides, the results were considered good.

Pourghasemi et al. (2012) mapped the susceptibility to landslides at the Haraz watershed in Iran using fuzzy logic and AHP. Verification results showed that fuzzy logic performed better than the AHP technique.

In Meghalaya and other parts of Northeast India, landslides are a frequent occurrence. Despite the plateau's formation, slope imbalance and slides are mostly caused by heavy rains due to the rugged relief and other factors. The Jaintia Hill Districts of Meghalaya are particularly prone to landslides. The majority of landslides in the Jaintia Hills were caused by short-duration, intense rainfall or days of nonstop rain. Every year during the monsoon season (June, July, August), this area receives an enormous amount of orographic rainfall, which is one of the main elements that causes landslides.

The lithology of the hilly regions is weak and brittle, with significant disintegration and compression. When such delicate lithology is exposed to intense rainfall, more damaging landslip processes are encouraged. In addition, devastating slope failure may happen from undercutting of the steep slope's base and loss of basal support due to a swiftly running mountain stream. At least 90% of landslip losses, according to Brabb (1984), can be prevented if the issue is identified prior to the landslip occurrence. In order to lessen the devastating impacts of landslides on human lines and their surroundings, it is necessary to study landslides in order to determine the relationship between incidental elements and landslide occurrence and to accurately anticipate future landslide sites.

Hence, this study aims at conducting geospatial technology-based analytics on the landslide susceptibility in Jaintia hills district with the following objectives.

- a. Determine the many contributing elements that lead to the landslip phenomena in the Jaintia Hills and create the data layers that match the contributing components.
- b. Using Fuzzy Analytical Hierarchy Process method to integrate various data layers and determine the risk of landslide in different zones in the study area and validation on the basis of landslide inventory data.
- c. Correlation of sensitive zones with tourist destinations and drainage channels.

### **Study Area:**

The Jaintia Hills are 3819 square kilometres in size and range in elevation from 1250 to 1750 meters above sea level. Its borders are as follows: Bangladesh to the south, the East Khasi Hills District of Meghalaya to the west, the Karbi Anglong District of Assam to the east, and Dimas Hasao District and Cachar district of Assam to the north.

The research region (Figure-1) Jaintia Hills district was further divided into East and West Jaintia Hills in 2013 for administrative conveniences. According to the 2011 census, the populations of East Jaintia Hills, which has its head office in Khliehriat, and West Jaintia Hills District, which has its head office in Jowai, are 2,72,185 and 1,22,939, respectively.

The remnants of the former Jaintia Kingdom, which formerly stretched from the river Surma in the south to the Gobha-Sonapur in the north, were known as the Jaintia Hills. The Kupli River is to the east, and the Brahmaputra River is to the west.

The Pnar, the War, the Bhoi (Karbis), the Lalungs, the Hadem of the Saitsama region, the Beates/Biates of the Saipung Sub Division, and the Hmars of Khaddum village are the current residents of the district.

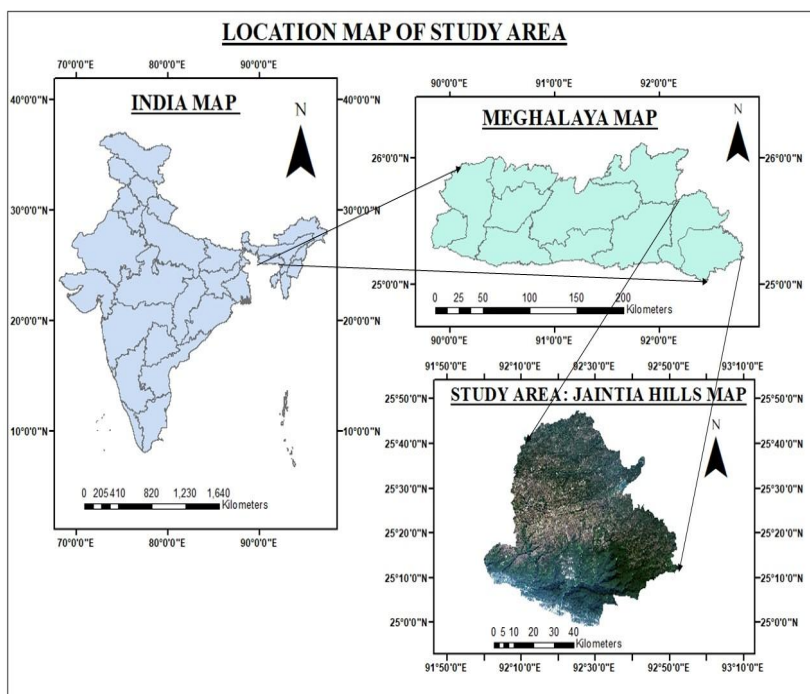


Figure-1: Location Map of Study Area

Landslide in Jaintia Hills, Meghalaya is an old active rock cum debris side along the National Highway-44 (NH-44). The vulnerable slide zone is made of sandstone, siltstone and shale sequence of Borail Group deposited during Oligocene age. The region is situated in the highest seismic zone, or zone V, which has a very high risk of earthquakes. The following table (Table-1) shows the common commencement areas of landslide and damages occurred for last few years.

Table-1: History of Landslide Hazards occurrences in Meghalaya

| YEAR OF OCCURRENCES | AREA AFFECTED                  | IMPACT ON LIFE                                         |
|---------------------|--------------------------------|--------------------------------------------------------|
| 2000                | NH-44, Sonapur                 | Road and Houses                                        |
| 2001                | NH-44, Sonapur                 | Road and Houses                                        |
| 2002                | Sonapur, Ratacherra            | Road Blockade and Lost of Houses                       |
| 2003                | Caroline, Jowai                | Communication, Food Supply, Houses                     |
| 2004                | Ratacherra, Sonapur            | Road Blockade for more than 11 days, Damaged of Houses |
| 2005                | Lumshnong                      | Road Damaged, Traffic for more than hour               |
| 2006                | Caroline Jowai, NH-44          | Communication                                          |
| 2010                | NH-44, Sonapur, Caroline Jowai | Food Supply and Communication                          |

|                                      |                                                                       |                                                                                                                                                                                                                                  |
|--------------------------------------|-----------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2013                                 | NH-44, Caroline Colony, Jowai                                         | Communication, Food Supply affected                                                                                                                                                                                              |
| 2016                                 | West Garo Hills, RiBhoi                                               | Road Traffic                                                                                                                                                                                                                     |
| 2018                                 | East Khasi Hills, East Jaintia Hills                                  | Felling down of trees and Disrupting Electric Supply, Electric Poles Collapsed                                                                                                                                                   |
| 2020                                 | Shillong, NH-44, Chud Jowai, Ratacherra, Dona, Tongseng area          | Lots of people washed away in Landslide, lots of people land and Houses, damage of sub-road, electric poles collapsed, disrupting electric supply, creates traffic jammed                                                        |
| 2021                                 | East Khasi Hills, West Garo Hills, South Garo Hills and Jaintia Hills | No casualties. The Sonapani Hydel Project that supplies electricity to the state was affected by landslides this year. NH 51 and NH 06 were some of the highways/road sections that were affected in the state due to landslides |
| 2022 – May, June, September, October | Sonapur, Darang Village, Mawphlang block, EJHD                        | Significant damage to roads, PHE pipelines, and agricultural areas, and resulted in the deaths of 4 villagers and 2 injured.                                                                                                     |
| 2023 - June, August, October         | Pynthor Langtein village in Meghalaya's West Jaintia Hills district   | 4 villagers died.                                                                                                                                                                                                                |
| 2024 - February                      | Near Sonapur Tunnel on NH-6                                           | Road blocked                                                                                                                                                                                                                     |

The landslide inventory map (Figure-2) shows the spatial distribution of the landslide occurrences in the study area. It can be seen that most of the events occurred near the road constructions due to the consequent slope instability.

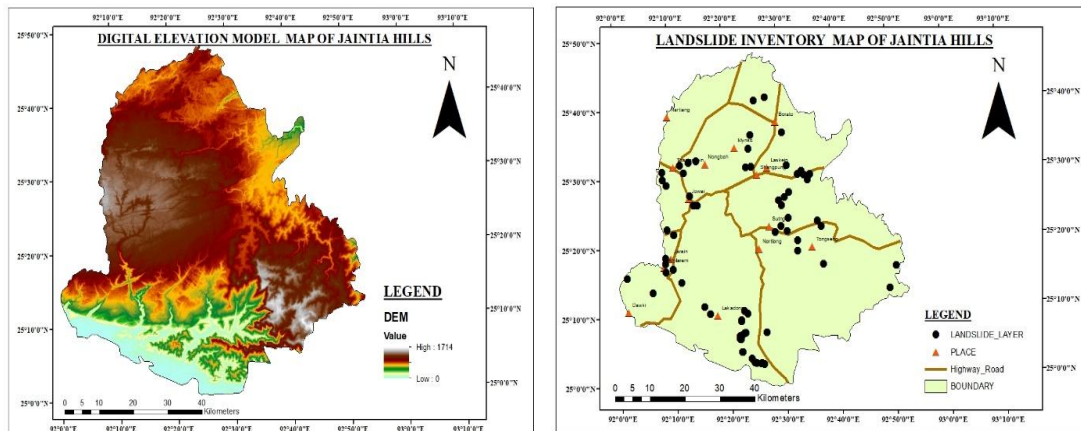


Figure-2: Landslide Inventory data of Jaintia Hills

The study area is an emerging tourist destination which will require the development of new infrastructures and with the help of landslide susceptibility map as an output of this study, the sensitive areas prone to land sliding can be avoided and the time of infrastructural set-up and that can bring-down the possibility of massive loss of lives and resources. The debris material as a result of landslide also chocks the river bed and can cause fluvial hazard. This study also identified the drainages that can be affected by slide debris and should be monitored regularly.

### **Data preparation and Methodology:**

#### *Preparing landslide factor layers*

Numerous internal and external factors limit the formation of landslides (Conforti et al., 2023; Zhang et al., 2019). Study areas differ in terms of the main causes influencing landslides. Based on a survey of pertinent literature and field research, ten criteria in all were chosen. The parameters that were chosen included slope, relative relief, TWI, soil, geology, land use/cover, distance to highways, drainage density, lineament density, rainfall, and quality of gathered data. Table-2 displays the sources of factor data as well as the processing stages. After being processed, the factors were united under the same projection coordinate system and translated into a raster data format with a resolution of 30 m×30 m. The outcomes are displayed in Figure- 3.

Table-2: Properties of the spatial database of various influencing factors

|    | FACTOR            | DATA SOURCES & PROCESSING                                                                                                | DATA TYPE  | DATA STRUCTURE | DATA ACCURACY / RESOLUTION |
|----|-------------------|--------------------------------------------------------------------------------------------------------------------------|------------|----------------|----------------------------|
| 1  | Slope             | Retrieved from Digital Elevation Model                                                                                   | Continuous | Raster         | 30 m                       |
| 2  | Drainage Density  | Line Density method applied on drainage data                                                                             | Continuous | Raster         | 30 m                       |
| 3  | Ruggedness Index  | Obtained from Relative Relief data extracted from DEM and drainage density, for an area followed by interpolation method | Continuous | Raster         | 30 m                       |
| 4  | TWI               | Determined based on water flow direction and slope data                                                                  | Continuous | Raster         | 30 m                       |
| 5  | Lineament Density | Line Density method applied on lineament data                                                                            | Continuous | Raster         | 30 m                       |
| 6  | Geology           | Extracted from Geology map of Meghalaya (GSI)                                                                            | Discrete   | Raster         | 30 m                       |
| 7  | Soil              | Soil map extracted from SWCD, Govt. of Meghalaya                                                                         | Discrete   | Raster         | 30 m                       |
| 8  | Rainfall          | Downloaded from Worldclim platform.                                                                                      | Continuous | Raster         | 30 m                       |
| 9  | Land Use/ Cover   | Interpretation of Landsat 8 Oli image of                                                                                 | Discrete   | Raster         | 30 m                       |
| 10 | Distance to Roads | Multiple Buffering based on existing road data                                                                           | Discrete   | Raster         | 30 m                       |

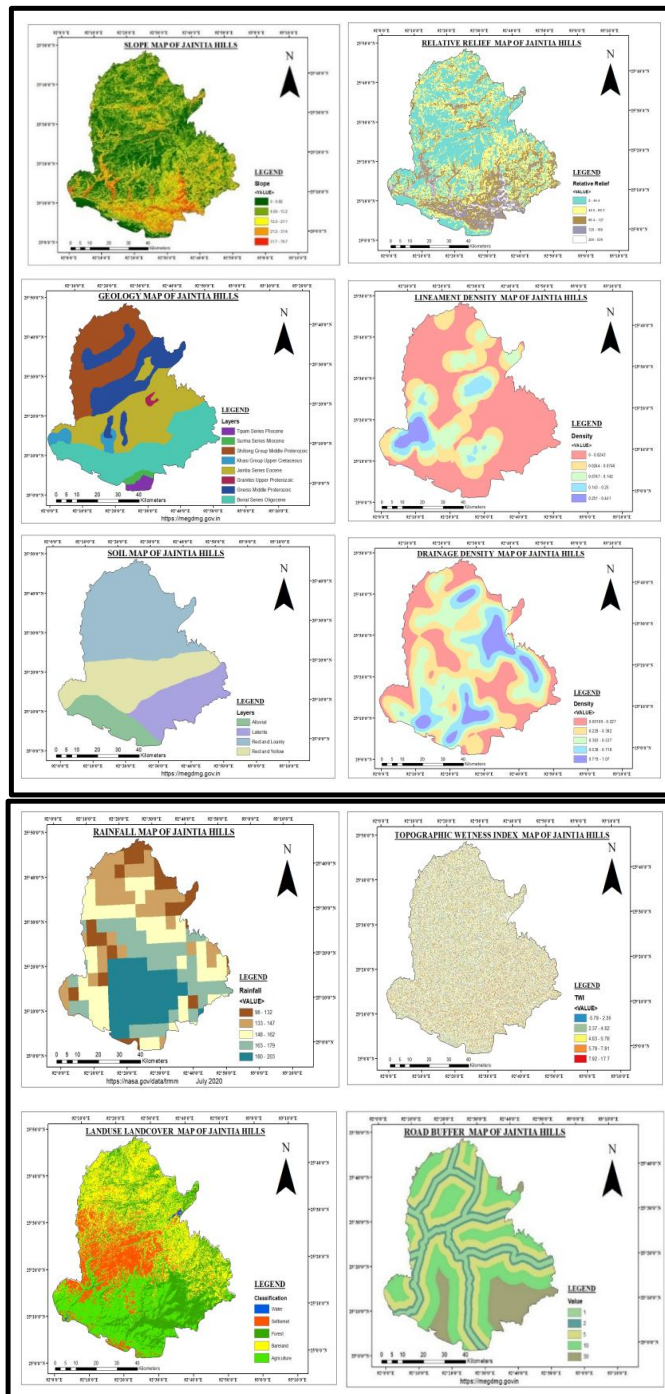


Figure-3: Spatial layers of various factors causing landslide

## Methodology

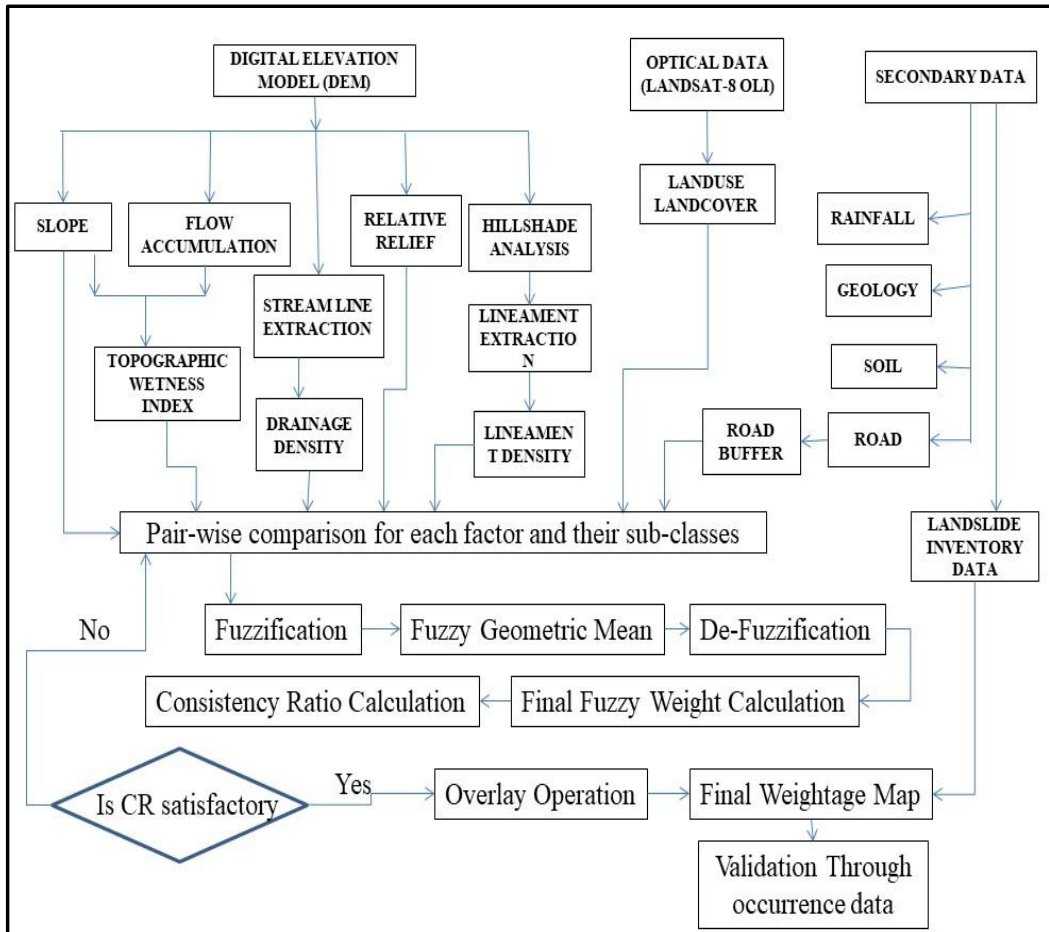


Figure-4: Flow chart of Landslide Analysis

## Results and Discussion:

Several landslide explanatory variables are taken into account while assessing the hazard of landslides. Determining the proportionate impact of each individual parameter to the incidence of landslides is an important challenge. Consequently, using a Multi-Criteria Decision-Making Approach (MCDA) is crucial when mapping LSZs. A novel approach to handling fuzziness and ambiguity in multi-criteria decision making is presented in this work. Thus, one may consider fuzzy AHP techniques to be an advanced approach to AHP. The Fuzzy Analytical Hierarchy Process (FAHP) comprises six stages: problem definition, comparison matrix creation, consistency checking, Triangular Fuzzy Number (TFN) setup, fuzzy vector weight calculation, decision ranking and selection. The AHP approach and fuzzy AHP are comparable. The AHP scale is set to triangle scale for accessed priority using fuzzy AHP methods, which is the only minor distinction.

Table-3: Saaty Scale Definition Fuzzy Triangular Scale

| Inverse Scale   | Fuzzy Scale | Linguistic Scales       |
|-----------------|-------------|-------------------------|
| (1, 1, 1)       | (1, 1, 1)   | Equally Preferred       |
| (1/4, 1/3, 1/2) | (2, 3, 4)   | Moderate Preferred      |
| (1/6, 1/5, 1/4) | (4, 5, 6)   | Strongly Preferred      |
| (1/8, 1/7, 1/6) | (6, 7, 8)   | Very Strongly Preferred |
| (1/9, 1/9, 1/9) | (9, 9, 9)   | Absolutely Preferred    |

In this study, the fuzzy Analytic Hierarchy Process (fuzzy AHP) method (Figure-4) was utilised to establish the weights of the attributes or criteria selected for analysis (Table-3). As a result, we first define the issue or the study's criteria for the components based on their significance. Next, we build a Pairwise Comparison Matrix for every factor, along with a sub-matrix for each factor (Table-4).

Table-4: Weights of sub-factors using FAHP Pairwise Matrix

| Factors           | Sub-factors                       | Weights |
|-------------------|-----------------------------------|---------|
| Slope             | 0-6.62                            | 0.017   |
|                   | 6.63-13.2                         | 0.043   |
|                   | 13.3-21.1                         | 0.107   |
|                   | 21.2-31.6                         | 0.260   |
|                   | 31.7-76.7                         | 0.574   |
| LULC              | Water                             | 0.086   |
|                   | Bareland                          | 0.140   |
|                   | Settlement                        | 0.210   |
|                   | Forest                            | 0.011   |
|                   | Agriculture                       | 0.553   |
| Geology           | Shillong Group Middle Proterozoic | 0.166   |
|                   | Jaintia Series Eocene             | 0.172   |
|                   | Gneiss Middle Proterozoic         | 0.164   |
|                   | Borial Series Oligocene           | 0.169   |
|                   | Khasi Group Upper Proterozoic     | 0.088   |
|                   | Granite Upper Proterozoic         | 0.034   |
|                   | Surma Series Miocene              | 0.044   |
|                   | Tipam Series Pliocene             | 0.164   |
| Rainfall          | 96-132                            | 0.017   |
|                   | 133-147                           | 0.043   |
|                   | 148-162                           | 0.107   |
|                   | 163-179                           | 0.260   |
|                   | 180-203                           | 0.574   |
| Proximity to Road | 1km                               | 0.313   |
|                   | 2km                               | 0.311   |
|                   | 5km                               | 0.266   |
|                   | 10km                              | 0.057   |
|                   | 30km                              | 0.054   |

|                  |               |       |
|------------------|---------------|-------|
| Drainage Density | 0.00109-0.227 | 0.017 |
|                  | 0.227-0.382   | 0.043 |
|                  | 0.383-0.537   | 0.107 |
|                  | 0.538-0.718   | 0.260 |
|                  | 0.719-1.07    | 0.574 |
| Soil             | Alluvial      | 0.018 |
|                  | Laterite      | 0.088 |
|                  | Red & Loamy   | 0.667 |
|                  | Red & Yellow  | 0.227 |
| Lineament        | 0-0.0243      | 0.017 |
|                  | 0.0244-0.0746 | 0.043 |
|                  | 0.0747-0.142  | 0.107 |
|                  | 0.143-0.25    | 0.260 |
|                  | 0.251-0.441   | 0.574 |
| TWI              | <2.36         | 0.017 |
|                  | 2.37-4.02     | 0.043 |
|                  | 4.03-5.78     | 0.107 |
|                  | 5.79-7.91     | 0.260 |
|                  | 7.92-17.7     | 0.574 |
| Relative Relief  | 0-44.4        | 0.017 |
|                  | 44.5-80.3     | 0.043 |
|                  | 80.4-127      | 0.107 |
|                  | 128-199       | 0.260 |
|                  | 200-539       | 0.574 |

$$a_{ij} = \frac{w_i}{w_j}, i, j = 1, 2, \dots, n$$

Where, n denotes the number of criteria compared,

w<sub>i</sub> are weights for the I criterion and a<sub>ij</sub> is the ratio of the weight of the i criterion and j.

