NATIONAL INSTITUTE OF TECHNOLOGY

TIRUCHIRAPPALLI – 620 015

CEPE40 – DISASTER MODELING AND MANAGEMENT

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MID-TERM PROJECT – GROUP 02

FLOOD HAZARD MAPPING FOR BRAHMAPUTRA RIVER BASIN

1 OBJECTIVES OF THE STUDY

Floods are among the most destructive natural disasters, causing widespread socio-economic and environmental damage. Their frequency and intensity have been increasing due to the compounding effects of climate change, deforestation, and unplanned urbanization. The Brahmaputra River region, encompassing Assam and North-eastern areas that extend into Bangladesh, is highly vulnerable to floods due to its unique geographical and hydrological characteristics. This region experiences intense monsoonal rainfall, coupled with rapid snowmelt in the Himalayas, which results in recurrent flooding. Additionally, the dynamic nature of the Brahmaputra River, with its braided channels and significant sediment load, contributes to unpredictable flood patterns. The objective of this study is to develop a spatially detailed flood hazard map for this region, identifying areas at varying levels of risk to aid in effective flood management and mitigation strategies.

To address this, the study integrates multiple datasets such as digital elevation models (DEMs) for deriving topographic parameters like slope and aspect, hydrological indices such as Stream Power Index (SPI) and Topographic Wetness Index (TWI), and proximity to stream networks. These datasets are further augmented with geospatial layers on Soil type, Geology, and Geomorphology to capture the region's complex land and hydrological dynamics. A key component of the analysis is the incorporation of Flood Inventory data, which provides a record of historical flood occurrences. This data serves as a critical input for machine learning algorithms, enabling the model to learn patterns associated with flood-prone areas and predict flood probabilities for other parts of the region.

The probabilistic flood hazard map produced by this study assigns values ranging from 0 to 1, indicating the likelihood of flooding, where 0 represents negligible risk and 1 represents high risk. Such a map provides actionable insights for disaster preparedness, enabling authorities to prioritize high-risk zones for flood defences, early warning systems, and evacuation planning. Moreover, this mapping framework supports sustainable regional planning by guiding infrastructure development away from high-risk areas. The study also aims to foster resilience in vulnerable communities by providing them with data-driven tools for risk assessment and mitigation. This work contributes to the global discourse on disaster risk reduction and aligns with the Sendai Framework for Disaster Risk Reduction by emphasizing the need for data-driven approaches to minimize losses and enhance adaptive capacity in flood-affected regions.

2 STUDY AREA

The study area encompasses the Brahmaputra River region, a transboundary river system that flows through the northeastern part of India, primarily Assam, and into Bangladesh, forming a vital part of the Ganga-Brahmaputra-Meghna basin. This region lies in the **Universal Transverse Mercator (UTM) Zone 46N** and is characterized by diverse topography, ranging from the Himalayan foothills to vast floodplains. The Brahmaputra River is one of the largest rivers in the world in terms of discharge and sediment transport, making it a significant hydrological entity in South Asia. Spanning an approximate length of 2,900 km, the river originates from the Angsi Glacier in Tibet, flows through Arunachal Pradesh and Assam in India, and ultimately merges with the Ganges and Meghna rivers in Bangladesh, draining into the Bay of Bengal.

Geographical and Climatic Features

The Brahmaputra basin is defined by its highly dynamic and braided river channels, frequent channel shifts, and seasonal variations in discharge. The region experiences a **subtropical monsoon climate**, with annual rainfall ranging from 1,500 mm to over 6,000 mm in certain areas. The monsoon season, from June to September, accounts for over 70% of the total rainfall, often triggering widespread flooding. Additionally, the melting of Himalayan glaciers during the summer months contributes significantly to the river's discharge, further exacerbating the flood risk.

Challenges in the Study Area

The Brahmaputra basin faces unique challenges, including rapid erosion, sedimentation, and the shifting of river courses, making flood management complex. Additionally, unregulated urban growth and deforestation in the region have increased the runoff rate, amplifying flood severity. The lack of high-resolution historical flood data and the transboundary nature of the river pose additional challenges for comprehensive flood management.

This study aims to address these challenges by integrating multi-source spatial datasets and advanced machine learning techniques to produce a reliable flood hazard map. By focusing on the Brahmaputra River region, this research contributes to the sustainable management of one of South Asia's most vital and vulnerable river systems.

3 METHODOLOGY AND DATA PROCESSED

The GIS-based flood hazard mapping in this study was performed using **ArcGIS**, a powerful geospatial software platform. ArcGIS was used for spatial data processing, analysis, and visualization. The software enabled the integration of various datasets, calculation of derived parameters, and machine learning-based flood probability prediction. Below is a list of the datasets used in this study, along with the purpose and relevance of each:

- **Digital Elevation Model (DEM):** Provides the foundational topographic data required to calculate slope, aspect, drainage patterns, and hydrological indices essential for understanding flood dynamics.
- **Distance from Stream:** Indicates proximity to rivers or streams, which directly influences flood susceptibility, as areas closer to water bodies are more prone to inundation.
- **Slope:** Derived from the DEM, slope data represents the steepness of the terrain. Steeper slopes are less likely to retain water, while flatter areas are more prone to flooding.
- **Aspect:** Represents the direction of slope faces. It helps analyze how terrain orientation affects water accumulation and flow during rainfall events.
- **Topographic Wetness Index (TWI):** A measure of potential water accumulation based on slope and upstream contributing area. High TWI values indicate areas with greater likelihood of water retention and flooding.
- **Drainage Density:** Quantifies the total length of streams and rivers per unit area. Higher drainage density reflects areas with an extensive drainage network, which can either increase or mitigate flood risks depending on terrain and land use.
- **Stream Power Index (SPI):** Derived from TWI, it estimates the erosive power of flowing water. Higher SPI values indicate areas with stronger water flow, which can increase flood hazard in those regions.
- **Soil Classes:** Provides information about soil type and its permeability. Different soil types influence water infiltration and runoff, affecting flood susceptibility.

- **Geology:** Indicates the underlying rock types and structural features, which play a role in water absorption and groundwater recharge, affecting flood dynamics.
- **Geomorphology:** Describes landform features and processes, such as floodplains, terraces, or hill slopes, which are critical in understanding flood-prone areas.
- **Precipitation/Rainfall:** Represents the spatial and temporal distribution of rainfall, which is the primary driver of flooding events in the region. Historical and current rainfall patterns help predict flood risk.
- **Flood Inventory Data:** Contains records of previous flood occurrences, including their spatial extent and intensity. This data is crucial for training machine learning models to identify flood-prone areas based on historical patterns.

Each dataset was pre-processed in ArcGIS to ensure compatibility and consistency. Layers were clipped to the study area's boundaries, resampled as needed, and converted to uniform spatial resolutions. Derived parameters (e.g., slope, TWI, SPI) were calculated using tools within ArcGIS. These processed datasets were then used in the subsequent analysis to develop the flood hazard map.

3.1 METHODOLOGY

1) DIGITAL ELEVATION MODEL:

