

NEUROMORPHIC STUDY OF LONGITUDINAL PROFILE OF THE RIVER BRAHMAPUTRA

A DISSERTATION

*Submitted in partial fulfillment of the
requirements for the award of the degree*

of

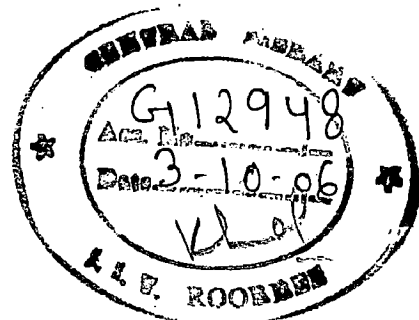
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in

IRRIGATION WATER MANAGEMENT

By

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CANDIDATE'S DECLARATION

I do hereby certify that the work which is being presented in the dissertation entitled "NEUROMORPHIC STUDY OF LONGITUDINAL PROFILE OF THE RIVER BRAHMAPUTRA" in partial fulfilment of the requirement for the award of the **M. TECH DEGREE in Irrigation Water Management** and submitted at the Department of Water Resources Development and Management (WRD&M), Indian Institute of Technology Roorkee, Roorkee is an authentic record of my own work carried out during the period from July 2005 to June 2006 under the supervision of **Prof. Nayan Sharma, IIT Roorkee, Roorkee (India)**.

The matter presented in this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

Date: June, 2006


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CERTIFICATE

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.



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ABSTRACT

The river Brahmaputra is well known to the world of river hydrologist, geologist and the researchers for its third rank in sediment transportation, fifth in fluvial discharge and eleventh in the size of the drainage basin area.

The morphological features of the river Brahmaputra is characterised by highly braiding river channels and higher slopes and ever changing trend due to the high energy environment of the fluvial processes. Unlike in the single channel river in fine alluvium bed for the complexity involved in highly braided channels and higher slopes it has been a formidable task in establishing of interdependencies among the resistance, velocities and other hydraulic parameters due to highly non linearity observed in the phenomena.

The river morphological indices: Plan form index, Braiding index, Flow geometry index, sinuosity, concavity index and slopes constitute the major parameters to describe the morphological aspects. In the present work, basic emphasis has been on the study of the longitudinal profile and other associated morphological parameters. The study area stretch over the length of 622.37km of the river Brahmaputra in the Assam valley of India.

The study is based on the hydrographic data (river cross sections) collected over the span of 40 years from 1957 to 1997 comprising seven discrete data years.

The foremost strategy of the study has been an application of a soft computing technique in Neuromorphic environment well known as Artificial Neural Network (ANN). The ANN models so developed were applied to generate all the intermediate average bed levels for entire study period from 1957 to 2005.

The observed variations of the average bed levels with the ANN predicted data base have quantified the aggradations and degradations in every single reach between the cross sections and has shown that aggradation phenomena is the most pronounced trend in the later periods, 1985 to 2005. In the three segments of the total length, the middle

reach is observed to be more susceptible to degradations due to joining of the tributaries to main stream of the river Brahmaputra in this reach.

The slope of the longitudinal profile has been varying from flatter in lower reaches to steeper in upper reach. Segment wise, the upper and the lower reaches have been observed to be decreasing trend in the variation of their slopes but the middle reach shows increasing trend in this respect.

The concavity of the river valley profile of the study length has been observed to best fit a second degree polynomial and an exponential curve with R^2 value above 0.98. The unsteady perceived in the concavity index value and the total longitudinal slope have been reflected to the plummeting stream power from 1985 to 2005 which has best described the aggradations in the majority of river length of the study reach.

The results of the study however, suggest that the morphological changes in the present study length of the river Brahmaputra could be understood as responding to a cyclic hydrological phenomena and maintains its fluvial capacity.

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June, 2006

(Raghu Nath Shrestha)

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NOTATIONS

Symbol	Description
δ_{np}	= error signal of neuron p in the hidden layer;
\bar{d}	= mean of the desired output;
σ	= statistical standard deviation;
$\frac{VS}{W}$	= non-dimensional unit stream power;
γ_w	= specific weight of water;
σ_{y_j}	= standard deviation of the model output y_j ;
\bar{y}	= mean of the model output;
σ_{d_j}	= standard deviation of the model output d_j ;
α	= momentum factor;
ϕ	= sigmoidal activation function;
α	= slope parameter;
γ	= unit weight of fluid ;
η	= learning rate
ΔE	= change in error function;
$C_{y_i d_j}$	= covariance between the model output (y_i) and desired output (d_j);
f	= activation function;
g	= acceleration due to gravity;
k	= number of neurons in the single hidden layer;
k_i	= of neurons that feed forward to neuron I;
L_{cmax}	= mid channel length of the widest channel through the reach;
L_d	= length of the down stream reach used in control volume computation;
L_m	= thalweg length of channel;
L_r	= length of the reach measured midway between the banks of the channel belt

- L_R = overall length of the meander belt reach measured along a straight line;
 P = modified sinuosity parameter, wetted perimeter;
 q = water discharge per unit width;
 Q = water discharge;
 Q_b = bank full discharge;
 R = correlation co-efficient;
 S = longitudinal bed slope;
 Ω = stream power;
 W = water surface width of stream / channel;
 W_h = weights of the h^{th} input node and p^{th} hidden layer neuron;
 w_{ij} = weight of the network;
 W_o = weights of the connection between p^{th} hidden layer neuron and q^{th} output neuron;
 Y_o = observed value;
 Y_p = predicted value;
 y_q = output;

SYMBOLS FOR UNITS

Cumec	Cubic metre per second
ha. m.	Hectare-meter
Kg	Kilogram
Km	Kilometre
km ²	Square kilometre
m	Meter
MCM	Million cubic meter

ABBREVIATIONS

CWC	:	Central Water Commission
DC	:	Determinant Coefficient (Nash Sutcliffe-Coeff)
DEM	:	Digital Elevation Model
FGI	:	Flow Geometry Index
FLI	:	Fluvial Landform Index
GIS	:	Geographic Information System
HEC	:	Hydrologic Engineering Center
HGI	:	Hydraulic Geometry Index
IRS	:	Indian Remote Sensing
LISS	:	Linear Imaging Self Scanner
NDVI	:	Normalised Difference Vegetation Indices
NOAA	:	National Oceanographic & Atmospheric Administration
NRSA	:	National Remote Sensing Agency
PFI	:	Planform Index
RMSE	:	Root mean square error
WRD&M	:	Water Resources Development and Management

INTRODUCTION

1.1 GENERAL

The river Brahmaputra from its berth place in the southern Himalayan of Tibet (China) to the final destination, the bay of Bengal (Bangladesh), exhibits a wide gamut of variations negotiating an entire fluvial length of 2880 km. The rapid fall in the levels of the riverbed imparts tremendous gravitational potential energy that is turned into kinetic energy and dissipated by erosion process has created world level braided river morphology. The rapid temporal variation in the geo-morphological appearances has been impeding decision making on implementation of Water Resources Development Strategies and the flood mitigation measures due to vague in the level of uncertainty and risk.

The satellites imageries of the area (Figures:1.1 a &b) for multi dates analysed in the earlier studies has depicted highly braided land form of the river channel featured by numerous independent channels within the river's active flow zone breaking and reuniting repetitively around submergible and non submergible islands representing an impression of fluvial net of channels on plan signifying the complexity of the fluvial process of high energy environment where the longitudinal slope is fairly high in the sloppy terrain.

Whilst the enormous flow of natural water in the river Brahmaputra is a great natural asset in maintaining the favourable climatological atmosphere in the area and a dependable lifeline of the inhabitants' water resource, however, it has yet to be taken a long stride to harness the benefits and save the lives and properties of the dwellers in the banks of the river at the events of the fierce deluges. The qualitative knowledge gained from the past studies are required to be framing the avenue to the quantitative works so that the facts and the figures so derived come purposeful in the planning and

implementation of development strategies. On this way ahead new principles and modern technologies which extensively use Remote Sensing tool and soft computing techniques like Artificial Neural Network(ANN), Fuzzy Logic could be improvingly employed.

The complexity and the non linearity of the numerous parameters in determining the characteristics of many entities of the river like Brahmaputra make it a formidable task to reach at useful conclusion with the established conceptual mathematical approaches alone. And hence, the routinely measurable information that could be collected in time and space after occurrences of floods in wet seasons should be explaining the under lying phenomena and probable future scenarios. The data driven approaches with possibility of updating every next time seem to be more amenable in the light of the consequences of the past fluvial processes minimising the tendencies of approximations to validate the concept. In doing so, close observation of the channel geometric synergized with other hydraulic and hydrologic parameters in spatial and time scale with the compound aid of Remote Sensing and computer environment can be anticipated as the basis of data driven techniques. *The study here endeavours to establish the idea of suitability of ANN application in tracing the river bed adjustment and its response to the longitudinal profile on spatio-temporal dimension to address the river morphological aspects of the river Brahmaputra.*

1.2 EARLIER RESEARCH

The existing published reference literatures are more detail on the work of the single channel system than in braided river system. The phenomena of braiding and braiding indices development have been the focus of the researches by Leopold and Wolman, 1957; Lane, 1957; Brice, 1964; Coleman, 1969; Howard et al., 1970; Schumm and Khan, 1972; Parker, 1976; Miall, 1977; Hong and Davies, 1979; Mosley, 1981;

Richards et al., 1982; Ashmore, 1991a; 1992; Friend and Sinha, 1993; Bristow and Best, 1993; Thorne et al., 1993; Ashworth et al., 1996; and Richardson and Thorne, 2001.

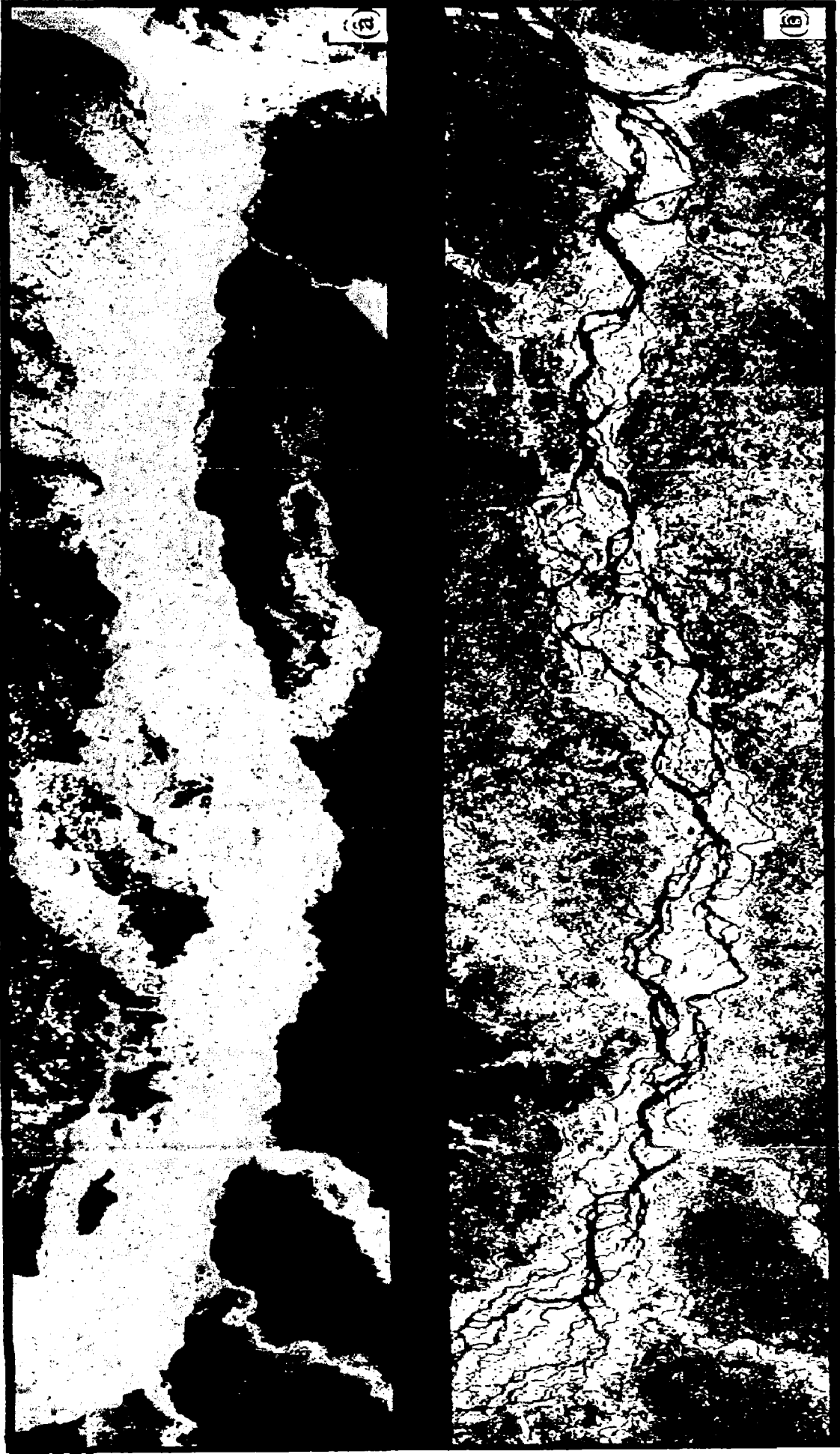


Figure 1.1 (a) Satellite image near the peak of monsoon flood of the river Brahmaputra (17/8/1987)
(b) Satellite image showing the braided pattern of the river Brahmaputra (7/2/1987)
(Best and Bristow, 1993; Images collected from ISPAN, FAP-19 Dhaka, Bangladesh)

Off late, ANN has become an attractive technique for solving many hydrologic problems, as established by Daniel (1991), Karunanithi et al. (1994), Zhu and Futija (1994) and Smith and Eli (1995). According to several authors, such as Bastarache et al. (1997), Muttiah et al. (1997), Clair and Ehrman (1998) and Wen and Lee (1998), multilayer perceptrons are powerful tools in solving non-linear water resources problems. Hsu et al. (1995), Minns and Hall (1996), Dawson and Wilby (1998), and Tokar and Johnson (1999) used multilayer perceptron to process rainfall-runoff relationships. Bhattacharya and Solomatine (2000), Raman and Sunilkumar (1995) and Thirumalaiah and Deo (1998) applied ANN to develop stage-discharge relationships and river stage forecasting respectively.

1.3 THE PROBLEM IDENTIFICATION

The ever increasing settlement of the inhabitants, rapid deforestation of the once thickly vegetated mountains and plains are accelerating the run-off process to speeding the erosion. The shortening of the lagging time to the out fall from the watersheds due to loss of resistance by vegetation has intensified the flow rates in the rivers resulting to high floods of several thousands cumecs. This huge mass of sediment laden flow of the water is choked when it reaches flattened topography. The high energy contained in the flow current could only be exhausted by eroding the bed & banks. The consequence would be shrinking of the agricultural land by bank erosion and raising of the bed by depositing the transported sediments. The process of bed rising would result the flood level rising and drainage congestion would drown a large area of settlement causing to lose lives and properties.

Reportedly, the magnitude of the impairment in term of lives and properties has ascended since 1950's Assam earth quake scaled to 8.7 Richter. The earth quake resulted lifting of the river bed which is reasoned to be the cause of the severity of the calamities of the floods in 15-954, 1962, 1966, 1972, 1974, 1978, 1983, 1986, 1988, 1996, 2000 and

2004. About 40% of the area of the Brahmaputra valley is reported to be susceptible to damage constituting 9.6% of flood prone area of the country

The registered maximum flood discharge levels up to of 48,060 m³/sec (Pancharatna) in August, 1998.

The aggrading bed profiles and the bank migration have been drawing the attention of the agencies involved. The vulnerability of the important landscapes like the Ramsar Heritage site (Kaziranga National Park), Numaligarh Oil Refinery, National Highway as well as important towns such as Dhubri, Guwahati, Tezpur, Jorhat and Dibrugarh has become a great concern.

1.4 OBJECTIVES

The aim of the study titled "Neuromorphic Study of Longitudinal Profile of the river Brahmaputra" is focused to assess the applicability of Artificial Intelligence(AI) in tracing the trend of river bed adjustment defined by the past history along the period wise temporal scale and the consequences on the river morphological aspects.

The study is aimed to :

- (i) Application of Artificial Neural Networks (ANN); a *Neuromorphic approach*, in the prediction of average bed variation trend on the Study of "Longitudinal Profile" in the Spatial-Temporal scale.
- (ii) Assessment of interdependencies among the bed level variations, widths and the deepest channel, thalweg and morphological changes.
- (iii) Analysis of Slope adjustment of the Longitudinal profile in as morphological changes based on the ANN predictions.
- (iv) Determination of the Concavity of the "Valley Longitudinal Profile" of the study reach and identification of best fit mathematical expression.

- (v) Determination of stream power subject to Slope variation to explain the observed morphological changes.
- (vi) An explorative application of ANN in developing Neural Network models of Average Bed Level variation corresponding to hydraulic parameters (Discharge, Water Surface Level and Sediment Discharge) and assessment of the performance of ANN models.

1.5 STUDY AREA

The area under the consideration for the present study encloses a 622.73 km river stretch encompassing 64 no. Of different cross section with kobo on the northern most(65no.) To Dhubri on the south(2no.). The cross section no 1. In the series lies in the territory of Bangladesh.

1.6 DATA COLLECTED AND USED

The prime data the study utilize is the survey data of the cross sections taken in the years 1957,1971,1977,1981,1988,1993 and 1997. The other hydrologic data of the river at different locations (Pandu, Pancharatna, Dhubri) for the years 1990 to 2002 sourced from Central Water Commission and Brahmaputra Board). Photographic images derived from different digital satellites imageries processing in the earlier works are incorporated to draw the idea of the area at a glance. The imageries includes satellite : Indian Remote Sensing(IRS) *Linear Image Self Scanner-I(LISS-I)&LISS-III* sensors geo-referenced with 39 sets of Topographic Survey Maps of the area.

1.7 THE METHODOLOGY

The strength of ANN is more explained to be pertinent in the fields where extreme non linearity exist among parameters and the traditional mathematical concept is far from reach to explain the phenomena. The algorithms established by the researchers referenced in the various literatures advocate success of ANN application depends on the size of the data covering wide patterns of phenomena. More the data

sets better is the results' reliability. However, in the present case, each individual cross section location assume to be a single entity and has its own pattern of adjustment to the river processes. There are seven patterns of the averaged values of the river bed cross section stations. The plotting of these average bed levels against the respective years shows a non linear curve as in the figure below.

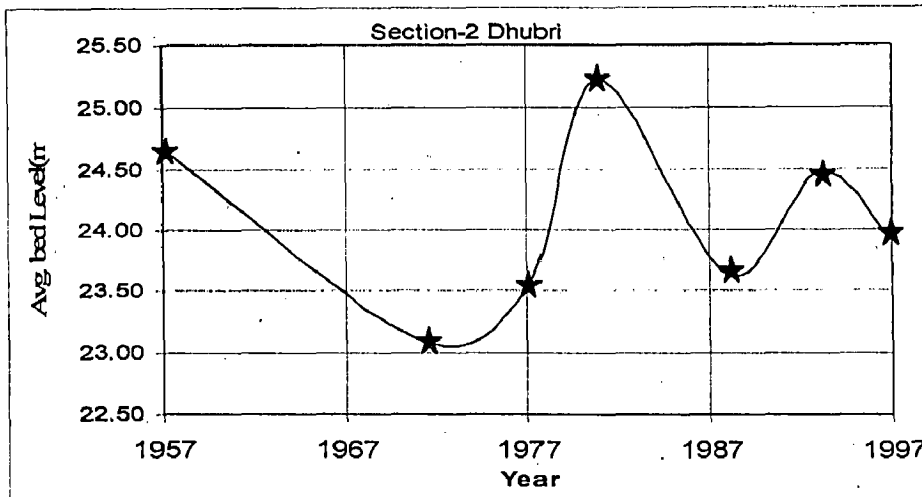


Figure:1.2
Avg. bed level variation profile of cross section-2

The profile of the changes has been observed to be an oscillatory damping disturbance. The period of the measurements of the ground profiles are unequal, therefore, an approximation of period of oscillation could be erroneous in further mathematical analysis. The changes in the profiles of the cross sections differs section to section due to the local morphological conditions and the control points.

Firstly, for *Morphometric Models*, average of the reduced levels of all stations across for each years of the given sections were determined to constitute the observed data patterns to be fed in to the ANN architecture. Missing data values for some of the cross sections were generated and filled to completeness with the help of ANN. Procedurally, as required by ANN technique the complete set of the data were fragmented to Training(calibration) set, Testing(cross validation) set and Validation set. Alternative training sets with different number of data patterns were prepared to observe the performance variation of training on validation.

Secondly, for *Hydrographic Models*, the hydrological data (Discharges, Sediment discharge and gauge levels) was available for few stations were fed into HEC-6 for generating the corresponding data values of rest of the stations. HEC-6 (Hydrologic Engineering Centre) is an application numerical river hydraulics computer software developed by U.S Army Corps of Engineers.

The hydrographic data, then, for the whole study reach were arranged to three sets as above for ANN implementation.

The prediction of the Morphometric ANN Models were validated with the observed values. The ANN model predicted average bed levels were further analysed to assess the aggradations and degradations phenomena in the different reaches and the total study reach as a whole. Width and Thalweg were picked up from the cross section data and developed to a complete data set as earlier with application of ANN and analysed for correlative study of the three river morphological parameters, bed variations, width changes and thalweg. Slope adjustment, aggradation/ degradation, concavity of the river valley have been determined to reveal the morphological changes in the study period.

1.8 VALIDATION OF RESULTS

The trained Neural Networks with different Learning Algorithms and input are subjected to predict the data to compare with the validation data. The predicted and the observed values are compared to evaluate the strength of the ANN model application in terms of the RMSE, Correlation (R) and Nash-Sutcliffe Coefficient.

1.9 SALIENT OUTCOMES OF THE STUDY

1.9.1 *Stream Bed Adjustment Models*

The Morphometric ANN Models have been found to be very adaptive to noisy data patterns of the average bed level variations and still holds better capability to generalisation. With the ANN model predicted values of the average bed levels the

aggradations and degradations quantification and attitude have been found to agree with the general consensus of the aggradations of the river bed.

1.9.2 Correlation of Bed Levels with Width and Thalwegs Variation

The analytical exercise on the comparative study of average bed levels with width variation and the thalweg has reflected the shallowing of the prominent river channels suggested by higher aggradation magnitude of the thalweg than the average bed levels. Since the normal discharge has to be passed downstream, the process of shallowing is an indication of small channel development for compensation of the shrunk in the area of flow leading to increase in the degree of braiding to higher values.

On the other hand, the width variation has been observed weakly correlated with the average bed level variation. The widths have varied in the magnitude of kilometres in successive periods. The width variations is directly communicative to the flood hazard mitigation works and the local morphological setting of the localities. This may suggest that an impact assessment of existing flood severity mitigation works would be a needful study.