Table-5: Calculation of Pairwise Matrix

|           | Geology | LULC | Lineament | Soil | Rainfall | TWI | Drainage Density | Road | Relative Relief | Slope |
|-----------|---------|------|-----------|------|----------|-----|------------------|------|-----------------|-------|
| Geology   | 1       | 1/2  | 1/3       | 1/4  | 1/5      | 1/6 | 1/7              | 1/8  | 1/8             | 1/9   |
| LULC      | 2       | 1    | 1/2       | 1/3  | 1/4      | 1/5 | 1/6              | 1/7  | 1/8             | 1/9   |
| Lineament | 3       | 2    | 1         | 1/4  | 1/6      | 1/7 | 1/7              | 1/8  | 1/9             | 1/9   |
| Soil      | 4       | 3    | 4         | 1    | 1/3      | 1/4 | 1/5              | 1/6  | 1/7             | 1/8   |
| Rainfall  | 5       | 4    | 6         | 3    | 1        | 1/3 | 1/4              | 1/5  | 1/6             | 1/8   |

|                  |   |   |   |   |   |   |     |     |     |     |
|------------------|---|---|---|---|---|---|-----|-----|-----|-----|
| TWI              | 6 | 5 | 7 | 4 | 3 | 1 | 1/3 | 1/4 | 1/5 | 1/7 |
| Drainage Density | 7 | 6 | 7 | 5 | 4 | 3 | 1   | 1/3 | 1/5 | 1/7 |
| Road             | 8 | 7 | 8 | 6 | 5 | 4 | 3   | 1   | 1/3 | 1/5 |
| Relative Relief  | 8 | 8 | 9 | 7 | 6 | 5 | 5   | 3   | 1   | 1/3 |
| Slope            | 9 | 9 | 9 | 8 | 8 | 7 | 7   | 5   | 3   | 1   |

In order to evaluate the impacts of each parameter on the susceptibility of landslides in relation to one another, these strategies first employed dual evaluation to determine the preferences in the effects of the parameters on the landslide susceptibility map. Parameter values are often determined by the decision-maker based on their choices in relation to each other. The pairwise comparison matrix was used to compute the weights for calculating the eigenvalues and eigenvectors (Table-5). The eigenvector that corresponds to the largest eigenvalue of the matrix indicates the relative priorities of the components; if an element has a preference, its eigenvector component is larger than that of the other. The sum of the components of the eigenvector is one. The outcome was the production of a vector of weights that indicate the relative importance of the various elements from the matrix of paired comparisons (Yalcin A. et al., 2011).

Thus, these pairwise matrices were fuzzified (Table-6) where the Triangular Fuzzy Number (TFN) setup was required. There are three numbers on the F-AHP scale: lower (lower, L), middle (median, M), and higher (upper, U). Once the geometric mean was determined, the first, second, and third numbers, and so on, of the factors fuzzy synthesis value had to be calculated for each factor.

$$GM = ((1*1/3*1/4.....n) + (1*1/2*1/3.....n) + (1*1/1*1/2.....1/9.....n))$$

Table-6: Fuzzification

|           | Geology | LULC          | Lineament     | Soil          | Rainfall      | TWI           | Drainage Density | Road          | Relative Relief | Slope         | Weights |
|-----------|---------|---------------|---------------|---------------|---------------|---------------|------------------|---------------|-----------------|---------------|---------|
| Geology   | 1, 1, 1 | 1/3, 1/2, 1/1 | 1/4, 1/3, 1/2 | 1/5, 1/4, 1/3 | 1/6, 1/5, 1/4 | 1/7, 1/6, 1/5 | 1/8, 1/7, 1/6    | 1/9, 1/8, 1/7 | 1/9, 1/8, 1/7   | 1/9, 1/9, 1/9 | 0.006   |
| LULC      | 2, 3, 4 | 1, 1, 1       | 1/3, 1/2, 1/1 | 1/4, 1/3, 1/2 | 1/5, 1/4, 1/3 | 1/6, 1/5, 1/4 | 1/7, 1/6, 1/5    | 1/8, 1/7, 1/6 | 1/9, 1/8, 1/7   | 1/9, 1/9, 1/9 | 0.010   |
| Lineament | 2, 3, 4 | 1, 2, 3       | 1, 1, 1       | 1/5, 1/4, 1/3 | 1/7, 1/6, 1/5 | 1/8, 1/7, 1/6 | 1/8, 1/7, 1/6    | 1/9, 1/8, 1/7 | 1/9, 1/9, 1/9   | 1/9, 1/9, 1/9 | 0.010   |
| Soil      | 3, 4, 5 | 2, 3, 4       | 3, 4, 5       | 1, 1, 1       | 1/4, 1/3, 1/2 | 1/5, 1/4, 1/3 | 1/6, 1/5, 1/4    | 1/7, 1/6, 1/5 | 1/8, 1/7, 1/6   | 1/9, 1/8, 1/7 | 0.016   |

|                     |         |         |         |         |         |                     |                     |                     |                     |                     |       |
|---------------------|---------|---------|---------|---------|---------|---------------------|---------------------|---------------------|---------------------|---------------------|-------|
| Rainfall            | 4, 5, 6 | 3, 4, 5 | 5, 6, 7 | 2, 3, 4 | 1, 1, 1 | 1/4,<br>1/3<br>,1/2 | 1/5,<br>1/4,<br>1/3 | 1/6,<br>1/5<br>,1/4 | 1/7,<br>1/6,<br>1/5 | 1/9,<br>1/8,<br>1/7 | 0.092 |
| TWI                 | 5, 6, 7 | 4, 5, 6 | 6, 7, 8 | 3, 4, 5 | 2, 3, 4 | 1, 1, 1             | 1/4,<br>1/3<br>,1/2 | 1/5,<br>1/4<br>,1/3 | 1/6,<br>1/5,<br>1/4 | 1/8,<br>1/7,<br>1/6 | 0.120 |
| Drainage<br>Density | 6, 7, 8 | 5, 6, 7 | 6, 7, 8 | 4, 5, 6 | 3, 4, 5 | 2, 3, 4             | 1, 1, 1             | 1/4,<br>1/3<br>,1/2 | 1/6,<br>1/5,<br>1/4 | 1/8,<br>1/7,<br>1/6 | 0.180 |
| Road                | 7, 8, 9 | 6, 7, 8 | 7, 8, 9 | 5, 6, 7 | 4, 5, 6 | 3, 4, 5             | 2, 3, 4             | 1, 1, 1             | 1/4,<br>1/3,<br>1/2 | 1/6,<br>1/5,<br>1/4 | 0.184 |
| Relative<br>Relief  | 7, 8, 9 | 7, 8, 9 | 9, 9, 9 | 6, 7, 8 | 5, 6, 7 | 4, 5, 6             | 4, 5, 6             | 2, 3, 4             | 1, 1, 1             | 1/4,<br>1/3,<br>1/2 | 0.189 |
| Slope               | 9, 9, 9 | 9, 9, 9 | 9, 9, 9 | 7, 8, 9 | 7, 8, 9 | 6, 7, 8             | 6, 7, 8             | 4, 5, 6             | 2, 3, 4             | 1, 1, 1             | 0.193 |

Following the computation by taking the inverse sum of the geometric mean the fuzzy weights were then obtained by adding up the weights. Finally, the weights of the criteria were used to rank the results (Figure-5) of the alternative weights matrix.



Figure-5: Ranking Graph which derived from the result of alternative weights matrix by weight of criterion

In order to create a suitable map that can identify areas in the research area that are susceptible to landslides, the final parameter weights were taken into account in this step of the process. This study used fuzzy AHP and GIS techniques to assess the spatial relationship between landslide occurrences and causative factors, such as slope, geology, land use/cover, distance to lineament, rainfall, soil layer, proximity to road, drainage density, topographic wetness index, and relative relief.

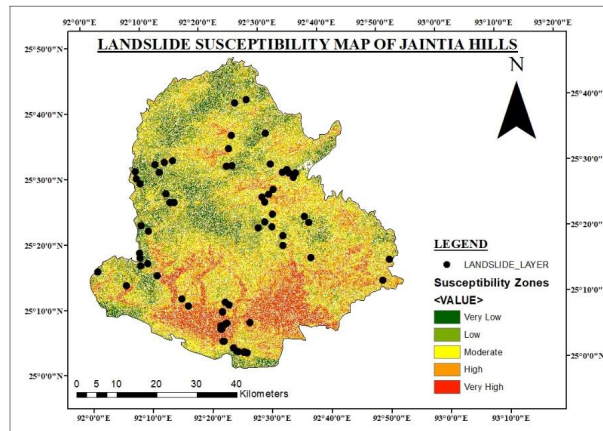


Figure-6: Landslide Susceptibility Zones of Jaintia Hills

The landslide susceptibility map using FAHP model was constructed using the following equation:

$$LSM_{FAHP} = ((\text{Geology} \times W_{FAHP}) + (\text{Land use / Land cover} \times W_{FAHP}) + (\text{Lineament} \times W_{FAHP}) + (\text{Soil} \times W_{FAHP}) + (\text{Rainfall} \times W_{FAHP}) + (\text{Topographic Wetness Index} \times W_{FAHP}) + (\text{Drainage Density} \times W_{FAHP}) + (\text{Distance to Road} \times W_{FAHP}) + (\text{Relative Relief} \times W_{FAHP}) + (\text{Slope} \times W_{FAHP}))$$

Where,  $W_{FAHP}$  is the weightage for each landslide conditioning factor.

The Jaintia Hills' landslide susceptibility map was created, and using the natural breaks approach, it was divided into five classes: Very Low (12.83%), Low (15.70%), Moderate (18.57%), High (21.91%), and Very High zones (30.99%). The landslide occurrence layer, which was recovered as secondary data, is shown by the black dot over the map (Figure-6), with the very high zones located along the southernmost portion of the study area. Due to the maximum rainfall in the study region, previous failure of the rocks or the unstrengthening of the soil, steepness of the slope or slope failure caused by rainfall, and other factors, this area is the most susceptible to landslides. The statistical link between each piece of evidence (conditioning factors) and the sites of landslides can be analysed to determine if and to what extent the evidence is responsible for the historical occurrence of landslides (Neuhäuser and Terhorst, 2007).

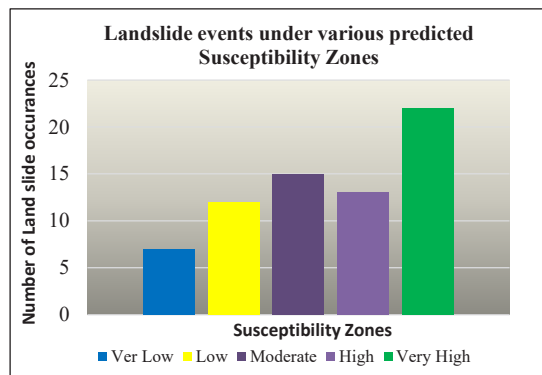


Figure-7: Landslide events under various predicted Susceptibility zones

The whole process of landslide susceptibility zonation in this study was validated by comparing the landslide occurrences with the different anticipated Susceptibility zones. The bar chart (Figure-7) is clearly representing a positive correlation where, we can observe that more landslip occurrences are coming under Very High Zones, whereas, the least number of landslides occurrences can be seen within the safest zone. Careful observation is necessary in the high and extremely sensitive zones. Careless mining, constructing homes and roads on steep slopes without doing sufficient surveys, and extending private property into forested regions are only a few examples of human activities that contribute to the occurrence of landslides.

Meghalaya state has been a hub for tourism and various newly emerged tourist destinations are expanding the tourism industry in the state. Jaintia Hill districts are part of tourism arena. Various tourism destinations already exist whereas, industry is getting supports to expand by the state tourism department. For the purpose of maintaining the existing and planning for the new ones, infrastructure development is needed for connectivity and amenities. Figure-8a is showing the tourist destinations in the study area and that can be correlated with the landslide susceptibility zones they belong to. It can be seen that a high density of tourist-spots is in the western side of the study area and the concentration of previous landslide occurrences as well. Mostly the concentration of tourist destinations is near to Jowai-Dawki road, the southern half of which is very highly susceptible to landslide as per the FAHP algorithm used for this study. Few tourist attractions are coming up in the northern and eastern portions of the study area, which is alarming because south-eastern and parts of north-eastern Jaintia is also susceptible to land slide.

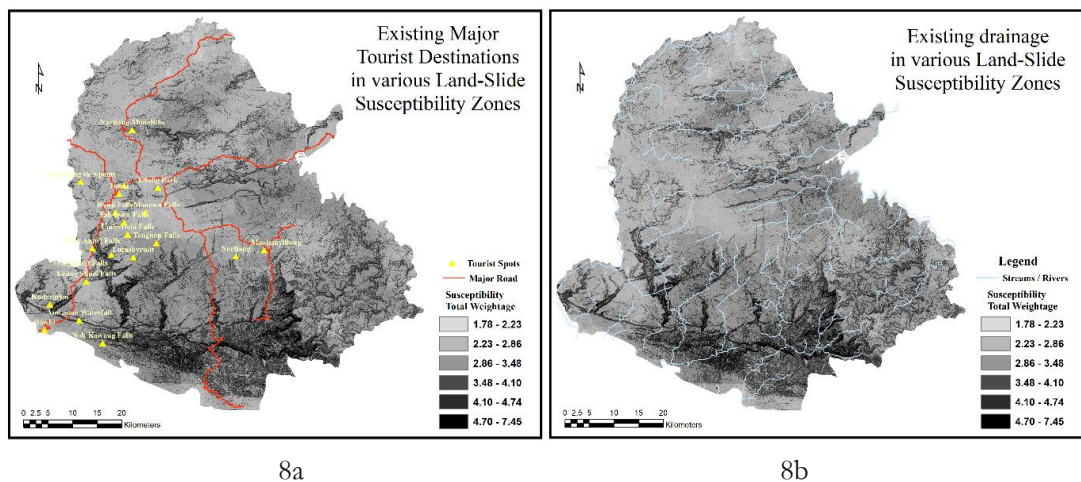


Figure-8a & 8b: Existing tourist attractions and drainage channels in various landslide susceptibility zones

In Figure-8b, authors tried to identify the water channels which can be choked due to the sudden accumulation of debris from land sliding. In this study mostly the river walls and road walls have been highlighted more with high weightage. This is mainly due to drastic fall in slope. All the drainages in southern part of the study area mostly flowing towards Bangladesh are at risk. Shari-Goyain River and Sonapur River with their tributaries are at alarming situation.

## Conclusion:

Landslides in the hills of the Shillong plateau have been deemed extremely dangerous within the last 20 years when combined with significant weather occurrences. Geomorphologically undulating, the Jaintia Hill areas are made up of low, devoid hills with deep valleys, and a shattered plateau. The district is a remnant of the Indian Peninsular shield's ancient plateau, which was severely carved, indicating multiple structural and geotectonic deformities that the plateau has endured. The plateau was raised to its current height by tectonic activity in the past. During the post-cretaceous epoch, Tertiaries were deposited on a platform formed by the southern sections. Topography ranges from very undulating to softly rolling. Every monsoon, landslides have been a regular occurrence. Therefore, this work used an integrated GIS-based fuzzy AHP-MCDM technique to identify the processes that contribute to landslides in order to comprehensively estimate the landslide danger in both the short and long term.

Five grades—very low susceptible, low susceptible, moderate susceptible, high susceptible, and very high susceptible zones—are used to categorise the study area's landslip susceptibility. Areas with a higher risk of landslides are primarily found in the south and north-east parts of the study area. Nearly 53% of the research area is categorised as high to extremely high-risk, according to the results. Nearly 28% of the research area's total area is made up of the areas with low and extremely low susceptibility, respectively. Medium-prone areas make up the remaining almost 19% of the land. The locations of previous landslip incidents served as validation for the output weighted prediction matrix. It was shown that the high and extremely highly vulnerable zones accounted for 71% of the total occurrence data. As a result, the created model may provide very reliable zoning maps of landslip susceptibility.

It has been noted that landslide influencing elements have a greater influence on landslides that occur along drainage corridors and roads. The impact of tourism on this landslip susceptibility was also examined in the study. The establishment of new tourist attractions and the development of infrastructure to support them should be handled carefully by the authorities. According to the study's findings, drainages in locations that are particularly vulnerable to flooding should be regularly inspected and maintained to prevent water from choking and overflowing into the surrounding areas.

Therefore, by implementing the necessary preventative and mitigation measures, decision-makers and engineers can use this study as a foundation to first understand the landslide vulnerability risk in Jaintia Hill Districts and to lessen the dangers and losses caused by current and future landslides. Consequently, the research area's decision-making about emergency preparedness, catastrophe reduction, and prevention can use these results as a guide.

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# MGNREGA and the Rise of Rural Livelihoods: A Ray of Hope in Arsha, Purulia

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## ABSTRACT

In India, women's empowerment has remained a subject of concern for decades. Despite efforts toward gender equality, significant challenges persist, including misogyny, limited access to employment, gender-based violence, lack of basic education, and inadequate social security. The Government of India regularly releases the *National Family Health Survey (NFHS) Fact Sheet*, which includes indicators aligned with the Sustainable Development Goal on gender equality (SDG-5). Women's empowerment refers to the process of enabling women to gain greater control over their lives and to make independent decisions related to health, major household purchases, visiting relatives, and their overall well-being. With a focus on the role of MGNREGA, this study aims to examine women's empowerment in Arsha Block of Purulia District, West Bengal. Several variables have been considered to analyse and compare the standard of living of women before and after the implementation of MGNREGA. The study employed an intensive questionnaire survey and focus group discussions, covering a sample size of 250 women across 8 Gram Panchayats. The findings suggest that MGNREGA has led to a range of positive outcomes, including enhanced economic security, improved health and well-being, and progress toward gender equality.

**Keywords:** MGNREGA, Women Empowerment, Empowerment Score, Consistency of standard of living, Economic Development

## Introduction

The United Nations' *2030 Agenda for Sustainable Development*, adopted in 2015, committed all member states to achieve gender equality and the empowerment of all women and girls under Goal 5 (United Nations, 2015). India, aligning with this global vision, has long nurtured the values of women's empowerment through the legacy of eminent reformers such as Ishwar Chandra Vidyasagar, Raja Ram Mohan Roy, Swami Vivekananda, and Acharya Vinoba Bhave, who challenged orthodox norms and advocated for the rights of women in education,

inheritance, and public life (Forbes, 1996; Chakravarti, 1993). Historically, Indian women faced systemic barriers to full participation in society—stemming from patriarchal traditions, limited mobility, lack of education, and male dominance in social and economic structures (Jejeebhoy, 1995; Pallavi, 2019). Social stigma and internalized fear discouraged many from stepping into public or economic roles. However, significant legislative interventions marked a turning point. Acts such as the Equal Remuneration Act (1976), Dowry Prohibition Act (1961), Immoral Traffic (Prevention) Act (1956), and Maternity Benefit Act (1961) provided a legal foundation for gender justice and equal opportunity (Government of India, 2021; Nair, 2000). Over time, increasing access to education, awareness, legal protections, and welfare schemes has improved women's ability to participate in all spheres of life—social, political, educational, and economic (Desai & Thakkar, 2001; Sen, 1999). While legislative rights are crucial, true empowerment is realized only when women experience an uplift in their standard of living—which includes access to quality healthcare, financial independence, safe environments, and control over personal decisions (Kabeer, 1999). To bridge gender gaps, the Indian government has implemented multiple flagship programmes, including Beti Bachao Beti Padhao, UJJAWALA, Sakhi Niwas, and the Mahila Shakti Kendra Scheme, focusing on protection, education, economic upliftment, and shelter (Ministry of Women and Child Development, 2023). These initiatives represent a move toward both welfare and empowerment-based approaches. According to Braidotti et al. (1994), empowerment includes five essential elements: (1) a strong sense of self-worth, (2) the right to make and act on decisions, (3) access to opportunities and resources, (4) power to control one's life within and outside the home, and (5) the ability to influence social change. Women often play a pivotal role in managing household crises, ensuring family welfare, and contributing to socio-economic stability—especially in rural and vulnerable communities (Agarwal, 1994; Duflo, 2012). Despite progress, challenges like wage disparity, gender-based violence, and limited land ownership persist. According to the World Economic Forum's Global Gender Gap Report (2024), India still ranks low in economic participation and opportunity, though educational attainment and political empowerment have seen marked improvement. Thus, empowerment must be viewed not only as a legal or policy outcome but as a lived reality—achieved when women can navigate society freely, safely, and with dignity.

Several studies have explored women's participation in rural development schemes, particularly MGNREGA. Bharti and Raj (2021) observed that MGNREGA not only provided wage employment but also empowered women through financial inclusion and community engagement. Singh et al. (2020) highlighted how female participation in MGNREGA led to increased household income and improved decision-making roles within families. Sharma (2018) emphasized the scheme's role in reducing seasonal migration and enhancing women's visibility in the rural labor force. In West Bengal, Ghosh and Dey (2019) found that MGNREGA significantly contributed to improving rural women's livelihood in Purba Medinipur, especially for marginalized groups. Similarly, Barman (2018) reported a notable increase in women's self-confidence and access to household financial decisions due to their active involvement in the scheme in Bankura district. Mandal (2021) observed that despite structural constraints, women in Purulia district increasingly participated in MGNREGA, indicating a gradual shift in gender roles and rural labour patterns. Despite these positive outcomes, gaps remain in assessing spatial-

temporal variations and local-level dynamics of women's participation, especially at the Gram Panchayat level. This study attempts to fill that gap through detailed panchayat-wise analysis over a decade.

The participation of women in MGNREGA has shown notable growth across states, especially in underdeveloped regions. Purulia district, situated in the western part of West Bengal, is characterized by economic underdevelopment, widespread poverty, and a high proportion of Scheduled Tribe and Scheduled Caste populations. Within this region, Arsha Block represents a rural landscape where agriculture remains the dominant occupation, but seasonal unemployment and low land productivity challenge household survival, especially for women. Despite progressive legislative intent, the real-world impact of MGNREGA on women—particularly peasant women—requires localized exploration (Dutta et al., 2012). The nature and extent of women's involvement, the transformative potential of earned income, and the systemic challenges they face are key areas demanding attention. By investigating the engagement level of women in Arsha block, this study aims to understand not just quantitative participation, but also the qualitative outcomes of the scheme—such as autonomy, financial independence, social mobility, and empowerment.

This study seeks to examine the role and impact of MGNREGA on rural women in the Arsha Block of Purulia district, West Bengal. First, it aims to assess the extent of women's involvement and engagement in MGNREGA activities, focusing on their level of participation in wage employment and community-based work. Secondly, it explores the broader aftermath of the programme among peasant women—specifically its influence on their livelihoods, economic autonomy, decision-making ability, and overall well-being. Finally, the study seeks to identify the key challenges and structural barriers faced by women beneficiaries under MGNREGA, including issues related to job allocation, wage payment delays, workplace conditions, and gender-based discrimination.

### **Revelatory of MGNREGA**

The Mahatma Gandhi National Rural Employment Guarantee act or (MGNREGA) was notified through the Gazette of India (Extraordinary) Notification dated September 7, 2005. Initially proposed by the former Prime Minister P.V. Narasimha Rao in 1991 and later accepted in the parliament, it became operational on February 2, 2006 in 200 backward districts. This scheme has given birth to the largest employment program since independence till the present time. MGNREGA is a people-centric, grassroots-level, rights-based program that aims to strengthen and enhance livelihood security in rural areas by providing at least 100 days of wage employment in a financial year to every household with adult members willing to undertake unskilled manual work as a reliable source of income. MGNREGA is one of the tools to ensure increased inclusion in rural India through its impact on social protection, livelihood security and social empowerment. 75% of the labor cost is borne by the central government and the remaining percentage is borne by the respective states. A positive impact of the empowerment and employment model on rural women is noticeable through reports of the past few years. The scheme has enabled rural women to engage in work within the boundaries of their own village including Gram Panchayat. The equipping aspects of MGNREGA are -

- Assurance of 100 days of employment of women.