Data Source: OpenTopography - https://opentopography.org/

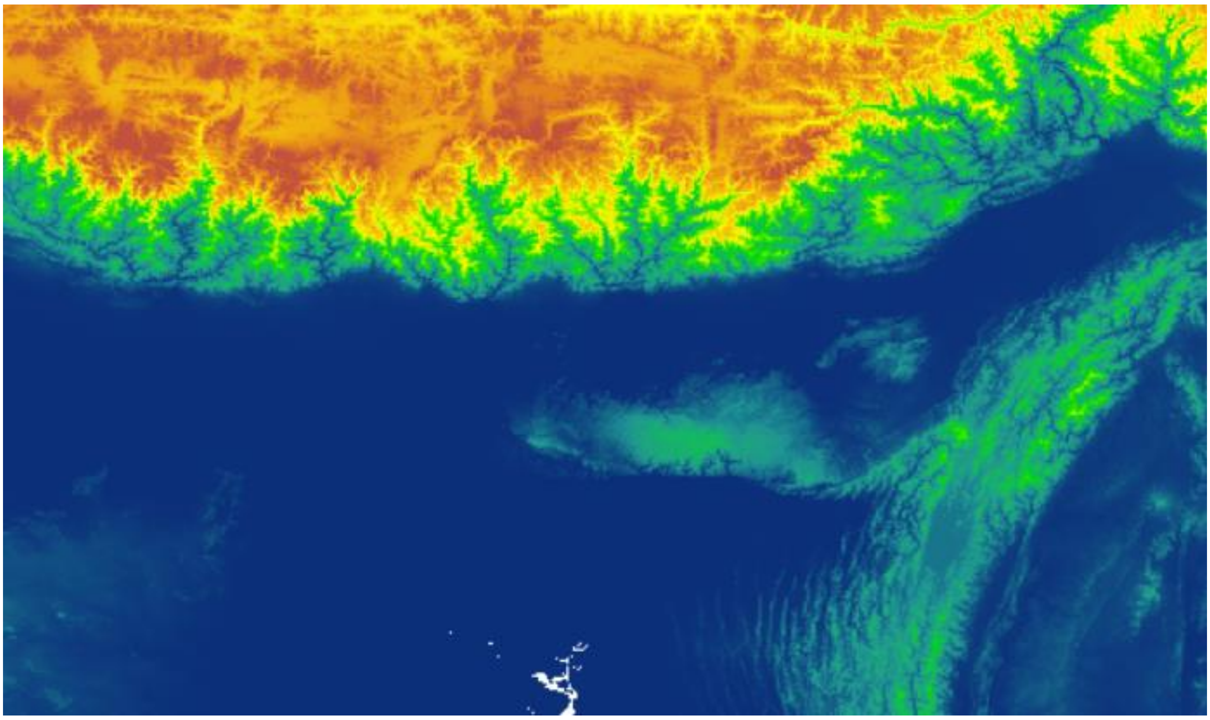
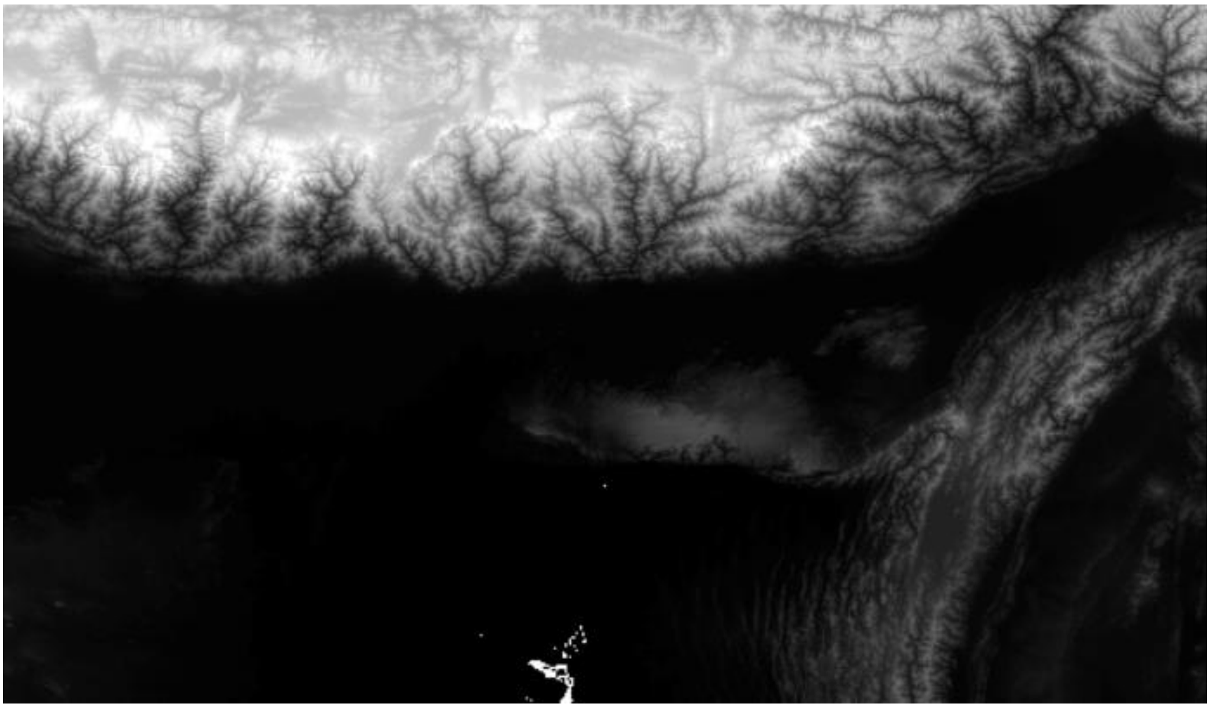
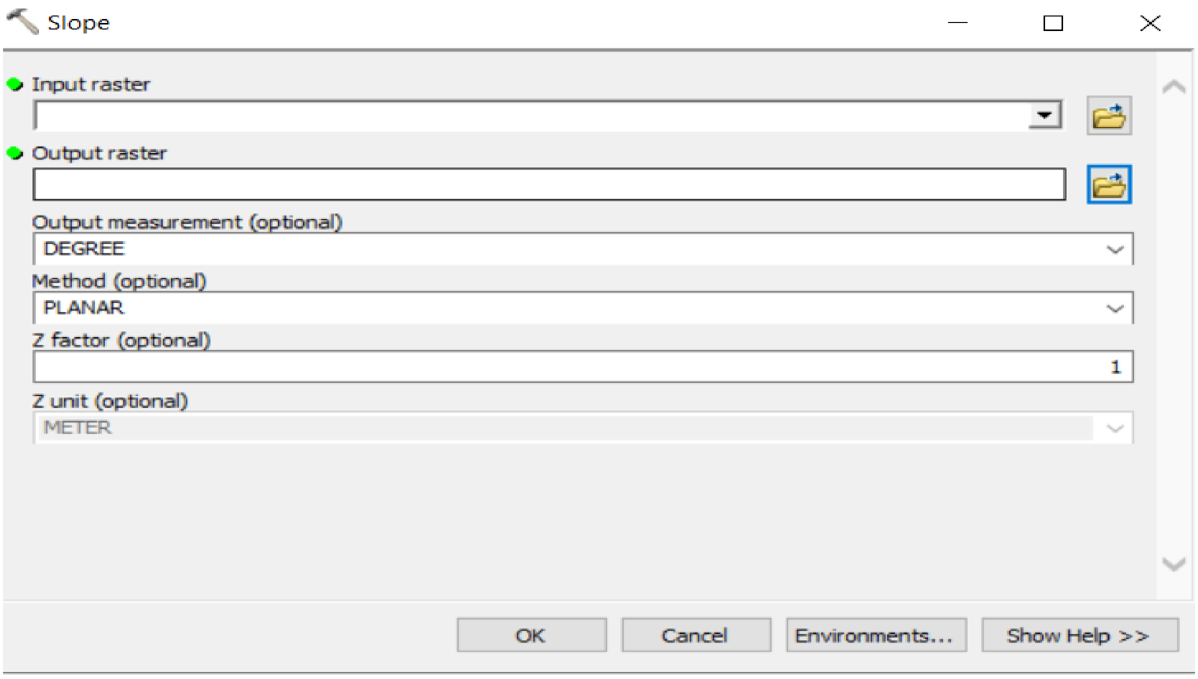


Fig 1: DEM map for the study area

Filled DEM:



2) SLOPE:



Here, The Digital Elevation Model raster is provided as the input raster

Slope Raster:

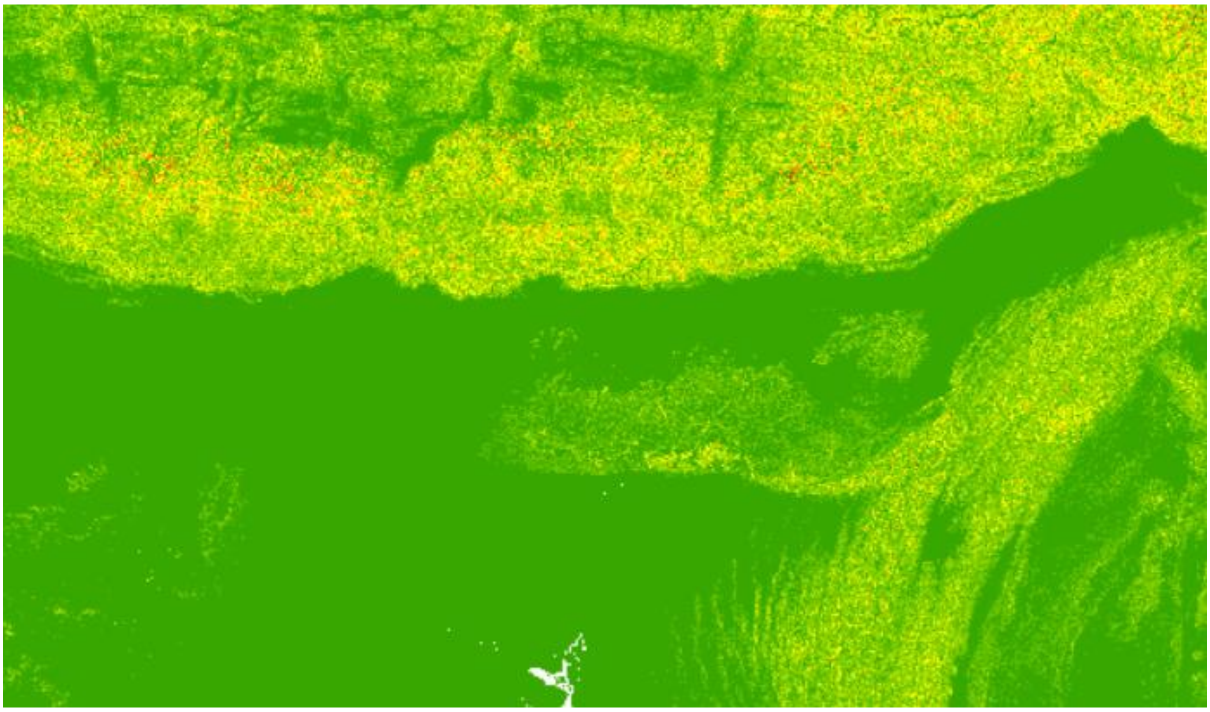
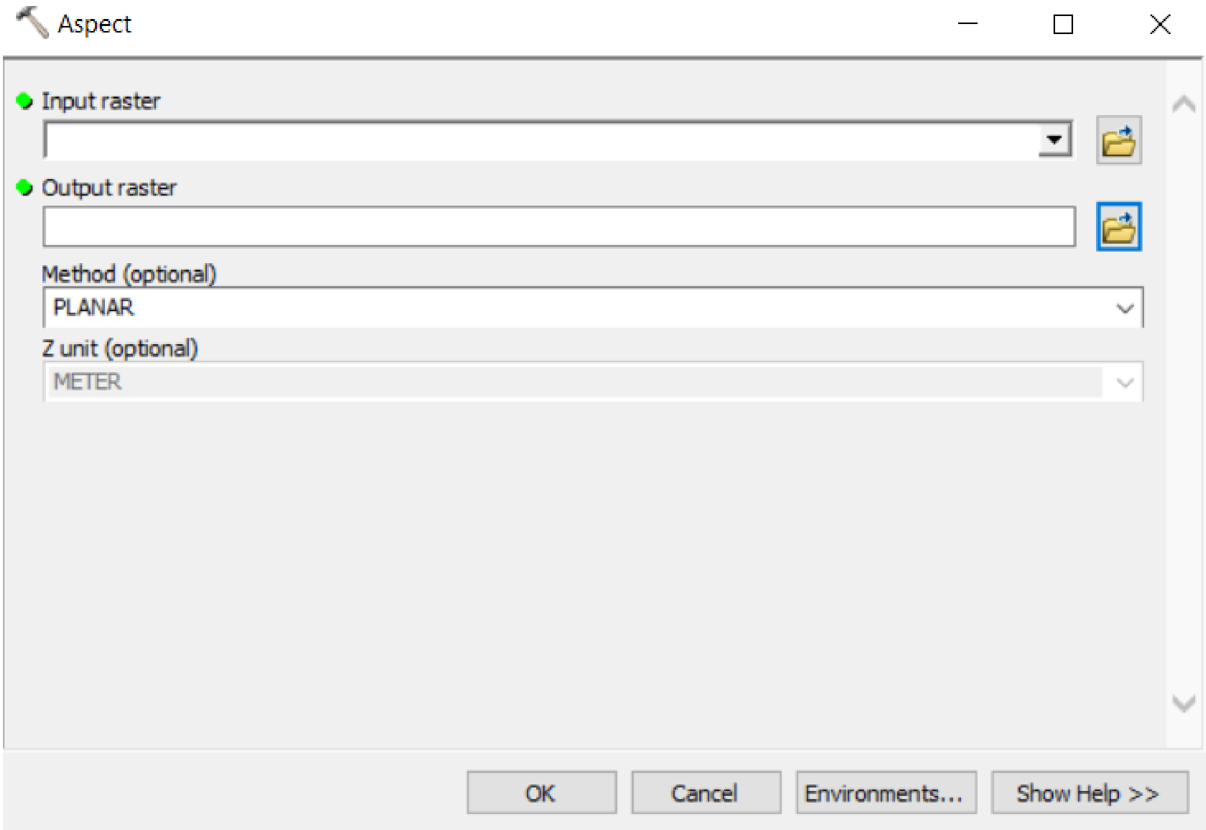


