<u>Objectives of your work :</u>

1) To measure the river velocity of the Ganges River and combined with measurements of river slope with other flow parameters to estimate the river discharge.

2) Increasing the efficiency of the methods behind determining discharge variables to determine the river morphology on a larger scale using Machine Learning Algorithm to measure the river width.

3) To calibrate the virtual station discharge data to the closest ground data to minimise the RMSE error in discharge estimation.

4) Estimation of Tidal Prism using the river discharge and volume of ocean water coming into estuary's on the flood tide

Objective 1: To measure the river velocity of the Ganges River and combined with measurements of river slope with other flow parameters to estimate the river discharge :

Sub Objectives:
1(i) <u>To measure the River velocity of the Ganges river</u>

METHODOLOGY:

A time lag analysis is carried out to estimate the time lag of the river width changes between any two station A and station B which lies in the path flow of the stream. A time lag is the time interval for the peak river width measurement observed at station A to be recorded at station B. The peak river width used in most of the cases is taken to be the average of the daily river width measurements. Using the time lag and the distance separation between stations A and B, the average river velocity (assuming a uniform velocity) can be computed. The time and distance separation allow average propagation speed to be computed.

MATERIALS REQUIRED:

In order to estimate river flow using remotely sensed data, the temporal river width observations from MODIS (Moderate Resolution Imaging Spectroradiometer) image can be used to determine of river discharge at a station. This is based on the previous findings on the high correlation coefficient observed between the river flow and temporal variation in the water-to-land ratio pixel observations

Sub Objectives:

1(ii) To measure the River roughness coefficient and River Reach slope

METHODOLOGY:

The roughness coefficient of river channels depends on a number factors such as the vegetation type and structure, the cross-section area, degree of meandering, and obstructions in the river (Coon, 1998).

Values for the computation of the roughness coefficient (Chow, 1959)

Channel Conditions		Values	
Material Involved	Earth	n0	0.025
	Rock Cut		0.025
	Fine Gravel		0.024
	Coarse Gravel		0.027
Degree of irregularity	Smooth	n1	0.000
	Minor		0.005
	Moderate		0.010
	Severe		0.020
Variations of Channel Cross Section	Gradual	n2	0.000
	Alternating Occasionally		0.005
	Alternating Frequently		0.010-0.015
Relative Effect of Obstructions	Negligible	n3	0.000
	Minor		0.010-0.015
	Appreciable		0.020-0.030
	Severe		0.040-0.060
Vegetation	Low	n4	0.005-0.010
	Medium		0.010-0.025
	High		0.025-0.050
	Very High		0.050-0.100
Degree of Meandering	Minor	m5	1.000
	Appreciable		1.150
	Severe		1.300

$$n = (n_0 + n_1 + n_2 + n_3 + n_4)\, m_5$$

In uniform and gradual channel changes, the value of *n* is not significantly affected by relatively large changes in the shape and size of cross-sections. Greater roughness is often associated with large changes in the shape and size of cross-sections. Greater roughness is often associated with alternating large and small cross-sections and sharp bends, constrictions, and side-to-side shifting of alternating large and small cross-sections and sharp bends, constrictions, and side-to-side shifting of the low-water channel.

MATERIALS REQUIRED:

The values of for the different roughness values can be computed using Landsat Images.

RIVER REACH SLOPE :

MATERIALS AND METHODS:
For computing the river reach slope we can use the Shuttle Radar Topographic Mission Digital Elevation Model (SRTM DEM). Slope can be determined from the water surface elevations, by measuring the change in elevation over length between pixels by using the Hydro SHEDS flow distance data against the elevation data presented from the SRTM data.

Sub Objectives:
1(ii) Estimation of River Depth

METHODOLOGY:

Reach average depth can be calculated from average annual discharge. The relationship between the average annual discharge and the catchment area determined from the literature (**Shahin, 2002**),

$$Q_m = 0.0287A^{0.9155}$$

The mean discharge estimates were applied to the depth formula:

$$\bar{D} = 0.27Q^{0.39}$$

This formula was developed through existing data sets in an attempt to calculate a universal scaling for width and depth (**Moody and Troutman, 2002**). This was used due to the fact that a method could not be devised to obtain depth measurement from remotely-sensed data. Taking from the above calculation and using it as an average for

depth in the below equation made it possible to calculate along every point in the flow path. This is simple an adjustment of depth based on width in sub-reach intervals.