- Pledge of equal wage for both genders.
- Engagement of 1/3rd women beneficiaries in particular area.
- Opening of bank/post office accounts of individual women beneficiaries for availability of payment
- Clear guidelines facilities at worksite which should be convenient.
- Participation of local or village SC/STs women in local care and monitoring committee

## **Functional concepts of phraseology used in the paper**

### *Women Empowerment*

Women empowerment means to let women survive and let them live a life with dignity, humanity, respect, self-esteem and self-reliance. Women is continuous process. Women participate in all spheres of life and attention should be given to all sectors affecting women to advance their empowerment. The family setup and its positioning also affect the economic decision-making of women, such as whether the family is nuclear or joint; whether the family resides in a rural or urban area, all such issues also affect the extent of economic empowerment of women in a family (Sharma & Mahajan, 2022). Women empowerment refers to status of social progressiveness, economic improvement and psychological advancement of women beneficiaries of MGNREGA (Pallavi, G. 2022). Women empowerment is a route of creating consciousness and capacity building.

### *Economic and social Empowerment*

The economic empowerment of women entails their capacity to grow and succeed economically. It involves controlling and sharing economic resources, making a choice under multiple economic alternatives, and the power to retain economic gains in an activity. (Sharma & Mahajan, 2022). Social empowerment of women beneficiaries of MGNREGA refers to the right to appropriate communication skills, household, decision making and social work leadership skills. The specific objectives of social empowerment are to raise the capacity of women to exert their rights and voice. Social empowerment in our nation refers to all elements of society having equal control over their lives, being able to make major life decisions, and having equal chances. A nation's growth trajectory will never be good unless all elements of society are equally empowered. But in our country economic imbalance, gender discrimination, caste differentiation, and technological barriers affect the youth's all development. This puts them at a disadvantage which eventually affects their community as well.

## **Study Area**

The westernmost district of West Bengal, Purulia, is a unique region known for its ethnic identity, geo-climatic conditions, administrative boundaries, and rich indigenous folk culture. Geographically, Purulia is located between 22° 42' 35" and 23° 42' north latitude and 85° 49' 25" and 86° 54' 37" east longitude. The present study is based on intensive fieldwork conducted in the Arsha Community Development (CD) Block shown in Figure 1, which is located in the central part of Purulia district and covers an area of 375.04 sq. km. Arsha Block has been selected due to its distinctive characteristics, particularly the active and widespread participation

of women in MGNREGA. The high response rate and effective involvement of women in this program make the block a significant and interesting area for this research.

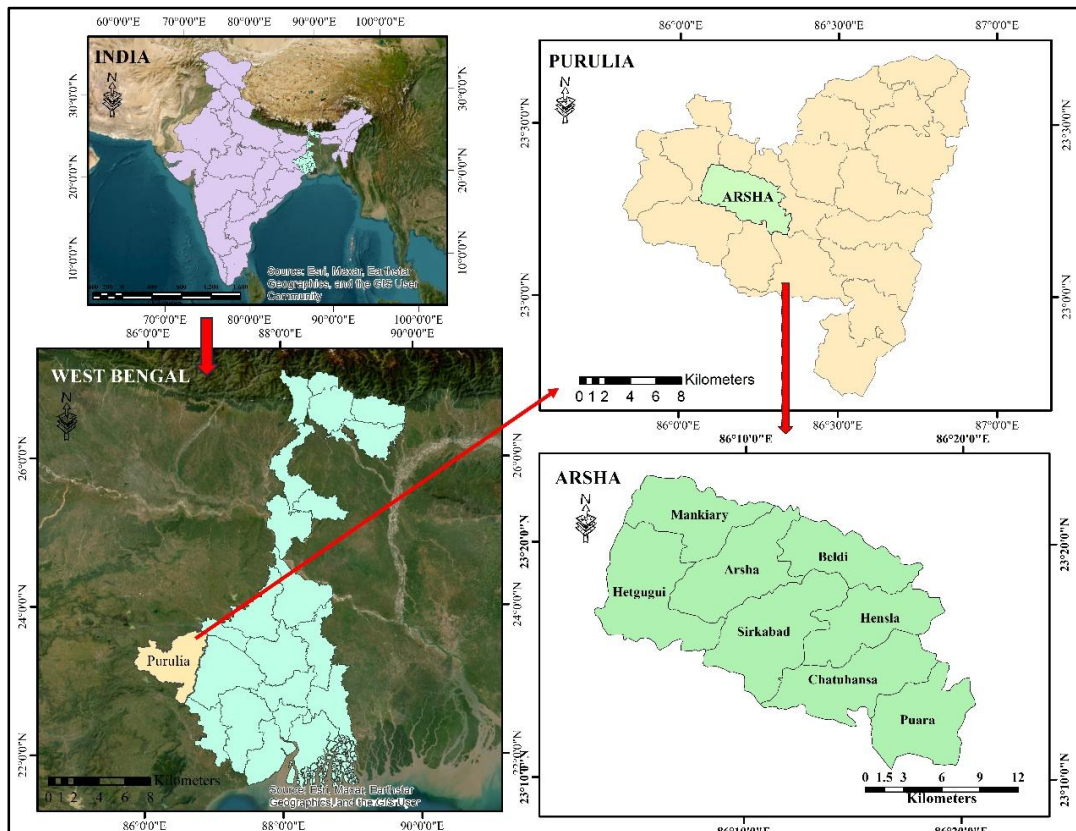


Figure 1: Study area

## Materials and Methods

### *Data Source*

Data has been collected from the Arsha C.D. Block in Purulia District, West Bengal. This block comprises eight Gram Panchayats: Arsha, Beldih, Chatuhansa, Hensla, Hetgugui, Mankiary, Puara, and Sirkabad. From each Gram Panchayat, two villages were selected—one located closer to the Gram Panchayat office and the other farther away—in order to examine the influence of distance on women's involvement. A simple random sampling method was used to select the sample units. Secondary data were collected from various sources such as journals, government publications, newspapers, websites, and research papers. The primary source of online data was the official MGNREGA website: <http://nrega.nic.in>.

## Methods

The present study is based on primary data collected from Arsha block of Purulia district, West Bengal. Data have been collected from 250 women who are engaged in MGNREGA and hold job cards. So, the sample size is 250. A structured questionnaire scheduled has been used during data collection from the women under MGNREGA scheme. Statistical software SPSS-20 has been used for analysis of ten variables. The variables are i) Increase in independent life ii) increase in family decision making iii) freedom to decide on children education iv) improvement in income v) increase in savings vi) increase employment opportunity vii) free from economic dependency viii) job satisfaction and security ix) social security x) standard of living is improvement for rural women in MGNREGS. All variables have been assessed using empowerment scores. A Likert scale was used to measure the intensity of responses. The calculated empowerment scores were then used to categorize levels of empowerment. Empowerment scores were calculated to classify respondents into different empowerment categories. The Women Empowerment Score (WES) was calculated as an average of four key indicators: social, educational, health, and economic dimensions. Each respondent's score for these indicators ( $V_1$  to  $V_{10}$ ) was first normalized and then averaged to compute the Women Empowerment Score (WES), using the following formula (Eq.1):

$$\text{Women empowerment Score} = \frac{V_1 + V_2 + V_3 + V_4 + V_5 + V_6 + V_7 + V_8 + V_9 + V_{10}}{X_n}$$

The WES for each respondent was then derived as the mean of the Dimension Indices calculated using this formula. Based on the individual WES, respondents were categorized into different levels of empowerment using quartile values. Based on the quartile value (3.6) and median value (4.0) of the WES distribution, respondents were categorized into three empowerment levels (Table 1) Lower Empowerment ( $\text{WES} \leq 3.6$ ), Moderate Empowerment ( $3.6 < \text{WES} \leq 4.0$ ), and Higher Empowerment ( $\text{WES} > 4.0$ ). These categorizations facilitated the analysis of empowerment disparities among the respondents. Now the factors leading to respondents can be categorised based on their empowerment score in to three major groups viz. Lower empowerment, Moderate empowerment, Higher empowerment.

**Table 1:** Empowerment Category with Women Category Score

| Empowerment Category | Women Empowerment score |
|----------------------|-------------------------|
| Lower Empowerment    | $\geq 3.6$              |
| Moderate empowerment | 3.6-4.0                 |
| Higher Empowerment   | $< 4.0$                 |

## Reliability of the data

The reliability of the measurement instruments was evaluated using Cronbach's Alpha. Reliability analysis shows the value of Cronbach's Alpha as .780, which lies between the accepted range of .05 to .09. The construct reliability tests reported scores above .05 which suggests that the constructs of the study are reliable enough to proceed for analysis.

## Result and Discussion

### *Engagement Level of Women in MGNREGA in Arsha Block*

MGNREGA is a special program aimed at providing livelihood assistance to the poor and vulnerable, with a focus on empowering both men and women through income generation and reducing inequality. It plays a significant role in promoting economic independence among rural women. A large proportion of women beneficiaries under this scheme are single, divorced, or widowed. The increasing participation of women in MGNREGA over the years highlights its positive impact on women's empowerment. The program has contributed notably to income generation and the improvement of living standards for rural women. The percentage of women's participation in MGNREGA varied across the financial years 2017–18 to 2022–23. The participation of women in different Gram Panchayats under Arsha Block of Purulia District is presented in the table below.

Table 2: Financial Year Wise Participation Rate (%) in eight Gram Panchayats in Arsha Block

The [Table 2](#) shows that Hetgugui Gram Panchayat recorded the highest percentage of women participation in MGNREGS in FY 2017–18, at 44.28%. In contrast, Hensla Gram Panchayat had the lowest participation in that year, with 32.57%. However, Hensla experienced a significant rise in women's participation in the following years, reaching 46.99% in 2018–19 and 60.35% in 2019–20. In Beldih Gram Panchayat, women's participation was 28.16% in FY 2018–19, which increased to 42.34% in 2019–20. In FY 2021–22, women's participation in Hensla and Mankiary Gram Panchayats was remarkable, with rates of 53.70% and 52.26%, respectively. However, in FY 2022–23, the participation rates in Arsha (31.00%), Beldih (23.74%), Chatuhansha (27.25%), and Sirkabad (23.07%) Gram Panchayats were relatively low. On the other hand, Hensla and Mankiary continued to show strong participation, confirming that these Gram Panchayats have consistently high levels of women's engagement in MGNREGS.

Table 3: Empowerment Category with Number of Participated Women in Arsha Block

| Empowerment Category | No of women | (%)  |
|----------------------|-------------|------|
| Lower Empowerment    | 72          | 28.8 |
| Moderate Empowerment | 127         | 50.8 |
| Higher Empowerment   | 51          | 20.4 |
| Total                | 250         | 100  |

Empowerment category ([Table 3](#)) has been classified into three types, namely lower, moderate and higher empowerment. In lower empowerment category the percentage 28.8, in moderate empowerment category the percentage is 50.8 and higher empowerment category the percentage 20.40.

### *Empowerment Categories with Caste*

Caste prejudice remains prevalent in rural India and is recognized as one of the key factors contributing to economic backwardness across the country. Lower-caste communities often face limited access to formal education and are subject to social discrimination, which restricts their opportunities for employment. However, MGNREGA operates without caste-based discrimination and, in fact, gives preference to marginalized and backward communities. This

inclusive approach has motivated individuals from these communities to challenge traditional caste norms and participate in MGNREGA employment opportunities. In Arsha Block, people from diverse caste backgrounds are engaged under MGNREGA. Table 4 presents the distribution of respondents in this study based on caste.

**Table 4** Empowerment Category Wise Frequency and percentage distribution of caste of respondents

| Caste  | Lower Empowerment (%) | Moderate Empowerment (%) | Higher Empowerment (%) | Total |
|--------|-----------------------|--------------------------|------------------------|-------|
| Gen    | 24(38)                | 32(50)                   | 8(12)                  | 64    |
| SC     | 4(44)                 | 3(34)                    | 2(22)                  | 9     |
| ST     | 24(26)                | 50(53)                   | 20(21)                 | 94    |
| Others | 20(24)                | 42(51)                   | 21(25)                 | 83    |

The present study found that among the 64 respondents belonging to the General Caste, 38% fell under the lower empowerment category, almost 50% were in the moderate empowerment category, and 12% were in the higher empowerment category. Among the 9 respondents from the Scheduled Caste category, 44% belonged to the lower empowerment category, 34% to the moderate category, and 22% to the higher empowerment category. Of the 94 respondents from the Scheduled Tribes, 26% were in the lower empowerment category, 53% in the moderate category, and 21% in the higher empowerment category. Among the 64 respondents from the Other Backward Classes, 24% were found in the lower empowerment category, 51% in the moderate category, and 25% in the higher empowerment category. These findings clearly indicate that respondents from the General Caste category showed relatively higher participation in MGNREGA compared to other caste groups.

#### *Empowerment Category with Education Level*

Higher literacy levels contribute to greater awareness, enabling individuals to demand employment under MGNREGA and to resist any violations of its prescribed guidelines. This, in turn, enhances the effectiveness of the scheme's implementation. Moreover, literacy also helps improve administrative efficiency among lower-level government officials, who play a crucial role in ensuring the successful execution of the programme. According to the 2011 Census Report, the gender gap in literacy in Arsha Block stands at 31.61%, highlighting a significant disparity between male and female literacy rates.

**Table 5** Linkage Frequency table between Empowerment Category and Education Level

| Empowerment Category | Educational level |         |           |        |
|----------------------|-------------------|---------|-----------|--------|
|                      | Illiteracy        | Primary | Secondary | above  |
| Lower Empowerment    | 37(51)            | 12(17)  | 11(15)    | 12(17) |
| Moderate Empowerment | 46(36)            | 21(17)  | 33(26)    | 27(21) |
| Higher Empowerment   | 23(45)            | 7(14)   | 14(27)    | 7(14)  |

Table 5 reveals a comparison between empowerment categories and education levels. It clearly shows that the percentage of illiterate women is high across all empowerment categories 51% in the Lower Empowerment category, 36% in Moderate Empowerment, and 45% in Higher Empowerment. Since there are no educational restrictions for participation in MGNREGS, many

women, regardless of their education level, have stepped forward to work under the scheme. In the Moderate Empowerment category, 26% of women have secondary-level education and 21% have education above secondary level. Also indicates that women with relatively higher education, who are unable to find suitable employment, are opting to work under MGNREGA to improve their standard of living and empower themselves.

#### *Empowerment Category and Age Group Comparison*

There is a noticeable difference in the empowerment categories across three age groups in the block below 30 years, 30–45 years, and above 45 years (Table 6). A comparison between the lower and higher empowerment groups reveals that women above 45 years account for 47.05% in the higher empowerment category, whereas those below 30 years represent only 19.61%. In contrast, in the lower empowerment category, only 26.39% of women are under the age of 30. In other words, a significant proportion of women over 45 years fall under the medium and higher empowerment categories, while the representation of women below 30 years in these categories is relatively low. This may be attributed to the fact that older women have been engaged in the MGNREGA scheme for a longer period, leading to noticeable gains in their economic and social empowerment. On the other hand, younger women under 30 years are often single or of marriageable age, and thus face social or familial discouragement from working outside the home. Middle-aged women, however, are more likely to be committed to supporting their families financially and therefore actively participate in the MGNREGA scheme. It is evident that the empowerment level of women aged 45 and above has improved due to their sustained participation in the program.

**Table 6:** Empowerment Category and age group in Arsha Block

| Empowerment Category | Age group |       |     | Total |
|----------------------|-----------|-------|-----|-------|
|                      | >30       | 30-45 | <45 |       |
| Lower Empowerment    | 19        | 31    | 22  | 72    |
| Moderate Empowerment | 21        | 60    | 46  | 127   |
| Higher Empowerment   | 3         | 18    | 30  | 51    |
| Total                | 43        | 109   | 98  | 250   |

#### *Duration Of Work with Empowerment Category*

Hypothesis:1

$H_0$ : No relation between duration of work and success of MGNREGA

$H_1$ : Duration of work is related to the success of MGNREGA

On the basis of the duration of work Chi-Square analysis has been done, where the degree of freedom is 6, and chi-square value is 13.748 and  $p = 0.032$ . So, it is significant and rejected the null hypothesis. conclusion is there is significant association between the duration of work and success of MGNREGA.

**Table 7:** Empowerment category with Duration work

| Empowerment Category | Below 3 years | 4-6 Years     | 7-9 Years     | 10 Years and above |
|----------------------|---------------|---------------|---------------|--------------------|
|                      | Frequency (%) | Frequency (%) | Frequency (%) | Frequency (%)      |
| Lower Empowerment    | 12(16.67)     | 20(27.78)     | 16(23.61)     | 24(33.33)          |
| Moderate Empowerment | 17(13.39)     | 47(37.01)     | 30(23.62)     | 33(25.98)          |
| Higher Empowerment   | 7(13.73)      | 8(15.69)      | 14(27.45)     | 22(43.14)          |

*Reason for joining with Empowerment Categories*

Hypothesis: 2

$H_0$ : There is no significant difference in the reason of joining of MGNREGA

The Table 8 shows the relationship between the main reasons for joining MGNREGA and the level of empowerment among women participants (Low Empowerment, Medium Empowerment, High Empowerment). The majority of respondents who joined only for earning money fall under the Medium Empowerment (ME) category, indicating that financial gain contributes significantly to moderate levels of empowerment. Similarly, those who joined for both empowerment and earning show a more balanced distribution across ME and HE, So, the combining income with personal empowerment leads to higher outcomes. However, those who joined only for empowerment are mostly in the Low Empowerment (LE) category, implying that without financial independence, the impact on empowerment is limited. Overall, the data reflects that economic participation plays a crucial role in achieving higher levels of empowerment, especially when combined with awareness and personal development goals.

**Table 8:** Empowerment category and reason for Joining

| Main Reason for joining     | Empowerment Category |                      |                    |
|-----------------------------|----------------------|----------------------|--------------------|
|                             | Lower Empowerment    | Moderate Empowerment | Higher Empowerment |
| Only empowerment            | 33                   | 9                    | 7                  |
| Only earned money           | 8                    | 47                   | 11                 |
| Only economic emp.          | 7                    | 29                   | 13                 |
| Employment and earned money | 21                   | 42                   | 20                 |

On the basis of the reason for joining with empowerment, Chi-Square analysis has been done, where the degree of freedom is 6, and chi-square value is 57.104. and  $p = 0.000$ , So it is significant and rejected the null hypothesis. There is a significance association between reason for joining and empowerment.

*Income level of active Job card Holders*

Hypothesis:3

$H_0$ : There is no association between yearly income and joining.

$H_1$ : There is a significant difference in the yearly income of the women Job Card holders.

There is significant association between yearly income and joining. For the improvement in standard of living, income acts as a major determinant. The income levels of the members has been increased after joining MGNREGA scheme (Table 9). The highest category is >5000₹ per year. This increase shows that members have raised their income level after joining the MGNREGA scheme. Only 8% of respondents lie in the income group of >5000₹ which has been increased to 47.6% after joining under this scheme. Again 22.4% of respondents lie in the income group 3000₹ to 5000₹ It is very significant. According to the data collected there is an impact that there is change in income after enrolment under MGNREGA scheme. Many women job card holders involved themselves in economic activities independently and to raise their income level and standard of living.

**Table 9:** Income level of active Job card Holders

| Yearly Income in Rs. | Before joining    |      | After Joining     |      |
|----------------------|-------------------|------|-------------------|------|
|                      | No of Respondents | (%)  | No of Respondents | (%)  |
| <1000                | 150               | 60   | 20                | 8    |
| 1000-3000            | 62                | 24.8 | 55                | 22   |
| 3000-5000            | 18                | 7.2  | 56                | 22.4 |
| >5000                | 20                | 8    | 119               | 47.6 |

A Chi-square test was conducted to examine the association between yearly income and participation in MGNREGA. The test yielded a Chi-square value of 15.678 with 6 degrees of freedom and a p-value of 0.0155. Since the p-value is less than 0.05, the result is statistically significant, indicating that there is a significant association between participation in MGNREGA and changes in yearly income. This implies that MGNREGA has had a positive impact on increasing the income levels of the respondents.

#### *Impact of MGNREGA on change in the control over the economic, social empowerment of women*

Overall, Figure 2 shows a positive trend in the impact of MGNREGA on women's empowerment. Regarding the criterion of leading an independent life, 68.4% of respondents agreed, while 24% strongly agreed. In terms of participation in family decision-making, 70% of women either agreed or strongly agreed with their increased involvement, with 20% falling in the "strongly agree" category. About 77% of women agreed or strongly agreed that they now have a say in decisions regarding their children's education. When asked about the increase in their annual income, 51.6% agreed and 17.2% strongly agreed that there has been a positive change. Most of the income earned by women is spent on household needs, children's education, and medical expenses. However, 24% of respondents disagreed with this statement, and 33.6% remained neutral. Regarding standard of living, nearly 50% of women reported that their living conditions have improved, while around 30% chose not to respond. This suggests a significant shift in women's social perspectives. They now participate more confidently in independent thinking, family decision-making, and household discussions. Furthermore, their financial earnings, along with savings deposited in bank accounts, reflect a substantial level of economic empowerment.

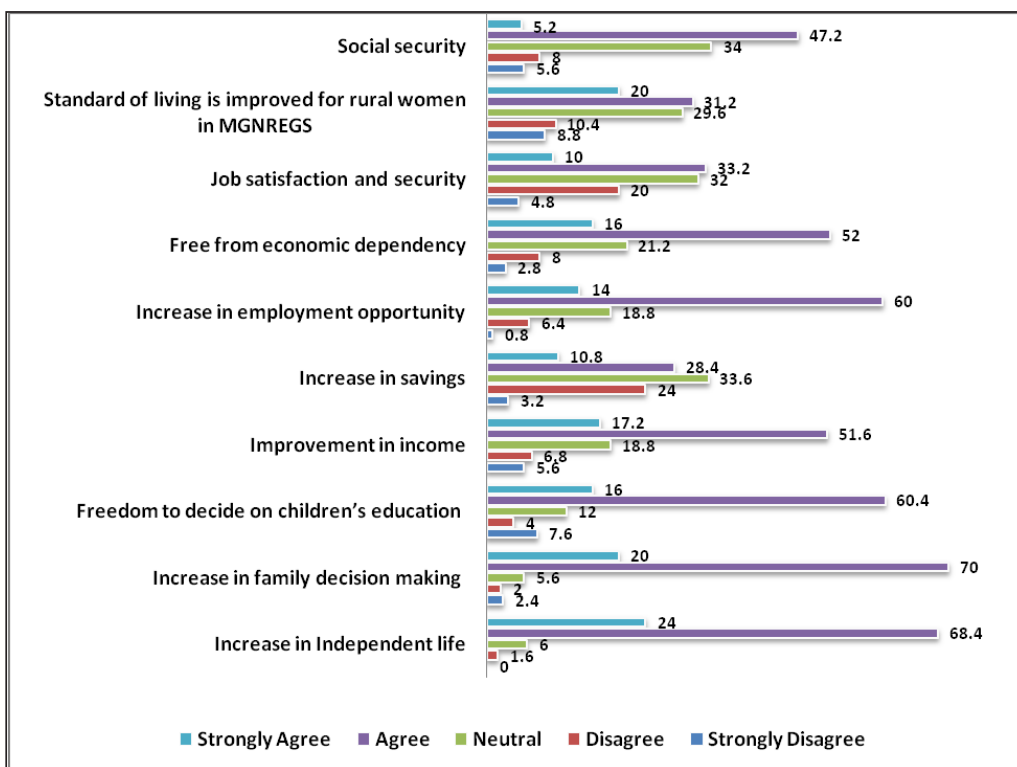


Figure 2: Graphical Representation of Women's Perception of the Importance of Their Opinion Across Different Criteria in Selected Gram Panchayats of Arsha Block, Purulia District

*Major issues and challenges of the rural women on MGNREGA scheme*

1. Delay in wage payment (Table 10) is a genuine issue under MGNREGA. The table reveals that, in Arsha Block, more than 50% of women in each empowerment category reported that their wages are credited late and do not reach their bank accounts on time.
2. Each family has one job card, and at a time, only one member from the family can be employed under that job card.
3. Most of the respondents highlighted the problem of limited and irregular employment provided under MGNREGS (Table 11). The provision of 100 days of employment per household per year is insufficient in the current context, as assured 100 days of work is not consistently available to every household.
4. In the last few years, all the work being done in the Rural development of the Panchayat, especially the digging of ponds, construction of check dams etc. are mostly being done with modern machines, so the participation of men and women in the work is decreasing.