Fig 2: Slope Raster

The output raster's measurement could be both in "DEGREE" or "PERCENTAGE RISE" but the latter is preferred in Flood Hazard Mapping.

3) ASPECT:



The DEM raster is again fed as the input to the Aspect tool.

Aspect Raster:

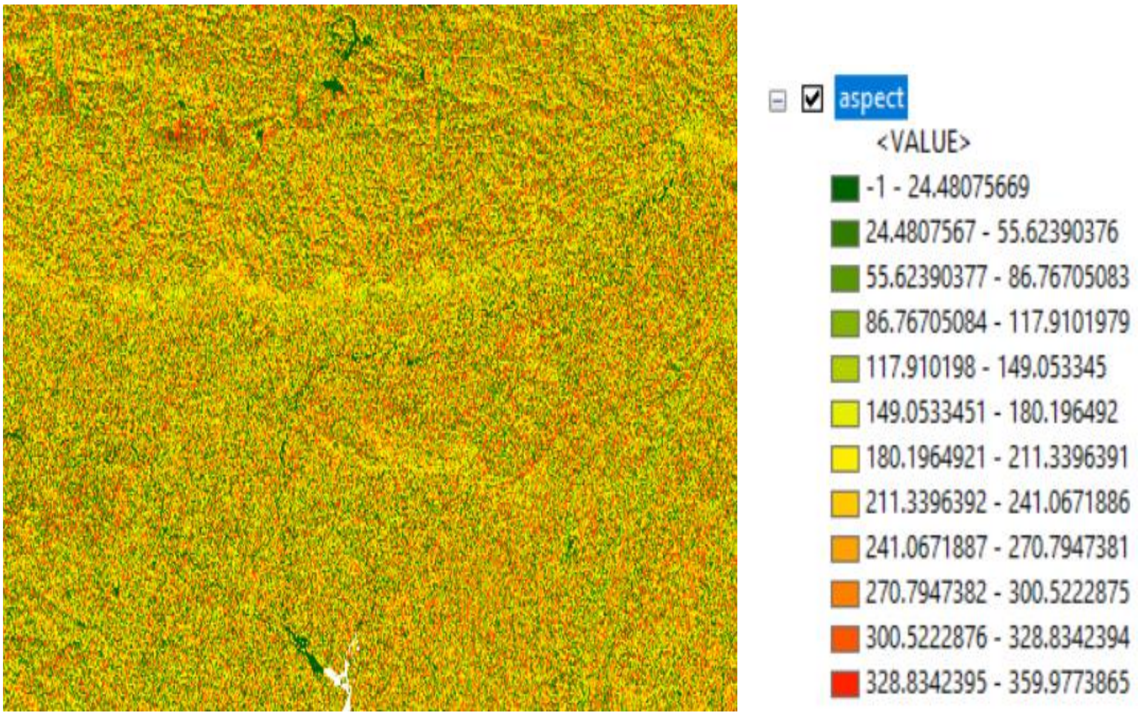


Fig 3: Aspect Raster

4) TOPOGRAPHIC WETNESS INDEX (TWI):

TWI (also known as the compound topographic index (CTI)) is an indicator that measure the potential on where water tend to accumulate. High index value indicates high potential of water accumulated due to low slope and vice versa.

Typically, the raw TWI indicators range from **–3** to **30**.

Steps to find TWI:

1) Project DEM: Use the "Project Raster Tool".

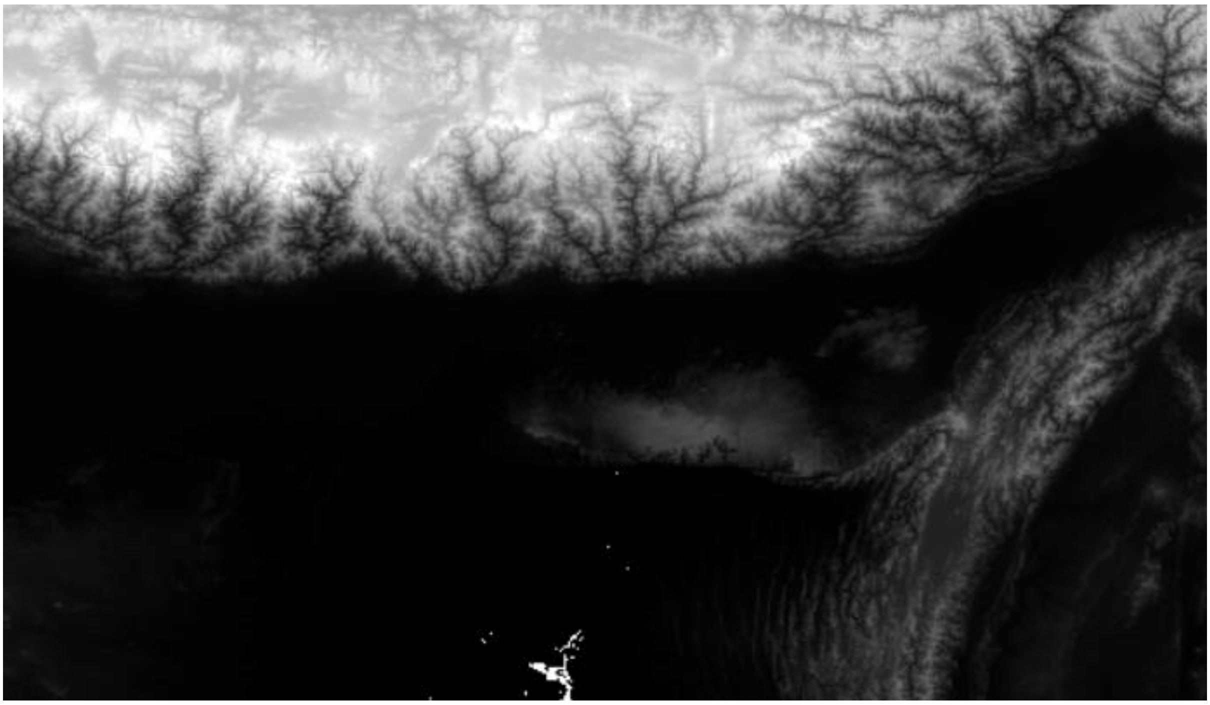


Fig 4: Projected Digital Elevation Model

2) Use the "Fill" tool to make the Filled DEM.

3) Devise the Flow Direction: Filled DEM goes as the input.