1.9.3 Concavity of Valley Profile and Slope Adjustment.

Globally, all the rivers studied are known to have their longitudinal profile shape with upward concavity and the fitted expression of the profile corresponding to the elevation and the distance are opined to be linear, exponential, logarithmic or power. The profile displays higher concavity index ranging from as low as 0.19 to as high as above 0.8 from the point of their origination to the final destination up to the sea shore.

However, the study reach, here, constitutes the lower flood plain of the river Brahmaputra in the Assam valley, it has been found that the concavity shape of the profile is best fitted with polynomials having R^2 significantly above 0.95 and its variation in the temporal scale has been worked out quantitatively in the present study.

1.9.4 Hydrographic Flow Characteristic Models

The ANN models developed with hydrological input parameters and the average bed levels have been traced the average bed level variation when validated. The performance levels of the models which are moderate to very good have justified the robustness of ANN models in river Hydrographic flow characteristic studies. Among the three hydrologic parameters selected to be the input parameters to the ANN architecture, the water surface level has been found to have more importance in the simulation of the averaged bed levels. This may be inferred that the water surface level as the representative of depth in governing the tractive force on the beds has the holds supremacy over other two parameters.

1.10 ORGANISATION OF THESIS

Organization of the Chapters:

Chapter -1- Description of introductory aspects of the topic studied, underlying objectives, the outcomes and the layout of the thesis.

Chapter -2- Review of the literature

Chapter -3- Description of the study area.

Chapter - 4- Development of Spatio-temporal morphological Models

Chapter - 5- Correlative study of Average bed levels with river widths and thalweg.

Chapter - 6 - Results and discussions

Chapter - 7- Conclusions and scope for future work

Bibliography

Appendices

REVIEW OF LITERATURE

2.1 INTRODUCTION

The evolution of the ancient civilization all over the world along the big rivers like Mississippi, Nile and many others holds the history of relation between living beings and the rivers. The fulfilment of water requirement for sustaining of lives attracted the settlements near the river flood plain which sometimes paid back at the cost of hazardous eventualities. The need of water and the safety against the disastrous calamities put pressure to the curiosity of mankind to understand the river behaviour. By the present time the interest has been developed to a full discipline with numerous works and researches.

Among the different aspects that are embodied in the subject "River-Morphology" bears one of the prime importance in the field of "River Mechanics". As defined in the literatures "River-Morphology is a dynamic process operated by a collective influences of natural forces; Climatic, Tectonic and predominantly river hydrodynamics through geological time period". The existing river morphologies, slopes of relief, longitudinal profiles, incision, lengths, plan form, bed changes constitute are some of the morphological variables determined by the nature and when coupled with hydrodynamic parameters yield the next generation river-morphological dimensions. And this has been observed as a continuous phenomena in time scale of million of years with tendency to approaching an equilibrium state as suggested by past historical background of many rivers studied all around the world. The present scenario of the morphological features represents the testament to the past history of the river system and a background to the future. Thus, the interrelationships are highly non

linear in their nature, yet to be understood. The hydrological and the hydraulic parameters: cross sections, bed forms, vegetation, bed profile, plan forms, bars and islands, sediment characteristics attributes are the fundamentals to analyse the river behaviour to be examined for river management strategies(5).

2.2 HISTORY

An exemplary representation of history of river channel evolution may be envisioned through the figure below (37).

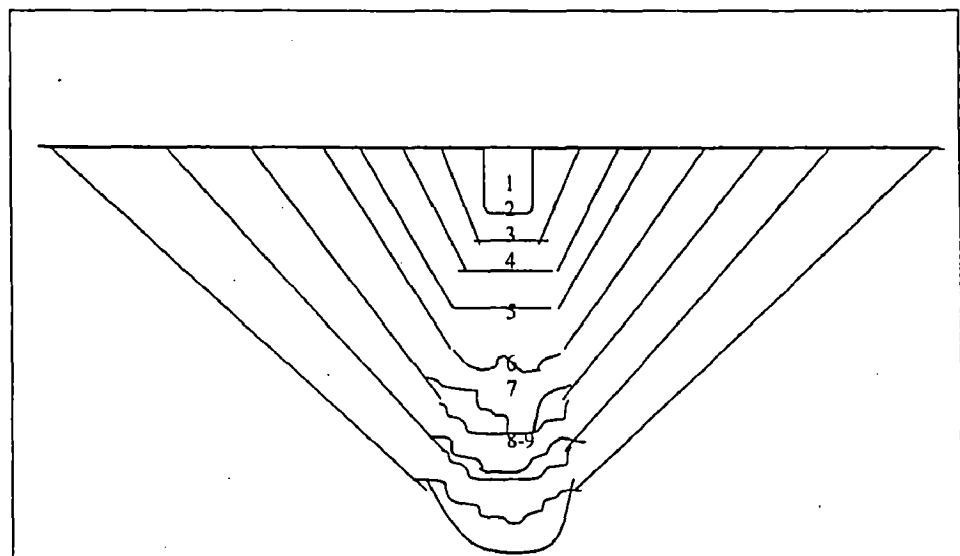


Figure:2.1

Cross section of valley and incising stream at time

The historical background of a river is based on how the channel evolved through the passage of time. In the **Figure:2.1**, the evolutionary transient phases of a channel in the vertical plane is presented. From 1-4 the channel is confined by the bed rock valley walls. During stages 5-7 the channel is constrained by bedrock valley wall and terraces of older alluvium. Finally, at the stage of 8-9 the channel has reached to regime(Schumm; Whipple et al.,2000)The length, meandering and their degree of sinuosity and confinement within a valley may be explored with the following block diagrams.

The underfit river channel within the valley can exhibit two cases. The figure 2.2 (a) to (d) presents two conditions of plan form development and the valley coverage by

the river channels.

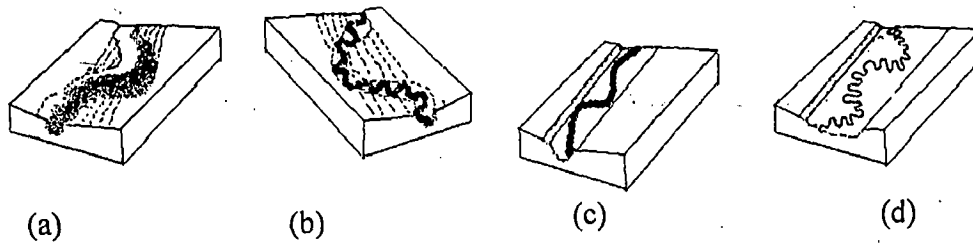


Figure:2.2

Underfit Streams and the valley patterns

After the discharge reduces the type (a) maintains the valley width and the type(c) maintains paleochannel. Although the channel width and the depth have decreased the slope is maintained to pass the proportionate sediment load in the flow. However, in the type (b) and (d), the decrease in the discharge and the sediment resulting into increase in the longitudinal gradient which is adjusted (absorbed) by increase in the sinuosity of the meandering(37).

Large braided rivers changing to large meandering streams and then to smaller meandering rivers during climate change of the Pleistocene is witnessed by modern rivers elsewhere in the world.

High floods are usually accompanied by high sediment charge, it could be speculated that the oldest streams were wide, shallow, steep, braided bed-load channel. The decrease in the sediment load perhaps were more rapid than the discharge a meander-braided transition pattern developed with a well defined single thalweg (Figure:2.3-b). The thalweg, in turn, became the channel as a new floodplain formed and the channel further narrowed with further reduction of sediment load (Figure: 2.3-c). Finally, as bed load became a fraction of its former volume, a meandering mixed load channel with large meanders formed (Figure:2.3-d).

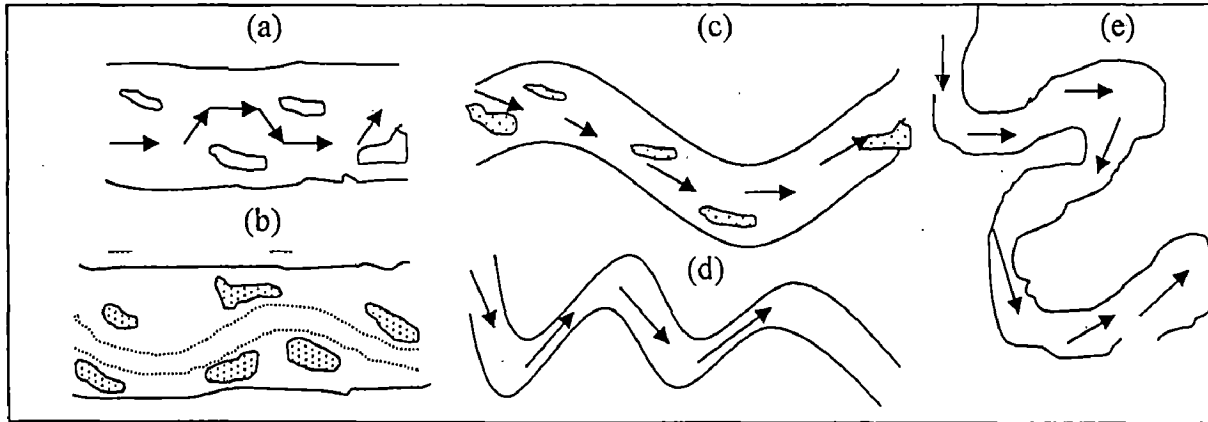


Figure:2.3

Sequence of channel changes with decrease in discharge and sediment load

2.3 PRINCIPLE MECHANISM OF MORPHOLOGICAL CHANGES

Mobile boundary flow of rivers in the alluvial zone of the earth crust makes the situation complex. Erosion and deposition are the most pronounced activities of alluvial river phenomena (39). River plan form observed from the Satellites have unveiled that evolution of river plan form is a historical dynamic process impelled by dominant discharges operating over a varied spans of time scale. The distinct plan form explained so far by the researchers are:

(a) ***Straight stream:*** Practically, straight channels has no existence in nature. Nevertheless, streams are accounted to be straight for a short length though the deepest level of the channel (thalweg) meanders between the high bank of the stream.(35).

(b) ***Braided Plan form:*** Imparted by steep vertical gradients almost of mountainous rivers at boulder stage where the river is still young flow in high energy environment. The uneven distribution of the flow intensities across the flow section tend to erode the bed at the zone of high intensities, conversely, it deposits the sediment load at low intensities zones developing multiple channels of varied depths. The process further aggravates due to differential bed levels and continue to develop bars and islands till a very high energy flood discharge passes washing down the coarse material deposited

in the bars and the islands (Leopold and Wolman-1957). The islands imposing flow constriction deflects the current of the flow increasing the discharge intensity on the bank sides provoking bank erosion. (35).

(c) *Meandering streams*: In the alluvial area of finer bed materials, following the braiding stage, the multiple channels tend to reunite into single channel tracing a deepest land topography. The irregularity in the plan-form of the deepest channel ultimately develops in to a smooth serpentine curve-linear path known as “meandering”(35)

2.3.1 Meandering Parameters(Sinuosity)

Leopold and Wolman (1957) have defined sinuosity of a stream as the ratio of the thalweg length to the valley length (Figure 2.4). They have arbitrarily classified streams with sinuosity greater than 1.5 as meandering streams. Friend and Sinha (1993) defined the meandering parameter (Sinuosity) as modified sinuosity parameter, and presented as

$$P = L_{cmax} / L_R \tag{2.1}$$

Where, P = Modified Sinuosity Parameter, L_{cmax} = mid channel of the widest channel

Where, there is more than one channel and L_R = overall length of the meander belt reach measured along a straight line.

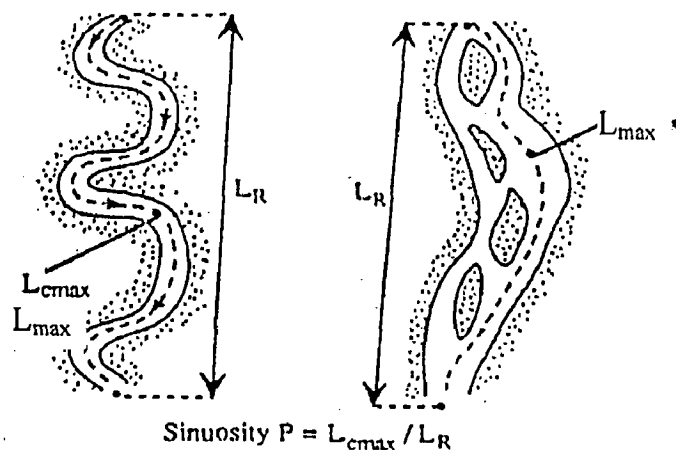


Figure 2.4: Schematic diagram representing the computation of sinuosity for single channel and multi-channel rivers

Function distinguishing between meanders and braided channels the basis of slope and discharge (Leopold and Wolman, 1957)

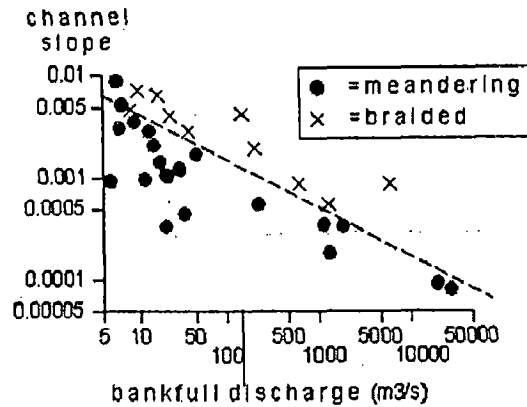


Figure 2.5(a)

Meandering and braiding threshold based on Parker's (1976) stability

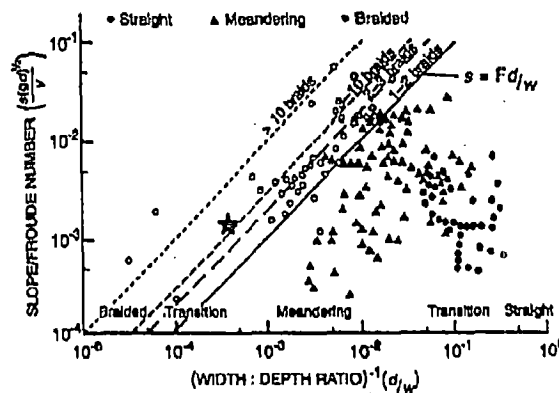


Figure 2.5(b)

2.3.2 Base-Level Variation

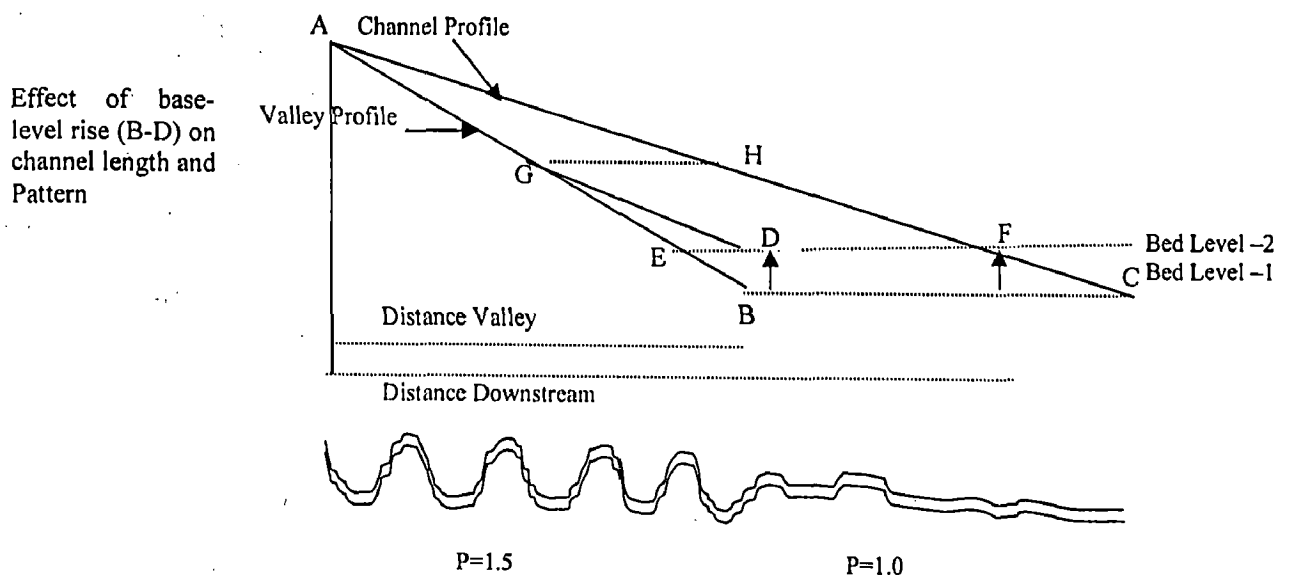
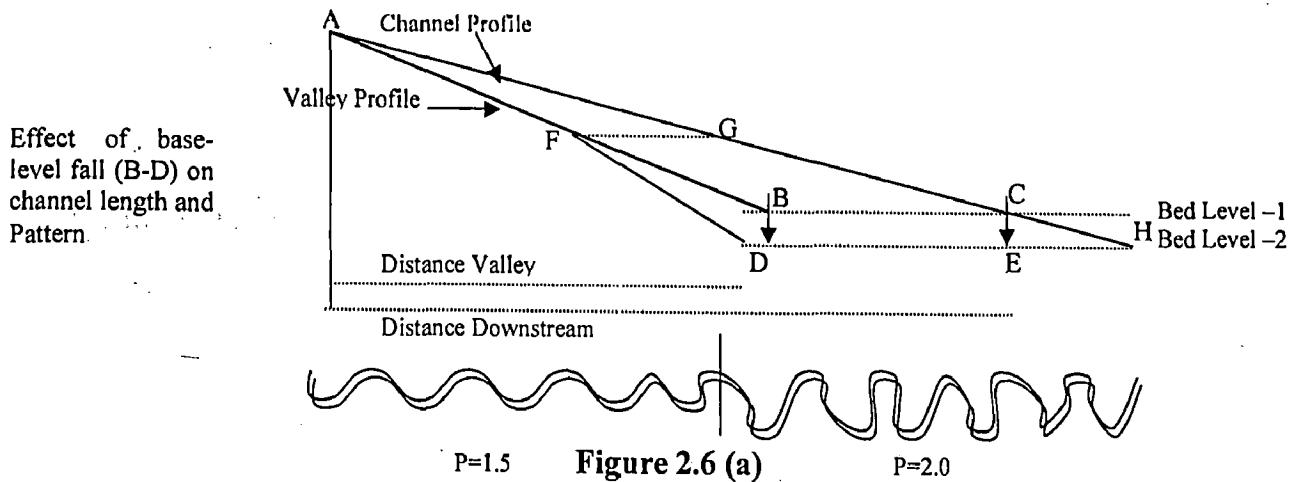
One of the reasons that the river plan form, slopes, aggradations/degradation, sinuosity, length are subjected to changes because of Base-Level Variation leading to adjustment of Longitudinal Profile. The experimental work (Holland and Pick, 1976; Schumm et al. 1987) and the observations of the headward incision of arroyos, gullies and channelized streams (Schumm et al., 1984) support that base level lowering revives the drainage network and deliver large amount of sediments downstream. Fisk (1944) concluded the Pleistocene sea-level lowering caused excavation of alluvium and bedrock incision by Mississippi River for a long distance upstream.

In the figure 2.6(a) the fall in the base level has subsequently steepened the valley profile by incision. If the channel is not restricted to lateral migration, the incision nearly ceases to the point F and the increase in the length of the channel from E to H

and the slope is adjusted by increase in the sinuosity of the channel pattern from 1.5 to 2.0.

In the other case, where the downstream bed level rises (Figure:2.6-b) , the reverse process takes place opposite to the previous. The rise in the base level subsequently rises the valley floor reducing the valley slope. However, the discharge and the sediment that to has be passed through is taken care by decrease in the length (from B-C to D-F) accompanied by decrease in the sinuosity from 1.5 to 1.0

The experimental demonstration(Jeff Ware ,1992-personal communication) of the base-level variation and the river channel response to it has supported the concept(37).



Primarily concerning to the Longitudinal bed profile it is found customary to mention the hydraulic characteristics of river flow dynamics with sediment discharge which constitutes and imparts dynamism to river streambed and other river morphological parameters. It is spontaneous to understand that a river originates from its watershed at higher altitudes of mountainous slopes which relatively receive high intensity rainfalls. Mainly, large river streams all around the world starts its voyages from higher mountainous elevation towards the sea. In the beginning the path of the flow is so steep that it has enormous potential to erode the bed in the vertical direction by virtue of which it develops V-shaped river section deep gorge or canyons. It has no flood plains and covers full width of its valley at all stages. A river at its young stage is characterized by presence of Rapids, Water Falls, Steep & Varying Gradients and Presence of Lakes.

According to Johnson

"When lakes are eliminated the young stage ends and turns to youth stage. Again when rapid and falls are eliminated boulder stage ends and turns in to mature stage(9)."

At this stage the river is said to become mature after its youth stage. The slope at this stage is so reduced that it can no more cut the bed but starts widening. The sediment transportation capacity is just adequate to transport the sediments in the flow from upstream and the sediment material is derived from bank widening.

If the sediment content in the flow is above the transporting capacity heavier sediments are settled on the bed upstream the profile slope. Conversely, if the transporting rate capacity is yet to be satisfied, the bed material picked up and the stream slope is reduced. Hence, a matured stream adjust its profile slope delicately. It is in the stage of maturity that the stream flows sinusoidal or meandering path in plan.

According to Lobeck

"Full maturity is attained when the width of the valley floor equals the width of the meandering belt(9)."

Width of a meandering belt in turn is approximately 10 to 20 times the width of the river.

A mature stream is many times known as

- Graded stream
- Poised-stream
- Balanced stream
- Stream in Regime or
- Stream in Equilibrium

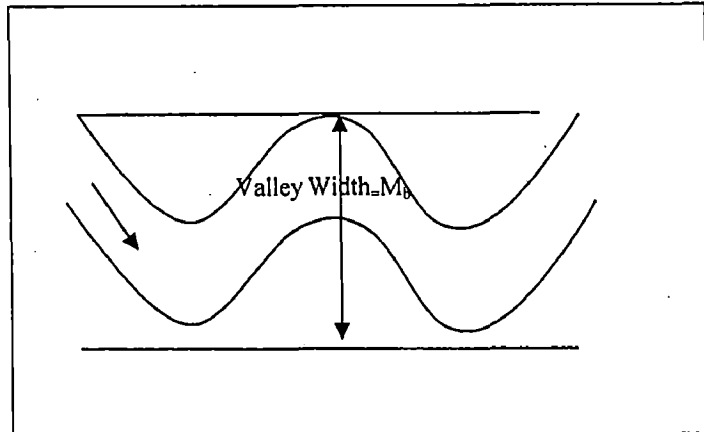


Figure: 2.7

According to Mackin

“A graded stream is one in which over a period of years, slope is delicately adjusted to provide , with available discharge and with prevailing channel characteristics just the velocity required for the transportation of the load supplied from the drainage basin. The graded stream is a system in equilibrium(9).”

2.3.3 Stream Slope

In general the longitudinal slope of a stream shows a continual decrease along its length. Examination of stream profiles would show that the slope is greatest near the source , decreasing more or less regularly as the river follows its course. Such reduction in slopes correspond to a longitudinal profile which is concave upwards. Several factors are responsible for this. The more visual delineation of longitudinal profile of Nile river has been shown in the figure.