5. They highlighted the problem of lower wage rate in MGNREGS than present market. This problem was found almost in all group under the research. [Table 12](#) reveals that more 60% women of each category has been said yes, low wage in present market.
6. Panchayat do not provide toilets or drinking water at workplaces, which is a big problem for working women.

**Table 10:** Empowerment category with wage payment time

| RECEIVED PAYMENT ON TIME |         |        |       |
|--------------------------|---------|--------|-------|
| Empowerment Category     | Yes (%) | No (%) | Total |
| Lower Empowerment        | 42(58)  | 30(42) | 72    |
| Moderate Empowerment     | 66(51)  | 61(49) | 127   |
| Higher Empowerment       | 34(67)  | 17(33) | 51    |
| Total                    | 142     | 108    | 250   |

**Table 11:** Empowerment category with No of days generated of Women

| Empowerment Category | How many day's Employment days provide under MGNREGS |            |            |            |          |
|----------------------|------------------------------------------------------|------------|------------|------------|----------|
|                      | >15Days                                              | 15-30 Days | 30-45 Days | 45-60 Days | <60 Days |
| Lower Empowerment    | 24                                                   | 31         | 12         | 4          | 2        |
| Moderate Empowerment | 17                                                   | 49         | 34         | 16         | 11       |
| Higher Empowerment   | 3                                                    | 14         | 19         | 9          | 6        |

**Table 12:** Empowerment category with low wage

| Empowerment Category | Perceived low wage under MGNREGA |    |
|----------------------|----------------------------------|----|
|                      | YES                              | NO |
| Lower Empowerment    | 46                               | 26 |
| Moderate Empowerment | 81                               | 46 |
| Higher Empowerment   | 35                               | 16 |
| Total                | 162                              | 88 |

#### *Achieving Gender Equality and Women's Empowerment through MGNREGA: Issues and Recommendations*

Achieving gender equality and empowering women is central to the realization of each of the Sustainable Development Goals (SDGs). Ensuring the rights of women and girls across all goals is crucial for achieving justice, inclusion, equitable economic growth, and environmental sustainability—both now and for future generations. Based on a thorough survey and detailed study in the Arsha Block, several issues have been identified, along with suggestions and recommendations:

1. **Increase in Workdays for Women:** It was found that less than 7% of women received more than 60 days of employment during the financial year. The government should take appropriate steps to ensure that at least 100 days of work are provided. This will result in additional income for rural households and greater economic empowerment for rural women.

2. **Improved Worksite Facilities:** Additional facilities at worksites—such as shaded areas for children, first aid kits, and access to safe drinking water—should be mandated and properly maintained to support women workers.
3. **Engagement of Educated Youth:** MGNREGA should aim to involve more educated rural youth. Their participation can help raise awareness about literacy, family planning, eliminating child labour, healthcare, and anti-liquor campaigns among rural populations.
4. **Provision of Free Midday Meals at Worksites:** A legislative provision should be introduced to offer free lunches to workers at the worksite. This would not only enhance food security in rural households but also improve workers' motivation and productivity through better nutrition.
5. **Timely Access to Information:** Clear and timely information should be provided to women participants to help them make informed decisions regarding job opportunities and entitlements under the scheme.
6. **Sanitation Facilities for Women:** Construction of community sanitary complexes, especially in areas with check dams or temporary work sites, should be prioritized. Safe and clean toilets are essential for the dignity, health, and safety of women. Although the female workforce is increasing, sanitation infrastructure is not keeping pace. Despite implementation challenges, efforts should be made to build toilets at every workplace.
7. **Involving Multiple Household Members under Job Cards:** The Job Card is a key document that enables rural individuals to access paid work and ensures transparency and protection from fraud. If more than one member from each registered household could be employed under a single Job Card, it would significantly improve their financial condition. As of December 2021, over 150 million Job Cards had been issued. If at least three members from each household could participate, the overall impact would be much greater.
8. **Creation of a 'Rainy Day Fund':** A small contingency fund could be established for Job Card holders to provide financial support during periods of scarcity (e.g., rainy seasons or economic downturns). This fund could serve as a form of social security for vulnerable households when employment is not available.

## Conclusion

Today, rural women are increasingly gaining access to education, productive resources, capacity building, skill development, healthcare services, and diverse livelihood opportunities through various government welfare schemes such as MGNREGA. These initiatives have contributed significantly to improving their socio-economic status and fostering greater self-reliance. However, true empowerment cannot be achieved through government schemes alone. It requires a combined effort involving society at large—including men, legal institutions, communities, and women themselves. Empowering women is not only a matter of social justice but also a crucial step toward sustainable national development. The need for women's empowerment has become even more pressing due to the deep-rooted gender discrimination and patriarchal mindset prevalent

in Indian society since ancient times. Bridging this gap is essential to ensure equality, dignity, and opportunities for all. Women's empowerment must be viewed as a continuous process that involves changing mindsets, creating equal opportunities, ensuring safety and rights, and giving women a voice in decision-making at all levels—household, community, and governance. When rural women are empowered, families thrive, communities prosper, and the nation progresses toward becoming a truly developed and inclusive society.

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# Estimating Household Carbon Footprints of Daily Food Products Among the Residents of Guwahati City

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### Abstract:

Carbon Footprint Analysis of household food products is an essential discourse in the current world. Consumption patterns have shifted in response to changing lifestyles. Research on the above topic has not yet been done regarding the estimation of carbon footprints of the daily food habits of households, especially in North-East India. The methodology used in calculating the carbon footprint is based on a GHG inventory, as per IPCC guidelines. This research paper mainly focuses on those daily used food products and the level of energy induced and the resultant production of waste generating GHG's (Greenhouse Gases). Generally, in Guwahati City, citizens prefer fresh food products in their daily lives, ranging from milk to fresh meat products. In this research, it is found that almost 80% of the emissions come from food production and preparation, and the remaining 20% is due to the transportation and processing of food products. For a balanced diet, an average adult man consumes 1200– 2000 kilocalories of food daily, combining all the necessary items and emits around 723.7 gCO<sub>2</sub>e. Moreover, a non-vegetarian meal emits a higher proportion of carbon footprint in comparison to a vegetarian meal, as per the study. Changes in lifestyle and food habits can offer a possible way to mitigate carbon footprint and emissions of GHGs among city residents.

*Keywords: Carbon Footprint, Food Habits, Greenhouse Gases, lifestyle*

### Introduction

Food consumption and related environmental impact have now become a serious concern around the world (Saner et.al., 2016). The global food system is a significant contributor to anthropogenic Greenhouse gas (GHG) emissions, accounting for approximately 21-37 percent of total emissions, primarily due to activities associated with production, processing, transportation and consumption (Shukla et.al., 2019). The increasing rate of population also increases the rate of consumption of food. From food consumption, Carbon Dioxide (CO<sub>2</sub>), and other Greenhouse Gases (GHG's) like Methane (CH<sub>4</sub>), Nitrous Oxide (N<sub>2</sub>O), etc. are released in the environment (Hannah et.al. 2023). Research has not yet been conducted on the emission of carbon footprint

in food consumption, its waste, and energy use, either in a regional or national perspective. It is observed that the food chain varies regionally, influenced by cultural traits (Sisitha et al., 2025). There are different stages of emission, starting from the production, processing, transportation, and consumption of food products (Irtiga et al., 2023). Thus, the research paper aims to examine the consumption patterns of citizens in Guwahati city regarding various food products. Stenfield et.al. (2006) reported that 18 percent of the Global GHG's emissions could be attributed to animal products alone. In the European Union, about 29 percent of the GHG emissions are related to food consumption (EIPRO, 2007). The Inter-Governmental Panel on Climate Change (IPCC) in its Fourth Assessment Report (AR4) pointed out that lifestyle changes and behaviour patterns can contribute to climate change mitigation across all sectors (Climate change, 2007). It is also argued that reducing the animal protein consumption can bring down GHG emission (Pathak et. al., 2010). The increasing purchasing power among citizens of developing countries has increased considerably in recent decades, which will not only cause major setbacks to global food security but also contribute to the mounting emissions of GHGs.

In the Indian perspective, several studies on carbon footprint and GHG emission have been done on the different sectors of agricultural production (Maheswarappa et. al., 2011), rice and wheat production (Kashyap, 2021), groundwater irrigation (Rajan et.al., 2020), forestry and land use sectors (Kumar, 2022), etc. The analysis of household carbon footprint (Grunewald et al., 2012) and the carbon footprint of food items (Pathak et al., 2010) has been conducted so far, analysing the expenditure of energy and the emission of different food products by households at the national level. As concerns surrounding climate change intensify, understanding the environmental impacts of food consumption at the household level has become crucial, particularly in rapidly urbanising regions of the Global South. One such region is Guwahati, the largest city in Northeast India, which has witnessed substantial urban growth and changing dietary patterns in recent decades.

Urban households are key actors in food systems, with their consumption behaviours having a direct impact on carbon emissions (Vermeulen et al., 2012). In India, where food consumption is highly diverse and region-specific, household-level carbon footprint assessments remain underexplored, particularly in northeastern cities like Guwahati. The city's unique socio-cultural dynamics, economic activities, and dietary preferences offer a valuable context for evaluating food-related carbon emissions and identifying sustainable consumption practices.

While studies have been conducted in metropolitan cities such as Delhi, Mumbai, and Bangalore (Roy et al., 2020; Sharma et al., 2021), there is a notable research gap in smaller tier-two cities, which are equally significant from an environmental planning perspective. Moreover, the carbon footprints of daily food products—staples such as rice, pulses, vegetables, dairy, and meat—vary widely depending on factors like production methods, transportation distances, and storage conditions (Poore et al. , 2018). Capturing these variations at the household level can inform both policy and public awareness regarding sustainable food choices.

Income is the main determinant leading to consumption of goods which in turn lead to the emission of carbon footprints. As income across households in a city, including Guwahati city vary greatly, the calculation of carbon emissions taking the average income of the respondents would have given a skewed result. To overcome the issue and to arrive at a more realistic result,

calculations of emissions at the household level has been undertaken in the present study. This method has enabled the findings of emission of carbon footprints in the different income groups categorized in the study. The calculation of emission of carbon footprints at the household level will also allow policymakers to formulate policies taking into account the emission of carbon footprints among the residents belonging to different income categories and also to suggest probable solutions accordingly.

This study aims to estimate the household carbon footprints associated with daily food consumption in Guwahati city. By evaluating emission patterns associated with commonly consumed food products, the research aims to contribute to broader discussions on urban sustainability, dietary transitions, and localised climate action in the Indian context.

The main objectives of the study are:

- To know the consumption pattern of the inhabitants of Guwahati city regarding some selected food products.
- To calculate the carbon footprints of the food consumed by the citizens of Guwahati city

## **Methodology**

### *Materials and Methods*

This study adopted a quantitative research design to estimate the household-level carbon footprints of daily food consumption among the residents of Guwahati city. The objective was to assess emissions associated with different food groups consumed on a daily basis, using standardized emission factors.

A stratified random sampling technique was employed to ensure representation across different socio-economic strata and geographical zones (East, West, North, and South Guwahati). Based on population estimates and household distribution data, a sample size of 600 households from the 60 wards of Guwahati Municipality Corporation was determined using the Yamane formula (Yamane, 1967) for a 95% confidence level and 7% margin of error. Statistical tool like bar diagrams are used from the excel sheet to indicate the results of the study.

Primary data were collected using structured questionnaires administered through in-person interviews. The questionnaire included sections on household demographics, food consumption frequency, quantity of food items consumed daily.

The data are calculated condising the income level and the amount of consumption of items per households in Guwahati city. The income level are categorised as very low income group (< Rs. 50000), low-income group (Rs. 50000 – Rs. 100000), middle-income group (Rs. 100000 – Rs. 150000), high-inocme group (Rs. 150000 – Rs. 200000) and the very high-income group (Rs. 200000 – Rs. 250000) among the households.

The carbon footprint of daily food consumption was estimated and each food item's emission factor (in kg CO<sub>2</sub>e per kg of product) was sourced from published databases (Poore et al., 2018).

### *The food items commonly used*

The study included the main cereals, along with a few protein sources, consumed by the surveyed residents to calculate their carbon footprint. Being a diverse cultural entity, the city comprises people coming from different socio-cultural backgrounds who follow their own food consumption patterns. Rice is the staple food for most households, whereas wheat is the alternative food source among them. However, the changing purchasing power has had a notable impact, resulting in a shift in food habits among residents.

#### *Calculation of carbon footprint of different food products*

Generally, food products go through a four-stage life cycle, i.e., production, processing, transportation, and consumption. In this research, we have focused on the individual emissions of certain food products and the total monthly consumption rate of the selected products in households. In order to calculate the carbon footprints of the selected items, the following formula is used (Shailesh, 2011):

$$\text{Input value (in kg/Kwh)} \times \text{emission factor} = \text{output value in KgCO}_2\text{eq.}$$

(kwh – kilo watt hour, KgCO<sub>2</sub>eq. – kilogram Carbon Dioxide equivalent)

To calculate the carbon footprints of selected food items, a formula is used by taking the average unit of the item (in kg/number) and multiplying it by the GHG emission factors. Here, we will only consider the item, the average unit of consumption per household, and the average GHG emission per household in the study area. Basically, the four-stage cycle requires a definite amount of energy to take it from production to the final consumption stage. For example, the output of poultry on a farm requires a definite amount of energy, including electricity, feed grain, transportation, processing at a meat shop, and finally consumption, as well as the cost of energy used in households for cooking. In simple words, it can be termed as a cradle-to-grave transition. Every unit of production has to meet its ultimate end following the four stages of the cycle. However, the most notable point here is that the unit of energy consumed varies at every stage of the cycle, up to its final utility. In this research paper, the final stage of preparation and consumption is examined to determine the amount of energy consumed and the CO<sub>2</sub>e released into the atmosphere by these selected items.

#### **Result & Discussion:**

This study was conducted in Guwahati, the largest city in the Indian state of Assam and the gateway to the northeastern region of India. Located on the southern bank of the Brahmaputra River, Guwahati lies between 26°14'45" N latitude and 91°73'62" E longitude (Authority G. M. D., 2020). As of the 2011 Census, the city had a population of over 960,000 within the municipal limits and over 1.5 million in the metropolitan region, making it one of the fastest-growing cities in eastern India (Census of India, 2011). Guwahati, the largest city in Assam, is part of the Kamrup Metropolitan district. The city is home to different linguistic groups consisting of the Assamese, Bengali, Punjabi, Rajasthani, etc. According to the Census of India, 2011, the religious breakdown in Guwahati city and the corresponding municipal/urban area is Hindus (85 percent), Islam (12.5 percent), Christian (0.9 percent), Jainism (0.9), Sikhism (0.4 percent) and others (0.5 percent). Guwahati is characterized by a humid subtropical climate, with significant rainfall during the monsoon season (June to September), which influences agricultural patterns and local food availability (IMD, 2020). The city exhibits a blend of urban and semi-urban

households, offering a representative sample of both traditional and modern food consumption behaviors. This diversity makes Guwahati an ideal case for studying carbon footprints of daily food products, as it reflects changing dietary patterns amidst ongoing urbanization (Pandey et.al., 2020).

Given its unique geographic location, evolving dietary trends, and socio-economic diversity, Guwahati city provides a pertinent context for assessing the household-level carbon footprint of food consumption.

The staple cereal consumed by the people of eastern India including the Assamese and the Bengali residing in the city is rice whereas the staple cereal consumed by the north Indian population residing in Guwahati city like the Punjabis and Rajasthanis is wheat. Majority of the surveyed respondents are non-vegetarians with mutton, chicken and egg constituting important items of their diet. Fish is a very common item of food among the Assamese and Bengali speaking people of the city. The calculation of carbon footprints in the present study has followed the methods used in other research studies carried out in various parts of India (Pathak et al., 2010). Since this is the first study carried out regarding emission of carbon footprint at the household level in North-East India, the researcher has followed the calculation methods used by earlier researchers as it will do justice to the present study.

### Rice:

Rice is one of the most important staple foods in the eastern and northeastern regions of India. Consumption of rice in the daily diet is common for most households. The consumption of rice among the different income groups varies as indicated below:

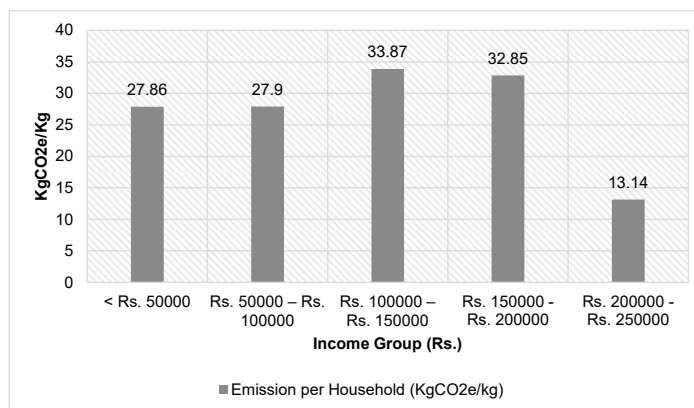


Fig. 1: Emission of CO<sub>2</sub>e from rice among different income groups of Guwahati city.

The above (Figure.1) shows the household emissions from the surveyed data and the variation in the consumption of rice. Consumption of one kilogram of rice emits around 2.578 - 4.45 KgCO<sub>2</sub>e (Ahmed et al., 2024). It is seen that the middle-income group is the highest emitter of Greenhouse gas which is 33.87 KgCO<sub>2</sub>e/kg, followed by high income group which is 32.85 KgCO<sub>2</sub>e/kg, the low-income group 27.86 KgCO<sub>2</sub>e/kg and the lowest by the very-high income group 13.14 KgCO<sub>2</sub>e/kg among the households. The emission per household (KgCO<sub>2</sub>e/kg) is

calculated from the sum of the total households' total consumption of rice per kg, divided by the total number of households in the individual income groups. The average consumption of rice is further multiplied by the emission factor of rice, and we obtain the Kg CO<sub>2</sub>e/kg of household GHG emissions in the different income categories. The consumption pattern of rice and the energy induced during the process of consumption of rice differ in the income groups, resulting in the variation of GHG emissions among them.

The high consumption of rice among middle-income households in Guwahati can be attributed to a combination of cultural preferences, affordability, and dietary habits. Rice is a staple food in Assam and forms the core of daily meals across socio-economic groups. However, middle-income households, which typically balance economic stability with cost-conscious spending, are more likely to rely on rice as an affordable and filling dietary option compared to higher-income groups that may diversify their diets with more expensive or varied food choices such as wheat-based products, processed foods, or international cuisines.

Moreover, middle-income families often maintain traditional food habits passed down through generations, where rice plays a central role and they usually have rice three times a day, for breakfast, lunch and dinner unlike high income families who have items other than rice for breakfast, as indicated in the study. This cultural continuity reinforces rice consumption within this demographic. Additionally, local markets in Guwahati offer easy access to a wide variety of rice types at reasonable prices, further supporting its prevalence in the middle-income household diet.

## Wheat

Wheat is one of the alternative staple foods consumed by the households of Guwahati city. The majority of families consume wheat flour as chapatti in their diet. The descriptive statistic(Figure 2) of the monthly consumption rate show that the consumption of wheat flour is relatively lower in comparison to rice among households. Presently, the shift from high-carbohydrate products like rice to wheat flour has been observed, considering the nutritional benefits of wheat among the households in the city.

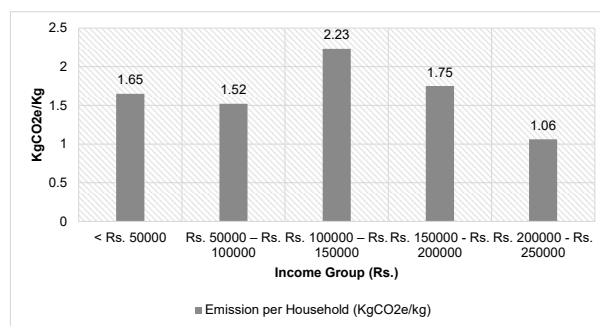


Fig 2: Emission of CO<sub>2</sub>e from wheat among different income group of Guwahati city.

Consumption of rice and wheat as staple food differs among the different income groups. From the above fig. 2 it is seen that in case of wheat the middle- income group is the highest emitter of GHG ( 2.23 KgCO<sub>2</sub>e/kg), followed by high-income group (1.75 KgCO<sub>2</sub>e/kg), very low-income group (1.65 KgCo<sub>2</sub>e/kg) and the lowest by the very high-income group of households in the city.

In comparison with the GHG emission of rice, wheat contributes a negligible amount in the different income groups of the city. The emission per household (KgCO<sub>2</sub>e/kg) is calculated from the sum of the total households' total consumption of wheat per kg, divided by the total number of households in the individual income groups. The average consumption of wheat is further multiplied by the emission factor of wheat and we get the KgCO<sub>2</sub>e/kg of the household GHG emission in the different income categories.

The pattern of wheat consumption in Guwahati city indicates a peak among middle-income households, which can be attributed to a blend of economic, cultural, and nutritional factors. Middle-income families often strike a balance between affordability and dietary preferences, making wheat-based products like chapatis, parathas, and bread staples in their daily meals. Unlike lower-income groups, who may prioritize lower-cost staples such as rice due to budgetary constraints, middle-income households have more purchasing power, allowing them to diversify their cereal intake. At the same time, they may not have access to the premium food options often favored by higher-income groups, who might opt for processed or exotic grains and convenience foods. Moreover, increasing urbanization and awareness of health and nutrition within this income segment have contributed to a shift toward wheat, perceived as a healthier and more versatile alternative to rice. Moreover, the study has found that among members of the same family, consumption of wheat in the form of chappatis is seen among the elderly for health related purposes whereas the younger members consume rice. This socio-economic positioning uniquely places the middle-income group at the forefront of wheat consumption in Guwahati, making them a critical demographic segment for studying changing food consumption trends in urban Assam.

### Chicken

The consumption pattern of meat varies across different regions in India. Religious beliefs and cultural traditions significantly influence dietary habits, with some religions imposing restrictions or preferences on meat consumption (Corichi [M., 2021](#)). Changing dietary habits, urbanisation, and increasing disposable incomes have brought a tremendous increase in the consumption of meat in India. Among the different types of meat, poultry is one of the widely consumed items among the respondents of Guwahati city.