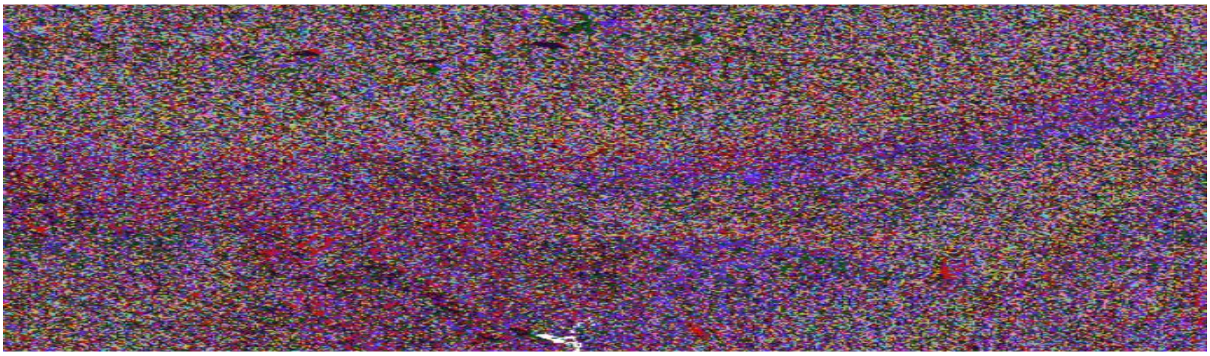


Fig 5: Point Flow direction

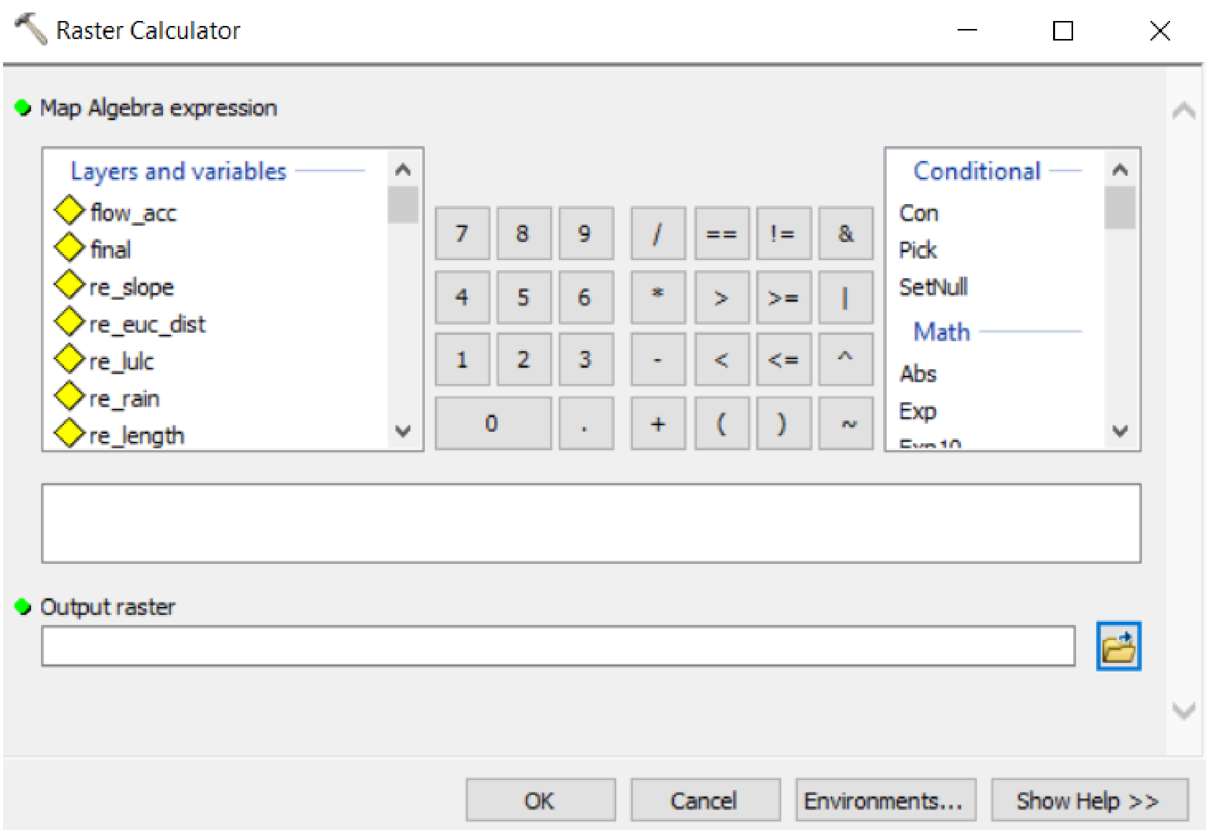
4) Prepare the Flow Accumulation raster: Flow Direction raster goes as the input. Use the “Flow Accumulation” tool.

5) Calculate Slope from DEM in Degree (or use the previously computed Slope raster)

6) Calculate the slope in radians. It’s the same as multiplying by ${}^{\pi}/_{180}$.

$$Slope\ (rad) = Slope\ (deg) * \frac{1.570796}{90}$$

This is calculated by the “Raster Calculator” tool.



7) Calculate Tan Slope:

$$Tan_{slope} = Con(slope > 0, tan(slope)\ \ 0.001)$$

If the slope is zero, then tan of zero will be zero and we will end up with undefined pixel. So, for a pixel value of zero one has to substitute a smaller value 0.001 or (0.00565 which is tan of a flat land close to zero slope). Use the “Raster Calculator” again for the same.

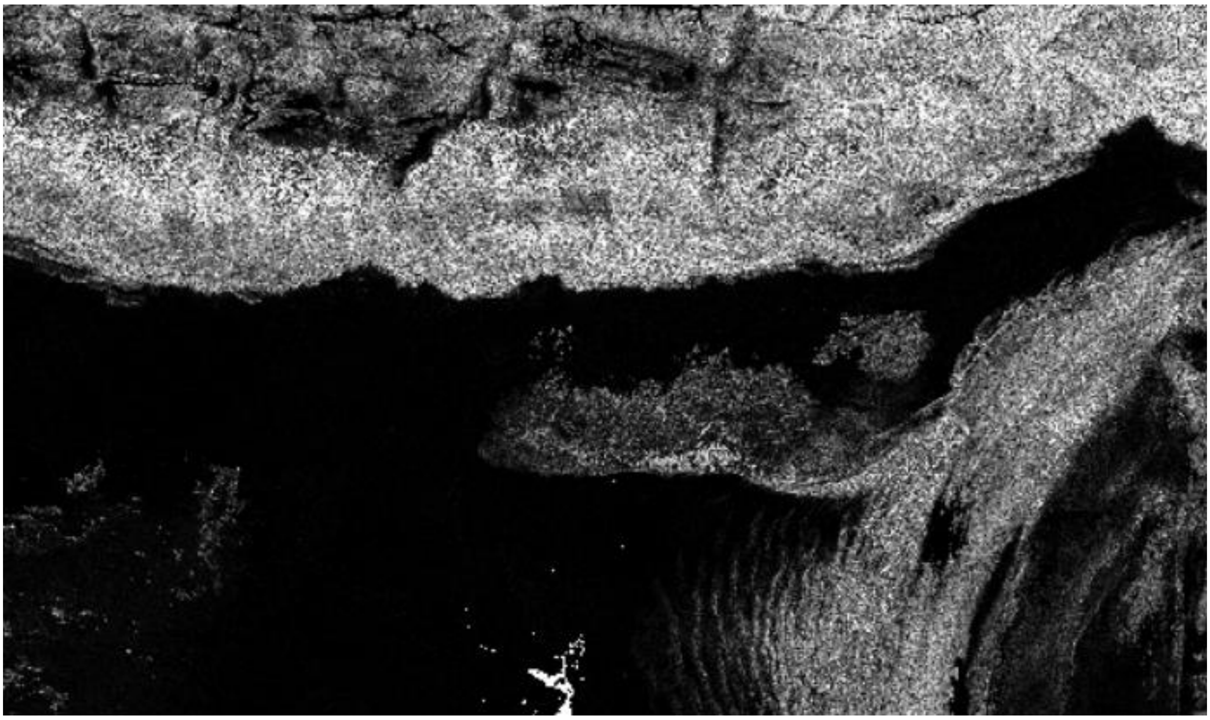


Fig 5: Tan Slope

8) Scale the Flow Accumulation:

$$FA_{Scaled} = (FA + 1) \times Cellsize(30)$$

One must add 1 since the border pixels have zero flow accumulation value. If 1 value isn't added, the watershed divides which has no flow accumulation will have a zero value and ln(0) will be undefined.

9) Calculate TWI:

$$Twi = \ln\left(\frac{Flow\_acc\_scaled}{Tan\_Slope}\right)$$

Use the "Raster Calculator"

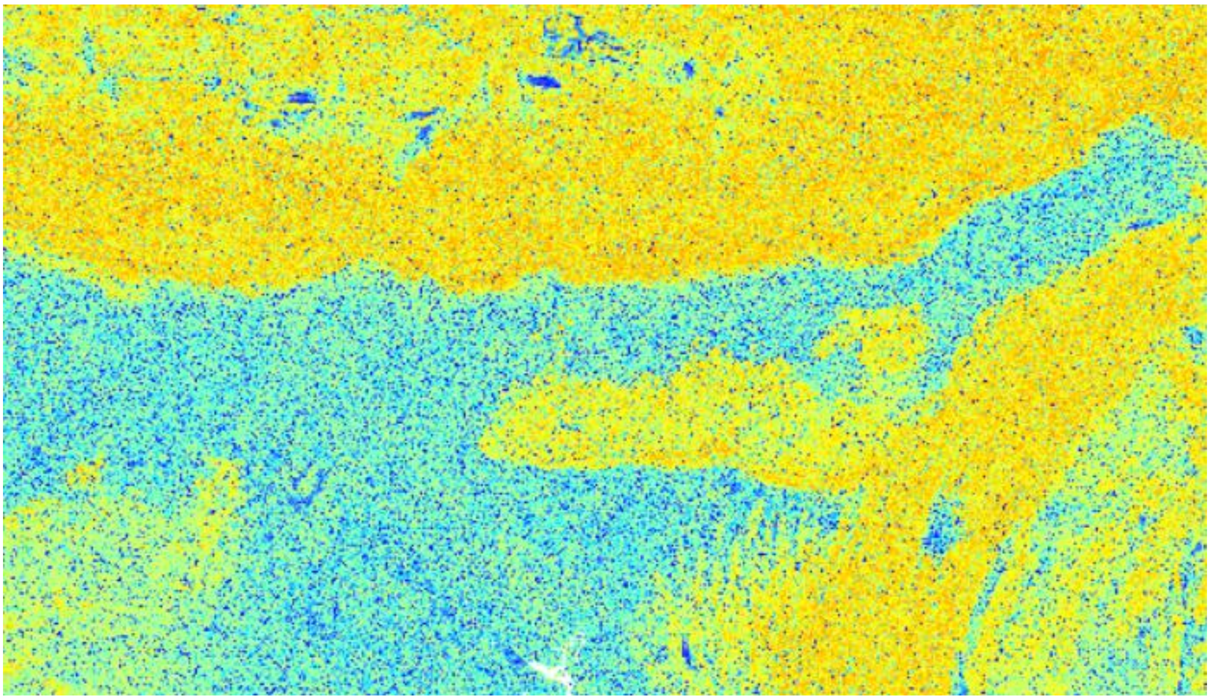


Fig 6: Topographic Wetness Index raster

5) STREAM POWER INDEX (SPI):

SPI is the product of the catchment area and slope, and measures the erosive power of overland flow. SPI can be used to identify suitable locarions for soil conservation measures, thereby reducing the effects of concentrated surface runoff.