$$D(i) = \left(\frac{\bar{W}}{W(i)}\right)^{\frac{3}{5}} \bar{D}$$

From Manning's equation (**Manning, 1891**),hydrological relationships that could potentially estimate the river discharge from space is as follows: The discharge equation (Q) can be deduced as:

$$\frac{Q}{A} = \frac{1}{n} R^{\frac{2}{3}} S^{\frac{1}{2}},$$

where n is the roughness coefficient, A is the cross- sectional area of the river, R is the hydraulic radius (A/Pwet, where Pwet is the wetted perimeter (total length of streambed from one bank to the opposite bank)), and *S* is the slope of the riverbed.

$$Q = \frac{1}{n} A \left(\frac{A}{P_{wet}}\right)^{\frac{2}{3}} S^{\frac{1}{2}}$$

OBJECTIVE 2: Increasing the efficiency of the methods behind determining discharge variables to determine the river morphology on a larger scale using Machine Learning Algorithm to measure the river width.

METHODOLOGY:

The combination of classes has to be made in order to segregate water from the rest of the classes. The default ENVI classification algorithms is used to perform the water mask determination. Finding Landsat images that are clear of cloud cover or mostly clear of cloud cover is one of the most time consuming parts of the analysis

After finding a usable image it is put through this classification process that ENVI offers and in doing this the user is required to pick the k-mean and iterations for the classification. This is dependent on the tile and can change. After classifying the image properly where water is identified in a separate class the combination of classes is then possible.

K-means clustering is an unsupervised learning algorithm which aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest centroid. The algorithm aims to minimize the squared Euclidean distances between the observation and the centroid of cluster to which it belongs. This would help in calculating the width accurately as sometimes the contribution of tributaries to the width of main river channel can lead to significant amount of errors. The parameter k is obtained by the number of iteration using the elbow method . Further Analysis of the work can be used improved by implementing Hierarchical Algorithm.

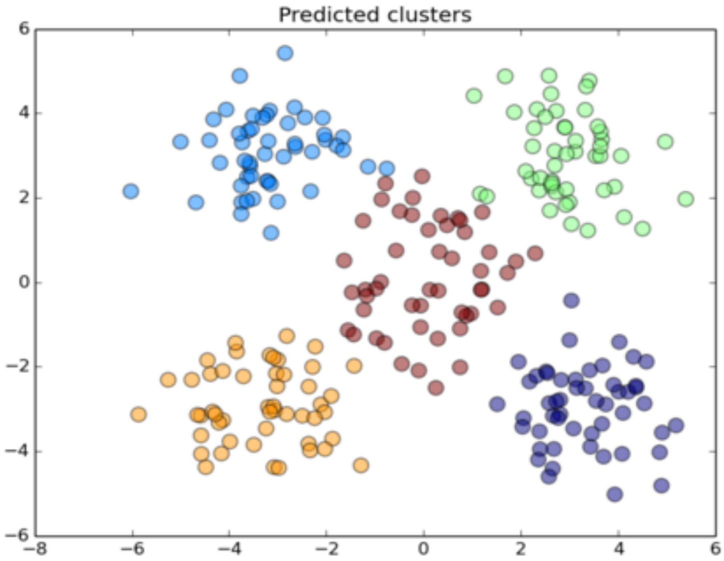

Figure 1: K-means clustering algorithm

Hierarchical clustering, also known as hierarchical cluster analysis, is an algorithm that groups similar objects into groups called clusters. The endpoint is a set of clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other. The dendrogram below shows the hierarchical clustering of six observations shown on the scatterplot to the left.