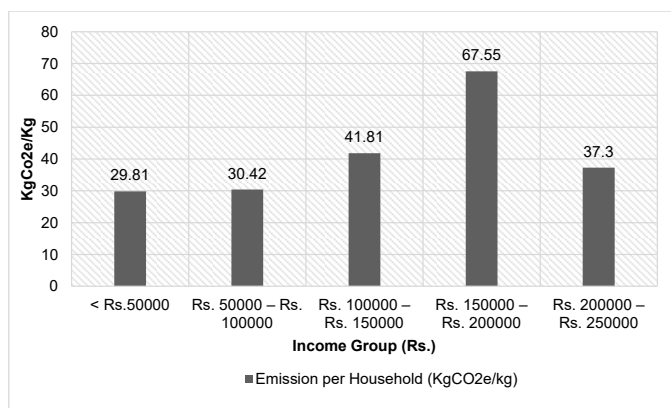


Fig.3: Emission of CO<sub>2</sub>e from chicken among different income groups of Guwahati city.

The GHG emissions from cradle-to-retail chicken meat average about 7–10 KgCO<sub>2</sub>e/kg Edible Weight (EW) but can range from 2.6 up to 20 KgCO<sub>2</sub>e/kg EW and out of this, most of the footprint is from cradle-to-farm gate: an avg. 6.4 KgCO<sub>2</sub>e/kg EW (Daesoo Kim, et al., 2022). It is evident from the above (fig.3) that the emission of chicken is maximum in the high-income group (67.55 KgCO<sub>2</sub>e/kg), followed by middle-income group (41.81 KGCo<sub>2</sub>e/kg), very high-income group (37.3 KGCO<sub>2</sub>e/kg) and the lowest by the very-low income group (29.81 KgCO<sub>2</sub>e/kg) among the surveyed households. The emission per household (KgCO<sub>2</sub>e/Kg) is calculated from the sum of the total households' total consumption of chicken per kg, divided by the total number of households in the individual income groups. The average consumption of chicken is further multiplied by the emission factor of chicken, and we obtain the Kg CO<sub>2</sub>e/kg of household GHG emissions in the different income categories.

Chicken (poultry) is typically positioned as a relatively high-quality source of animal protein compared to many vegetarian sources. As household income rises, the demand for more varied, or more convenient protein sources tends to increase. Higher income households also tend to have better access to refrigeration, frequent market visits or supermarkets, and can afford with fresh or branded poultry. High income households consume more chicken (in terms of quantity, frequency, or share in protein consumption) than lower income households. The reasons can be the ability to afford higher cost of chicken (fresh/broiler or local chicken), greater concern for quality, hygiene, and variety, better access (supermarkets, live markets) and storage facilities (fridge/freezer).

## Egg

The environmental impact of egg consumption, particularly in terms of Greenhouse gas (GHG) emissions measured in carbon dioxide equivalent (CO<sub>2</sub>e), varies notably across income groups due to differences in dietary patterns, purchasing power, and access to alternatives. Eggs are a significant source of animal protein and have a relatively lower CO<sub>2</sub>e footprint compared to red meat (Poore & Nemecek, 2018), but their contribution to total dietary emissions can be substantial depending on frequency and quantity of consumption. Households are the largest consumers of eggs, using them as a staple part of many diets. Moreover, eggs are also used in other food items like cakes, biscuits, snacks, bread, etc. So, eggs can be regarded as a daily supplement for most households.

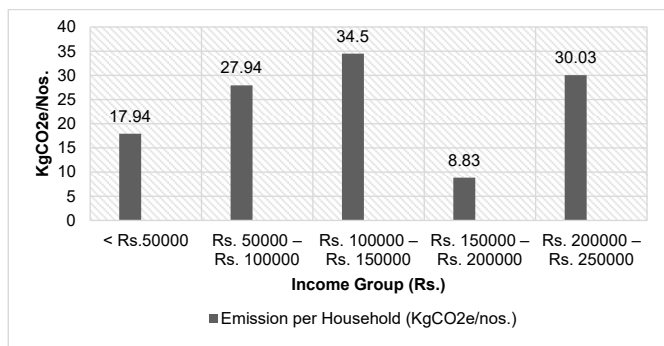


Fig. 4: Emission of CO<sub>2</sub>e from eggs among different income groups of Guwahati city.

The emission per household (KgCO<sub>2</sub>e/nos.) is calculated from the sum of the total households' total consumption of eggs per nos., divided by the total number of households in the individual

income groups. The average consumption of eggs is further multiplied by the emission factor of eggs, and we obtain the KgCO<sub>2</sub>e/number of households in the different income categories. In terms of GHG emissions, eggs play a vital role in carbon emissions, as they also emit the same amount of energy as the production of poultry. The middle-income group of the surveyed households contributes the highest emission (34.5 KgCO<sub>2</sub>e/nos), followed by the very high-income group (30.0 KgCO<sub>2</sub>e/nos.), and the lowest by the high-income group (8.83 KgCO<sub>2</sub>e/nos.) among the households in the city (Fig. 4). Population size, awareness, purchasing power, easy availability, and urbanisation are some of the critical factors contributing towards the higher consumption of eggs among the different income groups of households in the city.

Several studies indicate that egg consumption in Guwahati is significantly associated with household income level, with middle-income households tending to exhibit the highest consumption. For instance, A Study on the Attitude of Consumers Towards Egg Quality in Guwahati City (Sapcota et al., 2006) found that “large family size and medium income group had positive impact on egg buying.”

This means that among the different socio-economic strata in Guwahati, the middle income group is more likely both to purchase eggs and to do so more frequently. Middle income households have enough disposable income to include eggs regularly in their dietary patterns, while lower income households view egg purchases as more of a luxury or cost-related choice, and higher income households diversify protein sources or have different preferences.

## Mutton

Mutton (goat meat or sheep meat) is one of the more carbon-intensive non-vegetarian food items. In the Indian context, (Pathak et al., 2010) estimated that among 24 food items, mutton emits about 11.9 times as much GHG as milk, about 12.1 times as much as fish, and about 12.9 times as much as rice on a per weight-basis. Mutton is a popular meat choice, with a significant portion of the population consuming it. The maximum consumption reaches its peak during festivals such as Eid, Bakrid, and regional festivals like Bihu (especially Bhogali Bihu). The consumption pattern of meat in India indicates that poultry meat is more regularly consumed compared to other meat items. The high price of mutton often limits consumption compared to poultry, which is more affordable (Suresh, 2016). It is evident from the above (fig. 3 & fig. 5) that the consumption of chicken is more than that of mutton among the surveyed households in the city. People are likely to have chicken more often, as it is much cheaper than mutton, and it also takes less time to prepare.

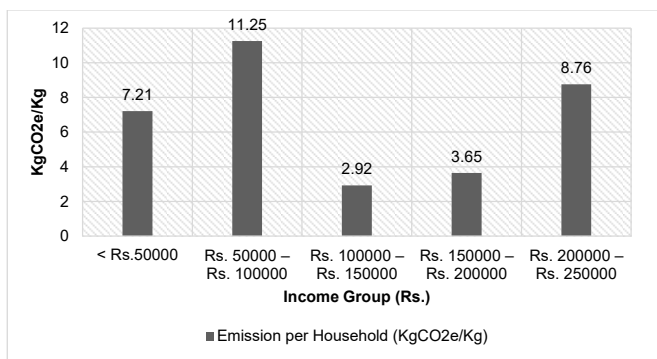


Fig.5: Emission of CO<sub>2</sub>e from mutton among different income groups of Guwahati city.

The GHG emission of mutton is estimated to be 5.84 KgCO<sub>2</sub>e/kg (Poore et al., 2018). The emission per household (KgCO<sub>2</sub>e/kg) is calculated from the sum of the total households' consumption of mutton per kg, divided by the total number of households in the individual income groups. The average consumption of mutton is further multiplied by the emission factor of mutton and we get the KgCO<sub>2</sub>e/kg of the household GHG emission in the different income categories. As per the surveyed data, the lower-income group of households is the highest emitter of GHG emission (11.25 KgCO<sub>2</sub>e/kg), followed by very high-income group (8.76 KgCO<sub>2</sub>e/kg), very low-income group (7.21 KgCO<sub>2</sub>e/kg) and the middle-income group is the lowest emitting (2.92 KgCO<sub>2</sub>e/kg) per household in Guwahati city.

Contrary to conventional expectations that higher-income households are the primary consumers of more expensive protein sources such as mutton, data from Guwahati city reveals a divergent pattern. The study found that lower-income households exhibited the highest frequency of mutton consumption, both in terms of volume and regularity. This trend stands in contrast to national-level dietary patterns where mutton is typically categorized as a luxury or occasional food item, primarily consumed by middle and upper-income groups (FSSAI, 2020)

Additionally, qualitative interviews revealed that for many households in this demographic, mutton is often purchased in smaller quantities or shared communally, making it economically feasible despite higher per-kilogram prices. Informal meat markets and direct purchases from local butchers at lower rates further facilitate access to mutton for economically constrained families (Roy et al., 2009)

## Fish

Consumption of fish contributes to dietary Greenhouse gas (GHG) emissions (measured in CO<sub>2</sub>e), and these emissions are mediated by both how much fish is consumed and what type of fish (wild-caught, farmed, species, feed inputs, transport, etc.). Income plays a significant role in determining both quantity and type of fish consumed, and thus influences CO<sub>2</sub>e emissions from fish in nuanced ways. Fish is an essential part of the Assamese diet, with a high percentage of people consuming it regularly. Fish consumption is deeply ingrained in Assamese culture and tradition, and fishing is an indispensable part of traditional livelihood. In Assam, the per capita fish consumption is around 11.72 kg per year, placing the state 5th among the top fish-consuming states in India. This means that on average, each person in Assam consumes about 11.72 kg of fish annually (Dutta, 2021).

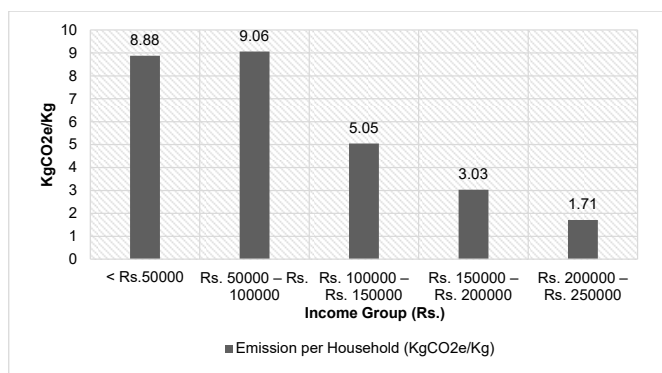


Fig 6: Emission of CO<sub>2</sub>e from fish among different income groups of Guwahati city.

The emission per household (KgCO<sub>2</sub>e/kg) is calculated from the sum of the total households' total consumption of fish per kg, divided by the total number of households in the individual income groups. The average consumption of fish is further multiplied by the emission factor of fish and we get the KgCO<sub>2</sub>e/kg of the household GHG emission in the different income categories. The GHG emission of fish is estimated at around 1.82 KgCO<sub>2</sub>e/kg (Poore et al., 2018). The lower-income group is found to be the highest consumer and GHG emitter contributing (9.06 KgCO<sub>2</sub>e/kg), followed by very low-income group (8.88 KgCO<sub>2</sub>e/kg), middle-income group (5.05 KgCO<sub>2</sub>e/kg) and the very high-income group contributes the lowest emission (1.71 KgCO<sub>2</sub>e/kg) per household in Guwahati city. Easy access, quick preparation, and traditional cuisines contribute to increased consumption of fish.

Fish is a staple dietary component in Assam, and its consumption is particularly prominent among the lower-income households in Guwahati city. Despite their limited financial resources, these households prioritize fish as a key source of protein due to its cultural significance, affordability compared to other animal proteins, and ease of access through local markets (Baruah et al., 2019). Studies have shown that lower-income families tend to consume fish more frequently than higher-income groups, who often diversify their protein intake with chicken, mutton, or processed alternatives (Baruah et al., 2019). This trend reflects both economic and cultural factors, where traditional Assamese diets emphasize freshwater fish, which is often sourced locally or even self-caught in peri-urban and rural fringe areas (Baruah et al., 2019). Consequently, fish continues to play a vital nutritional and cultural role, especially in the diets of economically disadvantaged populations in Guwahati.

### Key findings

Prior studies of the selected food items reveals that the highest emitter of carbon footprints per kilogram is mutton, followed by chicken, fish, eggs, and rice. The lowest emitter of carbon footprint is wheat (Poore et al., 2018).

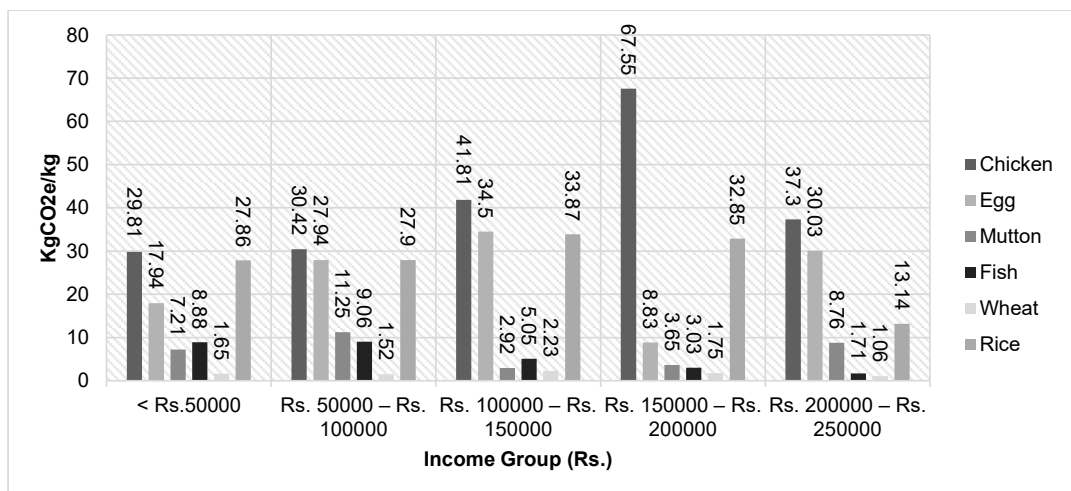


Fig. 7 Comparative analysis of the emission of CO<sub>2</sub>e of the selected food items.

From the present study of the selected food items, the highest emitter of carbon footprints is found to be chicken emitting 206 KgCO<sub>2</sub>e/kg from the total income groups of the households, followed by rice (135.62 KgCO<sub>2</sub>e/kg), egg (119.24 KgCO<sub>2</sub>e/kg), mutton (33.79 KgCO<sub>2</sub>e/kg), fish (27.73 KgCO<sub>2</sub>e/kg) and the lowest is wheat (8.21 KgCO<sub>2</sub>e/kg) among the surveyed households of the city.

Among the income groups, the highest emitter is the middle-income group (120.38 Kg CO<sub>2</sub>e/kg), followed by the high-income group (117.66 Kg CO<sub>2</sub>e/kg), the lower-income group (108.09 Kg CO<sub>2</sub>e/kg), the very low-income group (93.35 Kg CO<sub>2</sub>e/kg) and the lowest emitting by the very high-income group (92 KgCO<sub>2</sub>e/kg) among the households of Guwahati city.

The middle-income group constitutes the largest segment of the population in Guwahati city and plays a pivotal role in driving food consumption patterns. Their purchasing power, combined with aspirations for nutritional and diversified diets, positions them as the highest consumers of staple foods such as rice and wheat, as well as protein sources like meat. Unlike low-income groups, which may face affordability constraints, and high-income groups, which often shift toward premium or alternative diets (such as imported grains or organic foods), middle-income households tend to prioritize quantity and affordability while still seeking nutritional adequacy and taste preferences.

Rice and wheat form the staple dietary base in Assam, with rice being especially dominant. Meat consumption—particularly of chicken, fish, and mutton—is also prevalent among middle-income households, reflecting both cultural preferences and rising affordability due to improved economic conditions in urban areas. Guwahati, being the largest urban center in the region, reflects these trends most strongly.

Recent studies and consumption surveys in urban India also support the assertion that middle-income households show the highest aggregate consumption across various food categories, especially cereals and animal protein, due to their population size and transitional lifestyle changes that come with urbanization and rising incomes (Sharma et al., 2020).

### **Limitations**

While this study provides valuable insights into the household-level carbon footprints of daily food consumption in Guwahati city, several limitations must be acknowledged. Firstly, the estimation of carbon footprints heavily relied on self-reported data collected through surveys and interviews. Such data is susceptible to recall bias and social desirability bias, which may lead to under- or over-reporting of actual food consumption patterns (Clune et al., 2017). Additionally, the study utilized average emission factors for food products, which may not fully capture the variability in production methods, transportation distances, and storage conditions that influence the actual carbon emissions associated with each food item. The present study has considered six food items which has indicated the middle-income group as the highest emitter of Greenhouse gases. Further studies encompassing more food items might indicate different income categories to be the highest emitters of Greenhouse gases.

Secondly, the study's geographic focus on Guwahati city limits the generalizability of the findings to other urban or rural areas with different socio-economic, cultural, and dietary

patterns. Regional variations in infrastructure, supply chains, and climate can significantly affect the carbon footprint of food products (Clune et al., 2017). Moreover, the exclusion of indirect emissions, such as those related to land use change, packaging, and waste disposal, may result in an underestimation of the total carbon footprint.

Lastly, due to resource constraints, the sample size may not fully represent the diversity of the city's population in terms of income levels, food access, and lifestyle choices. Future research could address these limitations by incorporating life cycle assessment (LCA) tools, expanding the geographical scope, and integrating more granular consumption and production data.

## **Conclusion**

This study has highlighted the significant carbon footprints associated with the daily food consumption patterns among households in Guwahati City. The findings indicate that dietary choices—particularly high consumption of animal-based products such as meat and dairy—are major contributors to household greenhouse gas (GHG) emissions. Plant-based foods such as pulses, grains, and locally sourced vegetables were found to have considerably lower carbon footprints, reinforcing global literature on sustainable diets (Poore et al., 2018).

Furthermore, the study reveals that factors such as income level, awareness of environmental impacts, and accessibility to alternative food sources influence food-related carbon emissions. Conversely, households that relied more on traditional, local, and seasonal foods demonstrated a smaller environmental impact—emphasizing the role of indigenous knowledge and practices in promoting sustainability.

To mitigate food-related emissions in Guwahati and similar urban areas, there is a critical need to promote awareness about low-carbon dietary choices and support policies that encourage sustainable food systems. Initiatives such as community-supported agriculture, local farmer markets, and educational campaigns on food sustainability could play pivotal roles. As urbanization and dietary transitions continue across Indian cities, incorporating carbon footprint assessments into food policy planning will be essential in aligning with India's broader climate goals (Gerber et al., 2013).

In conclusion, this research not only quantifies the environmental burden of household food consumption in Guwahati but also underscores the urgent need for behavioral and systemic shifts towards sustainable food practices. Further studies integrating lifecycle assessments with socio-cultural aspects of food choices would provide a more comprehensive understanding of food-related emissions in diverse urban contexts.

The study has revealed that the carbon footprints of some major food items vary among different economic groups in the city. As dietary habits are ingrained in socio-cultural ethos, it is not easy to change one's dietary food choices. Specific steps have to be followed to reduce the amount of carbon footprints and the resultant alarming level of GHG's around the city. A proper balanced diet i.e. "Climate Smart Diets" with maximum proportion of vegetables and cereals should be included in the diet chart. Substitution of animal protein with other natural protein supplements should be obtained for at least 4 days a week. A study from Spain and Sweden also showed that vegetarian meals were associated with less environmental impact than meals with animal protein (Sonesson et al., 2009).

Thus, the calculation of GHG intensities provides interesting information that can be very helpful in formulating the most effective options to reduce GHG emissions, thereby reducing the carbon footprints of daily food products among residents of Guwahati city.

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**Web links:**

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# Landslide Susceptibility Zonation in the Rani Khola River Basin, Sikkim: A Comparative Analysis of Frequency Ratio and Logistic Regression Models

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### Abstract

The present study aims to evaluate and compare the performance of two widely used statistical models namely frequency ratio (FR) and logistic regression (LR) in generating landslide susceptibility zonation for Rani Khola River Basin, a highly landslide prone area in Sikkim. Using a landslide inventory of 269 events and ten inducing factors derived from remote sensing, field investigations and GIS datasets, susceptibility maps have been developed. Both models consistently identified slope, lithology, soil type, rainfall, landuse and proximity to roads as dominant landslide drivers. Model performance was assessed using ROC curves, AUC values and error matrices. LR model achieved higher AUC values (0.864 training and 0.865 testing) indicating its superior discriminatory power. On the other hand FR model achieved slightly higher kappa coefficient reflecting its better spatial accuracy. The results indicate that LR is more suitable for scientific analysis and policy level hazard modeling, while FR offers a simple and reliable approach for rapid assessments in data scarce settings. The study reveals the complementary nature of these models and recommends ensemble based approaches for robust landslide risk management in Himalayan terrains.

**Keywords:** *Frequency ratio, Logistic Regression, ROC-AUC, Error Matrix*

### Introduction

Landslides are among the most widespread and destructive natural hazards in mountainous region cause significant loss to life and property. This risk is particularly acute in the Himalayan region, which is marked by active tectonics and steep gradients. Complex geology and intense monsoonal rainfall further increase the likelihood of slope failures (Anbalagan & Singh, 1996; Dikshit et al., 2020; Saha et al., 2005). In India, excluding the permafrost regions in the north, about 0.42 Million sq.km areas of the landmass (12.6%) is landslide-prone. This region estimating roughly a monetary loss of Rs. 100 crore to Rs. 150 crore per annum at the 2011 prices for the country as a whole (National landslide Risk Management Strategy, NDMA, Govt. of India,

2019). Darjeeling-Sikkim Himalayas covers more than 40% (0.18 million sq. km) of landslide prone areas in India belongs to maximum earthquake-prone areas in India (Zone-IV and V; BIS, 2002). Even one concentrated shower of 50 mm per hour could initiate landslides endangering innumerable local people and their properties. A preliminary assessment of monetary losses due to rainfall induced landslide in 1998 carried out by the Government of Sikkim indicated a total loss of approximately Rs. 1,370 million. The worst situation was in the East Sikkim with 40 percent of its area was highly affected (Basu and De, 2003). The present study area, RaniKhola river basin is situated in the formerly East District of Sikkim. The region is located under seismic zone IV, a geologically fragile zone of lesser Himalaya. The Chandmari area of Gangtok town along with nearby settlements such as Tathangchen village, Syari, Deorali, Zero Point, Development Area, Rongey Basti (Donkan Dara) and Chongey Tar Basti on Gangtok-Rongey-Bhusuk-Assam (GRBA) Road, Bhusuk, JN Marg stretch Upper Sichey, 9<sup>th</sup> mile, Martam, 32<sup>th</sup> mile witness frequent massive landslides almost in every year (GSI, 2020; NDMA, 2019).