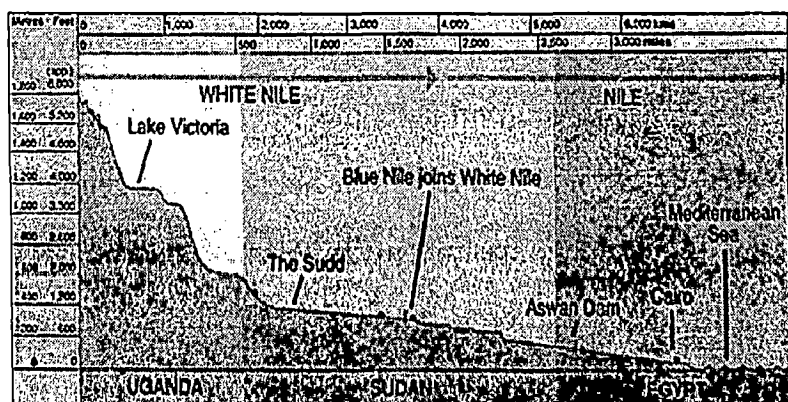


Figure:2.8
Natural bed Profile of the river Nile

The picture above depicts the stream bed profile of Nile river showing the variation in the longitudinal profile along the journey of the river towards the sea. The reasons put forward by different scientists and engineers have been summarized in the following lines.

Firstly, size of bed material being transported decreases in downstream direction due to abrasion.

Heck found slope varied as $d^{0.63}$ for stream in *Virginia and Meryland (USA)* .

Shulits assumed that the stream slope is proportional to the size of the bed material and accordingly proposed a slope reduction equation

$$S = S_0 e^{-\alpha x} \quad 2.2$$

S_0 and S are the slopes at $x=0$ and at any distance x being measured in downstream direction and α a coefficient.

Brush and Hack have shown that the stream slope is proportional to a negative power of the length of the stream up to that point indicating there by a decrease in slope along the length in conformity with the equation.

Low water profiles of the river Mississippi between Fort Jackson and Cairo of the Ohio between Cairo & Pittsburg (USA) and of several rivers in Europe are found to confirm the equation 2.2.

Secondly, in humid regions, the discharge in a stream increases in the downstream direction due to inflow from the tributaries . Unless there is a corresponding increase in the sediment inflow, the stream would necessarily flatten to the extent required by the increased sediment and water discharge.

Thirdly, the sediment contribution of the upper region of a drainage basin is large compared to the run-off contribution to the stream flow. Which mean higher sediment contribution necessitating higher slope. While the lower region of the same drainage basin contribute smaller sediment quantity compared to its run-off discharge contribution signifying flatter slope requirement.

Fourthly, on lower part of river sediments are usually finer and the streams are narrow with greater depth to width ratio leading to higher hydraulic efficiency requiring flatter slope.

Garde presented an analysis considering the change in the bed material size, discharge and sediment load in the direction of flow.

He gave following relationships.

$$d = d_0 e^{\alpha_1 x} \quad [\text{Variation in sediment size in the downstream direction}] \quad 2.3$$

$$Q = Q_0 e^{\alpha_2 x} \quad [\text{Variation in discharge } \alpha_2 \text{ between } 0.001 \text{ to } 0.0078/\text{km} \quad 2.4 \\ \text{for Indian rivers}]$$

$$Q_T = Q_0 e^{\alpha_3 x} \quad [\text{Variation in Total sediment load discharge } \alpha_3 \text{ between } 0.0006 \text{ to} \\ 0.002/\text{km for Indian rivers}] \quad 2.5$$

Combining the above mention equations with Kondap's relation for width & depth and a sediment transport law, it is shown that;

$$S = S_0 e^{(0.178\alpha_3 - 0.426\alpha_2 - 0.713\alpha_1)x} \quad 2.6$$

Thus, depending on the relative values of α_1 , α_2 & α_3 it is possible to get a decreasing, increasing, or constant slope in a long reach. The fact has been observed by investigators such as Hack(9).

2.4 STREAM BED CHANGES DURING THE FLOODS

On several alluvial streams, the stream bed elevation was seen to rise during flood while the bed was lower after the flood receded. On few other streams exactly opposite happenings have been recorded. These changes can be very rapid for example on the *Missouri river at Omaha, Nebraska (USA)*, the bed was found to be scouring at a rate of 0.3 m per minute during a flood. A few example of these river bed variations are cited below. Observation on scour during the flood of September- December 1941 on the *San-Juan river at Bluff, Utah (USA)* have been reported by Leopold and Maddock and shown in the figure(9).

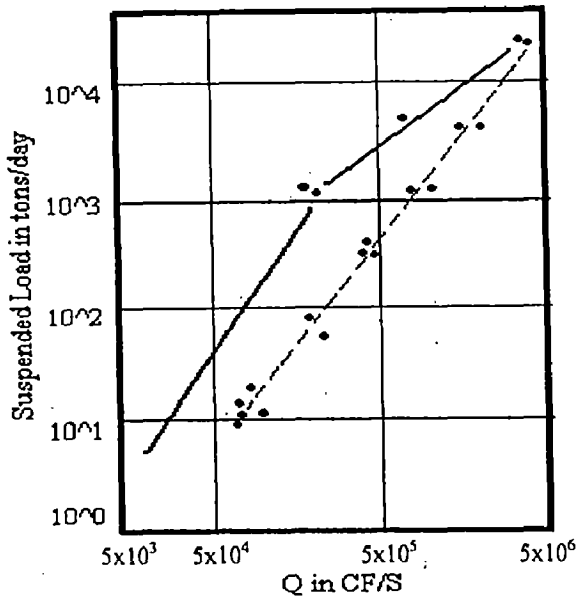


Figure:2.9(a)

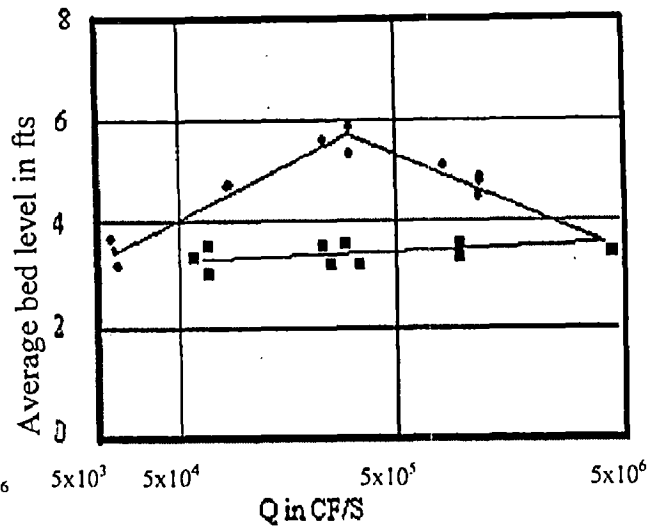


Figure:2.9(b)

Change in Stream bed elevation and suspended load during Sept Dec 1941

for the *San Juan river At Bluff(USA)* ($1\text{CF/S}=0.028\text{m}^3/\text{s}$; $1\text{ton}=10\text{kN}$)

At the gauging station the width of the stream changed very little with the discharge. As can be seen from the figure the bed elevation rose during the first part of the flood rise due to sediment deposition on the bed. This deposition continued progressively up to discharge of 5000cfs(141.9 m³/sec) the limit up to which the sediment load versus the discharge curve was steep. The slope of the sediment discharge curve was fatter in the discharge range from approximately 5000cfs(141.9 m³/s) to 60000cfs(1702m³/sec). In this range of discharge the bed level was lowered as can be seen from the figures above. During the falling stage the bed level was fairly constant. As against this type of deposition and scour, another type can be illustrated by considering the variation of the bed elevation and sediment load with discharge in the spring of 1948 on the *Rio Grande at Bernalillen, Maxico (USA)*.

Here, the bed scoured during the rising stage when the sediment concentration was high and the bed elevation rose during the falling stage when the concentration was lower.

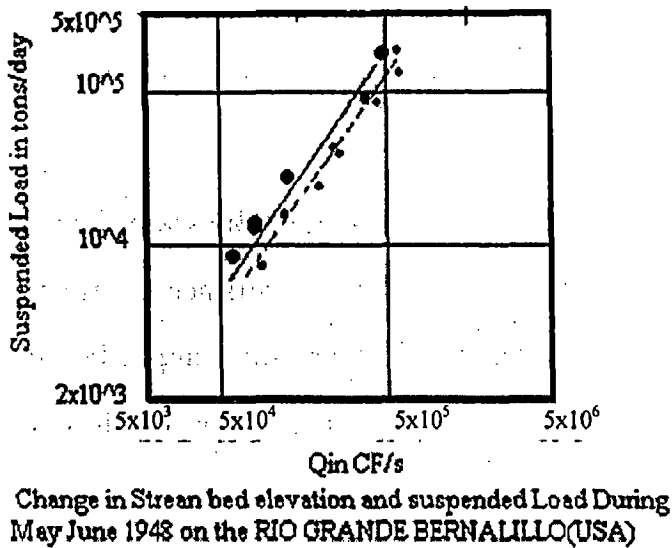


Figure: 2.10(a)

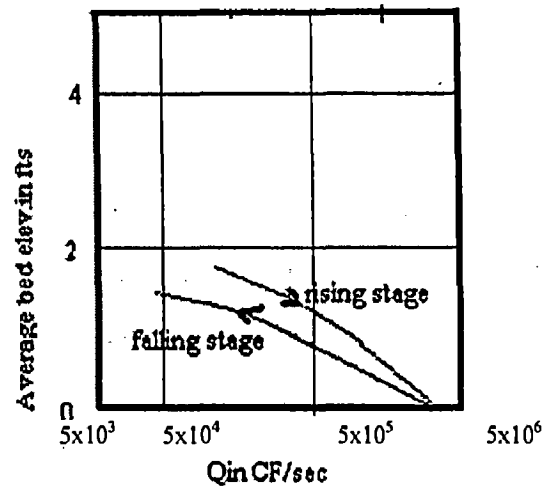


Figure: 2.10(b)

In the simplest form to understand the process of bed profile variation one has to assess the inflow out flow of sediment discharge in the reach under the consideration.

a) If the incoming amount or the rate of the sediment upstream of the reach is higher than outgoing from the reach downstream it is obvious that the difference of the two quantities must have been dropped within the length of the reach. This process of rising of the bed level is called Aggradation.

b) Conversely, if the incoming amount or the rate of the sediment upstream of the reach is lower than outgoing from the reach downstream then the difference of the two quantities must have been fulfilled by picking up the bed materials from within the length of the reach.

This process of lowering of the bed level is called Degradation.

2.4.1 OCCURRANCES OF AGGRADATION AND DEGRADATION

2.4.1.1 Occurrence of Aggradaion

Occurrence of aggradation is the most often observed phenomena on the upstream side of Dams, Barrages and any other disturbances caused by man made features or natural activities like barricade due to land slide. Because of disturbance in the equilibrium state of sediment flow in the stream causing reduction in the bed

profile slope the sediment carrying capacity of the flow is weakened which leads to settling of the sediment contained in the flow (basically bed load) is retained in the zone upstream to such features.

Other instance of aggradation of river bed is rising of the water level in the Lake or the sea which cause to reduce the slope of the water surface of river leading to a drop in the sediment transporting capacity and the result is aggradation.

The situation of aggradation involves lower rate of sediment outflow than the inflow so that

$$\frac{\partial z}{\partial t} = +ve \quad 2.7$$

in the sediment continuity equation

$$\frac{\partial z}{\partial t} + \frac{1}{(1 - \lambda)} \frac{\partial q}{\partial x} = 0 \quad 2.8$$

The consequences of aggradation more often reduce the conveyance capacity of the channel due to reduction in the flow area.

The figure below shows how the process of aggradation reach to final equilibrium condition.

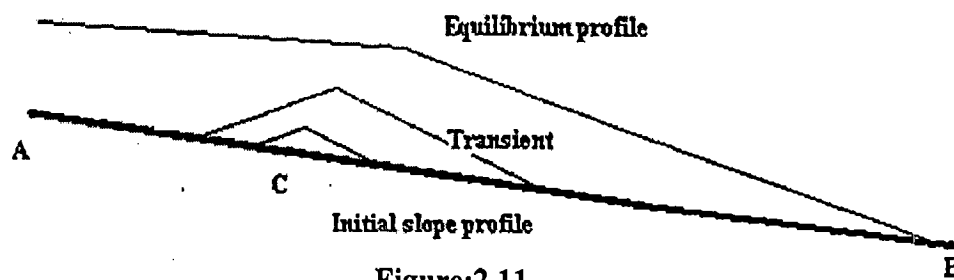


Figure:2.11
Aggradation and Equilibrium L-Profile

Where the aggradation takes place because of increase in the sediment load in the flow above its transport capacity part of the sediment of the bed load is disposed on the bed of the channel which gradually extends upstream and downstream (as shown

in the figure continues) till new profile is attained. This new profile is the equilibrium state of the profile adequate to transport the incoming sediment discharge.

2.4.1.2 *Effects of Aggradation*

- a) Firstly, aggradation shrink the active flow area of the river. Consequently, the flow is pushed to spread to wider coverage extending the flood affected area.
- b) In the reservoirs behind the storage dams, the filling up of the reservoir lead to decrease in the depth of the usable water. This necessitate to fix a dead level in the design of such structures.
- c) Bank erosion and river migration problems are more pronounced in the aggrading rivers like lower reaches of the river Brahmaputra.
- d) Aggradation of the river bed restricts the navigational opportunities of the river courses.
- e) The effect of aggradation extends the flood detention period over the flood plain during wet season causing water table to rise causing water logging.

2.4.2.1 *Occurrence of Degradation*

Most often degradation of streambed is observed to be lowered downstream of Large Capacity Reservoirs and Pools. Such degradation was observed in *Cherry Creek USA* where the extent of lowering being measured was 4.9m. But wherever sound rock exposures are encountered the process of degradation have found retarded.

Another prominent location of occurrence of degradation is confluence of two or more rivers. Tributaries, generally steeper than the main stream but carry less run-off cause to lower the bed.

At the instances, where the water discharges in the stream increases due to mixing of tributaries with relatively sediment free water discharge enhances the sediment transport capacity degradation occurs subsequently.

And one another cause of degradation is because of increase in water surface profile slope as the result of fall in level of a lake. This type of degradation was noted in White river in California USA.

Another location of degradation is where river has been started to flow along the cut-off developed in the meandered river. The cut-off shortens the length of the river. In the beginning the cut-off has narrow width which gradually open to accommodate the discharge through the channel.

In the meandered rivers, the meandering process advances to a stage that the river no more can negotiate a long serpentine path which impose more resistance and take a shortest channel route at an incidence of high flow.

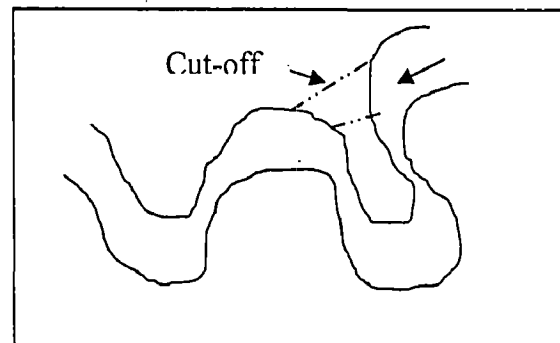


Figure:2.12

Shortening of the river flow path due to cut-off development

2.4.2.2 *Effect of Degradation*

Followings are some of the much pronounced effects both harmful as well as beneficial in the study of River Engineering.

- a) Formation of Hydraulic Jump is apparently pushed downstream in spillways and Barrages due to downstream bed level lowering jeopardizing the stability of the structure. This situation was faced in the *Wincosin* river at downstream of *Praire Du San Dam* (USA).
- b) Dams constructed in pervious strata exhibit increase seepage head due to increase in level difference between upstream and downstream water. The effect of this could be more uplift and seepage.
- c) While in case of lowering of tail water level downstream of a Power Generation point due to degradation leads to increase in available effective heads for more power generation. This has occurred at *Paraire Du Sac Dam* in the *Wincosin* river USA. And also at *Upperborn power house* at *Munich* on the *Saalach* river.

- d) Lowering of river bed by degradation process increases the capacity of the river channel to carry the flood flow, by lowering the high flood level of the river. Creating an artificial degradation by construction of a big reservoir was a method that had been suggested as a possible solution to the flood problem of the *Yellow river in China* and *Kosi river* in the Indian territory. Lowering of water level due to degradation reduces the height of the ground water table in the adjoining areas.
- e) Lowering of water level may expose pile foundation of bridges abutments and other structures to air and this may lead to deterioration of piling & stability endangering the whole structure. This problem has also been observed in many of the river bridges around on their downstream due to increased flow intensities aggravated by the construction of the bridges.
- f) Degradation also causes lowering of water level at the existing irrigation intakes and thus makes the diversion of water for irrigation more difficult.
- g) Degradation may cause substantial lowering of bed in navigable rivers and in extreme cases locks may become inoperative. Such difficulties have been encountered on a lock at the *Wincosin river (USA)* and on the *Mausa river (Holland)*(9).

2.5 SEDIMENT TRANSPORT MORPHODYNAMICS

A smooth concave configuration represents the most common quasi-equilibrium profile of alluvial rivers(Gary anf Parker,2004)(10). Various independent effects that drive concavity in longitudinal rivers are considered and classified. The driving mechanisms are (1) horizontal wavelike progradation of the river profile, (2) abrasion of bed particles, (3) aggradation of the river profile balancing subsidence at a constant speed, and (4) the effect of tributaries adding sediment and water to the main stem of the river. For simplicity it could be assumed that the long-term supply of water and sediment is constant; hence a single discharge, that is, bank-full discharge, represents

an approximate characterization of the hydrologic regime for each point along the river. The river may be treated to have uniform bed material, although the mean size may vary downstream. The quasi-equilibrium longitudinal profile created by each of the first three driving mechanisms mentioned above is concave. The degree of concavity varies, however, depending on a set of physical conditions that can be identified by a set of dimensionless numbers. A comparison of these numbers reveals the relative importance of the driving mechanisms for concavity. A condition for concavity driven by the fourth mechanism, that is, tributary input, is often delineated.

Evolution of Longitudinal profiles of rivers are attributed to the process of Sediment transport morphodynamics. In the simple form Longitudinal Profile of a river is a plot of bed elevation versus down-channel distance x .

The long profile of a river is called *upward concave* if slope $S = dz / dx$ is decreasing in the streamwise direction; otherwise it is called *upward convex*.

One of the study on the Longitudinal Profile of Amazon river (Pirmez-1994) showed upward concave everywhere.

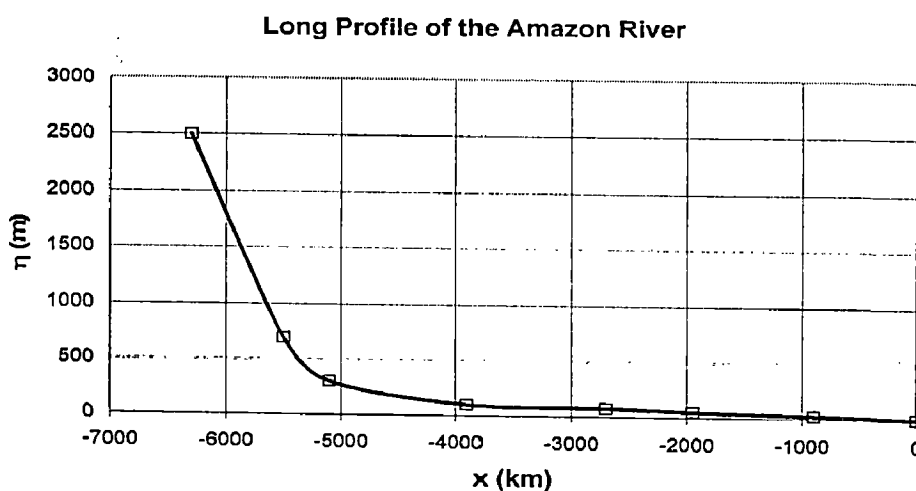


Figure:2.13

River morphology class GEO3-4305, 2006

2.5.1 Transient Long Profiles

Graded state rivers have constant slopes in the downstream direction, adjusted so that the rate of inflow of sediment to a reach equals the rate of outflow. When more

sediment is fed in than flows out, the river is forced to aggrade toward a new equilibrium. During this transient period of aggradation the profile is upward-concave. Likewise, when more sediment flows out of the reach than is fed in, the river is forced to degrade toward a new equilibrium. During this transient period of degradation the profile is upward-convex.

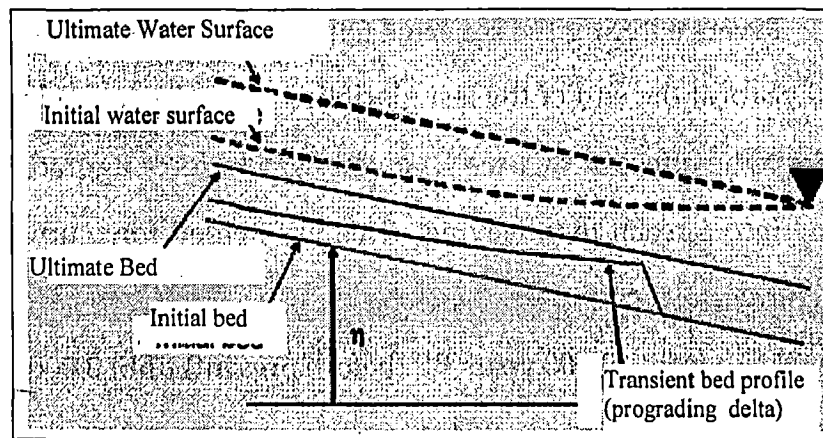


Figure:2.144

Transient Long Profiles (River morphology class GEO3-4305, 2006)

2.5.2 Quasi-Equilibrium Long Profiles

The long profiles of long rivers generally approach an upward-concave shape that is maintained as a quasi-equilibrium form over long geomorphic time. As the word "quasi" implies, this "equilibrium" is not an equilibrium in the sense that sediment output equals input over each reach.

Reasons for the maintenance of this quasi-equilibrium are summarized in Sinha and Parker (1996). Several of these are listed below(10).

- *Subsidence*
- *Sea level rise*
- *Delta progradation*
- *Downstream sorting of sediment*
- *Abrasion of sediment*
- *Effect of tributaries*

2.5.2.1 Subsidence

As a river flow into a subsiding basin, the river tends to migrate across the surface, filling the hole created by subsidence. As a result, the sediment output from a reach is less than the input, and the profile is upward-concave over the long term (e.g. Paola et al., 1992).

2.5.2.2. Sea Level Rise

Rivers entering the sea have felt the effect of a 120 m rise in sea level over about 12,000 years at the end of the last glaciation. The rise in sea level was caused by melting glaciers. The effect of this sea level rise was to force aggradation, with more sediment coming into a reach than leaving. This has helped force upward-concave long profiles on such rivers.