Formula:

$$SPI = \ln((Flow_{acc} + 0.001) \times (\left(\frac{Slope\_\%}{100}\right) + 0.001)$$

It shows negative values for areas with topographic potential for deposition and positive values for potential erosive areas. Highest values related to a strong slope gradient. This terrain morphology contributes significantly to the erosion's aggressiveness and land degradation risk process. The lowest values represent relatively flat areas influencing the susceptibility to flooding and sediment deposition and accumulation.

Steps to find SPI:

1) Project DEM raster
2) Calculate Flow Direction
3) Calculate Flow Accumulation
4) Calculate SPI

Use “Raster Calculator” tool for step 4.

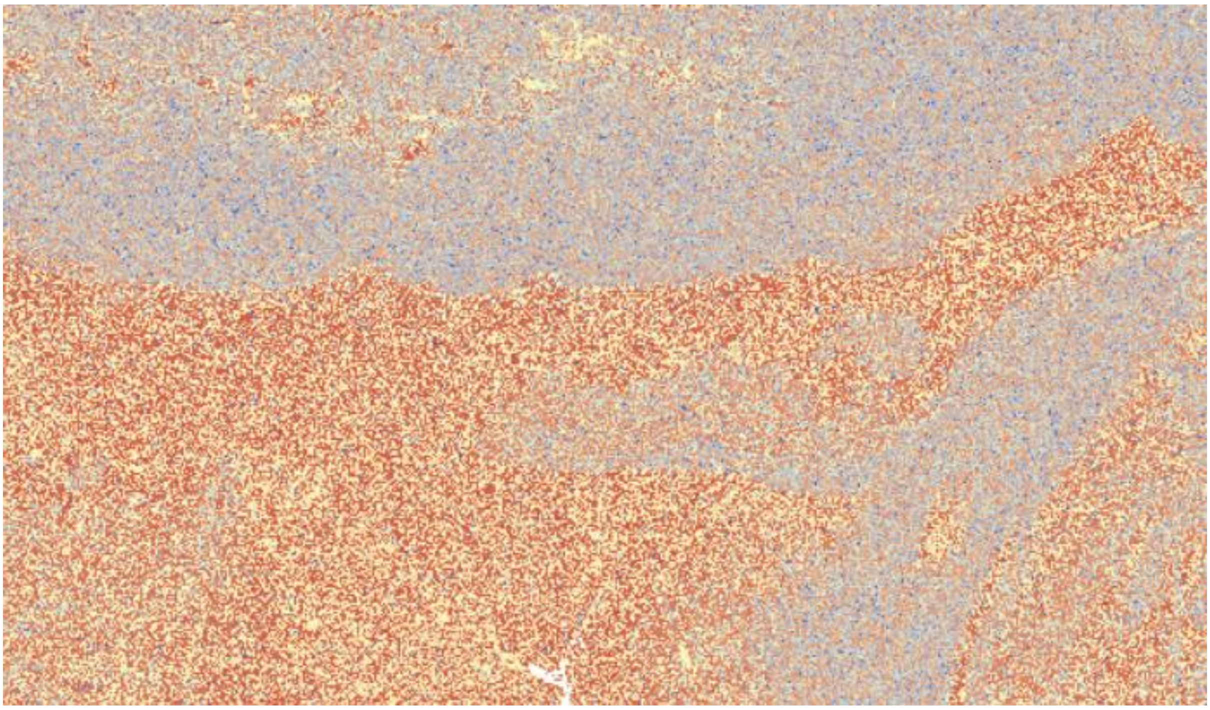


Fig 7: Stream Power Index Raster

6) SOIL CLASSIFICATION:

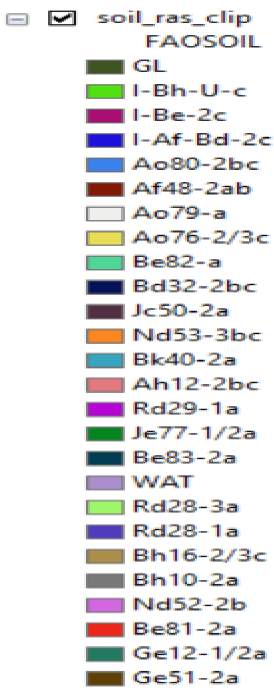
Data Source: Soil Map FAO – data.apps.fao.org/map/catalog/srv/eng

Use SQL queries to extract the soil map for INDIA by using Attribute table's parameters.

Fig 8: Soil Map for India

Clip the India's soil map using the study area.

Fig 9: Clipped Soil Classified Raster to study area



7) GEOLOGY AND GEOMORPHOLOGY

Data Source: Bhukosh - bhukosh.gsi.gov.in

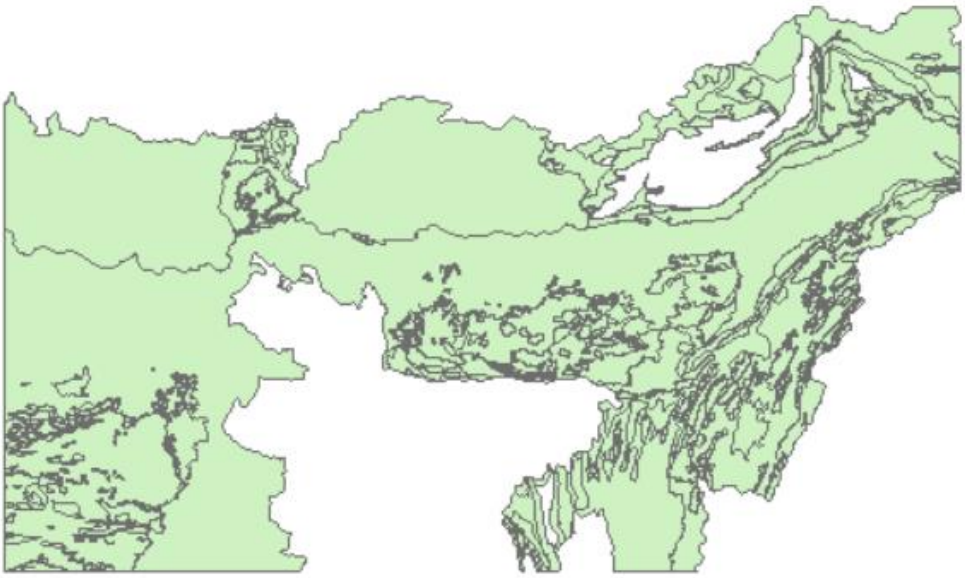


Fig 10: Geology Map for the study area

Attribute table looks like this:

Table

Geology 2M

FID	Shape	OBJECTID	INDEX_	AGE_CODE	AGE	SUPERGROUP	GROUP_	GEOM_ID	
86	Polygon	4520	YINGKIONG Gp.	38	EOCENE		YINGKIONG	384	384,Y
373	Polygon	2421	DUBRAJPUR Fm. (UPPER GONDWANA)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	646	646,D
374	Polygon	2420	DUBRAJPUR Fm. (UPPER GONDWANA)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	646	646,D
380	Polygon	4050	UPPER GONDWANA Gp. (DUBRAJPUR Fm.)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	649	649,U
384	Polygon	4277	UPPER GONDWANA Gp. (DUBRAJPUR Fm.)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	649	649,U
385	Polygon	4278	UPPER GONDWANA Gp. (DUBRAJPUR Fm.)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	649	649,U
449	Polygon	4276	UPPER GONDWANA Gp. (DUBRAJPUR Fm.)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	649	649,U
451	Polygon	3515	DUBRAJPUR Fm. (UPPER GONDWANA)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	646	646,D
457	Polygon	3514	DUBRAJPUR Fm. (UPPER GONDWANA)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	646	646,D
460	Polygon	3516	DUBRAJPUR Fm. (UPPER GONDWANA)	64	TRIASSIC - JURASSIC	GONDWANA	UPPER GONDWANA	646	646,D
464	Polygon	1600	UPPER GONDWANA Gp. (PANCHET, SUPRA PANCHET, PARSORA, Fm.)	63	TRIASSIC - EARLY JURASSIC	GONDWANA	UPPER GONDWANA	639	639,U
479	Polygon	1655	UPPER GONDWANA Gp. (PANCHET, SUPRA PANCHET, PARSORA, Fm.)	63	TRIASSIC - EARLY JURASSIC	GONDWANA	UPPER GONDWANA	639	639,U
484	Polygon	1654	UPPER GONDWANA Gp. (PANCHET, SUPRA PANCHET, PARSORA, Fm.)	63	TRIASSIC - EARLY JURASSIC	GONDWANA	UPPER GONDWANA	639	639,U
487	Polygon	1653	UPPER GONDWANA Gp. (PANCHET, SUPRA PANCHET, PARSORA, Fm.)	63	TRIASSIC - EARLY JURASSIC	GONDWANA	UPPER GONDWANA	639	639,U
489	Polygon	1652	UPPER GONDWANA Gp. (PANCHET, SUPRA PANCHET, PARSORA, Fm.)	63	TRIASSIC - EARLY JURASSIC	GONDWANA	UPPER GONDWANA	639	639,U
376	Polygon	1641	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
432	Polygon	1608	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
436	Polygon	1607	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
455	Polygon	3513	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
462	Polygon	2373	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
465	Polygon	3948	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
467	Polygon	2375	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
468	Polygon	1605	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
469	Polygon	2377	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
476	Polygon	4214	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
478	Polygon	1656	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
482	Polygon	4215	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
491	Polygon	2371	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
496	Polygon	2372	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
497	Polygon	1612	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
498	Polygon	1609	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U
499	Polygon	3703	UNCLASSIFIED METAMORPHICS Gp.	98	ARCHAEAN- PALAEOPROTEROZOIC		UNCLASSIFIED METAMORPHICS	981	981,U