After reviewing the existing literatures it has been found that several research works have been carried out on behalf of personal as well as govt. level on landslide occurrences in various parts of Darjeeling-Sikkim Himalaya. Yet majority of these demand oriented studies are subjective in nature, either depicting regional picture of the problem or more concentrated at some discrete locations for a site-specific purpose, rarely aimed at basin scale. Along with this different statistical techniques such as weight of evidence, information value, logistic regression, frequency ratio etc. have been widely applied in landslide susceptibility mapping across diverse geographic settings (Ayalew & Yamagishi, 2005; Chen et al., 2019; Lee & Pradhan, 2007; Yilmaz, 2009). However, comparative assessments between individual models are relatively limited. This limits the ability of planners to choose a suitable model for local scale hazard assessment and mitigation. To address these issues the present study aims to compare the performance of two widely used statistical techniques (Frequency ratio and Logistic Regression) in producing landslide susceptibility zonation for the Rani Khola river basin, Sikkim. The rationale for choosing Frequency Ratio and Logistic Regression is based on their complementary methodological structure. Frequency Ratio offers a simple, transparent, minimal data requirement based approach, ideal for preliminary susceptibility assessment (Yilmaz, 2009). In contrast Logistic Regression allows a more integrated understanding of the interaction between factors (Pradhan & Lee, 2010). Despite their widespread use, few studies have systematically evaluated their performance under identical conditions. Both models have demonstrated strong performance in similar mountainous environments (Park et al., 2013). This work would help in providing proper and better remedial measures, planning of various development activities and integrating landslide mitigation measures with watershed development projects in the study area.

## Study area

Rani Khola is one of the major tributaries of Teesta River, locally known as Rongni Chu. The river largely flows through Gangtok and Pakyong District of Sikkim State, India. The river basin lies between 27°13'9"N to 27°23'51"N and 88°29'31"E to 88°43'18"E with an area approximately 248 km<sup>2</sup>. Most of the basin area falls in high mountain region with very steep slopes. More than 50% of the area is made up of the rocks belonging to Gorubathan formation and concentrated in the central and western part of the basin. Gorubathan formation is followed by Chungthang

Formation (Paro), Lingtse Granite Gneiss rock formations (GSI, 2006). The average annual rainfall is more than 3300 mm. Most of the rainfall occurs from July to September. Many areas in the higher reaches of the basin also receive heavy snowfall during the month of January (Fig. 1).

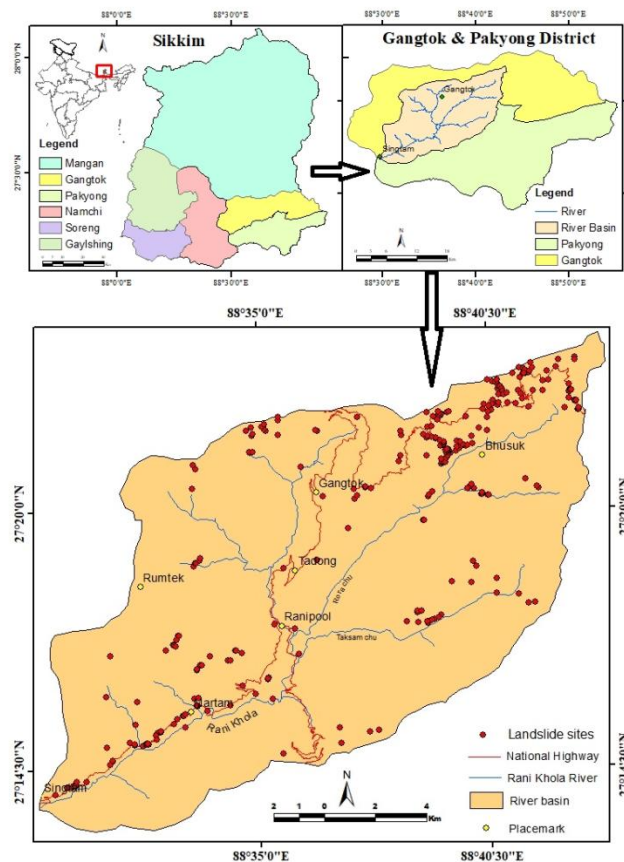


Fig. 1. Location map of Rani khola river basin with 269 landslide points

(source: Survey of India toposheet, 78A/8, A/11, A/12; Google Earth Pro; GSI; SSDMA)

## Database & Methodology

### Landslide inventory

A cumulative non-temporal landslide inventory has been prepared by integrating high-resolution **satellite imagery** from **Google Earth Pro (2017-2023)** and **secondary datasets** such as Geological Survey of India (2022), Sikkim State Disaster Management Authority (2022) reports (Fig. 1). This cumulative approach is standard for susceptibility modeling which needs spatial pattern rather than event timing (Van Westen et al., 2006; Fell et al., 2008). Field verification has been carried out through GPS survey to confirm landslide locations. Total 269 Landslides were manually delineated as point feature to ensure precise location (Guzzetti et al., 2000). The inventory was divided into two subsets, approximately **70% (188 points)** of the total dataset was

randomly selected as the **training set** to calibrate model and the remaining **30% (81 points)** as the **testing set** to validate the model (Chung & Fabbri, 2003; Yilmaz, 2009). The same inventory dataset has been used for both the models to ensure methodological consistency and a fair comparison (Guzzetti et al., 1999; Lee & Pradhan, 2007; Ayalew & Yamagishi, 2005).

### Inducing factors

Selection of landslide inducing factors was based on questionnaire survey among the local inhabitants (Mondal and Maiti, 2013), geomorphological relevance, data availability and prior empirical research on slope instability in Himalayan terrain (De, 2004; Ghosh et al., 2012). Accordingly, ten landslide inducing factors—slope, aspect, curvature, relative relief, topographic wetness index (TWI), lithology, soil type, rainfall, land use/land cover (LULC) and distance to road have been selected (Fig. 2). The ALOS PALSAR DEM (path – 504 & frame- 530; 12.5m; 2020) was used to derive slope, aspect, curvature, relative relief, and TWI through the *Spatial Analyst Toolbox* in ArcGIS. Mean annual rainfall gridded data ( $0.25^{\circ} \times 0.25^{\circ}$ , 1991-2021) from IMD, Pune was interpolated using the *Inverse Distance Weighting (IDW)* technique to generate spatial rainfall distribution map. Geological map (1:50000, 2020) by GSI and soil map by Forest and Environmental Department, Government of Sikkim were digitized and geo-referenced to the WGS 84 UTM projection. Vector layers were converted to raster format for analysis. SENTINEL-2A (Tile no – RXL; 10m; Bands - 2,3,4,8; 2022) satellite imagery was classified using the **Supervised Maximum Likelihood Method** into five major classes. Road network shape file (2020, OSM) was buffered at intervals of 50m by Euclidean distance in ArcGIS to assess the influence of road proximity. All the thematic layers were reclassified, resampled to 30m resolution and projected on WGS 84 UTM projection for further analysis. These layers collectively represent the topographic, lithological, hydrological and human influences on slope instability.

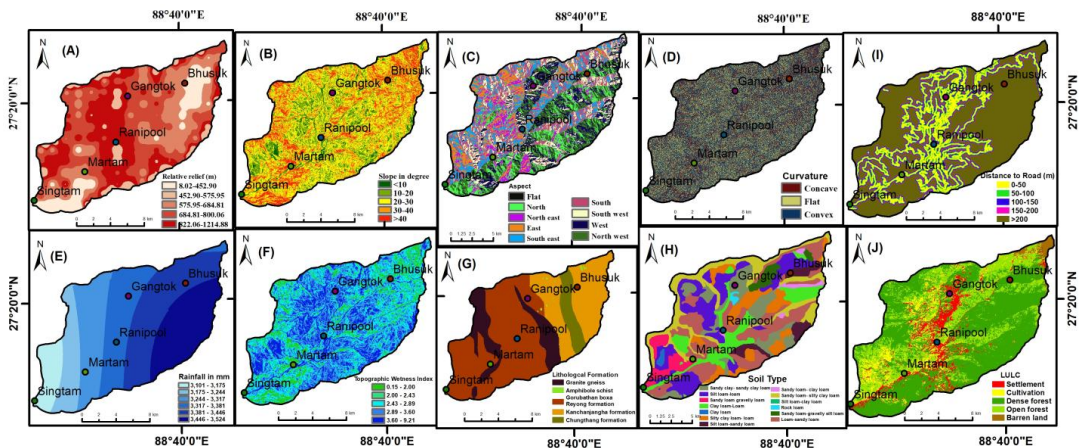


Fig. 2. Topographical Factors (A) Relative Relief, (B) Slope, (C) Aspect, (D) Curvature; Hydrological factors (E) Average annual rainfall and (F) Topographic Wetness Index; Lithological Factors (G) Lithological formation, (H) soil type and Anthropological factors (I) Distance to road, (J) LULC for landslide susceptibility zonation in Rani Khola River Basin

## Landslide Susceptibility Zonation model

### Frequency Ratio

After raster alignment of 10 conditioning factors and inventory, the total landslide pixels were extracted to calculate the proportion of landslides occurring in each factor class. The FR value for each class of a factor was calculated using the following equation:

$$FR = (N_{si} / N_s) / (N_{pi} / N_p) \dots\dots(i)$$

Where,  $N_{si}$  is the number of landslide pixels in class  $i$ ,  $N_s$  is the total number of landslide pixels in the study area,  $N_{pi}$  is the total number of pixels in class  $i$ ,  $N_p$  is the total number of pixels in the study area. FR value  $> 1$  indicates a strong positive correlation between the class and landslide occurrence, whereas  $FR < 1$  denotes low susceptibility or stability. The Landslide Susceptibility Index (LSI) was computed by summing the FR values corresponding to each pixel across all factors.

$$LSI = \sum_{i=1}^n \ln(FR_i) \dots\dots\dots(ii)$$

Where,  $n$  is the total number of conditioning factors. The resultant continuous LSI raster was then classified into five susceptibility classes—very low, low, moderate, high, and very high using the **Jenks's natural breaks** method (Lee & Talib, 2005; Pradhan, 2010; Yilmaz, 2009).

### Logistic Regression

For logistic regression, an equal number of non-landslide points (188) were randomly generated using a stratified sampling approach to ensure dataset balance. In GIS-based landslide studies, continuous variables are often categorized to address non-linear relationship, minimize noise, improve model interpretability and stability (Van Westen et al., 2003; Lee, 2005; Fell et al., 2008). Hence, all conditioning factors were standardized and reclassified into subclasses and subsequently converted into numeric form for regression analysis. To avoid perfect multicollinearity one class from each factor is dropped and treated as reference class. The most stable class has been chosen as the reference (Hosmer et al., 2013; Menard, 2010). For factor value extraction, each factor map was assigned with binary codes—1 representing landslide pixels and 0 representing non-landslide pixels. The probability of landslide occurrence has been estimated using the logistic equation:

$$P = \frac{1}{1 + e^{-Z}} \dots\dots\dots(iii)$$

Where,  $P$  represents the predicted **probability** (0 -1) and  $Z$  is the **linear combination defined as:**

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots\dots + \beta_n X_n \dots\dots\dots(iv)$$

Here,  $\beta_0$  denotes intercept,  $\beta_1$  to  $\beta_n$  are Regression coefficients,  $X_1$  to  $X_n$  represent conditioning factors. The logistic regression analysis including coefficient and statistical significance ( $Z$ -values,

p-values) has been carried out in **SPSS**. Variables with  $p < 0.05$  were considered statistically significant contributors to landslide occurrence. The predicted probability values (0–1) were exported to ArcGIS to generate a probability raster and reclassified into five zones using the **Jenks natural break method**.

#### *Validation and comparison*

##### *ROC curve and AUC*

To assess the predicted capability of LSZ models Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) have been computed. The ROC represents relationship between the true positive rate (TPR) and false positive rate (FPR) at varying thresholds (Park et al., 2013), where:

$$\text{TPR} = \text{TP} / (\text{TP} + \text{FN}) \dots\dots\dots (\text{v})$$

$$\text{FPR} = \text{FP} / (\text{FP} + \text{TN}) \dots\dots\dots (\text{vi})$$

The closer the ROC curve approaches upper left corner, the better the evaluation technique is.

To represent the overall model ability to discriminate between landslide and non-landslide points, AUC value was calculated using by the following trapezoidal rule:

$$\sum_{i=1}^n (X_{i+1} - X_i) (Y_{i+1} - Y_i) / 2 \quad \text{AUC} = \dots\dots\dots (\text{vii})$$

Where,  $X_i$  represents 1-specificity,  $Y_i$  represents sensitivity. AUC value closer to 1 indicates excellent predictive accuracy, while a value near 0.5 reflects poor or random prediction. Both training and testing datasets were used to assess the model's fitting accuracy and predictive capability.

##### *Error matrix*

Error matrix compares predicted class with observed field data (Mondal and Maiti, 2013). From the error matrices several accuracy indices are derived:

$$\text{Overall Accuracy (OA)} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \dots\dots\dots (\text{viii})$$

$$\text{Producer's Accuracy (PA)} = \text{TP} / (\text{TP} + \text{FN}) \dots\dots\dots (\text{ix})$$

$$\text{User's Accuracy (UA)} = \text{TP} / (\text{TP} + \text{FP}) \dots\dots\dots (\text{x})$$

$$\text{Kappa} = \text{Po} - \text{Pe} / 1 - \text{Pe} \dots\dots\dots (\text{xi})$$

Where,  $P_o$  is the observed agreement and  $P_e$  is the expected agreement by chance. Kappa values between 0.61–0.80 indicate substantial agreement, while values above 0.8 suggest near-perfect classification consistency.

## **Results and Discussion**

### *Areal distribution of susceptibility classes*

The landslide susceptibility map generated using the Frequency Ratio model is shown in Fig. 2 and Table 1. The results indicate that a substantial portion of the basin falls within very low to moderate susceptibility zones, covering 193.70 km<sup>2</sup>. In contrast, the very high susceptibility zone occupies a smaller area of 14.42 km<sup>2</sup>. These zones appear as localized pockets in the north-eastern and south-western parts of the basin.

On the other hand LSZ map by Logistic Regression (Fig. 4& Table 1) shows that the **very low susceptibility zone** covers approximately **115.91 km<sup>2</sup>**, accounting for the largest portion of the basin area and primarily occupies the lower reaches around **southeastern flanks**. The **low and moderate zones** occupy about **40.26 km<sup>2</sup>** and **27.96 km<sup>2</sup>**, respectively. The **high susceptibility zone** covers around **26.39 km<sup>2</sup>**, primarily distributed along mid-slope regions and areas adjacent to road networks and drainage intersections. The **very high susceptibility zone** accounts for **37.44 km<sup>2</sup>**, mostly concentrated in the **northern and northeastern sectors near Gangtok**.

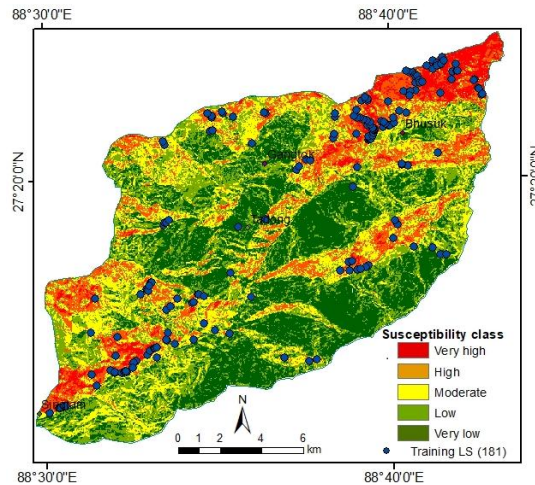


Fig. 3. Landslide susceptibility zonation map by Frequency ratio model for Rani Khola River Basin

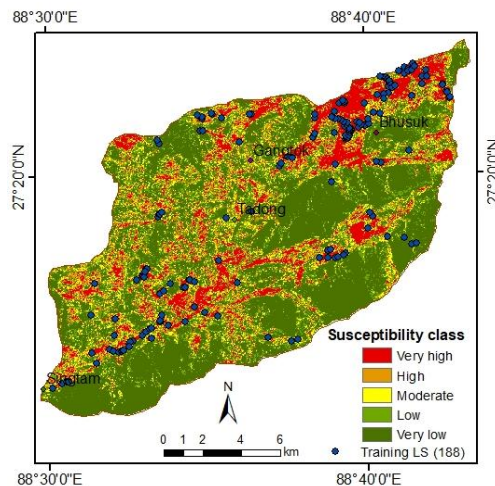


Fig. 4. Landslide susceptibility zonation map by Logistic regression model for Rani Khola River Basin

Table. 1. Area under different landslide susceptibility classes by frequency ratio and logistic regression model (in sq.km and percentage)

| Susceptibility class | FR           |           | LR           |           |
|----------------------|--------------|-----------|--------------|-----------|
|                      | Area (sq.km) | Area in % | Area (sq.km) | Area in % |
| Very high            | 14.42        | 5.83      | 37.44        | 15.10     |
| High                 | 39.26        | 15.87     | 26.40        | 10.64     |
| Moderate             | 58.20        | 23.53     | 27.95        | 11.28     |
| Low                  | 64.34        | 26.01     | 40.26        | 16.24     |
| Very Low             | 71.17        | 28.77     | 115.91       | 46.74     |

(Source: Compiled by the Authors)

Frequency Ratio model produces smoother and evenly distributed susceptibility class. This is because here each conditioning factor is related to landslide occurrences independently without considering the factor interdependence. In contrast, Logistic Regression produces high spatial contrast and sharp distinguish between stable and unstable zones. It is more sensitive to training data distribution, considering combined effects of all the predictors on landslide probability. So the areal differentiation observed among the two Landslide Susceptibility Zonation maps even from identical input data arises from the differences in the analytical principles, factor weighting and classification sensitivity of the models.

#### *Factor wise analysis of landslide drivers*

##### *Frequency ratio*

The frequency ratio values are presented in Table 2. Among the topographical factors, slope shows a clear positive relationship with landslide occurrence. The FR value increases steadily from 0.13 to 2.84 with increasing slope. It confirms that steeper slopes are inherently more unstable due to enhanced shear stress. South-east (FR=2.59), south (FR = 1.99) and south-west (FR = 1.66) aspects show more prone to failure due to stronger weather effects. Northerly aspects show stable condition. Concave slopes record highest FR (1.38) indicating enhanced instability due to surface water convergence. The mid relief zones (684-822m) are more prone to failure than very high or very low reflecting the role of deeply dissected terrain and active erosional processes. Under hydrological factors, low to moderate TWI classes indicates more susceptibility due to transient saturation while zone of rainfall having 3381 -3446 amplify failure by increasing pore water pressure and reduced shear strength (FR = 1.83). Lithology and soil emerge as dominant control. Chungthang formation and kanchanjangha formation (FR = 3.07-1.33) correspond to highly weathered and fractured bedrock, while weak soil textures particularly sandy loam- clay loam (FR = 3.25), sandy loam – gravelly loam (FR = 3.23) and sandy loam – gravelly silt loam (FR = 2.61) show high landslide frequencies due loose cohesion, high porosity. Fine textured rock dominated soils show less susceptibility. Under anthropological factors, area within 50 m of the road corridor (FR = 2.14), barren land (FR = 7.30), cultivation (FR = 2.68) and settlement (FR = 1.36) are more prone to failure due to destabilizing effects of cut slopes, inadequate drainage and vegetation loss. On the other hand dense forests are less prone to failure due to enhanced root cohesion.

According to Frequency Ratio model landslides in the Rani Khola River basin are primarily driven by slope, lithology, soil type, landuse and road proximity. Relief, rainfall, curvature and TWI play as modifiers.

Table. 2. Frequency ratio table for landslide susceptibility zonation in Rani Khola River Basin

| Factor              | Class             | No of pixel | No of landslide | FR    |
|---------------------|-------------------|-------------|-----------------|-------|
| Relative Relief (m) | 8.02- 452.90      | 17399       | 16              | 1.35  |
|                     | 452.90 - 575.95   | 73315       | 25              | 0.5   |
|                     | 575.95 - 684.81   | 91371       | 34              | 0.55  |
|                     | 684.81 - 822.06   | 65437       | 104             | 2.33  |
|                     | 822.06 - 1,214.88 | 27930       | 9               | 0.47  |
| SUM                 |                   |             |                 | 5.19  |
| SLOPE (in degree)   | 0-10              | 11013       | 1               | 0.13  |
|                     | Oct-20            | 59963       | 8               | 0.2   |
|                     | 20-30             | 98636       | 32              | 0.48  |
|                     | 30-40             | 73334       | 84              | 1.68  |
|                     | >40               | 32470       | 63              | 2.84  |
| SUM                 |                   |             |                 | 5.32  |
| ASPECT              | Flat              | 52          | 0               | 0     |
|                     | North             | 31907       | 0               | 0     |
|                     | North-east        | 20980       | 4               | 0.28  |
|                     | East              | 27931       | 11              | 0.58  |
|                     | South-east        | 36191       | 64              | 2.59  |
|                     | South             | 39716       | 54              | 1.99  |
|                     | South-west        | 37032       | 42              | 1.66  |
|                     | West              | 37795       | 10              | 0.39  |
|                     | North-west        | 43842       | 3               | 0.1   |
| SUM                 |                   |             |                 | 7.59  |
| General Curvature   | Concave           | 51910       | 49              | 1.38  |
|                     | Flat              | 85456       | 43              | 0.74  |
|                     | Convex            | 138184      | 96              | 1.02  |
| SUM                 |                   |             |                 | 3.14  |
| Rainfall (mm)       | 3101-3175         | 18874       | 8               | 0.632 |
|                     | 3175 - 3244       | 32018       | 21              | 0.978 |
|                     | 3244 -3317        | 44884       | 32              | 1.063 |
|                     | 3317 -3381        | 57839       | 15              | 0.387 |
|                     | 3381 – 3446       | 76464       | 94              | 1.834 |
|                     | 3446 -3524        | 50335       | 18              | 0.533 |
| SUM                 |                   |             |                 | 5.427 |
| TWI                 | 0.15–2.00         | 35832       | 58              | 2.37  |
|                     | 2.00–2.43         | 92619       | 89              | 1.4   |
|                     | 2.43–2.89         | 93939       | 27              | 0.42  |

|                      |                                |        |    |       |
|----------------------|--------------------------------|--------|----|-------|
|                      | 2.89–3.60                      | 45266  | 14 | 0.45  |
|                      | 3.60–9.21                      | 7175   | 0  | 0     |
| SUM                  |                                |        |    | 4.64  |
| Lithology            | Granite gneiss                 | 42575  | 10 | 0.35  |
|                      | Amphibole Schist               | 951    | 4  | 6.23  |
|                      | Gorubathanboxareyong formation | 136805 | 64 | 0.69  |
|                      | Kanchanjangha formation        | 75878  | 68 | 1.33  |
|                      | Chungthang formation           | 19269  | 40 | 3.07  |
| SUM                  |                                |        |    | 11.67 |
| Soil                 | sandy clay- sandy clay loam    | 31885  | 1  | 0.05  |
|                      | silt loam-loam                 | 47772  | 25 | 0.78  |
|                      | sandy loam gravelly loam       | 11917  | 26 | 3.23  |
|                      | clay loam-Loam                 | 31479  | 15 | 0.71  |
|                      | Clay loam                      | 1448   | 1  | 1.02  |
|                      | silty clay loam- loam          | 26413  | 5  | 0.28  |
|                      | silt loam-sandy loam           | 11525  | 2  | 0.26  |
|                      | sandy loam- clay loam          | 3641   | 8  | 3.25  |
|                      | sandy loam- silty clay loam    | 42897  | 43 | 1.48  |
|                      | Silt loam-clay loam            | 2      | 0  | 0     |
|                      | Rock loam                      | 1155   | 0  | 0     |
|                      | sandy loam-gravelly silt loam  | 6799   | 12 | 2.61  |
|                      | loam-sandy loam                | 58577  | 48 | 1.21  |
| SUM                  |                                |        |    | 14.89 |
| Distance to road (m) | 0-50                           | 53677  | 77 | 2.14  |
|                      | 50-100                         | 33348  | 17 | 0.76  |
|                      | 100-150                        | 24544  | 9  | 0.55  |
|                      | 150-200                        | 15022  | 6  | 0.6   |
|                      | >200                           | 153806 | 79 | 0.77  |
| SUM                  |                                |        |    | 4.81  |
| LULC                 | Settlement                     | 25917  | 24 | 1.36  |
|                      | Cultivation                    | 22936  | 42 | 2.68  |
|                      | Dense forest                   | 150198 | 23 | 0.22  |
|                      | Open forest                    | 71418  | 75 | 1.54  |
|                      | Barren land                    | 4815   | 24 | 7.3   |
| SUM                  |                                |        |    | 13.1  |

*(Source: Compiled by the Authors)*

### Logistic Regression

The regression coefficients, Z values, P values and odds ratios reflect the direction, strength, significance and magnitude of inducing factors on probability of failure. Table 3 reveals that although most of the topographical factors remain statistically insignificant, the coefficients and odds ratios show a geomorphologically meaningful trend. The coefficients increase progressively

with higher slope classes. This indicates higher the gradients greater the shear stress and reduced slope stability. South and south-east facing slopes also display higher slope instability (OR = 9-17). This is largely because of higher weathering rate, greater rainfall interception and more human habitation. Concave slopes show positive coefficient (0.87) and higher Odds (2.37) of Landslide occurrences reflecting zones of water concentration and stress accumulation. Even statistically insignificant, Relative relief values indicate that mid-relief landscapes are showing 2-3 times higher susceptibility. This could be attributed to greater incision and active erosion. The lack of statistical significance of slope, relative relief and curvature implies that they alone cannot trigger failure unless interacting with other terrain and material factor. Under hydrological variables intermediate TWI values (2.89 – 3.60) show high susceptibility (OR = 8.62) due to transient saturation on mid slope rather than saturated valley bottoms. Still statistically insignificant values indicate TWI only modifies local hydrological condition rather than acting as a primary factor. On the other hand, rainfall class ranging from 3244-3317mm displays a statistically significant and the strongest rainfall induced effect on failure. Lithology emerges as a highly significant factor. Chungthang formation exhibits the strongest effect. It is about **11 times** more prone to landsliding compared to the least susceptible lithology. These rock units are highly weathered, intensely fractured, and lithologically weak. Such conditions promote rapid slope failure during the monsoon season by substantially reducing shear strength. In contrast, soils such as silt loam–sandy loam, silt loam–loam, clay loam–loam, sandy loam–clay loam, and silty clay loam–loam show higher susceptibility, with odds ratios ranging from 7 to 52. These soil types are more prone to shallow and rapid failure under saturated conditions due to their loose and mixed textures. Under anthropological factors, road construction remains the most influential factors. This indicates areas close to roads (0-50m) show 8 times higher susceptibility due to slope modification, drainage alteration by excavation and blasting activities. On the other hand, settlement poses highest slope instability followed by barren land and cultivation due to altered natural drainage, vegetation clearance.