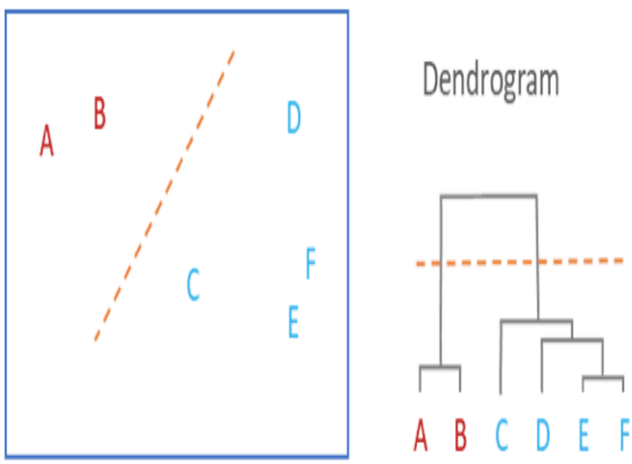

Figure 2: Hierarchical clustering algorithm

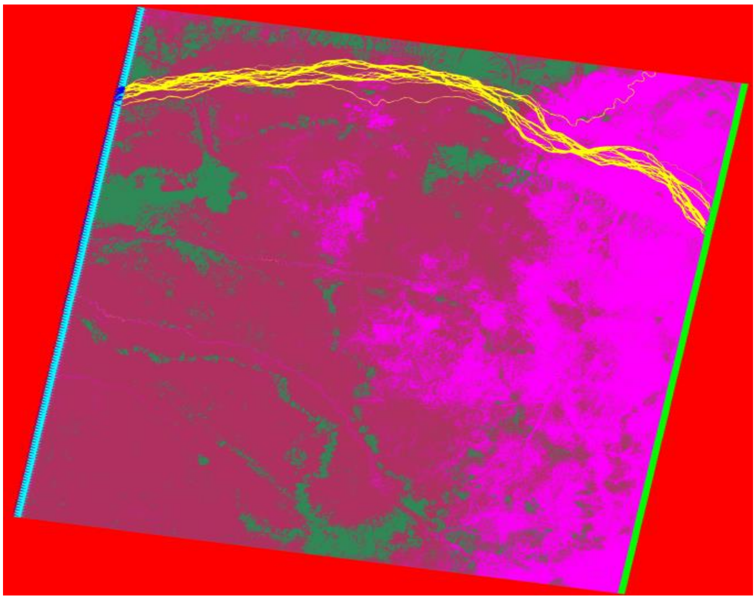
Figure 3: Unsupervised classification of tile 178/59 (Path/Row). The river is shown in yellow.

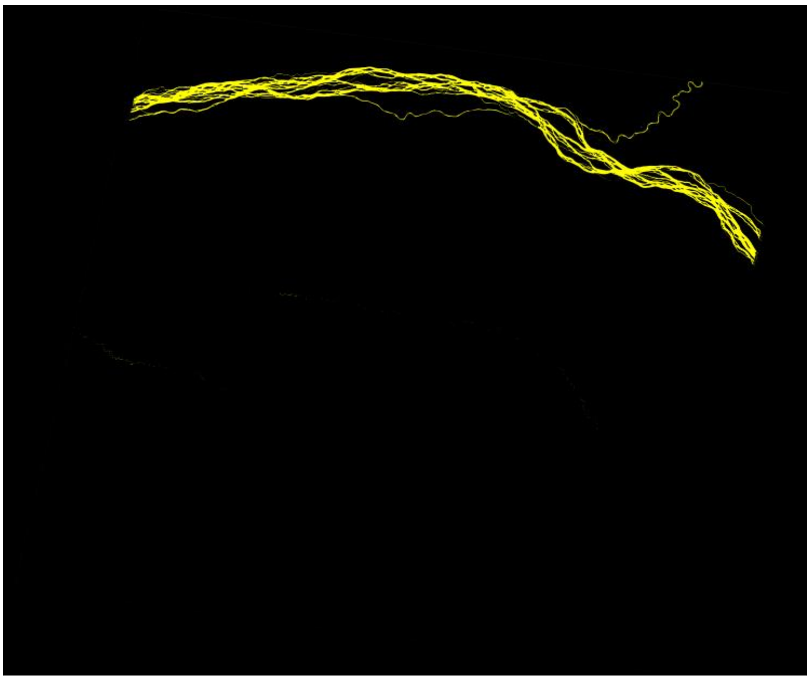
Figure 4: Water mask of tile 178/59 (Path/Row). The river is shown in yellow.

MATERIALS REQUIRED:

Landsat Images can be used for the classification algorithm to get the accuracy in the width measurement of the river.

OBJECTIVE 3: To calibrate the virtual station discharge data to the closest ground data to minimise the RMSE error in discharge estimation.

METHODOLOGY:
The depth estimates at the virtual stations were compared to the depths computed using the in situ ground discharge data. The depth comparison is meant to establish that the estimated values are within the range of the values obtained at the ground observation