Sea level rise from 19,000 years BP (before present) until 3,000 years BP according to the Bard Curve (see Bard et al., 1990).

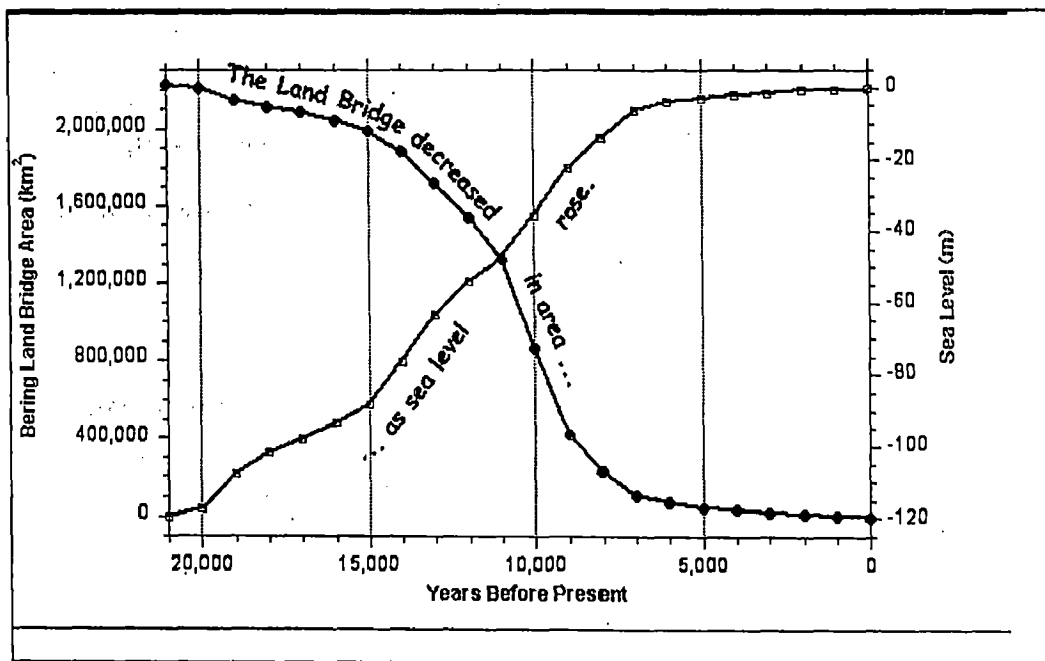


Figure :2.15

Sea level rise from 19,000 years BP (before present) until 3,000 years BP

2.5.2.3 Delta Progradation

Even when the body of water in question (lake or the ocean) maintains constant base level, progradation of a delta into standing water forces long-term aggradation and an upward-concave profile.

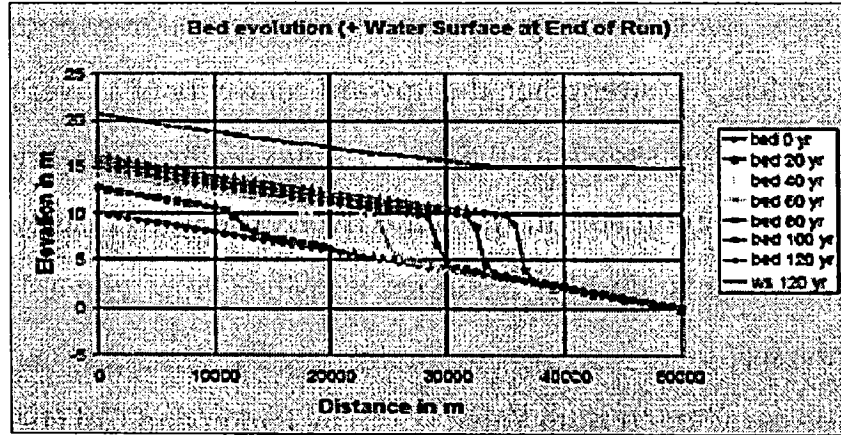


Figure:2.16 (River morphology class GEO3-4305, 2006)

Missouri River prograding into Lake Sakakawea, North Dakota.

2.5.2.4 Downstream Sorting of Sediment

Rivers typically show a pattern of downstream fining. That is, characteristic grain size gets finer in the downstream direction. This is because in a sediment mixture, finer grains are somewhat easier to move than coarser grains. Since finer grains can be transported by the same flow at lower slopes, the result is a tendency to strengthen the upward concavity of the profile.

Long profile and median sediment grain size on the Mississippi River, USA. Adapted from USCOE (1935) and Fisk (1944) by Wright and Parker.

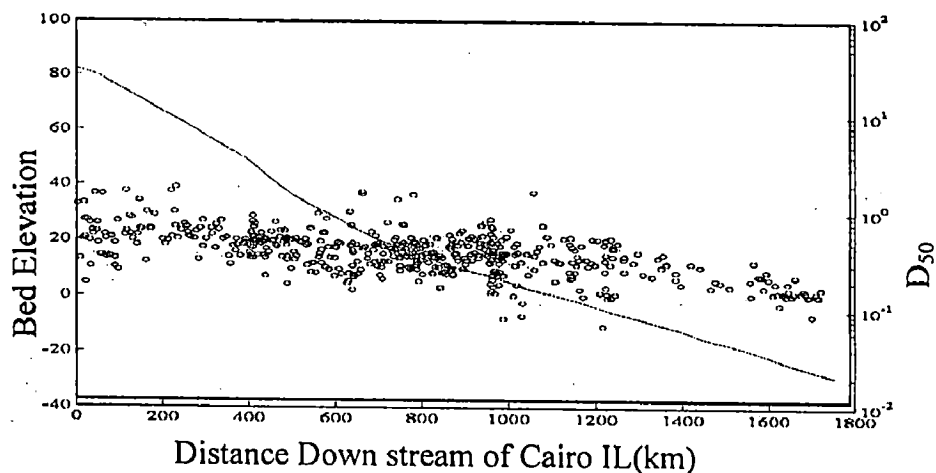


Figure:2.17

2.5.2.5 Abrasion of Sediment

In mountain rivers containing gravel of relatively weak lithology, the gravel tends to abrade in the streamwise direction. The product of abrasion is usually silt with

some sand. As the gravel gets finer, it can be transported at lower slopes. The result is tendency to strengthen the upward concavity of a river profile(10).

The image shows a) the long profile of the Kinu River, Japan and b) the profile of median grain size in the same river. The gravel easily breaks down due to abrasion. The river undergoes a sudden transition from gravel-bed to sand-bed before reaching the sea.

Image adapted from Yatsu (1955) by Parker and Cui (1998).

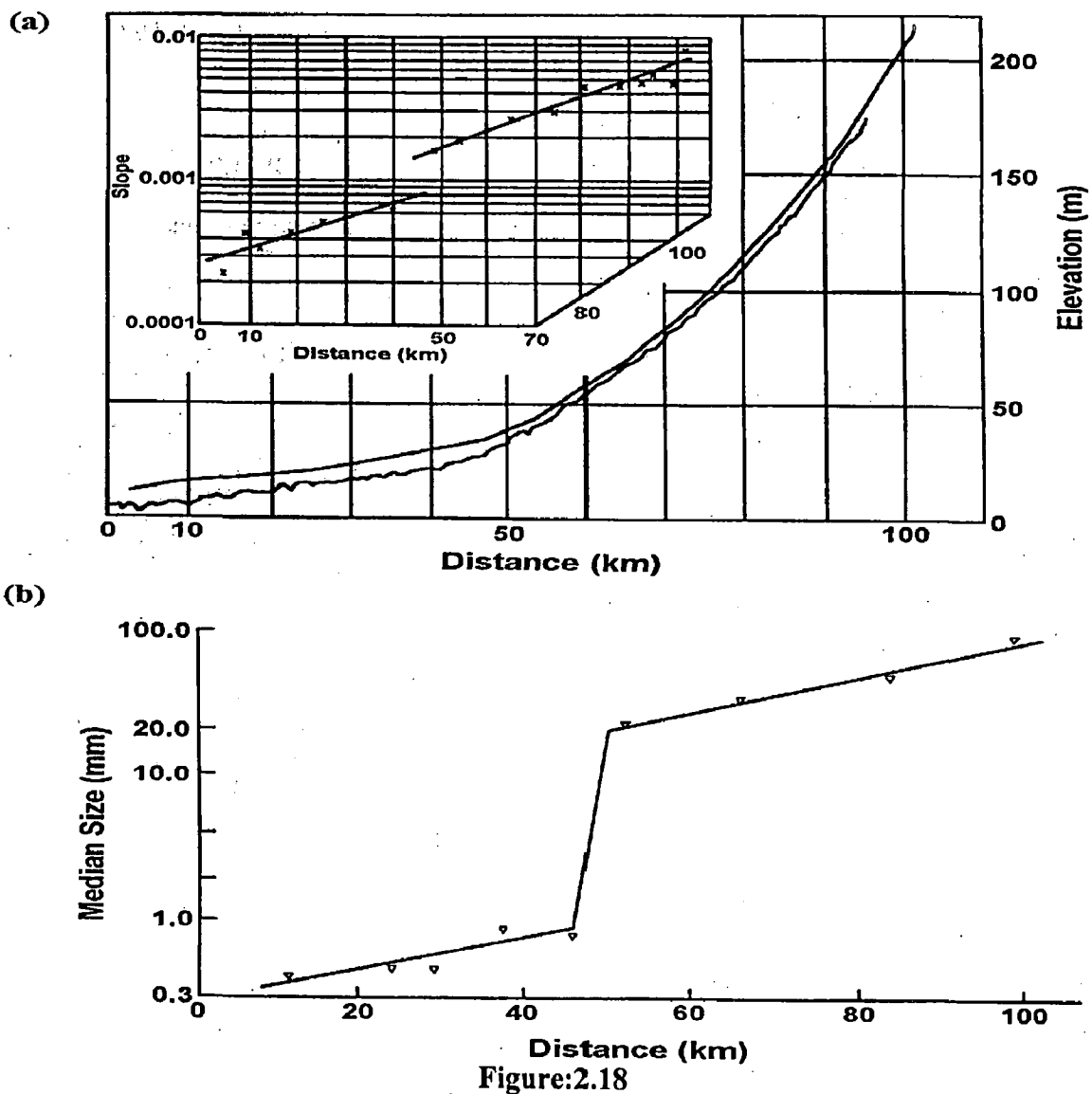


Figure:2.18

The Figure is adapted from Yatsu (1955) by Parker and Cui (1998).

2.5.2.6 Effect of Tributaries

As tributaries enter the main stem of a river, they tend to increase the supply of water more than they increase the supply of sediment, so that the concentration of sediment in the main stem tends to decline in the streamwise direction. Since the same flow carries less sediment, the result is a tendency toward an upward-concave profile(10).

2.6 MODELLING OF BRAIDED RIVERS

2.6.1 General Characteristics of Braided Streams

A stride to modelling of braided river is an intriguing step for the reason that many more has still to be quarried on the hydraulic of the flow over braided channels. The braided channels in isolation are less capable of transporting the sediments downstream due to divided-discharge however steeper slopes maintain them. The cross sections are characterised by shallow depths and wider cross sections with erodible banks. The distribution of the bars are random and the total cross sections are subjected to passing a wide variation of discharges laden with coarse to very fine sediments. the stream power.

2.6.2 Importance of Remote Sensing and GIS in River Engineering

The dynamism of river morphology could only be tract by continuous vigilance of the area under the view of the satellite sensors. Boundary of a study area like Brahmaputra which stretches hundred of kilometres in length as well in width is well brought to active surveillance by satellites. The changes in the plan forms, river migration , flood affected areas, sediment intensity , aggradation and degradation, development of bars and islands have been monitored with high resolution multi-band spectral imageries. The multi dated series of imageries are helpful to assess the trend of variation of the vegetative cover (NDVI-value) over the watershed are of a river system

signalling the possibilities of changes in the climatic behaviour of the area and the incipient flood hazards.

The digital elevation models are helping to abstract the nature of the ground topography

in planning and managements of Water Resources Development and other disciplines.

2.6.3 Earlier Works

The study on river morphology with the use of remote sensing data is a relatively new development, and has been in practice for not more than the last 20 to 25 years in India. Murthy (1990) has studied the flood plain of Brahmaputra river using satellite imageries. Hussain (1992) has carried out morphological studies of river Brahmaputra with the help of satellite imageries. Morphological studies of the river Brahmaputra has been undertaken by Brahmaputra Board, Government of India in 1993. Best and Bristow (1993) studied the braiding pattern of Brahmaputra in Bangladesh using satellite data. Arshad (1996) through satellite imageries has done morphological analysis for identification of river training sites in a stretch of the river Ganga. Oak (1998) worked on the prediction of bank erosion of bank of the Brahmaputra river on Gumi-Alikash reach (down stream of Pandu). Some erosion studies using satellite imageries in the vicinity of Majuli island and Kaziranga National Park had been studied by Space Application Centre, Ahmedabad.

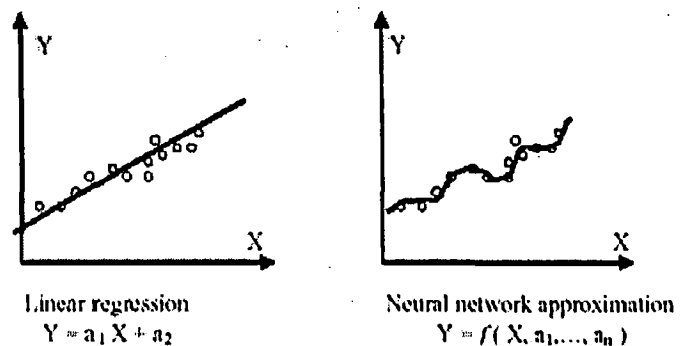
2.7 NEUROMORPHIC SYSTEMS

Numerical method of computation on practical problems of flow dynamics of river has been recognized as a universal technique now a days. This has been possible due to enhancement of computer capacity with fast processing micro processors and huge memory disk as well as development of high level user languages. Within no time the under taking of multiple alternative way to the solution of the problem is possible.

The problems which are often not possible to be idealized on the basis of the established concepts of physical interpretation of the problem have to be sorted out for data driven techniques, Artificial Intelligence (AI). The data driven models rely on the inputs and the out puts of the problem explaining the crux of the problem nature. The idea so generated from the data being exposed to the modeller (AI) is capable of generalizing the problem even extending to the range which was not included in the input-output set presented before. Therefore, Artificial Intelligence Techniques have been playing a complementary role in Physically based modelling.

Data-driven modelling uses results from such overlapping fields as artificial neural networks (ANN), rule-based approaches like fuzzy logic concepts. Sometimes "hybrid models" are built combining both types of models. More complex data-driven models are highly non-linear, allowing to have many inputs and many outputs. The neural models are different from the regression models in the sense that the former gives output from generalisation and the later by memorisation. ANN is resorted to when the dimension of input space is high, where regression analysis becomes ineffective in delivering a solution. They need a considerable amount of historical data to be trained, and if this is done properly, they are able not only to approximate practically any given function, but also to generalize, providing correct output for the previously unseen inputs.

Figure 2.19
 Linear regression and data driven model (ANN)



The origin of fuzzy logic approach dates back to 1965, since Zadeh's introduction of fuzzy-set theory and its applications. Since that period, fuzzy logic concept has found a very wide range of applications especially in the systems that are very complex,

uncertain and cannot be modelled precisely, even under various assumptions and approximations.

Neural network and fuzzy logic have been successfully applied to a wide range of problems covering a variety of sectors. Their practical applications, especially of neural networks expanded enormously, starting from mid 80s till 90s partly due to a spectacular increase in computing power. During the last decade ANN evolved from being only a research tool that is applied to many real-world engineering problems.

Neuro-fuzzy approach is comparatively new, and is a growing area of research. Neuro-fuzzy systems combine the advantage of fuzzy logic system, which deal with explicit knowledge that can be explained and understood, and neural networks, which deal with implicit knowledge, which can be acquired by learning. A faster rate of convergence by controlling the learning rate parameter with fuzzy rules can be obtained.

2.7.1 *Artificial Neural Networks*

An artificial neural network (ANN) is a computing paradigm designed to mimic the human brain and nervous system. Neural network (NN) has a big role to play in the field of hydrology where complex natural processes dominate. The high degree of empiricism and approximation in the analysis of hydrologic systems make the use of NN highly suitable. In other words, when the possibility of representing the complex relationships between various aspects of the processes in terms of physical or conceptual modelling is very remote, the NN plays an important role.

ANN is an information processing system that uses an approach entirely different from conventional algorithmic programming and roughly replicates the behaviour of a human brain by emulating the operations and connectivity of biological neurons. From a mathematical point of view, it is a complex non-linear function with many parameters that are trained in such a way that the ANN output becomes similar to the measured output on a known data set. ANNs are highly distributed

interconnections of adaptive nonlinear processing-elements (PEs) (Figure 2.20). When implemented in digital hardware, the PE is a simple sum of products followed by non-linearity. The connection strengths, also called the network weights, can be adapted such that the network's output matches a desired response.

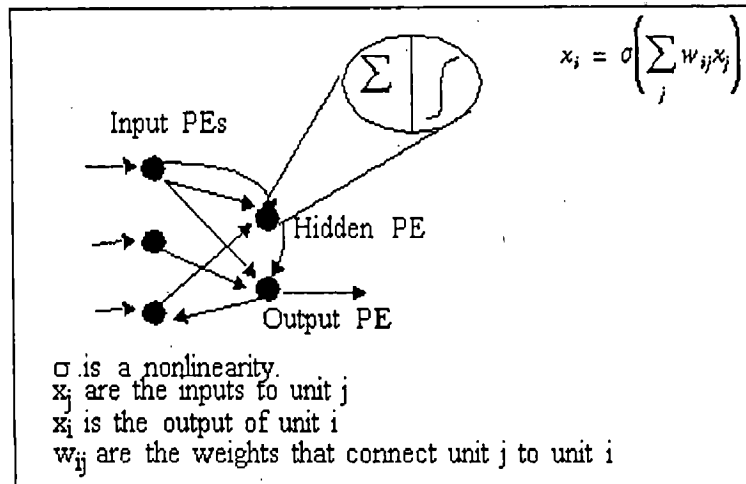


Figure 2.20

The building blocks of ANN

In multi-layered perceptron, hidden layer means a third layer of processing elements or units in between the input and output layers that increases computational power. In principle, the hidden layer can be more than one layer. In practice, the number of neurons in this layer is evaluated by trial and error. Hornik et al. (1989) proved that a single hidden layer containing a sufficient number of neurons could be used to approximate any measurable functional relationship between the input data and the output variable to any desired accuracy. In addition, De Villars and Barnard (1993) showed that an ANN comprising of two hidden layers tends to be less accurate than its single hidden layer counterpart.

The ANNs are not exactly the substitute to regression. General regression can not solve the problems where the input dimension space is high and there is restriction on the number of input data. Regression imposes a priori variable selection, with all the inherent pitfalls, where one is limited to a few inputs among hundreds available. Regressions are performed using simple dependency functions that are not very

realistic. In regression there is only one dependency function over the whole data set, instead of many distinct niches, which is taken care of by ANNs. Where dependency between the input variables and the output are not well-defined, ANNs solve it better. The most important difference between ANN and regression is that the former maps the output by generalization where as the later by memorization. Generalization refers to the neural network producing reasonable outputs for inputs not encountered during learning. To oversimplify, if an object is represented in a network as a pattern of activation of several units, and if a unit or two responds incorrectly, the overall pattern remains pretty well the same, and the network will still respond correctly to stimuli.

In 1943, McCulloch and Pitts studied the finest element of the brain, the neuron, with its cell body, axon, and synapses to create the perceptron. ANNs have become an attractive technique for approaching many hydrologic problems as established by Daniel (1991), Hall et al. (1993), Karunanithi et al. (1994), Zhu and Futija (1994) and Smith and Eli (1995). According to Bastarache et al. (1997), Muttiah et al. (1997), Clair and Ehrman (1998) and Wen and Lee (1998), multilayer perceptrons are powerful tools in solving non-linear water resources problems. Zealand et al. (1999) worked on short-term stream flow forecasting using ANN. Dastorani et al. (2002) used ANN for real time river flow prediction. Bhattacharya et al. (2000) used ANN to predict stage and discharge relationship. Kumar et al. (2004) forecasted the river flow using recurrent neural network. In general, neural networks offer viable solutions when there are large volumes of data to train the neural network. When a problem is difficult (or impossible) to formulate analytically and experimental data can be obtained, a neural network solution is normally appropriate.

2.7.2 Neural Network Topology

The arrangement of the processing units, connections, pattern input and output is referred to as topology. The processing units are arranged in three layers as input, hidden and output. The units of a layer are similar in the sense that they all have the

same activation dynamics and output function. The number of input and the number of output are problem specific. There are no fixed rules as to the how many units should be included in the hidden layer. If there are too less units in the hidden layer, the network may have difficulty in generalizing the problem. On the other hand, if there are too many units in the hidden layer, the network may take an unacceptably long time to learn. On the basis of direction of information flow and processing, the ANNs are classified as feed forward and feed backward network. The manner in which the neurons of a neural network are structured and intimately linked with learning algorithm ceased to train the network. The optimal architecture is one, which yields the best performance in terms of error minimization, while training simple and compact structure. The numbers of input and output nodes are problem dependent. The flexibility lies in selecting the number of hidden layers and is assigning the number of nodes to each of these layers.

2.7.3 Model of Neural Networks

The human nervous system may be viewed as a three-stage system. The forward and feedback arrows are shown for the movement of information. The neural (nerves) net continually receives information, perceives it, and makes appropriate decision. The receptors convert stimuli from the human body or the external environment in to electric impulses that convey information to the neural net (brain). The effectors convert electrical impulses generated by the neural net into discernible responses as system outputs. The operation of brain is believed to be based on simple basic elements called neurons, which are connected to each other with transmission lines, called axons and receptive lines, called dendrites (15). A simple illustration of biological and artificial neuron is shown in Figure 2.21(a) to (c).