Table. 3. Logistic Regression table for landslide susceptibility zonation in the Rani Khola River Basin

| Factor                                                     | Class           | Coefficient | Z value | P value | Odds ratio |
|------------------------------------------------------------|-----------------|-------------|---------|---------|------------|
| Relative relief in m<br>(reference = 822.06 -<br>1,214.88) | 8.02-452.90     | 1.24        | 1.11    | 0.27    | 3.46       |
|                                                            | 452.90 - 575.95 | 1.23        | 1.17    | 0.24    | 3.42       |
|                                                            | 575.95 - 684.81 | 0.92        | 0.96    | 0.34    | 2.50       |
|                                                            | 684.81 - 822.06 | 1.13        | 1.28    | 0.20    | 3.10       |
| slope in degree<br>(reference = 0-10)                      | 10-20           | -0.98       | -0.77   | 0.44    | 0.38       |
|                                                            | 20-30           | 0.30        | 0.25    | 0.81    | 1.35       |
|                                                            | 30-40           | 1.57        | 1.23    | 0.22    | 4.81       |
|                                                            | T:>40           | 1.56        | 1.20    | 0.23    | 4.74       |

|                                              |                                |        |       |      |       |
|----------------------------------------------|--------------------------------|--------|-------|------|-------|
| Aspect<br>(reference = North)                | East                           | 1.49   | 1.01  | 0.31 | 4.44  |
|                                              | North-east                     | 2.48   | 1.60  | 0.11 | 11.96 |
|                                              | North-west                     | 0.06   | 0.04  | 0.97 | 1.06  |
|                                              | South                          | 2.24   | 1.59  | 0.11 | 9.44  |
|                                              | South-east                     | 2.83   | 1.93  | 0.05 | 16.92 |
|                                              | South-west                     | 2.55   | 1.78  | 0.07 | 12.78 |
|                                              | West                           | 0.66   | 0.46  | 0.64 | 1.94  |
| Curvature<br>(reference = Flat)              | Concave                        | 0.87   | 1.57  | 0.12 | 2.39  |
|                                              | Convex                         | 0.03   | 0.06  | 0.96 | 1.03  |
| Rainfall in mm<br>(reference = 3101-3175)    | 3175 - 3244                    | 1.12   | 1.02  | 0.31 | 3.06  |
|                                              | 3244 -3317                     | 2.58   | 1.96  | 0.05 | 13.14 |
|                                              | 3317 -3381                     | 0.08   | 0.06  | 0.95 | 1.08  |
|                                              | 3381 - 3446                    | 1.68   | 1.20  | 0.23 | 5.35  |
|                                              | 3446 -3524                     | 2.49   | 1.61  | 0.11 | 12.11 |
| TWI<br>(reference = 3.60 - 9.21)             | 0.15 - 2.00                    | 0.29   | 0.09  | 0.93 | 1.34  |
|                                              | 2.00 - 2.43                    | 0.97   | 0.31  | 0.76 | 2.64  |
|                                              | 2.43 - 2.89                    | 0.30   | 0.10  | 0.92 | 1.35  |
|                                              | 2.89 - 3.60                    | 2.15   | 0.66  | 0.51 | 8.62  |
| Lithology<br>(reference = Amphibole Schist)  | Gorubathanboxareyong formation | 0.31   | -4.83 | 0.00 | 1.36  |
|                                              | Kanchanjangha formation        | 0.71   | -3.82 | 0.00 | 2.03  |
|                                              | Chungthang formation           | 2.42   | -4.54 | 0.00 | 11.27 |
| Soil<br>(reference = Silt loam-clay loam)    | Clay loam                      | -0.16  | -0.14 | 0.89 | 0.85  |
|                                              | Rock loam                      | -12.14 | 0.00  | 1.00 | 0.00  |
|                                              | clay loam-Loam                 | 2.29   | 1.13  | 0.26 | 9.91  |
|                                              | sandy clay- sandy clay loam    | 1.36   | 1.21  | 0.23 | 3.89  |
|                                              | sandy loam gravelly loam       | 2.16   | 1.82  | 0.07 | 8.67  |
|                                              | sandy loam- clay loam          | 2.08   | 1.76  | 0.08 | 7.98  |
|                                              | sandy loam-gravelly silt loam  | 1.20   | 0.95  | 0.34 | 3.31  |
|                                              | silt loam-loam                 | 3.05   | 2.21  | 0.03 | 21.17 |
|                                              | silt loam-sandy loam           | 3.96   | 2.25  | 0.02 | 52.54 |
|                                              | silty clay loam- loam          | 2.03   | 1.26  | 0.21 | 7.58  |
|                                              | loam-sandy loam                | 1.21   | 1.13  | 0.26 | 3.34  |
| Distance to road in m<br>(reference=100-150) | 0-50                           | 2.10   | 2.76  | 0.01 | 8.16  |
|                                              | 150-200                        | -1.99  | -1.33 | 0.18 | 0.14  |
|                                              | 50-100                         | 1.03   | 1.31  | 0.19 | 2.81  |
|                                              | >200                           | 0.06   | 0.08  | 0.94 | 1.06  |

|                           |             |        |      |      |       |
|---------------------------|-------------|--------|------|------|-------|
| LULC                      | Barren land | 2.56   | 2.48 | 0.01 | 12.94 |
| (reference= Dense forest) | Cultivation | 1.94   | 2.58 | 0.01 | 6.94  |
|                           | Open forest | 0.96   | 1.65 | 0.10 | 2.61  |
|                           | Settlement  | 3.50   | 4.06 | 0.00 | 33.23 |
| Intercept                 |             | -20.95 | 0.00 | 1.00 | 0.00  |

(Source: Compiled by the Authors)

The Logistic Regression model identifies lithology, soil type, rainfall, road proximity, slope orientation and landuse as the most influential factors in slope instability. Slope, relative relief, curvature and TWI act as modifiers of mechanical and hydrological conditions. Thus the result highlights the importance of material strength and human intervention on slope failure rather than terrain geometry alone.

The results show that several factors are statistically insignificant in Logistic Regression but indicate high Frequency Ratio values. This is because of Frequency ratio captures individual factor influence while Logistic Regression considers combined effects of all the conditioning factors. Overall, both LR and FR model highlight that **high and very high landslide susceptibility zones** are predominantly concentrated along **steep slopes, deeply incised valleys, weak lithological units, barren lands and anthropogenically disturbed areas of in and around Gangtok, Tadong, Martam, Bhusuk, Ranipool and Singtham**. In contrast, **low and very low landslide susceptibility zones** occupy **gently undulating, forested and lithologically resistant areas** away from anthropogenic influence in the peripheral parts of the basin.

#### Validation and comparison

##### ROC Curve and AUC

The Logistic regression model achieved AUCs of 0.864(training) and 0.865(testing). The findings indicate strong discriminatory capability of the model for landslide and non-landslide areas (Fig. 5). AUC Values above 0.85 indicate strong predictive performance (Pourghasemi et al., 2013). The almost identical values for both training and testing datasets suggest that the model does not suffer from either overfitting or underfitting.

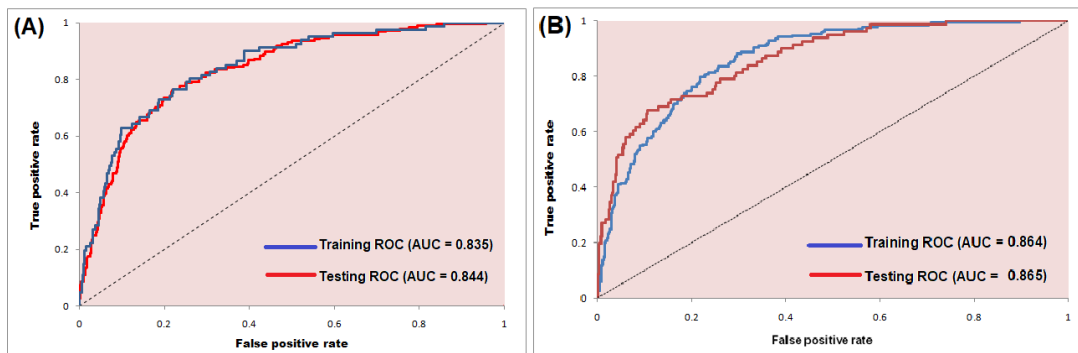


Fig. 5. Success rate and Prediction rate curve with AUC values for (A) Frequency ratio and (B) Logistic regression model

The Frequency ratio model also produced high AUCs (0.835 / 0.844) for both training and testing dataset which fall within the range of good predictive power (Fig. 5). The AUC for the training dataset is marginally higher than that of the testing dataset which suggests limited over fitting and confirms the model's reliability. It indicates a strong fit with the training samples and a consistent predictive ability for unseen data (Zhou et al., 2021).

#### *Error and accuracy matrices*

The results (Table 4) reveal that the Frequency ratio model correctly classifies 71 non-LS and 59 LS pixels with 10 false positives and 22 false negatives. This indicates that the model minimizes false alarms but misses more actual landslides. In contrast Logistic Regression correctly classifies 67 non-landslide and 61 landslide pixels. It produces a higher number of false positives (14) and slightly lower false negatives (20) than FR. This suggests that LR capture true LS pixels more but tends to overpredict unstable areas.

The accuracy matrix also supports this pattern. Frequency ratio model has higher user's accuracy (0.86) and slightly higher overall accuracy (0.80; Table. 4). This indicates more reliable landslide prediction with fewer false positives. On the other hand Logistic Regression model having a producer's accuracy of 0.75 detects more actual landslides than Frequency ratio but its slightly lower user's accuracy (0.81) indicates more false positives. Kappa values for both models indicate substantial agreement.

Table. 4. Error and Accuracy matrices for FR and LR models

| Model | TN | FP | FN | TP | Overall<br>Accuracy | Producer's<br>Accuracy | User's<br>Accuracy | Kappa |
|-------|----|----|----|----|---------------------|------------------------|--------------------|-------|
| FR    | 71 | 10 | 22 | 59 | 0.80                | 0.73                   | 0.86               | 0.60  |
| LR    | 67 | 14 | 20 | 61 | 0.79                | 0.75                   | 0.81               | 0.58  |

*(Source: Compiled by the Authors)*

Both AUC values and error matrix indicate that both models perform almost at the same level. Logistic Regression has marginally higher AUC. This indicates its better overall ability to distinguish between stable and unstable areas. The FR model shows higher user's accuracy. This means its landslide predictions are more reliable. The LR model has higher producer's accuracy and detects more actual landslides. Overall Logistic Regression performs slightly better because of its higher sensitivity. Frequency Ratio is more conservative and more reliable when predicts a landslide. Despite their methodological differences both models show consistent and complimentary understanding of landslide susceptibility.

#### **Conclusion**

This study aimed to assess and compare the suitability of frequency ratio and logistic regression models for landslide susceptibility zonation in the Rani Khola river basin. The analysis used a landslide inventory and ten conditioning factors. These were derived from remote sensing, field observations and GIS-based analysis. Both models effectively delineated landslide susceptibility zones for the Rani khola river basin showing similar spatial patterns and predictive capabilities. Logistic Regression model showed better performance in distinguishing landslide and non-landslide areas while Frequency ratio model presented better overall classification agreement

between predicted and observed landslide patterns. Logistic Regression is better suited for detailed scientific analysis. It is particularly useful for policy-level hazard modelling that requires assessment of combined factor effects. The frequency ratio method is simple and requires less data. It is therefore better suited for operational use, rapid assessment and planning in data-limited settings. The generated susceptibility maps can support site selection for development, prioritization of slope stabilization measures and early warning planning in the study area.

The present study has some limitations. The landslide inventory used is relatively small. Hence, it may affect the robustness of model predictions, particularly for logistic regression. Dynamic triggering factors such as rainfall intensity were not explicitly incorporated. In addition, model assumptions simplify the complex interactions among terrain, lithology, hydrology and human activities.

Future studies should focus on improving the modelling framework. The integration of multi-temporal data, rainfall intensity and seismic influences would improve representation of triggering processes. Higher-resolution spatial inputs and hybrid modelling approaches may further enhance predictive reliability and strengthen the applicability of landslide susceptibility maps for hazard management.

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# Analysis of Drainage Characteristics in the Context of Availability of Arable Land and Irrigation Potential in Lahaul-Spiti Region, North-Western Himalayas

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## Abstract

Drainage Characteristics of a geographical region reveal a great deal about water discharge, water potential, width of a valley and availability of arable land etc. Such study acquires more prominence in an encapsulated society of Himalayas in particular and hilly regions in general. Analysis of drainage characteristics in a region where only 0.36 per cent of geographical area is qualified as arable land acquires more significance. Lahaul-Spiti region is a 'cold desert region' located in the Indian part of North-Western Himalayas. It is characterised by arid to semi-arid conditions as temperature plummets below minus 20 Degree Celsius during winter months and seldom reaches 30 Degree Celsius during peak summer months. Precipitation is scanty as the region receives barely 49 mm of annual rainfall. Most of precipitation falls in the form of snow which indirectly determines the success of agricultural crops grown during short and single agricultural season barring some low lying river valleys during the summer months. It varies in elevation from 2850 metres to 6850 metres above mean sea level. Results show that there are thousands of streams which originate from the glacier laden peaks and mountainous ranges. Narrow longitudinal valleys provide only small amount of land for cultivation. A large part of the land surface characterised by moderate physiographic conditions cannot be brought under plough due to high altitude, steeper slopes and rock out-crops. *Spiti* valley is the widest and has better arable land and irrigation potential followed by *Chenab*, *Bhaga* and *Chandra* river valleys.

**Keywords:** Stream order, bifurcation ratio, drainage density, pattern and texture, arable land and irrigation potential

## Introduction

Any spatial and non-spatial aspects (spanning their comprehensibility) concerning watershed development as well as suitability of land as 'arable land' are closely intertwined and related to the overall drainage characteristics. These characteristics encompass natural drainage along

with its pattern, stream ordering, bifurcation ratio, drainage density and drainage texture etc. among others. All of these exert a very significant role in the development of landforms and consequently the availability of arable land to carry out spatial activities by human beings for their very survival and economic sphere as well. The study of drainage network provides an idea about the topography, climate, geology, and hydrological features of the region. Drainage is the most important natural agent in sculpturing landforms. It also has bearing on settlement patterns in this high altitude arid cold region. Therefore, it becomes necessary to analyse the drainage network in order to assess the role of natural environment and its impact on socio-cultural and economic aspects. Traditional management of biodiversity in India's cold desert region is described in terms of terrain, climate, people, flora and fauna, land use cover, village landscape, traditional farming, livestock and crop depredation, grazing practices, foraging, conventional conservation and interference with traditional grazing systems (Chandrasekhar 2003).

Being, a mountainous area with adverse climatic conditions, these affect the entire population, thus upsetting the entire range of economic activities. There is a lot of historical evidence to show that intensification of farming is likely to occur as a result of population growth. Population growth results in corresponding increase in pressure on natural resources with a danger of environmental degradation. It raises question about sustainable resource management in relation to contemporary land use and land cover change (Nusser 2000). Further, the scarcity of productive crop land has been defined through sustainable land management in marginal mountain areas of Himalayan region. It advocates that much marginal land exists between the cropland and forests and, if appropriate technologies were designed, these areas could be farmed sustainably. It is argued that these new approaches can combine successfully natural resource management with reasonable improvements in the livelihoods of local farming communities. These examples are then used to illustrate perspectives and processes for effective management of the marginal lands (Pratap 1999).

Any comprehensive study of agriculture and its allied activities requires analysis of various elements of physical environment such as physiography, climate, soil and water resources. Natural environment in different regions provide different set of possibilities to mankind. It plays a significant role in the efforts of human beings to modify the various elements of environment. It may permit modification even with low level of technological input in one region while it may restrict its appropriate utilisation even with higher level of technology in another. It is difficult to quantify technological development but it can be seen in relative terms. A kind of technology may hold relevance in one region while the same may not be of use in another region. The technical inputs those may prove to be a boon for plains may not be applicable in high mountainous regions. Man tries to modify the climatic constraints in the field of agriculture by moving into two directions. Firstly, with the help of artificial means like irrigation to overcome the moisture-deficiency. Secondly, by modifying the agricultural practices so that these correspond with the environmental limits, for example by introducing the early maturing varieties where temperature is very low over a longer period of the year or by cultivating crops, which require less water in the arid zones (Singh 1981). The size and shape of cultivable land puts a hindrance to put into use the bigger technical devices such like tractors with increasing altitude. However, these inputs are being used in some villages lying in the river terraces along the banks of both *Chenab* and *Spiti* rivers as well. Here, first of all, the availability of cultivable land is limited on account of topographic factors, alongside; it is equally difficult to bring more piece of land under the

category of cultivable land. Hence, one of the feasible alternatives could be through the adoption of high yielding crop varieties to maximise the crop production output, in such mountainous regions.

Since agriculture is directly related to the physical environment, thus variations in the latter are bound to affect agricultural land-use. Therefore, agriculture is not only an economic activity, but also a form of applied ecological activity (Coppock 1971). Irrigation is a very crucial input in such arid and high altitude regions of Himalaya for agriculture. Thus, irrigation helps in many specific activities to take advantage of market opportunities, as well as providing subsistence needs (Vincent 1995). The Lahaul-Spiti region is characterised by high mountainous environment which acts as a restrictive force on technological development within the region. The conventional and sustainable mountain agricultural development primarily depends on the effective and sustained utilisation of bio-resource base (Pratap 1992). Apart from this, it imposes constraints on its interaction with adjacent territories from where modern developmental impulses could possibly penetrate the region. All spatial interaction that takes place from the southern territory of the region comes to a standstill during winter months. This region is located in the highland terrain of the Great Himalayan Range and Trans-Himalayan Ranges. It is a land of extreme environment. The mountains adorn its surroundings with numerous ice-capped glaciers and the entire region has a very rugged terrain. The Great Himalayan Range keeps it largely isolated from the rest of the country and the neighbouring territories for almost half year. Thus, it becomes important to understand the following in order to comprehend the essential components of its physical environment a) to assess the components of natural drainage that reflects climatic conditions of this remote region and in turn gives shape to various landforms and resultant features in terms of availability of arable land; b) to see and qualitatively assess the significance of drainage network along with its various constituent parts in the moisture-deficit climate of the Lahaul-Spiti region. Generally, there seems to be lack of such studies to ascertain the relative availability of cultivable land and irrigation potential in cold desert region of Lahaul-Spiti. This study is exploratory in nature.

### **Study Area**

It is situated in the high altitude and isolated parts of the state. Prior to gaining the status of a district in 1960, Lahaul-Spiti was under Kullu sub-division of Kangra district. It extends between 31°44'57" N and 32°59'57" north latitude and between 76°46'29" E and 78°41'34" east longitude. This is the largest district of the state with an area of 13,835 square kilometres which constitutes 24.85 per cent geographical area of Himachal Pradesh. This region was inhabited by 33,224 persons in 2001, forming density of about 2 persons per square kilometres. There are 403 villages, out of which only 272 were inhabited in 2001 with no urban centre. At present, the district comprises three divisions, two tehsils and one sub-tehsil namely *Spiti*, *Lahaul* and *Udaipur* respectively. It is bounded by Kinnaur, Kullu, Kangra and Chamba district on the south, south-west and north-west while Jammu and Kashmir state and Tibet lie on the north and east of the district (Fig. 1).

Besides being the largest district of the state of Himachal Pradesh, only 0.36 per cent of the total geographical area is under cultivation. The district of Lahaul-Spiti has two major physiographic divisions, viz: mountain ranges and river valleys. Mountain ranges exhibit the striking intra-area variations from south to north than east to west with altitude varying between 3500 to 6000 metres above mean sea level (MSL).