Geomorphology:

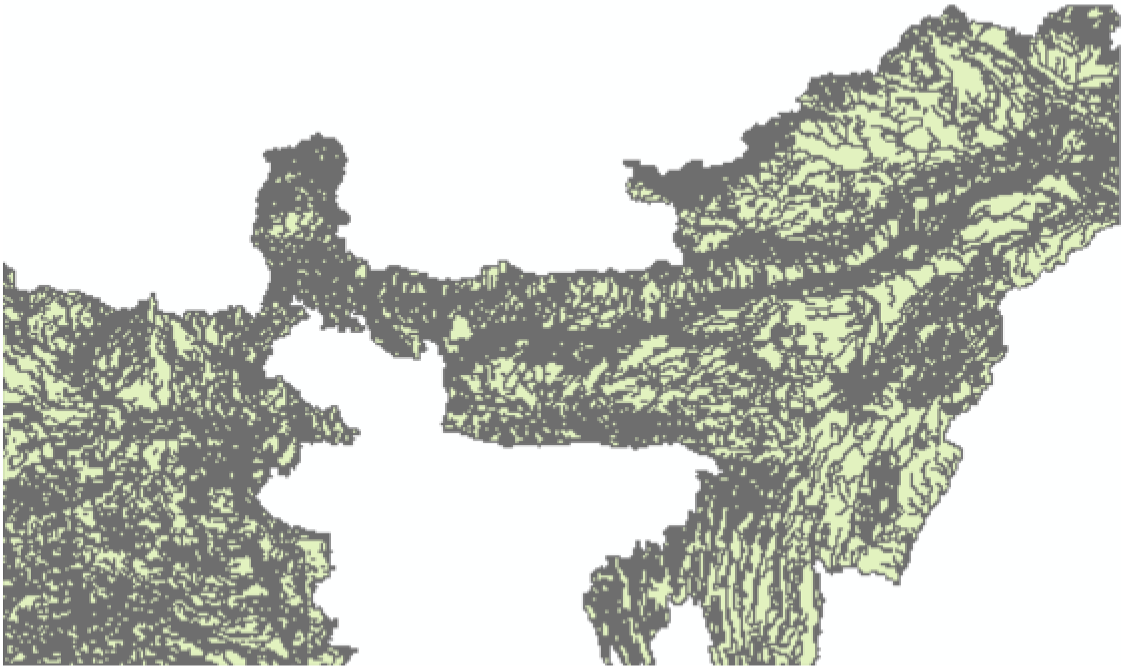


Fig 11: Geomorphology Map clipped to the study area

Attribute table looks like this:

Geomorphology 250K

FID	Shape	OBJECTID	SHAPE_LENG	DESCRIPTIO	LEGEND_SHO
1261	Polygon	215947	5031.565758	Abandoned Quarry	Quarry and Mine Dump
12629	Polygon	215948	2248.260986	Abandoned Quarry	Quarry and Mine Dump
15428	Polygon	216178	22617.34436	Abandoned Quarry	Quarry and Mine Dump
15430	Polygon	216175	1063.123837	Abandoned Quarry	Quarry and Mine Dump
15432	Polygon	216180	17123.481395	Abandoned Quarry	Quarry and Mine Dump
15439	Polygon	216176	896.205257	Abandoned Quarry	Quarry and Mine Dump
17341	Polygon	216179	1674.58552	Abandoned Quarry	Quarry and Mine Dump
17343	Polygon	216181	2981.3056	Abandoned Quarry	Quarry and Mine Dump
17345	Polygon	216184	5743.80431	Abandoned Quarry	Quarry and Mine Dump
17346	Polygon	216182	8014.792444	Abandoned Quarry	Quarry and Mine Dump
17347	Polygon	216183	10708.991956	Abandoned Quarry	Quarry and Mine Dump
17351	Polygon	216190	14071.205521	Abandoned Quarry	Quarry and Mine Dump
17353	Polygon	216187	8291.193936	Abandoned Quarry	Quarry and Mine Dump
17356	Polygon	216185	2997.904007	Abandoned Quarry	Quarry and Mine Dump
17358	Polygon	216186	4315.880347	Abandoned Quarry	Quarry and Mine Dump
17363	Polygon	216188	4773.049099	Abandoned Quarry	Quarry and Mine Dump
17375	Polygon	216192	4014.399993	Abandoned Quarry	Quarry and Mine Dump
17376	Polygon	216194	3750.130274	Abandoned Quarry	Quarry and Mine Dump
17382	Polygon	216193	1399.061005	Abandoned Quarry	Quarry and Mine Dump
17436	Polygon	216201	3233.855755	Abandoned Quarry	Quarry and Mine Dump
17444	Polygon	216198	1209.503347	Abandoned Quarry	Quarry and Mine Dump
17447	Polygon	216197	2526.860147	Abandoned Quarry	Quarry and Mine Dump
17454	Polygon	216191	2128.74004	Abandoned Quarry	Quarry and Mine Dump
17457	Polygon	216189	4273.661228	Abandoned Quarry	Quarry and Mine Dump
17475	Polygon	216177	8320.385389	Abandoned Quarry	Quarry and Mine Dump
17484	Polygon	216219	11312.871549	Abandoned Quarry	Quarry and Mine Dump
17485	Polygon	216217	8158.495114	Abandoned Quarry	Quarry and Mine Dump
17486	Polygon	216218	2273.461725	Abandoned Quarry	Quarry and Mine Dump
17687	Polygon	216210	8762.067978	Abandoned Quarry	Quarry and Mine Dump
17699	Polygon	216209	3135.779314	Abandoned Quarry	Quarry and Mine Dump
17700	Polygon	216207	1837.22913	Abandoned Quarry	Quarry and Mine Dump
17701	Polygon	216208	5782.225339	Abandoned Quarry	Quarry and Mine Dump

The values for all x-y co-ordinates are extracted and consolidated.

8) PRECIPITATION:

Data Source: https://crudata.uea.ac.uk/cru/data/hrg/

Use the "Make NetCDF Raster Layer" and feed the raster from the above link. Select the variable as "pre", and Band dimension as "time".

Change the data-frame properties where-in the UTM 46N zone is selected. Clip the world precipitation map to the study area and export.

From the newly formed map, select the last 12 bands (12 x 10 = 120 bands).

Use the tool "Composite Bands" and feed all these 12 layers and save the output raster.

Use the tool "Cell Statistics", feed the composite band from the previous step, and "SUM" to be the overlay statistics.

With the "Raster to Point" tool, convert the above overlay to point feature.

Now. The interpolation is done using the "IDW" tool, with the point feature as the input.

Output:

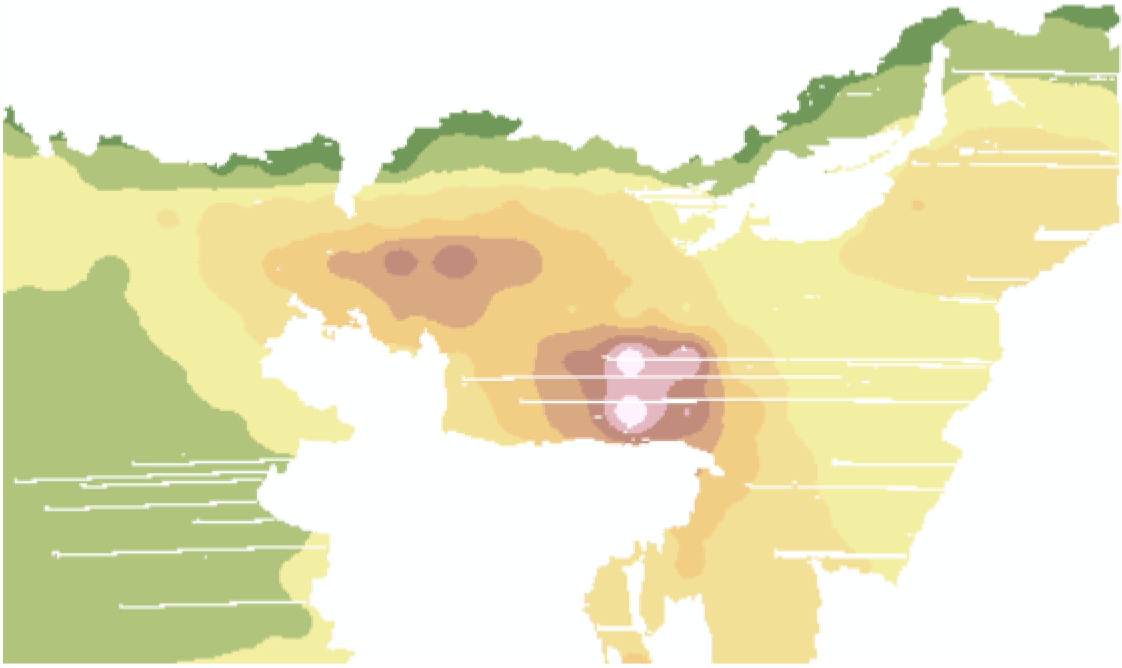


Fig 12: Rain Map for the study area

9) FLOOD INVENTORY MAP:

Flood inventory map is the conglomerate of all the historic flood incidents and their corresponding event cause, of which flood regions just due to the "Brahmaputra River" are extracted using SQL queries, later which is converted to a point feature, where-in every co-ordinate falling in the flood region denotes a flood point (1).