The accuracy of river depth estimates can be determined using the root mean square error (RMSE), relative root mean square error (RRMSE), and relative error (RE). The performance of the resultant discharge estimates was then evaluated using the Nash–Sutcliffe (NS) equation, RMSE, RRMSE, and RE as the evaluation criterion

$$\mathrm{RMSE} = \sqrt{\left(\frac{\Sigma(Q_m - Q_e)^2}{n}\right)},$$

$$\mathrm{NS} = 1 - \frac{(Q_m - Q_e)^2}{(Q_m - \overline{Q_m})^2},$$

$$\mathrm{RRMSE} = \frac{\mathrm{RMSE}}{\overline{Q_m}} \times 100\%,$$

$$\mathrm{RE} = \frac{\Sigma_1^n Q_e - \Sigma_1^n Q_m}{\Sigma_1^n Q_m} \times 100\%,$$

where Qm is the measured discharge, Qe is the estimated discharge, Qm is the mean measured discharge, and n is the number of observations. The values of NS range from −∞ to 1. When NS is equal to one, it represents a perfect match of the estimated discharge to the measured discharge. We can further evaluate the performance of estimating discharge using the satellite-derived parameters. The discharge error contribution from each parameter can be obtained by varying the parameters by the measurement errors associated with each.

The discharge estimates at virtual station 1 and virtual station 2 can be validated using the closest ground stations to the the virtual station (1) and the virtual station (2) respectively. If, there are no tributaries in the given sections, therefore the discharge at the ground stations and virtual stations can be assumed to be the same.

MATERIALS REQUIRED:

The Insitu data for the river discharge can be collected from the GRDC (Global Run off data centre).

OBJECTIVE 4: Estimation of Tidal Prism using the river discharge and volume of ocean water coming into estuary's on the flood tide.

METHODOLOGY:

A tidal prism is the volume of water in an estuary or inlet between mean high tide and mean low tide, or the volume of water leaving an estuary at ebb tide.

The inter-tidal prism volume can be expressed by the relationship:

$$P=H\ A,$$

where H is the average tidal range and A is the average surface area of the basin. It can also be thought of as the volume of the incoming tide plus the river discharge. Simple tidal prism models states the relationship of river discharge and inflowing ocean water as Prism. = Volume of ocean water coming into an estuary on the flood tide + Volume of river discharge mixing with that ocean water; however, there is some controversy as to whether traditional prism models are accurate. The size of an estuary's tidal prism is dependent on the basin of that estuary, the tidal range and other frictional forces.

Freshwater fraction and tidal prism models are simple methods for estimating the turnover time of estuarine water. The freshwater fraction method prominently features flushing by freshwater inflow and has sometimes been criticized because it appears not to include flushing by seawater, but this is accounted for implicitly because the average estuary salinity used in the calculation reflects all the processes that bring seawater into the estuary, including gravitational circulation and tidal processes.