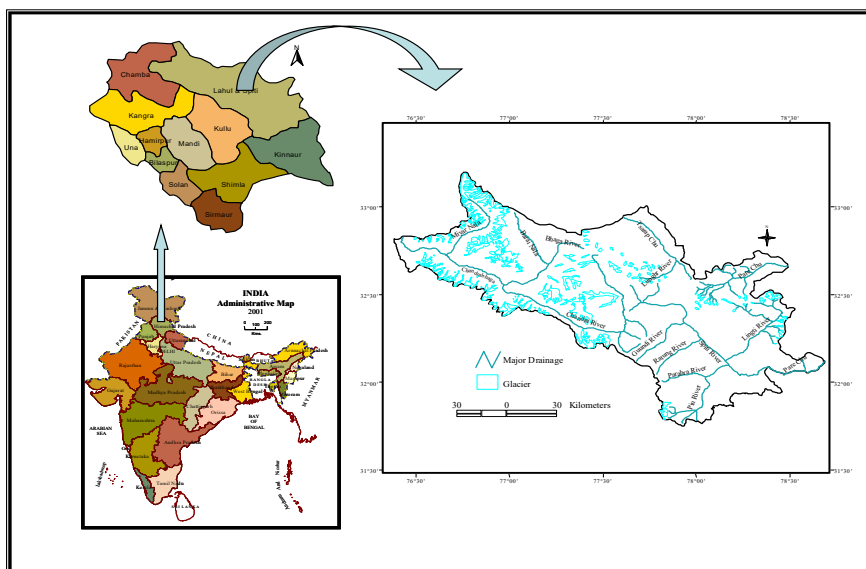


Fig. 1. Location of study area

The entire region falls in the rain-shadow area of the Himalayan ranges. Therefore, very meagre amount of annual precipitation i.e., 45.9 centimetres is received. Most of the rainfall comes in the form of snow and therefore is of little direct use. The region receives deficient amount of rainfall which is unevenly distributed. Almost all of the cultivated land is under irrigation. There is limited forest in the district lying in the southern and western portions. It is a cold desert region designated as a core zone of proposed biosphere region by the Ministry of Environment and Forests (MOEF). It forms a hot spot area from a view point of scanty natural vegetation and biodiversity conservation from low altitude to high altitude (Kuniyal 2009).

Due to inhospitable climate and rugged topography, the region historically remained largely isolated. Earlier prior to the opening of state of the art 'Atal Tunnel' in 2020, the area used to remain cut-off from the rest of the country from mid October to March-April due to heavy snowfall on the mountain passes linking the region with the outside World. Now, Atal Tunnel has facilitated the spatial access and eased out this problem to a considerable extent especially in Lahaul administrative division whereas Spiti division still remains cut-off for a considerable point of time (from Kunzum la mountain pass side). However, Spiti remains accessible through arduous Shimla-Kinnaur side for round the year except during severe winter months. These mountain passes provide sole access for all possible spatial interaction with the neighbouring territories and outside world. All economic activities except household activities come to standstill during long and severe winters. Living under such harsh environmental conditions, human beings try to modify the nature with available low level technology and at the same time adapt themselves to the needs of nature. Thus, in the light of above, it becomes vital to see and analyse the varied components of drainage elements across the altitudinal zones in different river valleys of the Lahaul-Spiti region. It is more so important in order to comprehend the spatial variations with reference to integrated water resource management which is closely knotted with the very lifeline

of the agricultural economy of the region. Being a part of the Himalayas, it has witnessed important geological and physiographic changes.

### Material and Methods

In order to fulfil the above objectives, secondary data sources have been used in order to comprehend the role of natural environment in context of the availability of arable land (AAL) and irrigation potential through the analysis of drainage characteristics. These are Shuttle Radar Topography Mission (SRTM) Digital data, 2000 and Thematic map 2000, Lahaul-Spiti, NATMO, Department of Science and Technology, Ministry of Science, Government of India. Drainage pattern has been analysed from the drainage map shown in Fig. 2. Stream ordering is worked out with the help of Strahler's scheme. Bifurcation ratio has been calculated by dividing the number of First order stream with the number of Second order stream and so on. Drainage density is a product of total length of streams in a unit area. Drainage texture furnishes an idea regarding the potential land suitable for agriculture and other economic purposes. It is a product of stream frequency and drainage density in a unit area (Smith 1950). The formula for calculating drainage texture has been given below:

$$DT = DD \times SF$$

Where, DT is Drainage Texture in the form of an index;

DD is Drainage Density i.e., total length of all streams in per unit area;

SF is Stream Frequency i.e., number of streams per unit area.

### Result and Discussions

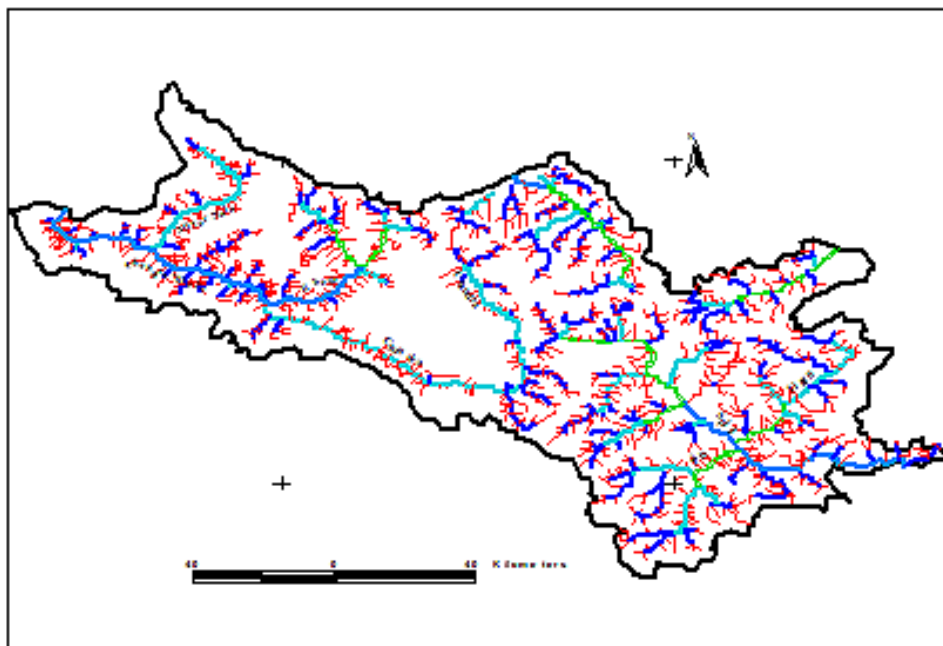
Lahaul-Spiti has three major rivers namely *Chandra*, *Bhaga*, and *Spiti* along with their numerous tributaries. River *Chandra* and *Bhaga* after their confluence at *Tandi* becomes '*Chandra-Bhaga*' also known as '*Chenab*'. These are the major drainage basins of the entire area evident from Fig. 2.

#### Chandra River

It originates from a huge snowfield on the south-eastern base of the '*Baralacha Pass*' around '*Chandra Tal*'. It flows in a south-westerly direction for the first 48 kilometres. Then, it takes sharp north westerly and western direction for further 64 kilometres up to *Tandi*, where it joins *Bhaga* river. On its upper left bank is situated a beautiful glacial lake known as '*Chandra Tal*' that straddles between a low ridge and '*Kunzum range*'. The lake is about a kilometre long and half a kilometre wide with an outlet into the river. *Chandra* river is fed by a number of glaciers. The biggest being the *Shigri* on its left bank and the *Samundri*, *Sonapani* glaciers on the right bank. It registers an average fall of about 12.5 metres per kilometre upto its confluence with *Bhaga* at *Tandi*.

#### Bhaga River

This river has its origin from south-western side of the '*Baralacha Pass*' at an altitude of about 4800 metres. It flows in a north-west direction for almost 13 kilometres and then takes south-westerly course. It has a total length of about 65 kilometres upto *Tandi*. The main tributaries are *Barsi*, *Milang nullah* (*nullah* is a local word for stream) and *Billing nullah* etc. Its valley is barren and rocky upto *Darcha*. It has an average fall of about 28 metres per kilometre.



### Chenab River

After their confluence at 'Tandi', *Chandra* and *Bhaga* rivers are called *Chandra-Bhaga* or *Chenab*. The River is entirely fed by a number of glacier tributaries from either side. The right bank tributaries include *Shansha nullah*, *Thirot nullah*, *Chokang nullah*, and *Miyar nullah* etc. *Lingar nullah*, *Rashil nullah*, *Nalda nullah*, *Ghor nullah*, and *Galigorh* are the left bank tributaries. Among these, *Miyar nullah* is the largest tributary with a length of about 32 kilometres. *Chenab* runs in a north-westerly direction for about 75 kilometres until its exit to Chamba district. It has an average fall of about 6 metres per kilometre from a height of 2800 metres.

*Yunan* River in the north-eastern part flows into the *Zaskar*. It joins *Lingti Chu* and further become the *Tsarp Chu*, a sub-tributary of the *Indus* river system.

### Spiti River

The *Spiti* river originates from far north on the eastern slopes of the mountain ranges between Lahaul-Spiti. It begins at the base of the *Kunzum range* with the confluence of '*Kunzum La Tagpo*' and the streams *Kabzina* and *Pinglung*. Broad and flat valleys bordered by high vertical cliffs mark the *Spiti* river. The total length of the river is about 130 kilometres on the south-east within Spiti. It continues upto *Khabo* in Kinnaur district where it joins the *Satluj* river. Several tributaries join the *Spiti* River on both sides. On its right bank are *Chiomo*, *Gyundi*, *Rabtang*, *Pin* and *Sumra* etc. *Thanar*, *Hanse*, *Tagling*, *Shila*, *Kaza*, *Lingti*, *Tabo*, and *Parechu* streams join on the left bank. The *Pin* river is the most important right bank tributary of the *Spiti* river. The length of the *Pin* river is about 50 kilometres.

*Lingti* river is about 40 kilometres long, which is an important left bank tributary of the *Spiti* river. Valleys of these important tributaries accommodate large number of villages.

These are an important source of irrigation for agriculture. Whole area is a cold desert as it receives only scanty precipitation. High mountain ranges impose a climatic barrier in the way of moisture carrying winds. Therefore, the entire area remains arid due to rain-shadow effect of the Himalayan ranges. Thus, the role and importance of natural drainage get enhanced in the cold and arid mountainous regions like Lahaul-Spiti.

The drainage pattern denotes the spatial geometric arrangement of the streams in a particular region. It depends on a large number of factors; some of the important ones are the nature of slope, structural control, lithological characteristics, tectonic factors and vegetal characteristics etc. It becomes quite clear from Fig. 2 that the most prominent is dendritic drainage pattern. It can be seen in almost every river basin. The second pattern discernible is that of trellis pattern. Drainage pattern also furnishes a general idea about the settlements.

Stream ordering provides an idea regarding the dimension of the basin of each tributary and about the extent of water discharge. There is generally a positive correlation between water discharge and width of the valley with the stream order. In other words, higher the stream order wider will be the valley and higher will be the water discharge. It gives an indirect idea about the water resources of the area.

Fig. 1.3 and Table 1 shows stream ordering and bifurcation ratio in Lahaul-Spiti. The *Chenab* river attains fifth order from its starting point at *Tandi* where *Chandra* and *Bhaga* meets. *Bhaga* is the only one important tributary that attains fourth order before its confluence with *Chandra* river. There are one fifth order, two fourth order, twelve third order, seventy two second order and 482 first order streams those join to make *Chenab* river. The overall bifurcation ratio between 1<sup>st</sup> and 2<sup>nd</sup> order is nearly seven, six between 2<sup>nd</sup> and 3<sup>rd</sup> and six between 3<sup>rd</sup> and 4<sup>th</sup> order streams. The bifurcation ratio decreases between 4<sup>th</sup> and 5<sup>th</sup> order streams i.e., two respectively.

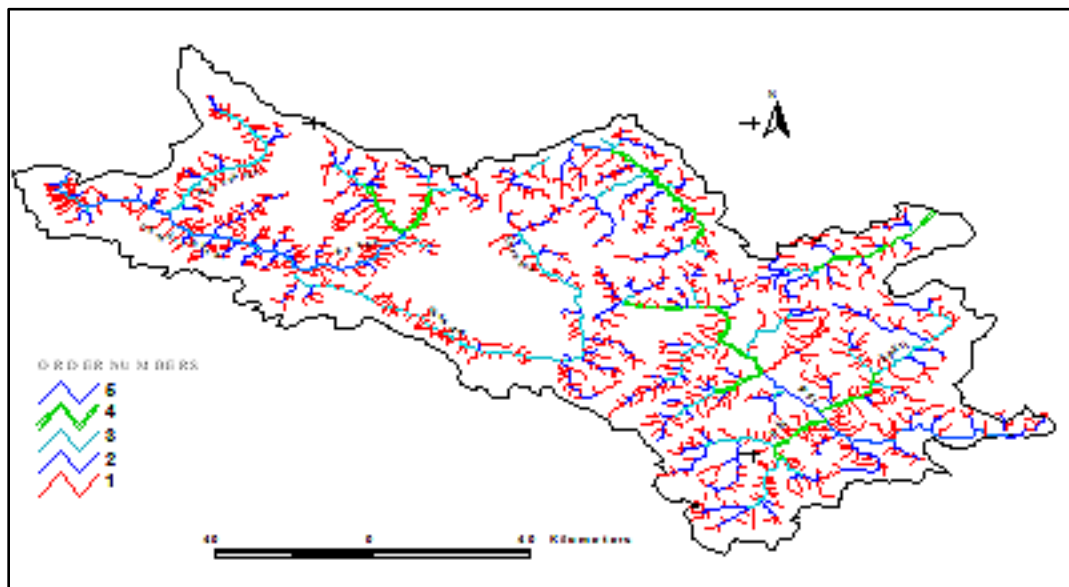


Fig. 3. Stream Orders in Lahaul – Spiti

*Bhaga* is the only major stream which has fourth order constituted by 5 third order, 16 second order and 127 first order streams. The bifurcation ratio between 1<sup>st</sup> and 2<sup>nd</sup> order is nearly eight and between 2<sup>nd</sup> and 3<sup>rd</sup> order is nearly three. It is five between 3<sup>rd</sup> and 4<sup>th</sup> order streams. The *Chandra* river basin has one third order, 18 second order, and 152 first order streams. The ratio between its successive streams stands nearly eight between first and second order stream and between second and third order is nearly eighteen. The *Mijar* river has 1 third order stream, 10 second order and 70 first order streams. The bifurcation ratio is seven between first and second and ten between second and third order streams respectively.

*Spiti*, the main river in Spiti tehsil of Lahaul-Spiti district becomes fifth order stream. It has one fifth order, 10 fourth order, 17 third order, 67 second order and 362 first order streams. The river has predominately first and second order streams. It shows bifurcation ratio of nearly five for first two successive orders and it is nearly four between second and third order streams. It is nearly two between third and fourth order streams. It increases sharply between fourth and fifth order i.e., ten respectively. *Pin* is the important right bank tributary of Spiti river having 89 first order, 14 second order, 3 third order and 1 fourth order streams. It reflects bifurcation ratio of nearly 6 between first and second order and nearly 5 between second and third order streams. It is 3 between third and fourth order streams. *Lingti* is the left bank tributary having 72 first order, 12 second order, 4 third order and 1 fourth order streams. It shows bifurcation ratio of 6 between first two successive orders, 3 between second and third order and 4 between third and fourth order streams, respectively.

Table 1. Bifurcation Ratio in Lahaul - Spiti

| Stream order | Miyar |         |      | Bhaga  |        |      | Chandra |         |      | Chenab |         |      |
|--------------|-------|---------|------|--------|--------|------|---------|---------|------|--------|---------|------|
|              | No.   | Length* | B.R. | No.    | Length | B.R. | No.     | Length  | B.R. | No.    | Length  | B.R. |
| 1            | 70    | 184.75  | 7.0  | 127    | 322.67 | 7.9  | 152     | 343.44  | 8.4  | 482    | 1204.13 | 6.7  |
| 2            | 10    | 28.48   | 10.0 | 16     | 77.81  | 3.2  | 18      | 104.35  | 18.0 | 72     | 319.29  | 6.0  |
| 3            | 1     | 52.78   |      | 5      | 29.69  | 5.0  | 1       | 123.58  |      | 12     | 208.59  | 6.0  |
| 4            |       |         |      | 1      | 33.26  |      |         |         |      | 2      | 33.26   | 2.0  |
| 5            |       |         |      |        |        |      |         |         |      | 1      | 103.82  |      |
| Stream order | Pin   |         |      | Lingti |        |      | Spiti   |         |      |        |         |      |
|              | No.   | Length  | B.R. | No.    | Length | B.R. | No.     | Length  | B.R. |        |         |      |
| 1            | 89    | 272.36  | 6.4  | 72     | 240.60 | 6.0  | 362     | 1130.15 | 5.4  |        |         |      |
| 2            | 14    | 90.67   | 4.7  | 12     | 79.70  | 3.0  | 67      | 406.87  | 3.9  |        |         |      |
| 3            | 3     | 42.13   | 3.0  | 4      | 48.31  | 4.0  | 17      | 163.91  | 1.7  |        |         |      |
| 4            | 1     | 20.34   |      | 1      | 20.10  |      | 10      | 101.36  | 10.0 |        |         |      |
| 5            |       |         |      |        |        |      | 1       | 73.49   |      |        |         |      |

The above analysis clearly indicates that *Spiti* river valley is the widest of all valleys and has highest water discharge. It is followed by *Chenab*, *Bhaga* and *Chandra* river valleys. The analysis of river valleys gives us an idea regarding the extent of cultivable land and potential for irrigating the agricultural fields. These valleys are situated in the *Zaskar*, *Great Himalayan* and *Pir Panjal* mountain ranges respectively. Thus, it becomes important to analyse the relationship between stream ordering and drainage density in order to see the potential for irrigating the crop fields.

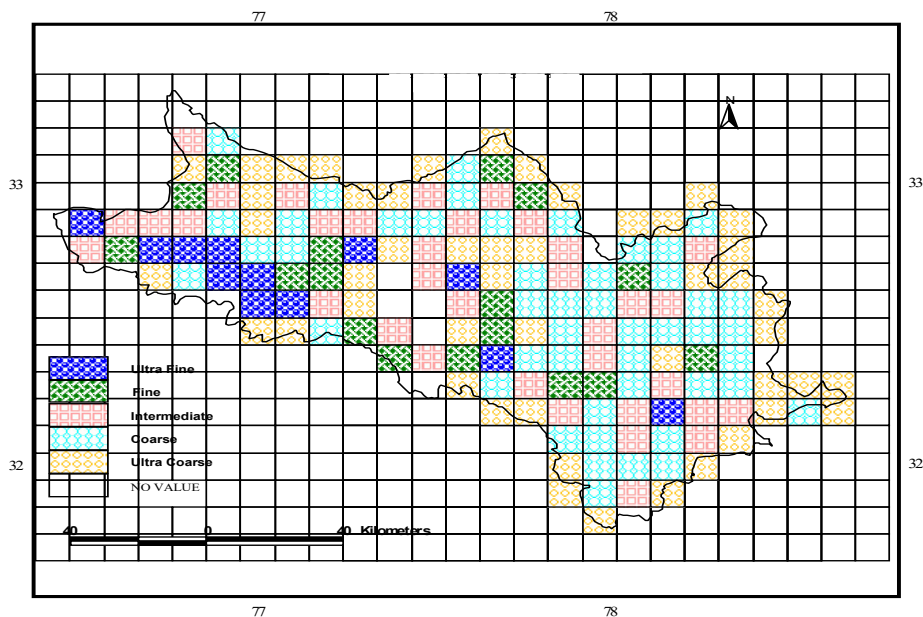


Fig. 4. Drainage Density of Lahaul - Spiti

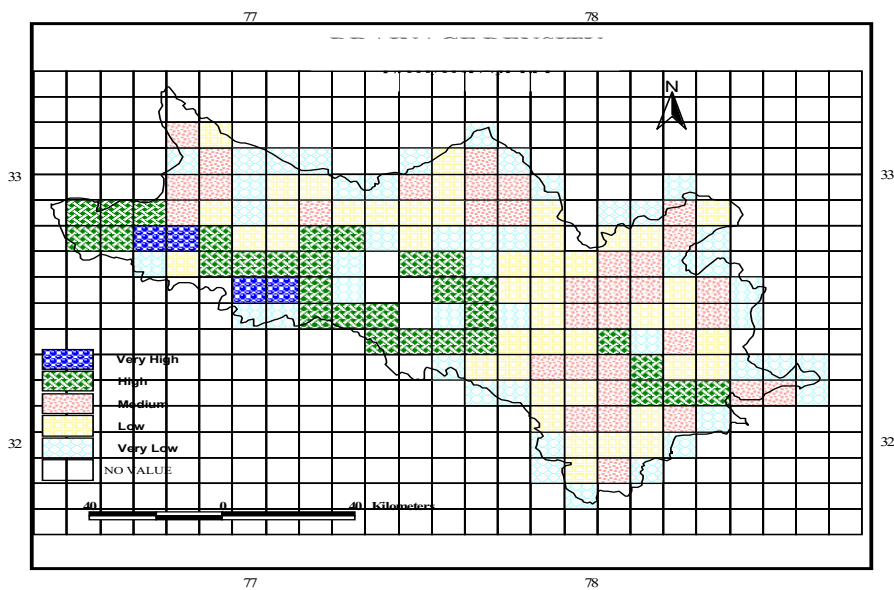


Fig. 5. Drainage Texture of Lahaul - Spiti

It becomes clear from the Fig. 5 that *Pattan* and *Chenab* valleys have very fine drainage texture among all the valleys. North-eastern parts of *Bhaga*, south-eastern *Chandra* valley and south-central *Spiti* valley has very fine drainage texture. Most of the lower parts of *Lahaul* and south-central *Spiti* valley have fine drainage texture. A very large proportion is situated in the lower river courses. It reflects the dense network of streams as well as longer courses of their flow. This occurs due to the formation of gullies and dissection of surface. A significant part of the land situated in the north-west and south-west portions of Lahaul-Spiti reveals intermediate drainage texture. Most of the upper part of the Lahaul-Spiti district shows coarse and ultra coarse drainage texture. A significant proportion of this land is either covered under glaciers and snowfields or pastures at higher altitude, hence not suitable for agriculture.

Higher index of drainage texture because of gullies and dissection of land makes difficult use of land for economic activities. It becomes clear from the above discussion that a significant proportion of the Lahaul-Spiti has fine and ultra-fine drainage texture, especially in the lower parts. This makes larger tracts along the river courses available for agriculture.

### **Conclusion**

Overall analysis of the drainage characteristics makes it clear that very large parts of the land have high altitude, steep-slopes and highly rugged rocky terrains. Narrow longitudinal valleys provide only small amount of land for cultivation. A large part of the land surface characterised by moderate physiographic conditions cannot be brought under plough due to inaccessibility and rock out-crops. These aspects make the utilisation of land very difficult for agricultural purposes. Only a fraction of the total geographical area i.e., 0.36 per cent is available as arable land in high altitude cold desert region of Lahaul-Spiti.

Drainage characteristics such like stream ordering, bifurcation ratio, drainage density and drainage texture tells us about the width of a valley, water discharge, water potential (here considered in terms of irrigating the agricultural fields) and the availability of arable land. Study of these parameters may provide an indirect idea about the water potential (crucial input for growing of crops in moisture-deficit cold desert region) and potential of availability of cultivable land across the river valleys. Of all the valleys, *Spiti* valley is the widest and has relatively better arable land and has highest water discharge. It is followed by *Chenab*, *Bhaga* and *Chandra* river valleys. Moreover, twin valleys of *Chandra* and *Bhaga* are characterised by the youthful stages of the respective river systems. This paper also points out that a significant proportion of the Lahaul-Spiti region has fine and ultra-fine drainage texture, especially in the lower parts. This aspect qualifies the larger tracts of land along the river courses as arable land to carry out the agricultural pursuits.

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