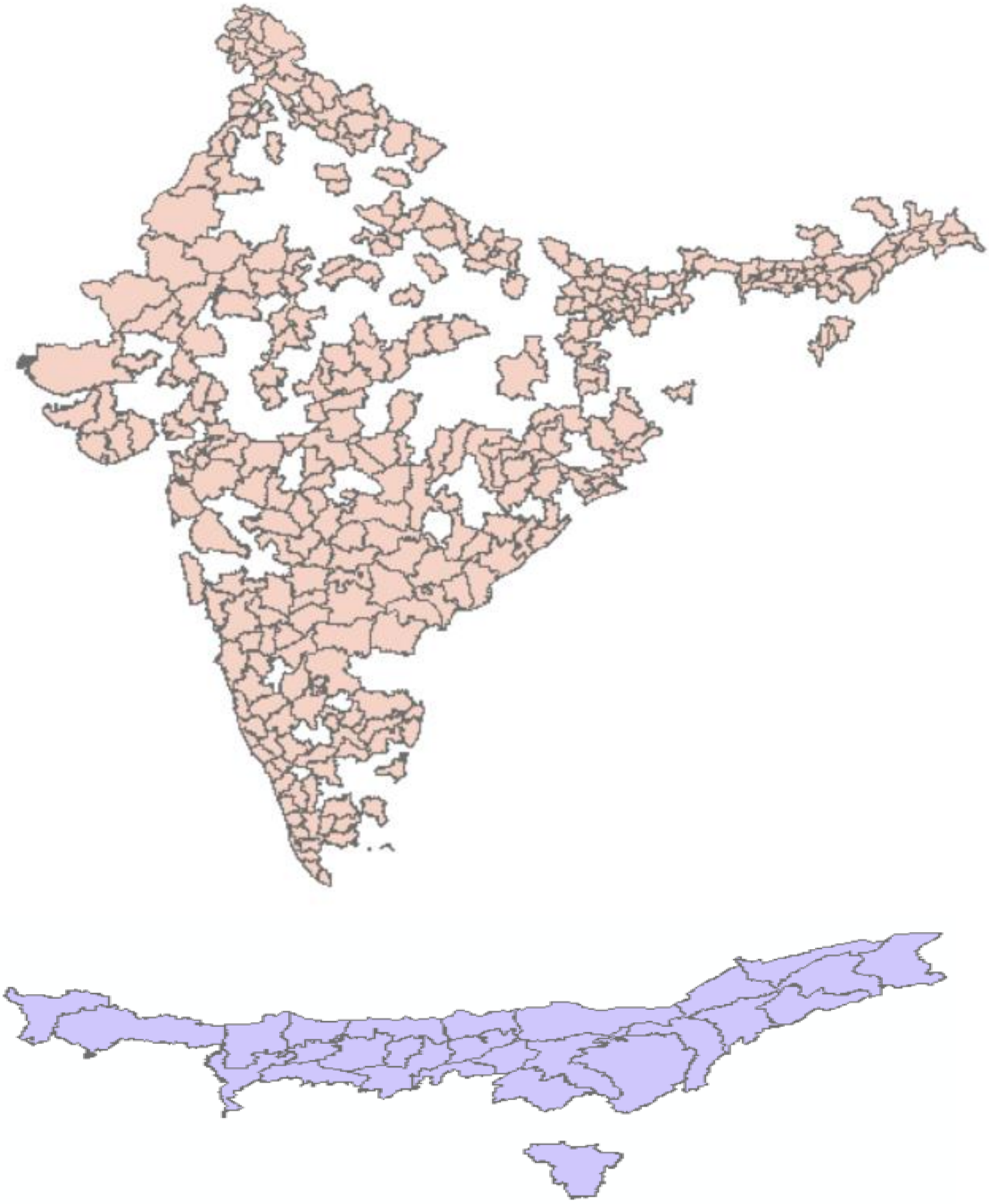


Fig 13: Flood inventory map for whole of India and Floods only due to river Brahmaputra

10) LULC MAP:

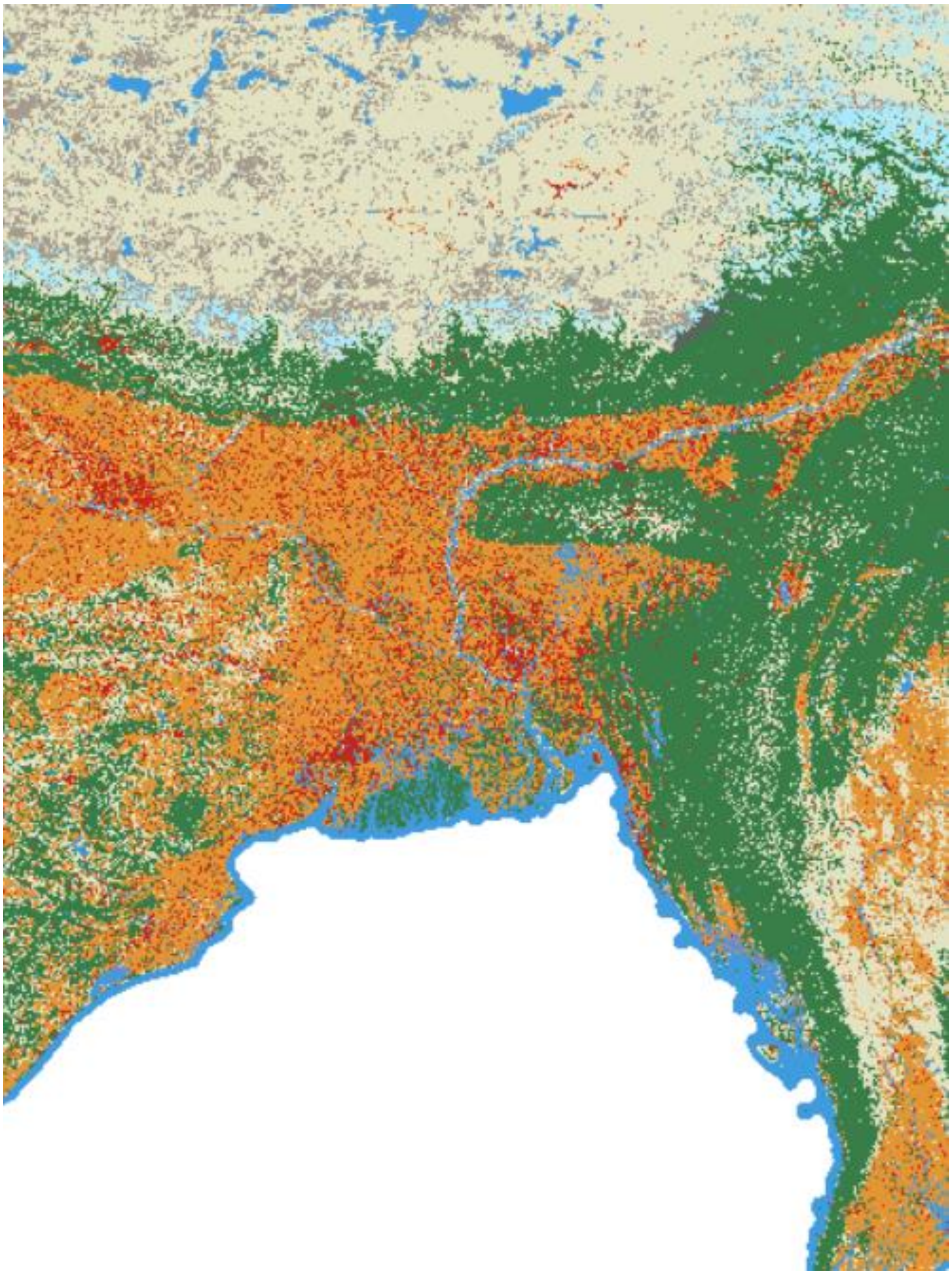
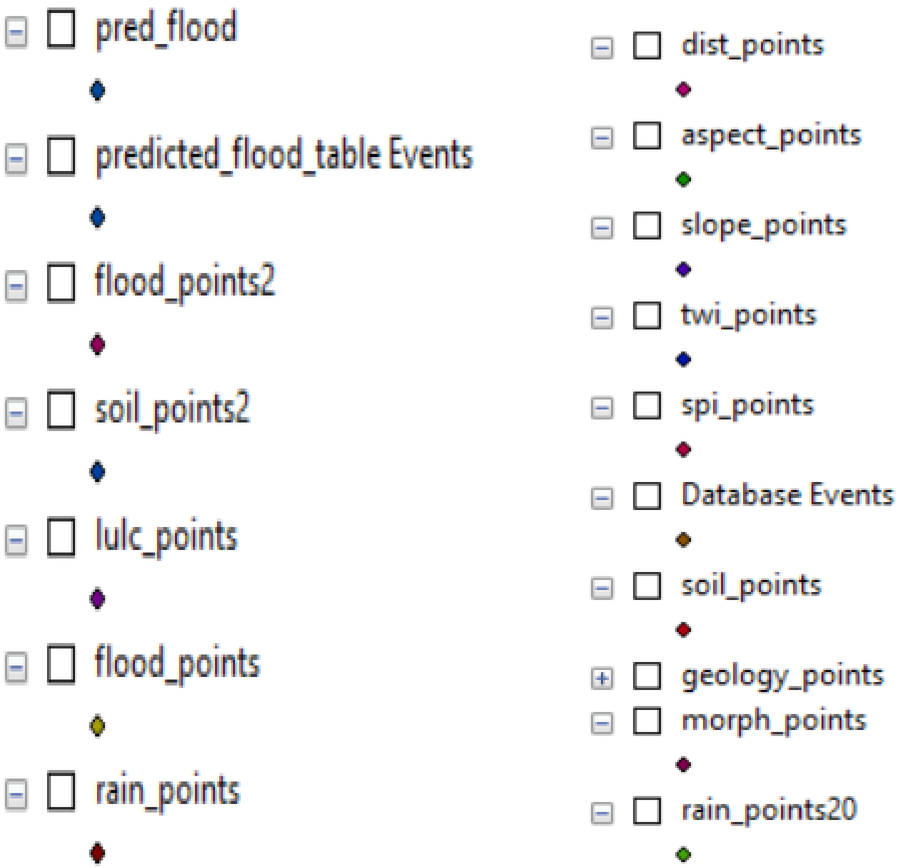


Fig 14: LULC Map spanning 4 UTM quadrants engulfing the study area

This LULC map is then clipped to the study area

3.2 DATA PROCESSED

All rasters are converted to point features, later which all the attribute tables are extracted with respect to the x-y coordinates and consolidated.