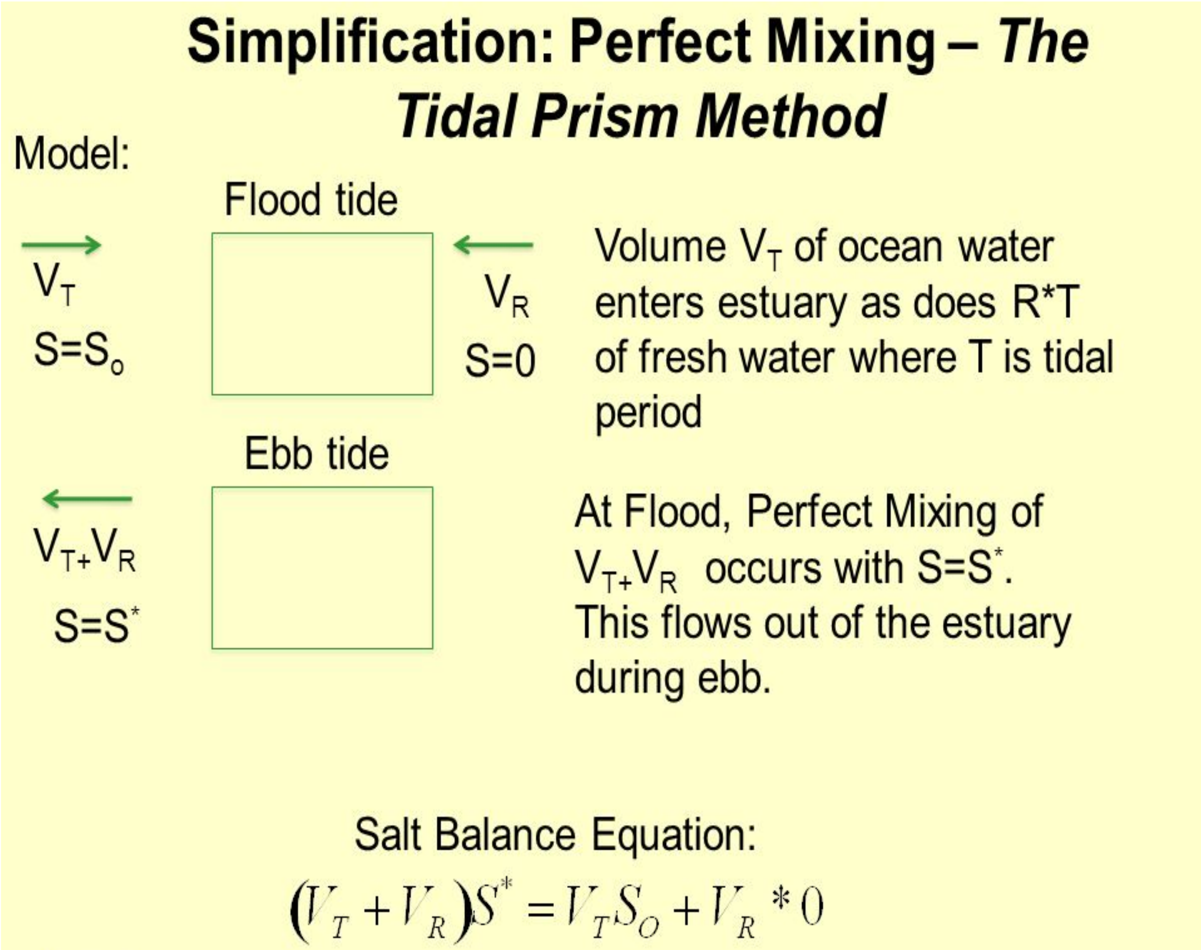

Figure 5: Tidal Prism Method

REFERENCES:

1. Smith, L.C.; Isacks, B.L.; Bloom, A.L.; Murray, A.B. Estimation of discharge from three braided rivers using synthetic aperture radar satellite imagery: Potential application to ungaged basins. Water Resour. Res. **1996**, 32, 2021–2034.
2. Smith, L.C.; Pavelsky, T.M. Estimation of river discharge, propagation speed, and hydraulic geometry from space: Lena River, Siberia. Water Resour. Res. **2008**, 44.
3. Tarpanelli, A.; Barbetta, S.; Brocca, L.; Moramarco, T. River discharge estimation by using altimetry data and simplified flood routing modeling. Remote Sens. **2013**, 5, 4145–4163.
4. Papa, F.; Bala, S.K.; Pandey, R.K.; Durand, F.; Gopalakrishna, V.V.; Rahman, A.; Rossow, W.B. Ganga-Brahmaputra river discharge from jason-2 radar altimetry: An update to the long-term satellite-derived estimates of continental freshwater forcing flux into the Bay of Bengal. J. Geophys. Res. Ocean. **2012**, 117, C11021.
5. Sichangi, A.W.; Wang, L.; Yang, K.; Chen, D.; Wang, Z.; Li, X.; Zhou, J.; Liu, W.; Kuria, D. Estimating continental river basin discharges using multiple remote sensing data sets. Remote Sens. Environ. **2016**, 179, 36–53.
6. Brakenridge, G.R.; Nghiem, S.V.; Anderson, E.; Mic, R. Orbital microwave measurement of river discharge and ice status. Water Resour. Res. **2007**, 43.
7. Birkinshaw, S.J.; O'Donnell, G.M.; Moore, P.; Kilsby, C.G.; Fowler, H.J.; Berry, P.A.M. Using satellite altimetry data to augment flow estimation techniques on the mekong river. Hydrol. Process. **2010**, 24, 3811–3825.
8. Leopold, L.B.; Maddock, T. The Hydraulic Geometry of Stream Channels and Some Physiographic Implications; Geological Survey Professional Paper 252; US Government Printing Office: Washington, DC, USA, 1953; 57p.
9. Coon, W.F. Estimation of Roughness Coefficients for Natural Stream Channels with Vegetated Banks; US Geological Survey: Reston, VA, USA, **1998**.
10. Manning, R. On the flow of water in open channels and pipes. Trans. Inst. Civ. Eng. Irel. **1891**, 20, 161–207.
11. Sichangi, Arthur & Wang, Lei & Hu, Zhidan. (2018). Estimation of River Discharge Solely from Remote-Sensing Derived Data: An Initial Study Over the Yangtze River. Remote Sensing.
12. Brakenridge, G.R.; Cohen, S.; Kettner, A.J.; De Groeve, T.; Nghiem, S.V.; Syvitski, J.P.M.; Fekete, B.M. Calibration of satellite measurements of river discharge using a global hydrology model. J. Hydrol. **2012**, 475, 123–136.