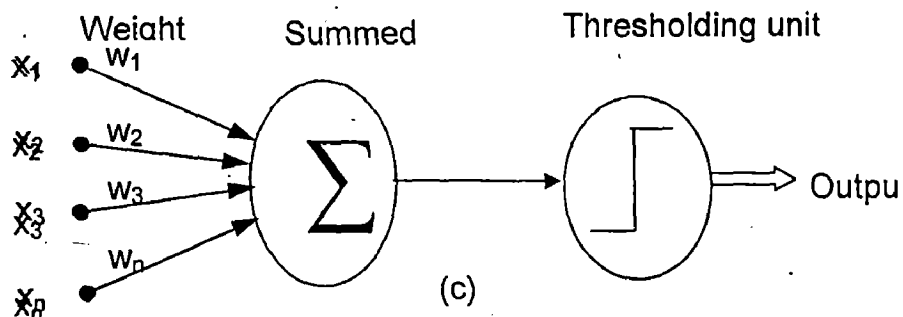
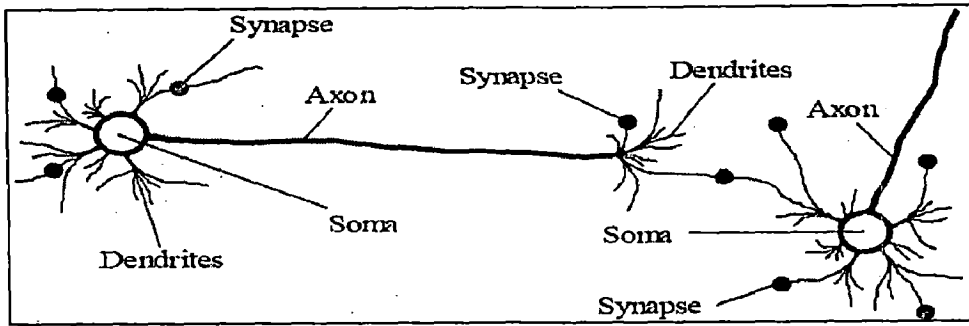
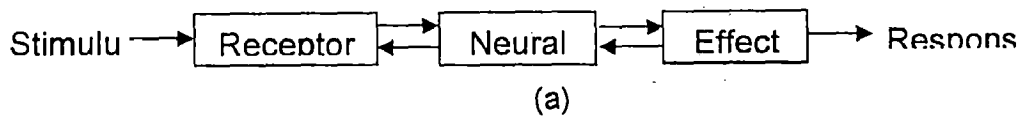


Figure 2.21 Simple illustration of biological and artificial neuron

Each input x_i ($i = 1, \dots, n$) is attenuated by a factor w_{ij} , more commonly called a weight of the network, which is associated with the connection linking input x_i to hidden neuron j ($j = 1, \dots, k$), where k is the number of neurons in the single hidden layer. The weighted sum of the incoming signals entering a neuron is fed via an activation function, which is non-linear, producing a value that in turn acts as an input signal sent to the output layer. This is repeated for the output weights. The following expression gives the output value of the network:

$$y = \phi \left[\sum_{j=li}^N \phi \left\{ \sum_{i=1}^N x_i w_{ij} \right\} a_j \right] \quad 2.11$$

Where ϕ is a sigmoidal activation function (described at para 2.7.6.1)

To obtain the best approximations, it is needed to determine the optimum set of weights w_{ij} and a_j that will yield the least mean square value of the desired response. Thus, the following performance criterion needs to be satisfied.

$$\min_{a_j, w_{ij}} \frac{1}{2} E[(y - y_D)^2] \quad 2.12$$

Where, E is the statistical expectation operator, the factor $\frac{1}{2}$ is included for convenience of presentation.

2.7.4 ANN Modelling Processes

Neural networks concentrate on machine learning which is based on the concept of self-adjustment of internal control parameters. The ANN environment consists of five primary components; learning domain, neural nets, learning strategies, learning process and analysis process. Accordingly, neural network based modelling process involves five main aspects which are: (i) data acquisition, analysis and problem representation, (ii) architecture determination, (iii) learning process determination, (iv) training of the network and (v) testing of the trained network for generalization evaluation (47). Elazouni et al. (1997) classified ANN modelling into three main phases: (a) design, (b) implementation and (c) use for problem solving. The design phase consists of two tasks - problem analysis and problem structuring. The implementation consists of three main aspects: (1) acquiring the knowledge (including data collection); (2) selecting the network configuration; and (3) training and testing the network.

2.7.5 Representing the Variables

Smith (1993) explained that the way independent variables are represented by input nodes of the network has a major impact on the training of the network and on the performance of resulting model. The ability of the network is mainly referred to as its effectiveness in generalizing. The amount of computation and the time required for learning are both greatly influenced by the form of representation used. There are two types of independent and dependent variables: (1) quantitative; and (2) class variables.

The quantitative or continuous valued variable can be any number. It is not necessary to fall within the bounds of the applied sigmoid function. It also is possible to normalize the quantitative variables to some standard range such as 0 to 1, -1 to 1, or none (41; 5). Elazouni et al. (1997) opined that the networks usually provide improved performance when the data are normalized. When the variables fall in the range, it smoothes the solution space and averages out some of the noise effects.

2.7.6 *Summation and Transformation Function*

Summation function is a function which finds the weighted average of all inputs elements to each processing elements. It simply multiplies the input values by the weights and totals them up for a weighted sum. The transformation function (or transfer function or local memory) is a relationship between the internal activation level (N) of the neuron (called activation function) and the outputs. The transformation function is a kind of sigmoid function. A function $f(N)$ will be a sigmoid function if it has two certain characteristics: (1) it is bounded; and (2) the value of a sigmoid function always increases as N increases (41). A number of different functions have these characteristics, and thus qualify as sigmoid functions. Any of them may be used in the neural network.

2.7.6.1 *Sigmoid & Tan hyperbolic*

This function is a continuous function (Figure 2.22) that varies gradually between asymptotic values 0 and 1 or -1 and +1 and is given by:

$$\phi(I) = 1 / (1 + e^{-\alpha I}) \quad \text{Tan-hyperbolic} \quad \phi(I) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad \text{for } -1 < x < +1 \quad (2.13)$$

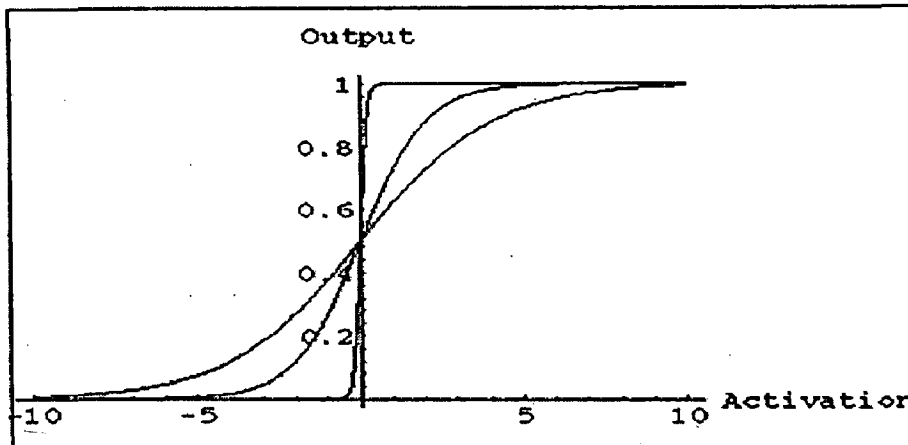


Figure 2.22

Activation function (Rajasekharan, 1996)

Where, α is the slope parameter, which adjusts the abruptness of the function as it changes between the two asymptotic values. Sigmoid functions are differentiable, which is an important feature of neural network theory. Experimentally, observations of biological neurons demonstrate that the firing is roughly sigmoid, when plotted.

The problem with linear type processing elements is that their transfer functions are not differentiable (29). Because of this fact, networks using linear type processing elements are difficult to train. To overcome the linear behaviour of networks using linear-threshold type transfer functions, smooth nonlinear transfer functions, which are continuous and differentiable everywhere, i.e. the sigmoidal type has been used. The output of a sigmoidal unit asymptotically goes to 1 as the weighted sum of its inputs approaches positive infinity, and to 0 as the weighted sum of its inputs approaches negative infinity. This function is defined as: $f(x) = 1/(1 + e^{-x})$, where x is the net input to the unit. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered as rough approximations (16).

2.7.7 Initial Weights

The initial weights of a multilayer feed forward network strongly affect the ultimate solution. They are typically initialized by small random values. Equal weights values cannot train the network properly if the solution requires unequal weights to be developed. The initial weights cannot be large, otherwise the sigmoid will saturate from the beginning, and the system will stuck at a local minimum. The saturation is avoided by choosing the initial values of the synoptic weights to be uniformly distributed inside a small range of values. The range should not be too small as it can cause the learning to be very small. The range of initial weight w_{ij} is $(-3/\sqrt{k_i}$ to $3/\sqrt{k_i})$, where, k_i is the number of neurons that feed forward to neuron i (43).

2.7.8 Number of Neurons in the Hidden Layer

In multi-layered perceptron, hidden layer means a third layer of processing elements or units in between the input and output layers that increase computational power. In principle, the hidden layer can be more than one layer. The network can approximate a target function of any complexity, if it has enough hidden nodes. The output of hidden nodes can be considered as a new variable, i.e. an input to the nodes on the next layer or the nodes on the output layer. They contain interesting information about the relationship being modelled.

Too few hidden nodes for a given problem will cause back-propagation not to converge to a solution (19). However, many hidden nodes cause a much longer learning period. At some point, increasing the number of hidden nodes does not greatly increase the ability of the neural network to classify (46). On the other hand, too many units on a layer can make a network to become over specific, particularly on the extreme case where the number of units on the first processing layer is equal to the number of examples in the training set (36). Too many hidden nodes can over fit, such that the network can model the accidental structure of the noise in the sample as well as the inherent structure of the target function (41). Therefore, minimum sized network which

uses as few hidden units as possible is important for efficient classification and good generalization (21). Berke and Hajela (1991) suggested that the number of hidden nodes should lie between the average and sum of nodes on the input and output layers. Rogers and Lamarsh (1992) suggested that a good initial guess for hidden nodes is to take the sum of nodes on the input and output layers. Soemardi (1996) suggested that the number of hidden nodes should be 75% of the input nodes. Thus, experience shows that the number of hidden nodes has a maximum limit of the sum of the input and output nodes but the minimum could be either 75% of the input nodes or the average of the input and output nodes. The size of a hidden layer is usually determined experimentally.

2.7.9 Weights and Biases

Weights are defined as the strength of input connections which are expressed by a real number. The processing nodes receive inputs through links. Each link has a weight attached to it. The sum of the weights makes up a value that updates the processing nodes, the output excitation to get either on or off. The weights are the relative strength (mathematical value) of the initial entering data that transfer data from layer to layer. They are the relative importance of each input to a processing element (28). In practice, the weights would be initiated and assigned to the network prior to the start of training. The weights initiation techniques are also important in order to control and obtain the convergence of training and training time. For each network, the number of unknowns is equal to the sum of the weights and biases. For a given network, the number of weights is the product of the number of nodes on all links, and the number of biases is the sum of numbers of all the nodes.

2.7.10 Training and Generalization

Network training means adjusting neural network weights. The weights and biases are initialized randomly. During training, the network analyzes the data provided and changes weights between network units to reflect dependencies found in

the data. Training is the process whereby it (1) computes outputs, (2) compare outputs with desired outputs, and (3) adjusts the weights and repeats the process (110). The main purpose of training is to determine the set of connection weights that cause the neural network to estimate outputs that are sufficiently close to target values.

A good subset of input variables can substantially improve model performance. Presenting as large a number of input variables as possible to ANN models usually increases network size, resulting in a decrease in processing speed and a reduction in the efficiency of the network. An approach is that appropriate input variables can be selected in advance based on a priori knowledge (26). Another approach used by some researchers is to train many neural networks with different combinations of input variables and to select the network that has the best performance. A step-wise technique described by Maier and Dandy (2000) can also be used, in which separate networks are trained, each using only one of the available variables as model inputs. The network that performs the best is then retained, combining the variable that resulted in the best performance with each of the remaining variables. This process is repeated for an increasing number of input variables, until the addition of any extra variables results in no improvement in model performance.

ANNs perform best when they do not extrapolate beyond the range of the data used for calibration (7; 31). Therefore, the purpose of ANNs is to non-linearly interpolate (generalize) in high-dimensional space between the data used for calibration. Unlike conventional statistical models, ANN models generally have a large number of connection weights and can therefore over fit the training data, especially if the training data are noisy. In other words, if the number of degrees of freedom of the model is large compared with the number of data points used for calibration, the model might no longer fit the general trend, as desired, but might learn the idiosyncrasies of the particular data points used for calibration leading to 'memorisation', rather than 'generalisation'. Consequently, a separate validation set is needed to ensure that the model can generalise within the range of the data used for calibration. It is common

practice to divide the available data into two subsets; a training set, to construct the neural network model, and an independent validation set to estimate the model performance in a deployed environment (26). A modification of the above data division method is cross-validation (42), in which the data are divided into three sets: training, testing and validation. The training set is used to adjust the connection weights, whereas the testing set is used to check the performance of the model at various stages of training and to determine when to stop training to avoid over fitting. The validation set is used to estimate the performance of the trained network in the deployed environment. There are no guidelines in the literature for the optimal proportion of the data to use for training, testing and validation. In many situations, the available data are small enough to be solely devoted to model training and collecting any more data for validation is difficult. In this situation, the leave-k-out method can be used (30), which involves holding back a small fraction of the data for validation and the rest of the data for training. After training, the performance of the trained network has to be estimated with the aid of the validation set. A different small subset of data is held back and the network is trained and tested again. This process is repeated many times with different subsets until an optimal model can be obtained from the use of all of the available data.

As ANNs have difficulty extrapolating beyond the range of the data used for calibration, in order to develop the best ANN model, given the available data, all of the patterns that are contained in the data need to be included in the calibration set. For example, if the available data contain extreme data points that were excluded from the calibration data set, the model cannot be expected to perform well, as the validation data will test the model's extrapolation ability, and not its interpolation ability. If all of the patterns that are contained in the available data are contained in the calibration set, the toughest evaluation of the generalisation ability of the model is if all the patterns are contained in the validation data. In addition, if cross-validation is used as the stopping criterion, the results obtained using the testing set have to be representative of those obtained using the training set, as the testing set is used to decide when to stop training

or, for example, which model architecture or learning rate is optimal. Consequently, the statistical properties (e.g. mean and standard deviation) of the various data subsets (e.g. training, testing and validation) need to be similar to ensure that each subset represents the same statistical population (30). However, it was not until recently that systematic approaches for data division have been proposed in the literature.

The available data set is randomly partitioned into a training set and a test set. The training set is further partitioned into two disjointed subsets:

- (i) Estimation set used to select the model
- (ii) Validation set used to validate the model

The training data submitted to the network for it to learn and generalize the relation between input and output should be sufficient and proper. There is no rule for choosing the training data. Networks with too many trainable parameters for a given amount of training data learn well but do not generalize well. This phenomena is called over fitting with too few trainable parameter, the network fails to learn the training data. Once a network has been structured for a particular application, that network is ready to be trained. To start this process, the initial weights are chosen randomly, and then the training or learning begins. Supervised and unsupervised are two methods used to train the neural network.

2.7.10.1 Methods of training

Training is a process of adjusting the connection weights in the network so that the network's response best matches the desired response. Although, this can be addressed as an optimization method, the back-propagation methods avoid this costly exercise by using an approximation to a gradient descent method. A network learns because the strength of the connections between neurons changes. The efficiency of a neuron in exciting or inhibiting another is not constant. Specifically, at each setting of the connection weights, it calculates the error committed by the network simply by taking the difference between the desired and the actual response determined by the

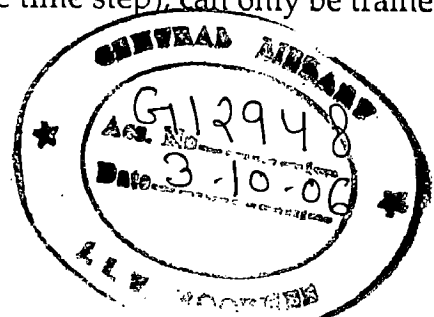
network. In training a network, error is used to modify the weights so that next time the network gives a more correct answer. It may increase or decrease over time, depending systematically on experience. There are two categories of training (41), i.e. supervised and unsupervised.

2.7.10.1.1 Supervised training

The learning is said to be supervised, when the performance function is based on the definition of an error measure. Normally, the error is defined as the difference of the output of the ANN and a pre-specified external desired signal. In engineering applications, where the desired performance is known, supervised learning paradigms become very important.

In supervised training, both the inputs and the outputs are provided. The networks then process the inputs and compare its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights, which control the network. This process occurs over and over as the weights are continually tweaked. During the training of a network, the training data set is processed many times as the connection weights are ever refined.

For supervised learning, there are three basic decisions that need to be made: choice of the error criterion, how the error is propagated through the network, and what constraints one imposes on the network output. The first issue is related to the formula that computes the error. The second aspect is associated with the mechanisms that modify the network parameters in an automated fashion. The gradient descent learning is the most common in supervised learning schemes. The third aspect is associated with to constrain the network output with respect to the desired signal. One can specify only the behaviour at the final time (fixed point learning). A feed forward network, since it is an instantaneous mapper (the response is obtained in one time step), can only be trained by fixed-point learning.



2.7.10.1.2 *Unsupervised training*

The unsupervised training has been introduced by Kohonen (1988a) and is a far more plausible model of training in biological systems. Target vector is not required for the outputs. The training process extracts the statistical properties of the training set and groups similar vectors into classes, applying a vector from a given class to the input will produce a specific output vector. There is no way to determine prior to training which specific output pattern will be produced by a given input vector class. Hence, the outputs of such a network must generally be transformed into a comprehensible form subsequent to the training process.

2.7.10.2 *Learning factors of back propagation*

One of the major issues concerning back-propagation algorithm is its convergence. The convergence of back-propagation is based on some important learning factors, such as the initial weights, the learning rate, the nature of training set and the architecture of the network.

2.7.10.2.1 *Learning rate (η)*

Back-propagation is a time consuming algorithm when either the size of the net is large or the number of the training patterns is large (21). Back-propagation has some limitations. There is no guarantee that the network can be trained in a finite amount of time. It employs gradient descent, i.e. follows the slope of the error surface downward and constantly adjusts the weights towards minimum. Therefore, it has the danger of getting trapped in a local minimum before achieving the global minimum. It is important to select the correct learning rate and momentum term when using back propagation. Unfortunately, there is little guidance available other than experience, which is based on trial-and-error (2;21).

Learning rate η is the constant of proportionality which provides dynamic access to the rate at which weights may be changed. A high learning rate corresponds to rapid learning which may push the training towards a local minimum or cause oscillation. In

turn, when applying small learning rates, the time to reach a global minimum will considerably be increased (21). Learning rates for each layer of the same network can be different.

The remedy for problems of choosing learning rate is to apply a momentum factor, which is multiplied by the previous weight change so that while the learning rate is controlled the changes are still rapid (21). The role of the momentum term is to smooth out the weight changes, which helps to protect network learning from oscillation (2). A rule of thumb is that the learning rate for the last hidden layer should be twice that of the output layer.

- The values of learning rate (η) ranges between 10^{-3} to 10 (Umamahesh and Rao, 2001).
- The best value of the learning rate of the beginning of training may not as good in later training.
- A more efficient approach is to vary the learning rate as the training progresses.
- The effectiveness of the learning rate may be checked as the training progresses, and the value of the learning rate can be changed based on the change function.

If after a particular weight update, the error function has increased, then η can be increased.

$$\Delta\eta = \begin{cases} +a & \text{if } \Delta E < 0 \text{ consistently} \\ -b\eta & \text{if } \Delta E > 0 \\ 0 & \text{otherwise} \end{cases} \quad 2.14$$

where, ΔE is the change in error function, and a & b are positive constant.

2.7.10.2.2 Momentum

A simple method of increasing the rate of learning and yet avoiding the danger of instability is to include a momentum term to the normal gradient descent method.

The greater the momentum, the more the current weight change is affected by the weight change that took place during the previous iteration. The remedy for problems of choosing learning rate is to apply a momentum factor, which is multiplied by the previous weight change so that while the learning rate is controlled the changes are still rapid. The role of the momentum term is to smooth out the weight changes, which helps to protect network learning from oscillation. The scheme is implemented by giving a contribution from the previous step to each weight change.

$$\Delta w_{ij}(n) = \eta \delta I_{x_j} + \alpha \eta w_{ij}(n-1) \quad 2.15$$

Where, α is usually a positive number, in the range (0, 1) called the momentum factor. A value of 0.9 is generally used for momentum factor.

2.7.10.2.3 Gradient descent learning algorithm

Gradient descent learning is the most widely used principle for ANN training. The reason is that trivial computation is required to implement this method, and the fact that the gradient can be computed with local information. The principle of gradient descent learning is very simple. The weights are moved in a direction opposite to the direction of the gradient. The gradient of a surface indicates to the direction of the maximum rate of change (Figure 2.16). Therefore, if the weights are moved in the opposite direction of the gradient, the system state will approach points where the surface is flatter.

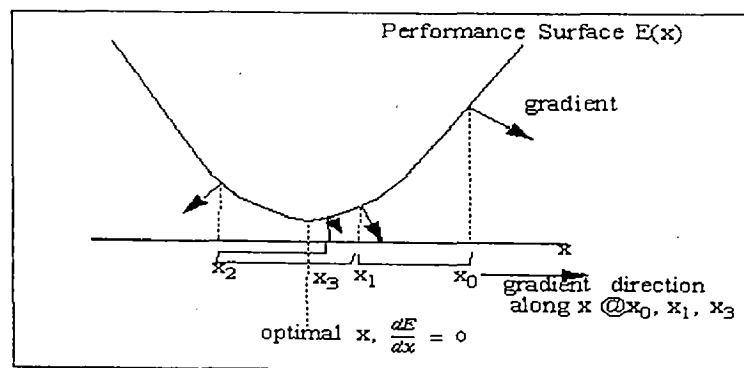


Figure 2.23
Gradient descent in one dimension

2.7.11 Back-propagation Training Algorithm and Generalized Delta Rule (GDR)

In the mid 1950's, Rosenblatt proposed a neural net model, called perceptron. Widrow and Hoff established an algorithm that can be expressed in terms of the delta rule for learning the value of weights and known as Widrow-Hoff Rule (25). In 1986, Rumelhart, Hinton and Williams extended this learning procedure to establish the back-propagation learning rule, called Generalized Delta Rule-GDR. Back-propagation has been the most popular and widely implemented of all neural network paradigms. It is based on a multi-layered feed forward topology with supervised learning. The propagation of error operates into two modes: (1) mapping; and (2) learning. In mapping mode, information flow forward through the network, from inputs to the outputs. In the learning mode, the information flow alternates between forward and backward. A key element in the back-propagation paradigm is the existence of a hidden layer of nodes. The back-propagation procedure there is an intrinsic data flow. First, the inputs are propagated forward through the network to reach the output. The output error is computed as the difference between the desired output and the current system output. Then errors are propagated back through the network upto the first layer after which the delta rule can be applied to each network PE.

Smith (1993) summarized five ways in which the power of back-propagation can deliver significant benefits, as follows:

- (1) Using back-propagation may reduce the cost of building the model as it allows the user to substitute machine time.
- (2) Back-propagation may produce a better model if two conditions are met. First, the form of relationship between inputs and desired outputs is more complex than the form of function that is imposed on the model by conventional tool. Second, the sample is large enough in order to permit it to find the relationships underlying the noise in the data.

(3) Using back-propagation provides assurance that the model is as good as it can be, since the cost of finding out or time required to know the complexity of the problem may be prohibitive.

4) Back-propagation provides an opportunity to build a single model with multiple outputs that is not possible for conventional techniques.

5) There are advanced form of back-propagation with capabilities that are not found in conventional methods.