Separate excel files for each parameter have also been curated.

A	B	C	D	E	F	G	H	I	J	K	L	M
x_cordinat	y_cordinat	aspect	dist	flood	geology	lulc	morph	rain	slope	soil	spi	twi
85.6336	23.0642	149.951	35000	0	63	11	3	1459.81	2.87199	113	-1.58651	9.68631
85.6336	23.0892	295.379	35000	0	63	5	3	1457.02	1.23784	113	-1.84468	10.481
85.6336	23.1142	204.349	35000	0	63	5	3	1453.98	0.666225	113	-11.3273	9.01576
85.6336	23.1392	231.453	34986.9	0	63	11	3	1450.71	1.29723	118	-6.20447	8.77294
85.6336	23.1642	98.7428	33791.2	0	63	5	3	1447.29	1.20056	118	-10.73	8.37195
85.6336	23.1892	266.4	32996.9	0	63	5	4	1447.29	1.19286	118	0.516601	12.9318
85.6336	23.2142	240.364	32312.9	0	63	11	3	1443.79	2.2665	118	-3.1076	8.50863
85.6336	23.2392	29.5656	31628.2	0	63	5	3	1437.96	1.86408	118	-8.3783	8.12136
85.6336	23.2642	280.888	30942.7	0	63	5	3	1434.81	0.853226	118	-10.2485	8.85038
85.6336	23.2892	157.284	30256.7	0	63	5	3	1432.03	1.01262	118	-7.18647	9.20587
85.6336	23.3142	208.375	31130	0	63	11	3	1432.03	6.5857	118	-9.02131	6.6662
85.6336	23.3392	173.296	35000	0	63	2	2	1419.37	21.7382	118	-3.31532	5.89347
85.6336	23.3642	168.08	35000	0	61	11	3	1414.83	1.62607	118	-10.2518	8.14441
85.6336	23.3892	317.241	35000	0	61	2	2	1414.25	4.82627	118	-9.90024	7.56832
85.6336	23.4142	309.693	35000	0	61	2	2	1413.78	5.92885	118	-7.24111	6.98806

4 RESULTS AND DISCUSSION

Machine Learning Model used: XGBoost

Precision Snippet:

```
Initial class distribution:
flood
0    40215
1     9175
Name: count, dtype: int64
New class distribution after SMOTE:
flood
0    40215
1    40215
Name: count, dtype: int64
Confusion Matrix:
[[9905   84]
 [  46 2313]]

Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      9989
           1       0.96      0.98      0.97      2359

    accuracy                           0.99     12348
   macro avg       0.98      0.99      0.98     12348
weighted avg       0.99      0.99      0.99     12348

Predicted probabilities saved to /content/drive/MyDrive/predicted_flood_probabilities.xlsx
```

Final Probabilities:

probability_no_flood	probability_flood	x_coordinate	y_coordinate
0.002417922	0.997582078	91.9836	23.9642
0.005980611	0.994019389	91.9586	25.5892
0.006690264	0.993309736	89.7836	26.3392
0.006752253	0.993247747	92.3836	24.8392
0.008252621	0.991747379	91.7336	23.0642
0.010846198	0.989153802	92.8836	25.0892
0.012860715	0.987139285	89.7336	28.1142
0.015303731	0.984696269	90.1586	27.9892
0.016005278	0.983994722	93.4086	28.6642
0.023697495	0.976302505	91.0586	27.0642
0.026612461	0.973387539	93.6086	25.0142
0.026800275	0.973199725	88.8836	25.2142
0.029159307	0.970840693	88.3336	23.5892
0.030838966	0.969161034	90.1836	27.0142
0.03090775	0.96909225	89.9336	28.0142
0.033116162	0.966883838	93.3086	24.0642
0.034613848	0.965386152	91.8086	23.7642
0.05558145	0.94441855	90.9586	27.1642
0.057828069	0.942171931	89.4836	26.3392
0.058111906	0.941888094	89.4586	26.4642
0.066222072	0.933777928	92.9086	24.3142
0.082435489	0.917564511	93.4086	28.6392
0.091084719	0.908915281	90.8836	25.8392
0.091935813	0.908064187	90.0336	26.9142
0.102451742	0.897548258	91.0586	27.1142

The Excel file containing the flood probabilities corresponding to the x-y co-ordinates is then imported to ArcGIS and then a “Point Shapefile” is made with probabilities as values in the Attribute table which further is converted to the Final **Flood Hazard Mapping** Raster.

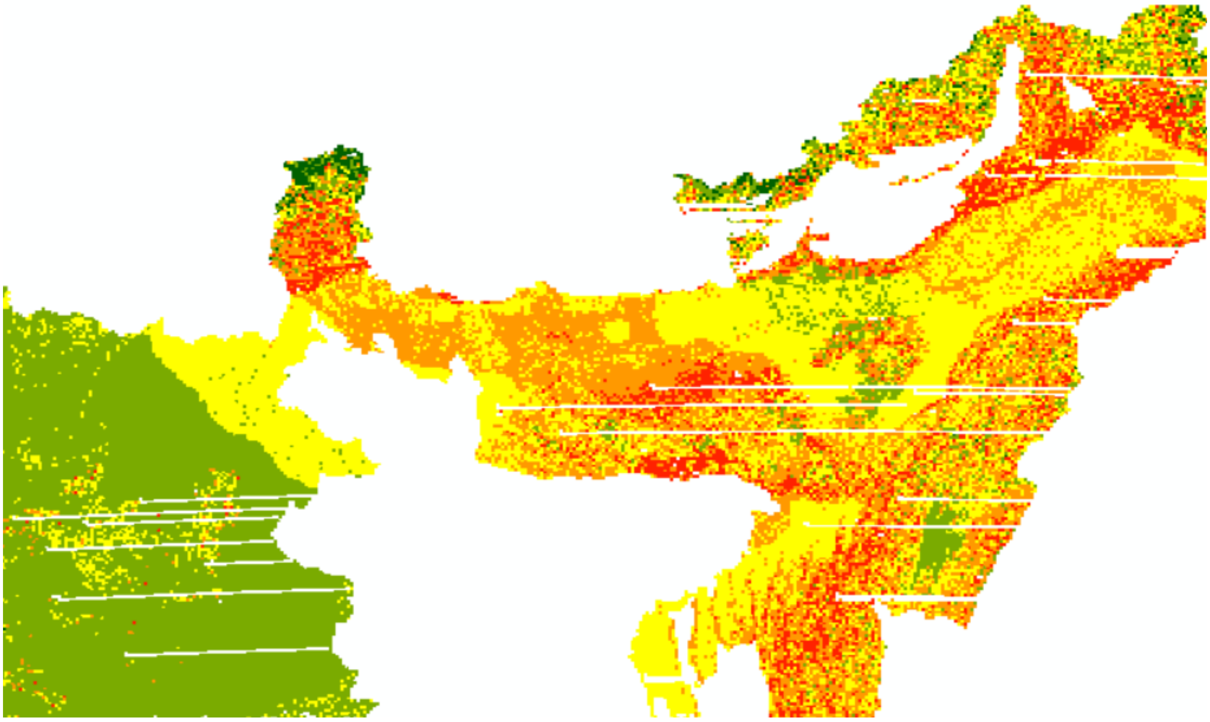
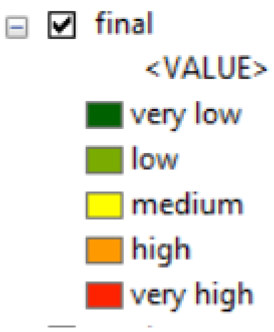


Fig 14: Final Flood Hazard Map for the study area



5 CONCLUSION

This study successfully developed a flood hazard map for the Brahmaputra River region, covering Assam and the northeastern areas extending into Bangladesh. Using advanced GIS techniques and machine learning, a spatial representation of flood susceptibility was generated, categorized into five levels: **very low, low, moderate, high, and very high flood hazard zones**.

The integration of diverse datasets, including topographic, hydrological, and environmental parameters, ensured a comprehensive analysis of flood risk factors. Key contributors to flood vulnerability were identified, such as **proximity to streams, low slope gradients, soil permeability, geomorphology, and high precipitation zones.** The inclusion of flood inventory data allowed the model to be trained on historical flood occurrences, enhancing its predictive accuracy for unmonitored areas.

The final hazard map (as shown above) highlights regions of varying flood susceptibility. Areas categorized under **very high flood hazard** are predominantly located along the Brahmaputra River and its tributaries, where the combination of low elevation, high drainage density, and frequent rainfall makes them highly prone to flooding. Conversely, areas under **very low hazard** are generally located in regions with higher elevations and better drainage conditions.

The map is a critical tool for flood risk management, offering actionable insights for disaster preparedness, mitigation, and urban planning. **Authorities can use this information to:**

- Prioritize high-risk areas for early warning systems, evacuation plans, and flood control measures.
- Guide infrastructure development and land-use planning away from flood-prone zones.
- Enhance the resilience of communities by implementing targeted interventions, such as embankments and afforestation.

While the study provides a robust framework for flood hazard assessment, it also highlights the need for further improvements. The lack of high-resolution rainfall data and limited temporal coverage of flood inventory datasets are constraints that can be addressed in future studies.

Contributions:

1. Sashank K (103121050) – DEM, Slope/Aspect, TWI, SPI, Inventory Data fit, Precipitation, ML Model
2. Naveen Jain (103121072) – Soil, HAND, Drainage Density, ML Model, Data Cleaning, Report
3. Aditya Pant (103121006) – Land Use, Land Cover, ML Model, Drainage Density, Report
4. Sanjana P (103121098) – Geology, Geomorphology, ML Model, Raster to points, Report