The stepwise algorithm is narrated below:

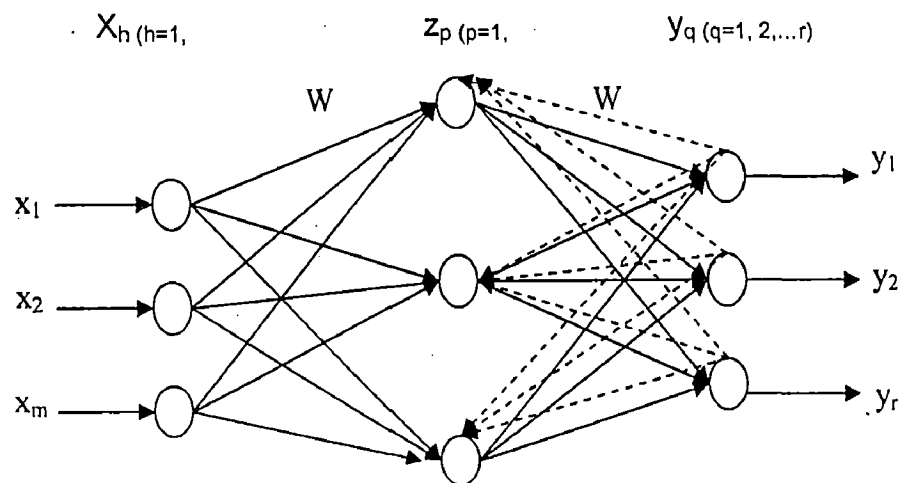


Figure 2.24

Two layered back-propagation network (Umamahesh and Rao, 2001)

Back-propagation is a systematic method of training multilayer artificial neural networks. This learning algorithm is applied to multilayer feed forward network consisting of neurons with continuous differentiable activation functions. Such network associated with the back-propagation learning algorithm is called back-propagation networks.

Considering a two layer feed forward neural network, the network has m nodes in the input layer, n neurons in the hidden layer and r neurons in the output layer. The weight associated between the h^{th} input node and p^{th} hidden layer neuron is represented by W_h , while W_o represents the weights of the connection between p^{th} hidden layer neuron and q^{th} output neuron and also considering an input-output training pair (x,d) .

Given an input pattern x , a neuron p in the hidden layer receives a net input

$$net_p = \sum_{h=1}^m W_h x_h - b_i \quad 2.16$$

Where b_i is the bias (certain minimum value) and gives an output of

$$Z_p = f(net_p) = f\left(\sum_{h=1}^m W_h x_h - b_i\right) \quad 2.17$$

$f\left(\sum_{h=1}^m W_h x_h - b_i\right)$ is an activation function of neuron

The net input for a neuron q in the output layer is

$$net_q = \sum_{p=1}^n W_o Z_p = \sum_{p=1}^n W_o f\left(\sum_{h=1}^m W_h x_h - b_i\right) \quad 2.18$$

and it gives an output of y_q as

$$y_q = f(net_q) = f\left(\sum_{p=1}^n W_o Z_p\right) = f\left(\sum_{p=1}^n W_o f\left(\sum_{h=1}^m W_h x_h - b_i\right)\right) \quad 2.19$$

The error function for a given input-output pair is

$$\Delta E = \frac{1}{2} \sum_{q=1}^r (d_q - y_q)^2 \quad 2.20$$

Where, d_q is an object output

The objective of the back-propagation algorithm is to adjust the weights of the network such that the error function is minimized.

$$\Delta W_o = -\eta \frac{\partial E}{\partial W_o} \quad 2.21$$

Where, η is a positive number called learning rate, which determines the rate of learning. Using equations (2.18), (2.19), (2.20) and (2.21):

$$\begin{aligned}
 \Delta W_o &= -\eta \left[\frac{\partial E}{\partial y_q} \right] \left[\frac{\partial y_q}{\partial netq} \right] \left[\frac{\partial netq}{\partial W_o} \right] \\
 &= \eta \left(\sum_{q=1}^r (d_q - y_q) \right) (f'(netq))(Z_p) \\
 &= \eta \delta_{oq} Z_p
 \end{aligned} \tag{2.22}$$

Where δ_{oq} is the error signal at q^{th} node in output layer which is equal to

$$\begin{aligned}
 \delta_{oq} &= \frac{\partial E}{\partial (netq)} = - \left[\frac{\partial E}{\partial y_q} \right] \left[\frac{\partial y_q}{\partial (netq)} \right] \\
 &= [d_q - y_q] [f'(netq)]
 \end{aligned} \tag{2.23}$$

Similarly, the weight is updated from the input to hidden layer connection, the weight connecting neuron j in the input layer to neuron q in the hidden layer.

$$\begin{aligned}
 \Delta W_h &= -\eta \frac{\partial E}{\partial W_h} = -\eta \left[\frac{\partial E}{\partial net_p} \right] \left[\frac{\partial net_p}{\partial W_h} \right] \\
 &= -\eta \left[\frac{\partial E}{\partial Z_p} \right] \left[\frac{\partial Z_p}{\partial netp} \right] \left[\frac{\partial netp}{\partial W_h} \right]
 \end{aligned} \tag{2.24}$$

From equation (2.20), the error term $(d_q - y_q)$, $q = 1, 2, \dots, r$ is a function of Z_p , i.e.

$$\begin{aligned}
 \Delta W_h &= -\eta \left[\frac{\partial E}{\partial netq} \frac{\partial netq}{\partial Z_p} \right] f'(net_p) x_h \\
 &= +\eta \sum_{q=1}^r [(d_q - y_q) f'(netq) W_o] f'(net_p) x_h
 \end{aligned} \tag{2.25}$$

Using equation (2.18) to equation (2.21)

$$\begin{aligned}
 \Delta W_h &= \eta \sum_{q=1}^r [\delta_{oq} W_o] f'(netp) x_h \\
 &= \eta \delta_{np} x_h
 \end{aligned} \tag{2.26}$$

Where δ_{np} is the error signal of neuron p in the hidden layer, i.e.

$$\begin{aligned}\delta_{np} &= \frac{\partial E}{\partial(\text{net}_p)} = - \left[\frac{\partial E}{\partial Z_p} \right] \left[\frac{\partial Z_p}{\partial \text{net}_p} \right] \\ &= f'(\text{net}_p) \sum_{q=1}^r \delta_{oq} W_o\end{aligned}\quad 2.27$$

In general with an arbitrary number of layers, the back-propagation update rule is in the form

$$\Delta W_{qh} = \eta \delta_q x_h = \eta \delta_{\text{output}-q} x_{\text{input}-h} \quad 2.28$$

Where $\text{output}-q$ and $\text{input}-h$ refer to the two ends of the connection from neuron h to neuron q, x_h is the proper input-end activation from a hidden neuron or an external input, and δ_q is the error signal.

In case of activation function

$$y_h = \frac{1}{1 + e^{-u_h}} \quad 2.29$$

Where u_h is the net activation internal activation level of neuron h and y_h is the output of the neuron. Then the error is

$$\begin{aligned}\delta_{oq} &= [d_q - y_q] [f'(\text{net}_q)] \\ &= [d_q - y_q] y_q (1 - y_q)\end{aligned}\quad 2.30$$

$$\delta_{np} = Z_p (1 - Z_p) \sum_{q=1}^r \delta_{oq} W_o \quad 2.31$$

2.7.11.1 Feed forward back-propagation network

The feed-forward network is also known as the error back-propagation network because of the method used in its training. The nodes are generally arranged in layers, starting from first input layer and ending at the final output layer. There can be several hidden layers with each layer having one or more nodes. Information propagation is in the forward direction from the input to the output side, and errors are propagated back in the other direction to change the weights to obtain a better performance. The neurons

in one layer are connected to those in the next, but not to those in the same layer. Thus, the output of a node in one layer is only dependent on the input it receives from previous layers and the corresponding weights.

2.7.12 Criteria for Stopping Training

There are two common criteria to stop training a network: (1) training cycles (epochs); and (2) desired errors. The other criterion is to limit the difference between desired output and output calculated by the network (21; 44). The training process may be brought to halt using either the worst error difference after complete presentation of all input-output patterns, or the root mean square error summed over all patterns. In practice, it is sometimes necessary to apply or compare both approaches to ensure the capability of the trained network in generalizing on the tested samples and application. The errors of tested samples are generally higher than the error of training sample as the network is trained to reduce the latter, not the former. However, the over-trained network would occasionally result in over-fitting. Over-fitting means the network can converge and yield a minimum or desired error in training samples but it cannot generalize well when validated with testing sample.

Weigend et al. (1991), Hergert et al. (1992) showed that the validation error decreases to a minimum for the simulations involving back propagation and then starts to increase even though the training error continues to decrease. This global minimum of the validation error curve, which is a function of the number of the hidden neurons in the ANN, determines the number of learning epochs and optimal step to stop the network.

2.7.13 Testing and Validation

Testing is a phase to examine the performance of the network by using the derived weights. It is to measure the ability of network to classify the testing samples correctly (28). This set is not used during training and thus can be considered as consisting of new data entered by the user for neural network application. Then

forecasting error is measured on each case and used as the estimation of network quality. It is a part the input data set used only to test how well the neural network will perform on new data.

The cross-validation provides an appealing guiding principle (15). The use of cross-validation set is to determine the best number of hidden neurons, and when it is best to stop the training. The use of cross-validation set is appealing, particularly when a large neural network is to be designed with good generalization as goal (42).

2.7.14 Strength of ANNs

ANNs offer certain advantages over the traditional rule-based system, i.e. conventional programming and knowledge-based expert systems. ANNs are preferable because of the following reasons:

1. They are weighted connection and massively parallel processing with fault tolerance in the sense that their performance degrades gracefully under adverse operating conditions and they can automatically learn from experience. This is called internal representation (22).
2. They have the generalization capability to learn complex patterns of inputs and provide meaningful solutions to problems even when input data contain errors, or are incomplete, or are not presented during training. In other words, they have the ability to integrate information from multiple sources and incorporate new features without degrading prior learning.
3. They are distribution free because no prior knowledge is needed about the statistical distribution of the classes in the data sources in order to apply the method for classification. This is an advantage over most statistical methods that require modelling of data. Neural networks could avoid some of the shortcomings of the currently used statistically or empirically based techniques.
4. They take care of determining how much weight each data source should have in the classification, which remains a problem for statistical methods (19). The non-

linear learning and smooth interpolation capabilities give the neural network an edge over standard computers and rule-based systems for solving certain problems (47).

5. They are able to recognize the relation between the input and output variables without knowing physical consideration.
6. They work well even when the training set contains noise and measurement errors. There is no need to make assumptions about the mathematical form of the relationship between input and output. Moreover, the ability to perform repeated simulations, thus allowing simulation tests and what-if-then scenario can be valuable aid in environmental planning and management.

2.7.15 The Problem of Explanation

ANNs are unable to reason in a sequential or stepwise manner that results in precise conclusions. These restrictions could be critical when dealing with situations that demand exact answers and lucid justifications (14). Due to the difficulty in explaining, the only way to test the system for consistency and reliability is to monitor the output (14).

Back-propagation networks suffer from four main problems. The first problem is that network structuring is a versatile, intuitive, and highly solution-dependent trial-and-error task. The second is that the algorithm is slow in training, and convergence is very sensitive to the initial set of weights. The third is that training can be trapped in local minima. The fourth is that the design of an optimum network configuration for a given problem is a non-guided or trial-and-error process that does not guarantee adequate generalization.

2.7.16 Applications of ANN Techniques in River Morphology

A wide range of application of ANN techniques has been investigated in the field of river engineering. From more general point of view, AI techniques can be applied for prediction and simulation in river engineering. If significant variables are known,

without knowing the exact relationships, ANN is suitable to perform a kind of function fitting by using multiple parameters on the existing information and predict the possible relationships in the coming future. This sort of problem includes water level and discharge relations, flow and sediment transport. Also, restoring of missing data in a time series can be considered as a kind of prediction.

DESCRIPTION OF STUDY AREA**3.1 INTRODUCTION**

Stretching within the basin periphery of 82°E to 97° 50' E longitudes and 25° 10' to 31° 30' N latitudes the river Brahmaputra envelopes a drainage area of 580,000 sq.km and recognized to be one of the most braided channel river. The hugeness of the river system in terms of the drainage area and the lengths it encompasses may be realised from its aerial extent as under.

Table: 3.1 The aerial distribution of the total drainage basin.

Country	Basin area (Km ²)	Channel Length (Km)
1. Tibet (China)	293,000	1,625
2. Bhutan	45,000	-
3. India	194,413	918
(a) Arunachal Pradesh	81,424	278
(b) Assam	70,634	640
(c) Nagaland	10,803	-
(d) Meghalaya	11,667	-
(e) Sikkim	7,300	-
(f) West Bengal	12,585	-
4. Bangladesh	47,000	337

Originating in a great glacier mass at an altitude of 5,300 m just south of the lake Konggyu Tso in the Kailas range, about 63 km southeast of Mansarovar lake in southern Tibet at an elevation of 5300m, the Brahmaputra flows through China (Tibet), India and Bangladesh for a total distance of 2880 km, before emptying itself into the Bay of Bengal

through a joint channel with the Ganga. It is known as the Tsangpo in Tibet (China), the Siang or Dihang in Arunachal Pradesh (India), the Brahmaputra in Assam (India) and the Jamuna, Padma, and Meghana in Bangladesh.

Before entering India, the river flows in a series of big cascades as it rounds the Namcha-Barwa peak. The river forms almost trough receiving the flows of its tributaries both from North and South. The river, with its Tibetan name Tsangpo in the uppermost reach, flows through

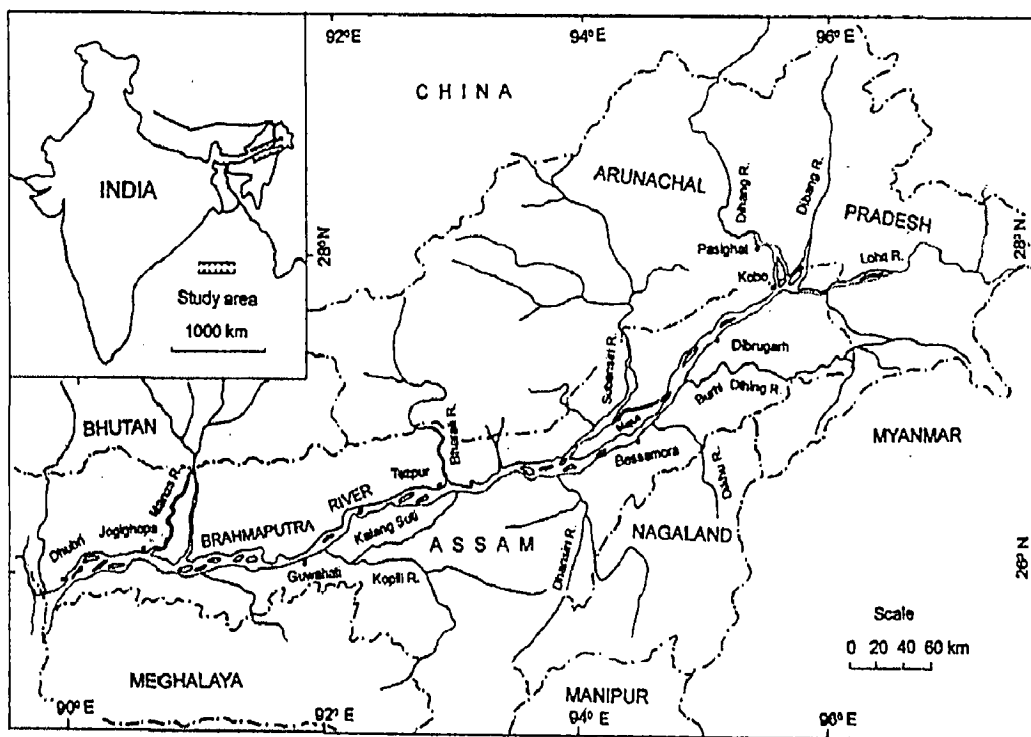


Figure:3.1
Location Map of the Brahmaputra River in Assam, India.

southern Tibet for about 1,625 km eastward and parallel to tributaries, viz., the Nau Chhu, the Tsa Chhu, the Men Chhu, the Charta Tsangpo, the Raga Tsangpo, the Tong Chhu, the Shang Chhu, the Gya Chhu, the Giamda Chhu, the Po Tsangpo and the Chindru Chhu and the right bank tributaries, viz. the Kubi, the Kyang, the Sakya Trom Chhu, the Rhe Chhu, the Rang Chhu, the Nyang Chhu, the Yarlang Chhu, and the Trulung Chhu join the river along its uppermost reach. At the extreme eastern end of its course in Tibet the Tsangpo suddenly enters a deep narrow gorge at Pe, where in the

gorge section the river has a gradient ranging from about 4.3 to 16.8 m/km (Figure 3.2).

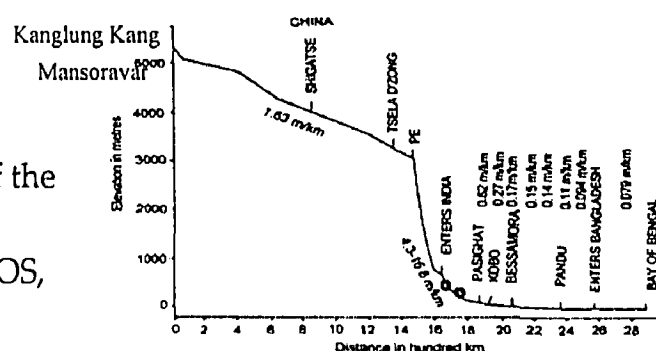
The river enters in India near Tuning in Arunachal Pradesh. After travelling for a distance of 278 km up to Kobo, it meets with two rivers the Dibang and the Lohit in Assam near Kobo. Below this confluence point, the river is known by the name of the Brahmaputra. It passes through Assam into Bangladesh and at last it meets with the Ganga near Goalundo in Bangladesh before joining the Bay of Bengal. Its total length is 2,880 km comprising of 1,625 km in Tibet, 918 km in India and 337 km in Bangladesh. It is also one of the most braided rivers in the world with width variation from 1.2 km at Pandu near Guwahati to about 18.13 km near Gumi few km distances downstream to this point.

Traversing through deep narrow gorges of the Himalayan terrain the Tsangpo takes a southward turn and enters Indian territory at an elevation of 660 m. The river then enters the State of Assam (India) taking two important tributaries the Dibang and the Lohit. At the exit of the gorge the slope of the river is only 0.27 m/km. At the head of the valley near Dibrugarh the river has a gradient of 0.09-0.17 m/km, which is further reduced to about 0.1 m/km near Pandu (Figure 3.1). The mighty Brahmaputra rolls down the Assam valley from east to west for a distance of 640 km up to Bangladesh border (Table 3.1).

3.2 LONGITUDINAL SECTION OF THE BRAHMAPUTRA RIVER

The longitudinal section of the Brahmaputra river from its origin to the outfall point is depicted in Figure 3.1:

Figure: 3.2 Longitudinal profile of the Brahmaputra river (modified after WAPCOS, 1993)



3.3 THE BRAHMAPUTRA BASIN

The Brahmaputra basin is confined by the great Himalayan ranges in the North and Northeast, Naga-Patkai hills in the East, and Mikir hills and Shillong plateau in the South. The Assam valley is the eastern continuation of the Indo-Gangetic plains of the Indian subcontinent valley. It is very narrow in the east and gradually expands to the west to nearly 80 km width, covering an area of about 5,62,704 km². In this valley, the river itself occupies a width of 6 to 12 km in most places. The basin of the river extends from parts of Tibet, Nepal, Bangladesh, Northeast India and Bhutan. The state wise distribution within India and the country wise distribution of the basin are presented in Table 3.1.

The Indian part of the basin has a maximum east-west length of about 1,540 km and a maximum north-south width of about 682 km along 93° east longitude. The basin is characterized by large variations in relief slope, landforms, climate, vegetation and land use. The upper basin lying in Tibet (China) and in the eastern Himalayas of Arunachal Pradesh, Sikkim and Nagaland comprise mostly mountain ranges and narrow valleys and the channels are restricted within steep and narrow valleys in the mountains. In Assam and Meghalaya, the basin consists of hills, plateaus and plains covered by forests, tea gardens, agricultural lands and built-up areas. In West Bengal also, the basin covers hills and valleys dominated by forests, tea gardens, agricultural lands and built-up areas. The lower portion of the basin in Bangladesh consists largely of fertile plains and delta regions.

The Brahmaputra basin in India is most generously gifted with a fabulous water wealth that accounts for nearly 30% of the total water resources and about 40% of the total hydropower potential of the country. However, so far the utilisation of this enormous water resources potential of the region is limited. For example, less than 5% of the existing hydropower potential, 10% of the irrigation potential and about 4% of the ground water potential have so far been harnessed.

The Brahmaputra river is characterized by high intensity flood which flows during the monsoon season, June through September, with an average annual flood discharge of 48,160 m³/sec (August, 1998 at Pancharatna). The highest flood discharge recorded in the Brahmaputra at Pandu (Assam) was of the order of 72,148 m³/sec (in year 1962), which had a recurrence interval of 100 years (45). The daily hydrograph of the river at Pandu exhibits drastic fluctuations in discharge during the monsoon season, whereas the time series of annual maximum flood events for the period 1955-2000 do not indicate any perceptible trend (11).

Analysis of 100-year rainfall records at Guwahati also does not show any distinct long term trend (11). However, there is a considerable variation in the spatio-temporal distribution of rainfall with marked seasonality. For example, precipitation varies from as low as 120 cm in parts of Nagaland to above 600 cm in the southern slopes of the Himalayas. A gradual increase in rainfall from the valley bottom towards the lower ranges of the Himalayas, followed by a decrease towards the higher ranges is evident from the observed records at Dibrugarh (285 cm) in the eastern part of the valley through Pasighat (507 cm) in the foothills to Tuting (274 cm) further up in the Himalayas. Monsoon rains from June to September accounts for 60-70% of the annual rainfall. These rains that contribute a large portion of the runoff in the Brahmaputra and its tributaries are primarily controlled by the position of a belt of depressions, called the monsoon trough, extending from northwest India to the head of the Bay of Bengal. In the course of the north-south oscillations in summer, when this axis moves closer to the foothills of the Himalayas, heavy precipitation occurs in Assam and adjoining highlands. The severity of rainstorms occasionally reaches as high as 40 cm per day. The years 1998 and 2004 which saw extremely high floods in the region also recorded excessively high rainfall, especially in the upper basin areas. Rainfall recorded at Guwahati during the monsoon months in 1998, June through September, is 922 mm, while at Dibrugarh it is 2002 mm and Pasighat in Arunachal Pradesh 4,573 mm

accounting for 60%, 67% and 75% of the annual rainfall respectively (11). During the flood season, all the districts in Arunachal Pradesh receive rainfall much above the normal rainfall. The intensity of rainfall recorded at Dibrugarh on June 28, 1998 is of the order of 17 mm/hr.

The Brahmaputra basin, especially its monsoon dominated wetter parts, is enormously rich in biotic resources with a great diversity of flora and fauna types marked by significant variations, both in vertical and horizontal distributions. The forest cover of the basin in India, as indicated by recent satellite surveys, is 144,922 km², which accounts for 59% of the total geographical area (Myint and Hofer, 1997). In contrast to this, the total basin forest cover including the portion outside India accounts for only 14.07% of the total geographical area of the basin. The distribution of forest cover in different states lying within the basin in India is estimated as: Arunachal Pradesh (82.8%), Nagaland (68.9%), Meghalaya (63.53%), Sikkim (39.52%), West Bengal (21.4%) and Assam (20.56%) (Myint and Hofer, 1997). In fact, Arunachal Pradesh accounts for about 60% of the forest cover in the Indian part of the basin.

The vegetation changes from tropical evergreen and mixed deciduous forest in the Assam valley and the foothills, through temperate coniferous belts in the middle Himalayas to alpine meadows and steppes in the still higher ranges. There has been considerable decline in the forest cover due to deforestation, land use conversion and land degradation in the basin. Shifting cultivation, involving traditional slash and burn technique of agriculture which is widely being practiced in the hills of northeast India, is a major cause of environmental degradation leading to deterioration of forest cover, loss of biodiversity, soil erosion, loss of soil fertility and crop yield, reduction in ground water recharge, increase in surface runoff, lowering of water table and acceleration in the rates of sedimentation in rivers and reservoirs downstream.

The Brahmaputra basin in northeast India provides a unique habitat for an exquisite variety of fauna, some of which belong to the most rare and endangered

species. The floodplain of the Brahmaputra river in Assam is dotted with a large number of wetlands, numbering more than 3,500, which have great significance as unique habitats for exquisite varieties of flora and fauna and also as natural flood water retention basins. Degradation and destruction of these wetlands have considerable impact on the deteriorating flood hazard scenario in the state.

3.4 THE BRAHMAPUTRA RIVER SYSTEM

The Brahmaputra river, termed as a moving ocean (45), is an antecedent snow-fed large Trans-Himalayan river which flows across the rising young Himalayan range. Considerable variations in width, gradient, discharge and channel pattern occur throughout its course. Geologically, the Brahmaputra is the youngest of the major rivers of the world and unique in many respects. It happens to be a major river for three countries, viz., China, India and Bangladesh. The river basin of the Brahmaputra is bounded on the north by the Kailas and Nyen- Chen-Tanghla ranges of mountains; on the east by the Salween river basin and the Patkai range running along the Indo-Myanmar border; on the south by the Nepal Himalayas, the Naga and Barail ranges and the Meghalaya Plateau; and on the west by the Ganga river basin.

The maximum meridional extent of the basin is 1,540 km along 29°30' N latitude and maximum latitudinal extent is 780 km along 90° E longitude. The total length of the river is 2,880 km (Table 3.1). Several tributaries join the river all along its length. The average annual runoff of the Brahmaputra at Pasighat, Pandu and Bahadurabad in Bangladesh is 186,290,494,357 and 589,000 million cubic metre respectively. The monsoon flow of the Brahmaputra at Tesla Dzong in Tibet is 36.27% of the flow at Pasighat (45).

Throughout its course within India, the Brahmaputra is braided with some well defined nodal points where the river width is narrow and restricted within stable banks. All along its course in the valley, abandoned wetlands and back swamps are common.

The river carries about 735 million metric tons of suspended sediment loads annually.

The Indian section of the Brahmaputra river receives innumerable tributaries flowing down the northern, north-eastern and southern hill ranges. The mighty Brahmaputra along with the well-knit network of its tributaries controls the geomorphic regime of the entire region, especially the Brahmaputra valley. In the north, the principal tributaries are the Subansiri, the Jia Bhareli, the Dhansiri, the Puthimari, the Pagladiya, the Manas and the Champamati. Amongst these, the Subansiri, the Jia Bhareli and the Manas are the Trans-Himalayan rivers. The principal south bank tributaries are the Burhi Dehing, the Disang, the Dikhow, the Dhansiri (south), the Kopili and the Krishnai. Hydrological characteristics of 18 important north bank tributaries and 10 important south bank tributaries are presented in Table 3.2.

It is observed that three Trans-Himalayan tributaries, the Subansiri, the Jia Bhareli and the Manas on the north have a basin more than 10,000 km², i.e., only two south bank tributaries namely the Dhansiri and the Kopili form a basin area more than 10,000 km². The Manas river combined with the Aie and the Beki rivers drains biggest area of 41,350 km². The 442 km long Subansiri river and the 360 km long Burhi Dehing river are considered longest, respectively, among the north-bank and south bank tributaries (Water Year book, CWC, 2002). In terms of the average annual discharge, the Subansiri carries a discharge of 755-771 m³/sec, which ranks first among all the important tributaries. The Jia Bhareli and the Manas in the north carrying an average annual suspended sediment load of 2,013 ha.m and 2,166 ha.m, respectively, are the leading rivers in the case of sediment discharge (11). Of all the north and south bank tributaries, as many as fourteen have sediment yields in excess of 500 tons/ km²/year, the highest being 4,721 tons/km² /year.

3.5 THE TRIBUTARIES OF THE BRAHMAPUTRA RIVER

In the past, the Dibang and the Lohit, two major rivers joined the Dihang a short distance upstream of Kobo to form the Brahmaputra. Now, the situation has undergone a radical change. Dibang and Lohit joined Dihang through another channel Dibru, developed through phenomenon river avulsion. Dibru is receiving major part of the discharge of Lohit for the last few years. The river receives numerous tributaries from both sides all along its course, thereby progressively growing in its size. Some of the tributaries are trans-Himalayan rivers with considerable discharges. In the north, the principal tributaries are the Subansiri, the Jia Bhareli, the Dhansiri (north), the Puthimari, the Pagladiya, the Manas, the Champamati. On the south bank the main tributaries are the Burhi Dehing, the Disang, the Dikhow, the Dhansiri (south) and the Kopili. The Brahmaputra also has some important tributaries, like the Teesta, the Jaldhaka, the Torsa, the Kaljani and the Raidak flowing through North Bengal.

The important tributaries on both the north and the south bank of Brahmaputra are listed in Table 3.3 along with chainage in km of their present outfalls from Indo Bangladesh border. The position of the outfall changes whenever bank erosion takes place there. Besides these tributaries, there are many other small streams which drain directly into the river.

Certain fluvio-geomorphic features which are found in the Brahmaputra basin have a significant bearing on the characteristics of the north and south bank tributaries. The variations in environmental settings, including geology, geomorphology, physiography, relief, precipitation and soils of the two regions belonging to the north bank and south bank river basins bring about notable differences between these two groups of rivers. On the north, the rainfall is heavier and the hills are less stable and more liable to soil erosion and landslides. In consequence, the north bank tributaries carry larger silt charge. The characteristics of north bank and south bank tributaries (45) reveal the following points of differences -

3.5.1 The North Bank Tributaries

- (i) The north bank tributaries have higher rainfall and pass through the Himalayan reaches with steep channel gradient.
- (ii) In case of northern tributaries, the long section of river course is in the hilly terrain while the small section is in the plains.
- (iii) The northern tributaries carry an enormous sediment load as compared to the southern tributaries. On an average, the sediment yield of the north-bank tributaries is three times higher than that of the south bank tributaries coming out of the Naga, Mikir hills and the Meghalaya plateau (45).
- (iv) Due to steep slope and heavy sediment load, these streams are braided over major portion of their travel. These have shallow braided channels for a considerable distance from the foot of the hill and in some cases right up to the outfall.
- (v) The northern tributaries have generally coarse sandy beds with occasional gravel beds up to some distance from the foothills.
- (vi) These tributaries generally have flashy floods.
- (vii) The basins of all the north bank tributaries have hypsometric curves with a plateau indicating a relatively youthful stage in their development.
- (viii) The north bank tributaries show a general parallel drainage pattern.
- (ix) The northern tributaries have shallow braided channels.
- (x) The northern tributaries are characterized by frequent shifting of their channels during floods. As revealed by the study, the northern tributaries have peculiar channel shifting patterns. The Subansiri and all other eastern rivers shift their channels westward, while the rivers between the Pagladiya and Subansiri shift eastwards. Again from the Manas up to the river Sonkosh in the west, all the rivers migrate westward.

3.5.2 The South Bank Tributaries

- (i) These tributaries have comparatively flatter gradient and deep meandering channels almost from the foot hills.
- (ii) The southern tributaries have beds and banks composed of fine alluvial soils.
- (iii) The southern tributaries have their long courses over the plains.
- (iv) These tributaries have comparatively less silt charge with finer fractions.
- (v) In contrary to the north bank basins, the basins of the tributaries from the south bank indicate much mature stage with hypsometric curves showing a continuously decreasing profile.
- (vi) The south bank tributaries while keeping the parallel drainage pattern, show signs of dendritic configuration.
- (vii) The southern tributaries change their courses less frequently.
- (viii) The southern ones have their meandering channels over the plains.

3.6 HYDROLOGICAL CHARACTERISTICS OF SOME MAJOR TRIBUTARIES

The hydrological characteristics such as basin area, length, average annual discharge, average annual suspended load and the sediment yield of some major tributaries are outlined in Table 3.2 (45).

Table: 3.2 Hydrological characteristics of some major tributaries

Tributaries	Basin Area (Km ²)	Length (Km)	Average annual discharge (m ³ /sec)	Average annual suspended load (ha. m)	Sediment yield (ton/ Km ² /year)
Northern Tributaries					
1. Subansiri	28,000	442	755,771	992	959
2. Ranganadi	2,941	150	74,309	186	1,598
3. Burai	791	64	20,800	16	529
4. Bargang	550	42	16,000	27	1,749
5. Jia Bhareli	11,716	247	349,487	2013	4721
6. Gabhru	577	61	8450	11	520
7. Belsiri	751	110	9300	9	477
8. Dhansiri (North)	1,657	123	26,577	29	463
9. Noa Nadi	907	75	4450	6	166
10. Nanoi	860	105	10,281	5	228
11. Bamadi	739	112	5756	9	323
12. Puthimari	1,787	190	26,324	195	2,887
13. Pagladiya	1674	197	15201	27	1,883
14. Manas-Aie-Beki	41,350	215	307,947	2,166	1,581
15. Champamati	1,038	135	32,548	13	386
16. Gaurang	1379	98	22,263	26	506
17. Tipkai	1,364	108	61,786	31	598
18. Gadadhar	610	50	7,000	0.21	272
Southern Tributaries					
1. Burhi Dehing	8,730	360	1,411,539	210	1,129
2. Disang	3,950	230	55,101	93	622
3. Dikhow	3,610	200	41,892	34	252
4. Jhanzi	1,130	108	8,797	16	366
5. Bhogdoi	920	160	6072	15	639
6. Dhansiri (South)	10,242	352	68,746	147	379
7. Kopili	13,556	297	90,046	118	230
8. Kulsi	400	93	11,643	0.6	135
9. Krishnai	1,615	81	22,452	10	131
10. Jinari	594	60	7,783	3	96

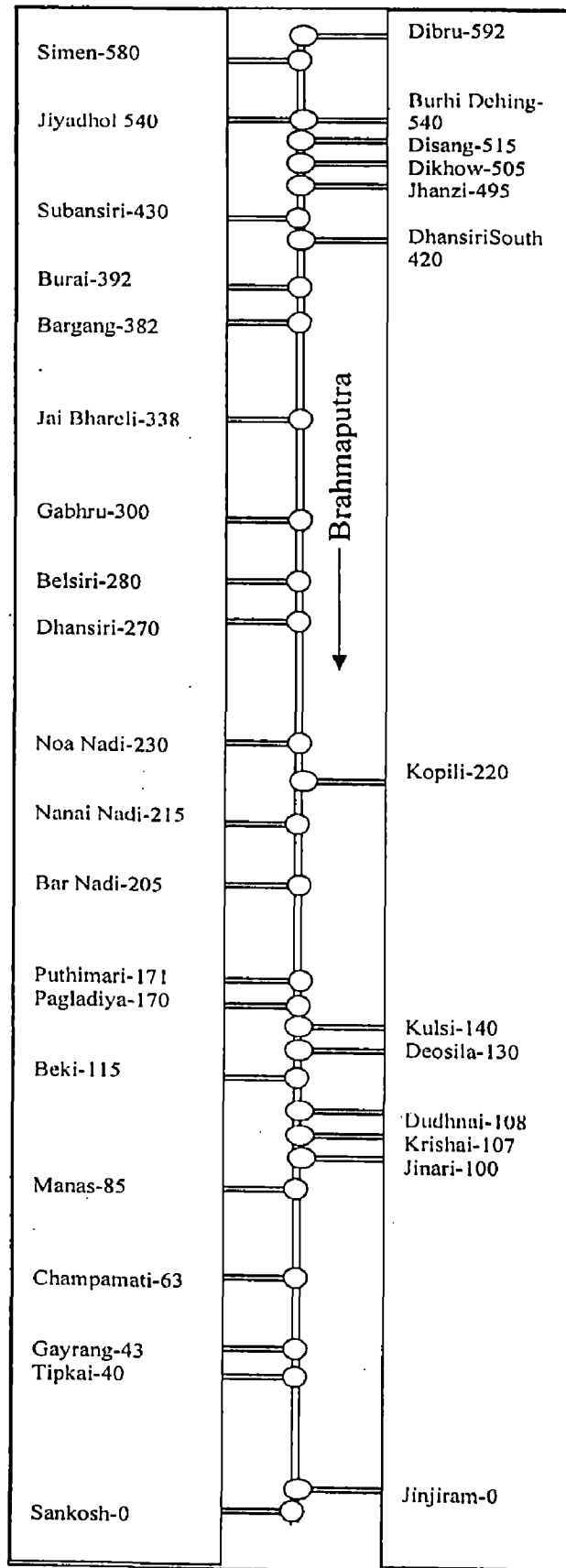


Figure 3.3 Schematic Layout of the tributary distances measured from Indo-Bangladesh border (Along the upstream) (WAPCOS, 1993)

3.7 HYDROLOGIC AND PHYSIOGRAPHIC CHARACTERISTICS OF THE BRAHMAPUTRA RIVER

The hydraulic characteristics describing the average annual runoff of the Brahmaputra and its major tributaries are represented in Figure 3.2 a schematic diagram. The statistical details of the river are described below:

(a)	Total basin area from its source to its confluence with Ganga at Goalundo in Bangladesh	580,000 km ²
(i)	Basin area within Tibet	293,000 km ²
(ii)	Basin area in Bhutan and India	240,000 km ²
(iii)	Basin area in Bangladesh	47,000 km ²
(b)	Length from its source to outfall in Bay of Bengal	2,880 km
(i)	Length within Tibet	1,625 km
(ii)	Length within India	918 km
(iii)	Length within Bangladesh	337 km
(c)	Gradient	
(i)	Reach within Tibet	1 in 385
(ii)	Reach between Indo-China border and Kobo in India	1 in 515
(iii)	Reach between Kobo and Dhubri	1 in 6,990
(iv)	Reach within Bangladesh	
	First 60 km from Indian Border	1 in 11,340
	Next 100 km stretch	1 in 12,360
	Next 90 km stretch	1 in 37,700
(d)	Observed discharge	
(i)	Maximum observed discharge at Pandu (on 23.8.1962)	72,727 m ³ /sec
(ii)	Minimum observed discharge at Pandu (on 20.2.1968)	1,757 m ³ /sec
(iii)	Average dry season discharge at Pandu	4,420 m ³ /sec

(iv) Normal annual rainfall within basin ranges between 2,125 mm in

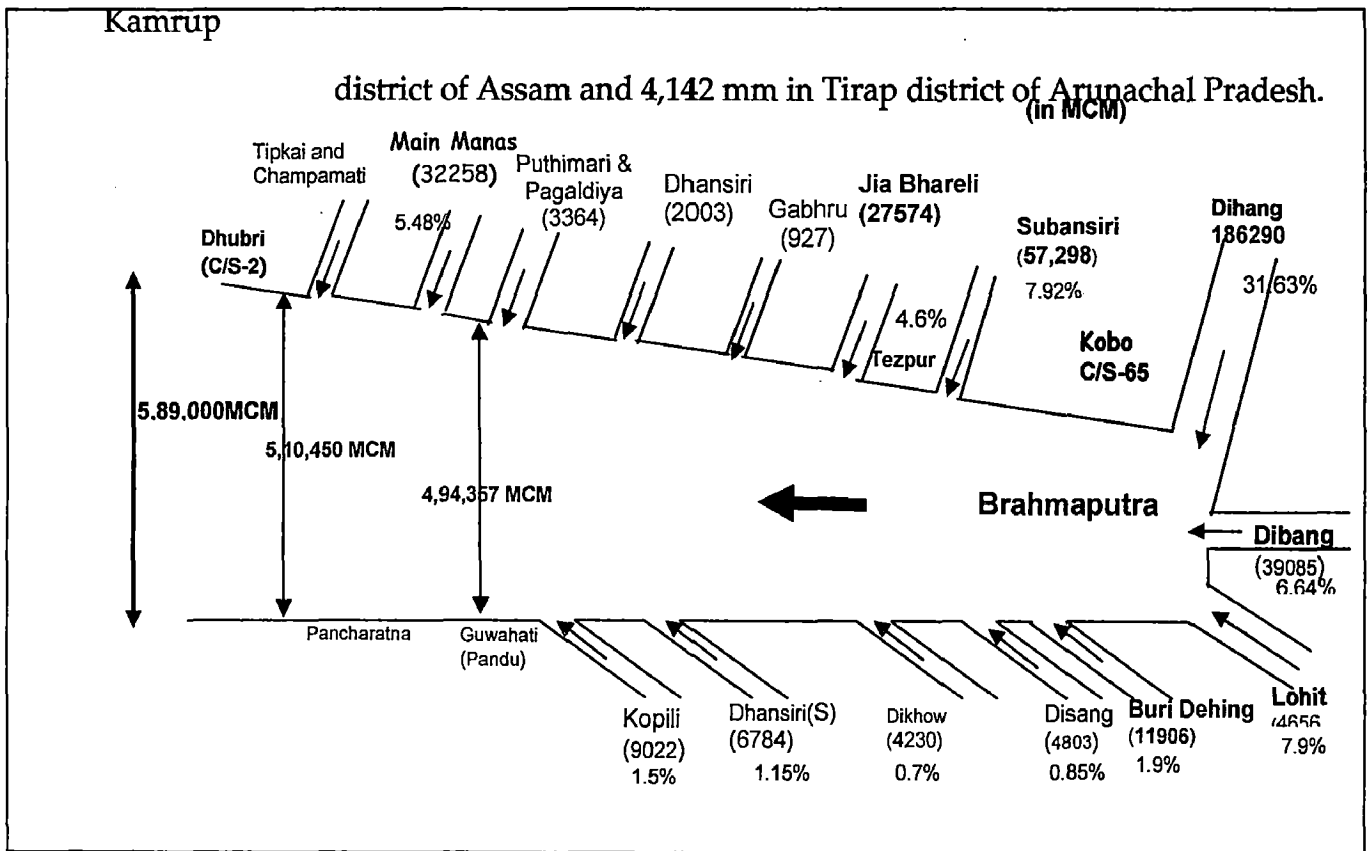


Figure 3.4 Average annual runoff of the Brahmaputra and its tributaries

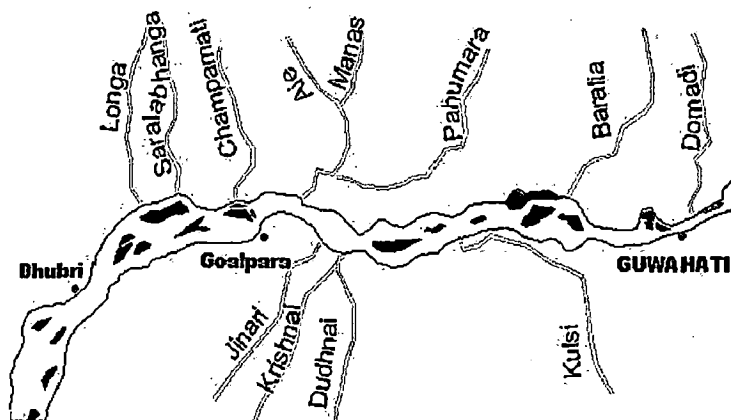


Figure 3.5 Plan of the study reach showing the gauging stations Pandu, Pancharatna and Dhubri

3.8 GEOLOGY AND GEOMORPHOLOGY

The Brahmaputra basin in India, comprising of varying geologic and geomorphic characteristics, represents its peculiar physiographic make-up. The basin is bounded by the eastern Himalayas on the north and east, the Naga-Patkai ranges on the northeast and Meghalaya Plateau and Mikir hills on the south. The region can be geologically and tectonically divided into four major zones, viz. the Himalayan folded and Tertiary hills and mountains, the Naga-Patkai ranges, the Meghalaya Plateau and Mikir hills and the Brahmaputra valley in Assam.

The Himalayan zone comprises of three topographic units that rise progressively to the north. The lowermost ranges, called sub-Himalayas with an average elevation of 1,000 m, consist mainly of Tertiary sand stones, and are conspicuous by the presence of many raised, relatively young terraces (12). The middle Himalayas, having an average elevation of 4,000 m are underlain by lower Gondwana (Palaeozoic) deposits comprising shales, slates, and phyllites overlain by a thick horizon of basaltic rocks. The greater Himalayas with an average elevation of 6,000 m consist primarily of granites and gneisses (12). The Himalayan Mountains with their syntaxial N-E bends originated out of the Tethyan Geo-syncline (Wadia, 1968) and are essentially composed of loose sedimentary rocks. The sub Himalayas and the lower Himalayas are characterized by piedmont zones, low discontinuous ridges, low linear ridges, high rugged hills and upland valley depressions.

The Patkai-Naga ranges stand on the eastern and south-eastern border of the Brahmaputra valley in Assam. These ranges, with an average elevation of 1,000 m, are composed of Tertiary sediments and characterized by the presence of a large number of active faults. This zone consists of piedmont plains, anticlinal ridges and synclinal valleys with terraced alluvial fills, undifferentiated sharp ridges and narrow valleys, upland valley depressions and plateau remnants. The Meghalaya plateau and the Mikir hills attaining an elevation ranging from 600 m to 1,800 m are made up primarily of

gneisses and schist. This part, being a rigid mass, belongs to the Deccan plateau of the stable Indian peninsular block of Pre-Cambrian age. It is characterized by plateau remnants, inselbergs, deeply dissected uplands with faulted monoclines of Tertiary cover, denuded hills, basement controlled structural ridges covered with Tertiary rocks and upland valley depressions.

The Brahmaputra valley in Assam, on the other hand, is underlain by recent alluvium approximately 200-300 m thick, consisting of clay, silt, sand, and pebbles. The valley is developed over the fore deep in between the peninsular mass and the Tethyan geosynclines. The fore deep is characterized by some complicated tectonic features represents a series of faults and thrust extending in the NE-SW direction from the eastern margin of the Meghalaya plateau across the North Cachar Hills to Tirap District of Arunachal Pradesh. These thrusts are originated at the time of the late Himalayan-Patkai-Naga Hills orogeny and pushed the tertiary deposits into folds and faults. The fore deep is believed to be under the sea till the sub-recent period received deposits during all the periods of the tertiary and quaternary ages. The tertiary deposits consist mainly of sand stones, shale, grit, conglomerate and lime stones.

Towards the close of the Pleistocene period, alluvium began to be deposited in the form of sand, pebbles and gravels especially along the northern foothills of the Brahmaputra valley. These valley deposits of reddish brown sandy clay with some pockets of unasserted pebble, cobble, sand and silt have been identified as older alluvium. The tertiary beds of the valley are overlain by a thick layer of newer alluvium composed of sand, silt and clay, which are being brought down from the rising Himalayas in the north, the Patkai Naga ranges in the east and south-east and the Meghalaya plateau in the south by numerous tributaries of the Brahmaputra. The characteristic geological and tectonic framework coupled with structural complexities has rendered the Brahmaputra basin geo-morphologically a most complicated one. A variety of landform under varied climatic conditions has formed over the geologic and

tectonic base of the region. The peri-glacial, glacio-fluvial, and fluvial processes are dominantly operative in the basin at varying altitudes.

The higher elevations of the Himalayas experience peri-glacial and glacio-fluvial erosion and deposition. The bare relief of the sub-Himalayas and greater Himalayas suffer from immense sheet erosion owing to peri-glacial solifluction. The low hill ranges with hot and humid climate and heavy rainfall concentrated to a few months of the year experience solifluction, sheet erosion and landslides.

The incidence of landslides is high in the Himalayan foothills, where heavy rainfall, high seismicity and toe cutting of hill slopes by the streams are most frequent. Heavy rains often loosen soil and the soft rocks of the young Himalayan ranges. Rainwater percolates through joints, fractures, foliations, and pores of rocks and soils and finally makes them loose and heavy, which cause heavy slope failure. Fluvial processes are, on the other hand, significantly dominant on the valley bottoms and plains where alluvial deposition takes place due to erosion of the higher surface by rivers and flooding in the valleys. The erosional and depositional processes conspicuously intensified by copious rainfall and frequent seismic movements, however, play a dominant role in creating various fluvio-geomorphic environments in the basin.

3.9 CHANNEL PROCESSES

The Brahmaputra river in India forms a complex river system characterized by the most dynamic and unique water and sediment transport pattern. The Brahmaputra is the fourth largest river in the world (12). The water yield from per unit basin area is among the highest of the major rivers of the world. The Jia Bhareli, a major tributary, carries a mean annual water discharge in the order of $0.0891 \text{ m}^3/\text{sec}/\text{km}^2$ (Bora, 1990). As estimated by Goswami (1982), the Brahmaputra yields $0.0306 \text{ m}^3/\text{sec}/\text{km}^2$ at Pandu. As regards sediment transport, the river has also set records in carrying large volumes of sediment. The high intensity of monsoon rains, easily erodible rocks, steep slopes, and

high seismicity contribute a lot by rendering the river a heavily sediment-laden one. Thus, the Brahmaputra becomes one of the leading sediment carrying rivers of the world. Amongst the large rivers of the world, it is second only to the Yellow river in China in the amount of sediment transport per unit of basin area (12).

At Pandu, the river carries an average suspended load of 402 million metric tons. A river with such gigantic water and sediment discharge magnitudes represents its most dynamic fluvial regime. Its large alluvial channel having a width of 6 to 10 km is, therefore, marked by intense braiding, rapid aggradation and drastic bank line changes. The Brahmaputra is a uniquely braided river of the world. Although braiding seems to be best developed in rivers flowing over glacier outwash plains or alluvial fans, perfect braiding is also found to occur in large alluvial rivers having low slope, such as the Brahmaputra in Assam (India) and Bangladesh or the Yellow River in China. The Assam section of the Brahmaputra River is in fact, highly braided and characterized by the presence of numerous lateral as well as mid channel bars and islands.

The high degree of braiding of the Brahmaputra channel near Dibrugarh and downstream of Guwahati is indicated by the calculated braiding indices of 5.3 and 6.7 respectively for the two reaches, following the method suggested by Brice (1964). A braiding Index of 4.8 for the entire Assam section of the river calculated on the basis of satellite data of 1993 also suggests a high degree of braiding of the Brahmaputra river.

The basin with varied terrain characteristics and being an integral part of the monsoonal regime of south-east Asia shows a marked spatial variation in the distribution of precipitation. The rainfall in the Teesta valley varies from 164 cm in the south to 395 cm in the north. The average annual rainfall in the lower Brahmaputra valley is 213 cm while the same in the north-eastern foothill belt is 414 cm. The basin as a whole has the average annual rainfall of 230 cm with a variability of 15-20%. The Himalayan sector receives 500 cm of rainfall per year, the lower ranges receiving more than the higher areas (12). During the monsoon, months of May to October receive

about 12% of the annual total.

In the sub-Himalayan belt soils with little depth developed over the Tertiary sand stones generally belong to red loam, laterite, and brown hill soil type with admixtures of cobbles and boulders. The greater part of the Brahmaputra valley is made up of new alluvium of recent deposition overlying Tertiary, Mesozoic and Archaean bedrocks. Along the piedmont zone, there occur some patches of older alluvium extending along the interfluves of the tributaries flowing from the Himalayan foothills. The soils of the Meghalaya plateau and the Mikir Hills in the south are of laterite and loamy silt and fine silt types.

In general, braiding in the Brahmaputra follows the mechanism of central bar type of braid formation. During high flow, a central bar is deposited in the channel and gradually the bar accretes vertically to the level of the floodplain. It also builds on the downstream end through deposition of bed load material due to the slack water occurring behind the bar. The bar growth causes a decrease in total cross-sectional area leading, thereby, to the instability of the channel. Lateral erosion then follows on one or both the banks. Through repetition of this process in the divided reach, a well developed braided reach with multiple sandbars and islands is produced.

In the Assam section of the river, the presence of such nodes of stable banks is found to effect the formation and location of the bars. There are nine nodal reaches of narrow constriction at various locations along the Brahmaputra, which are at Murkongselek (4.8 km), Disangmukh (5.10 km), downstream of Jhanjimukh (3.75), upstream of Dhansiri north (4.0 km), downstream of Dhansirimukh (4.4 km), upstream of Tezpur (3.6 km), Pandu, Guwahati (1.2 km), Sualkuchi (2.4 km) and Pancharatna (2.4 km). Since banks are relatively stable in these reaches, the river scours deeper to accommodate the flood discharge. The scoured debris is then deposited in the channel immediately downstream from the narrow section. As a result, the channel becomes wider and bars and islands are produced. Formation of bars causes reduction in cross

sectional area and the river, therefore, cuts its banks laterally to accommodate the discharge. Thus, the downstream of the nodes intense braiding develops resulting in channel widening through continuous migration of both banks of the Brahmaputra.

As reported from the studies carried out on braided rivers of the world, the major factors thought to be responsible for braiding and bar formation are steep channel gradient, high erodibility of bank materials, great variability in discharge, overabundance of load, and aggradation of the channel bed. In case of the Brahmaputra river in Assam bar formation and channel division are owing to a combination of factors like high variability in discharge, excessive sediment transport, easily erodible bank materials and aggradation of the channel. Being the fourth largest river in the world with an average discharge of 19,830 m³/sec at its mouth, the Brahmaputra carries 82% of its annual flow at Pandu (Assam) only during the rainy season from May to October. The maximum and minimum mean monthly flows in the river during 1990-2002 are 48,160 m³/sec and 3,072 m³/sec, respectively. On an average, therefore, the maximum flow is more than fifteen times the minimum.

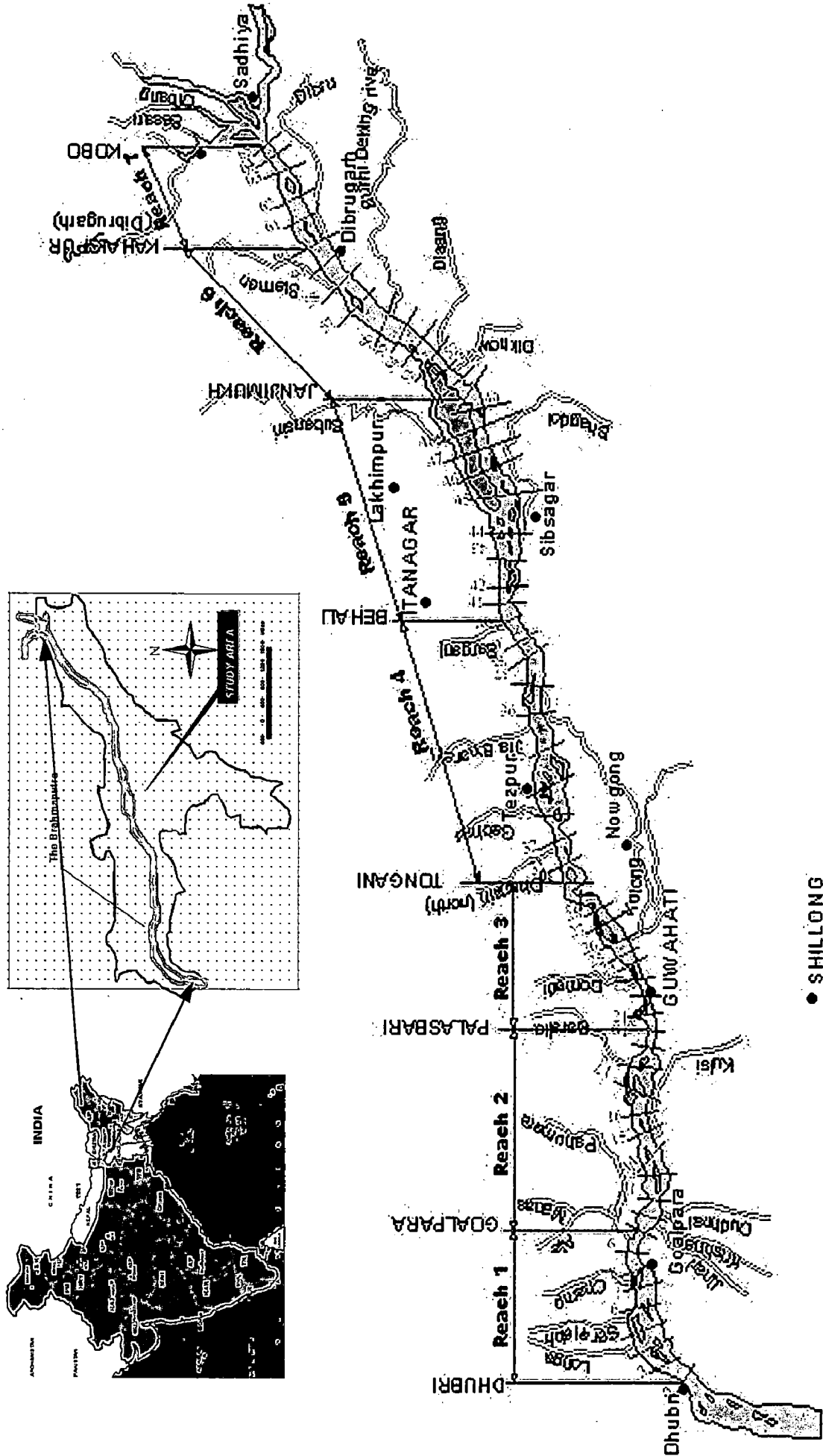
High variability in discharge of the river is mainly caused by seasonal rhythm of the monsoon and the freeze-thaw cycle of the Himalayan snow. As regards the pattern of sediment transport, the river has the record of carrying excessive sediment load which is believed to be one of the important factors responsible for braiding.

3.11 THE STUDY AREA

Considering the river flows, the gradients and the confluence of river tributaries, the study area has been divided into seven reaches (Figure 3.3). The reaches are described as under in Table 3.4.

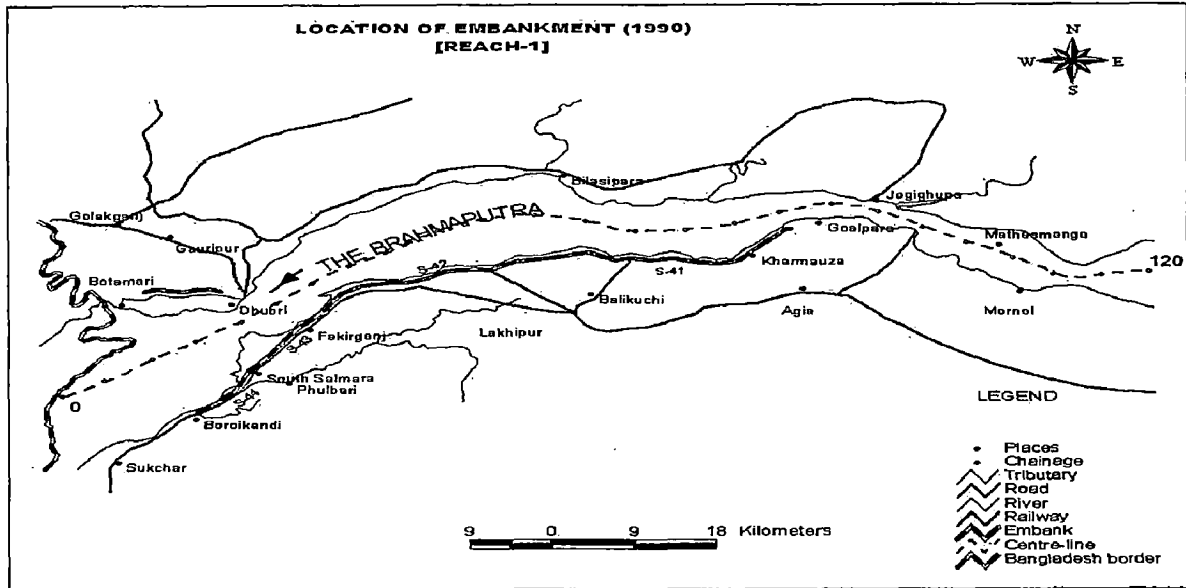
Table 3.3 Study reaches

In segment of 6 Cross section for Agg/Degr Study			In 3 Segments for slope study			
REACH	CROSS SECTION		REACH	CROSS SECTION		DISTANCE (Km)
	From	To		From	To	
Reach-I	2	7	Reach-I	2.00	25	201.45
Reach-II	8	13	Reach-III	26	44	204.52
Reach-III	14	19		45	65	216.76
Reach-IV	20	25				
Reach-V	26	31				
Reach-VI	32	37				
Reach-VII	38	43				
Reach-VIII	44	49				
Reach-IX	50	55				
Reach-X	56	61				
Reach-XI	62	65				

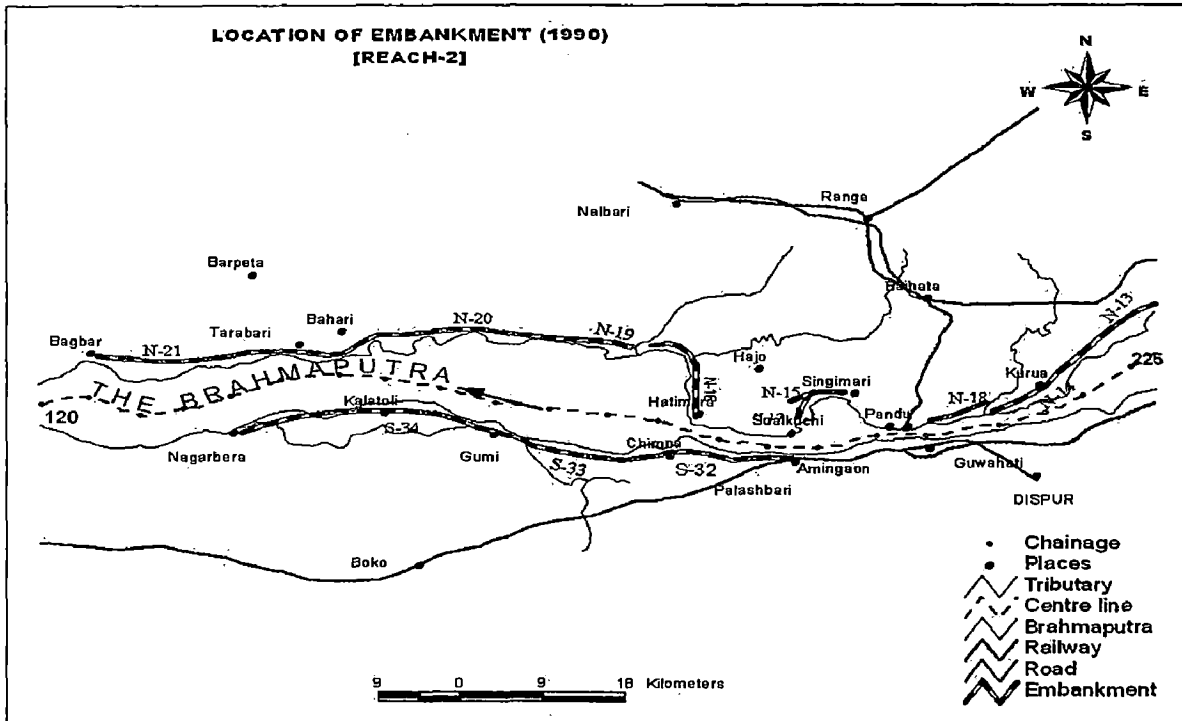


● SHILLONG
Figure 3.6
 Reaches of the study area

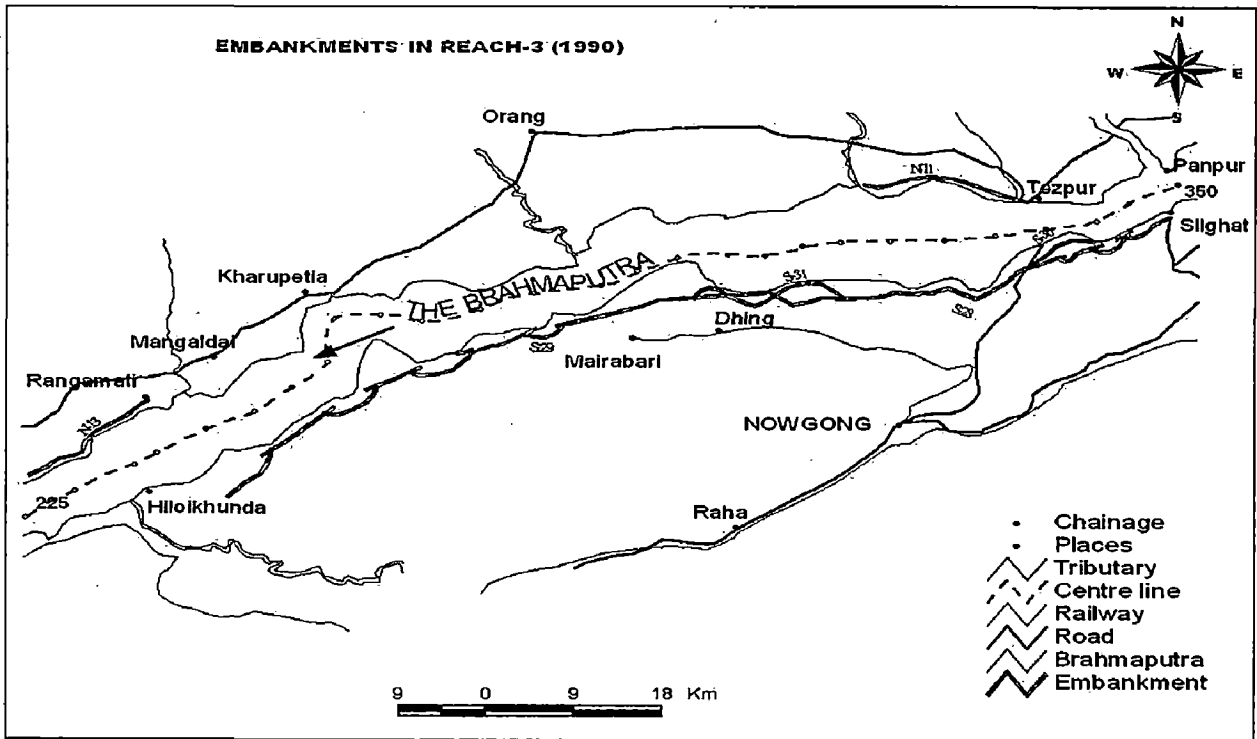
The informative satellite imageries of the river Brahmaputra



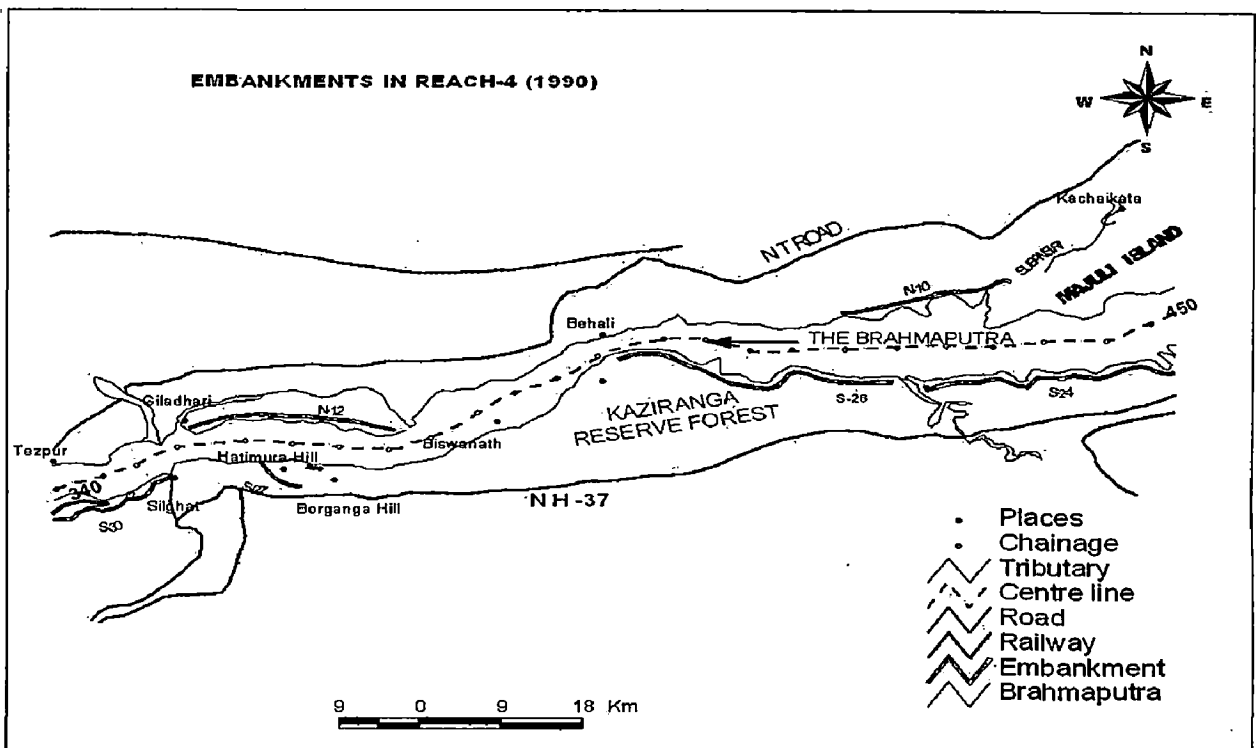
Planform & embankment locations in Reach I along the Brahmaputra, before 1990



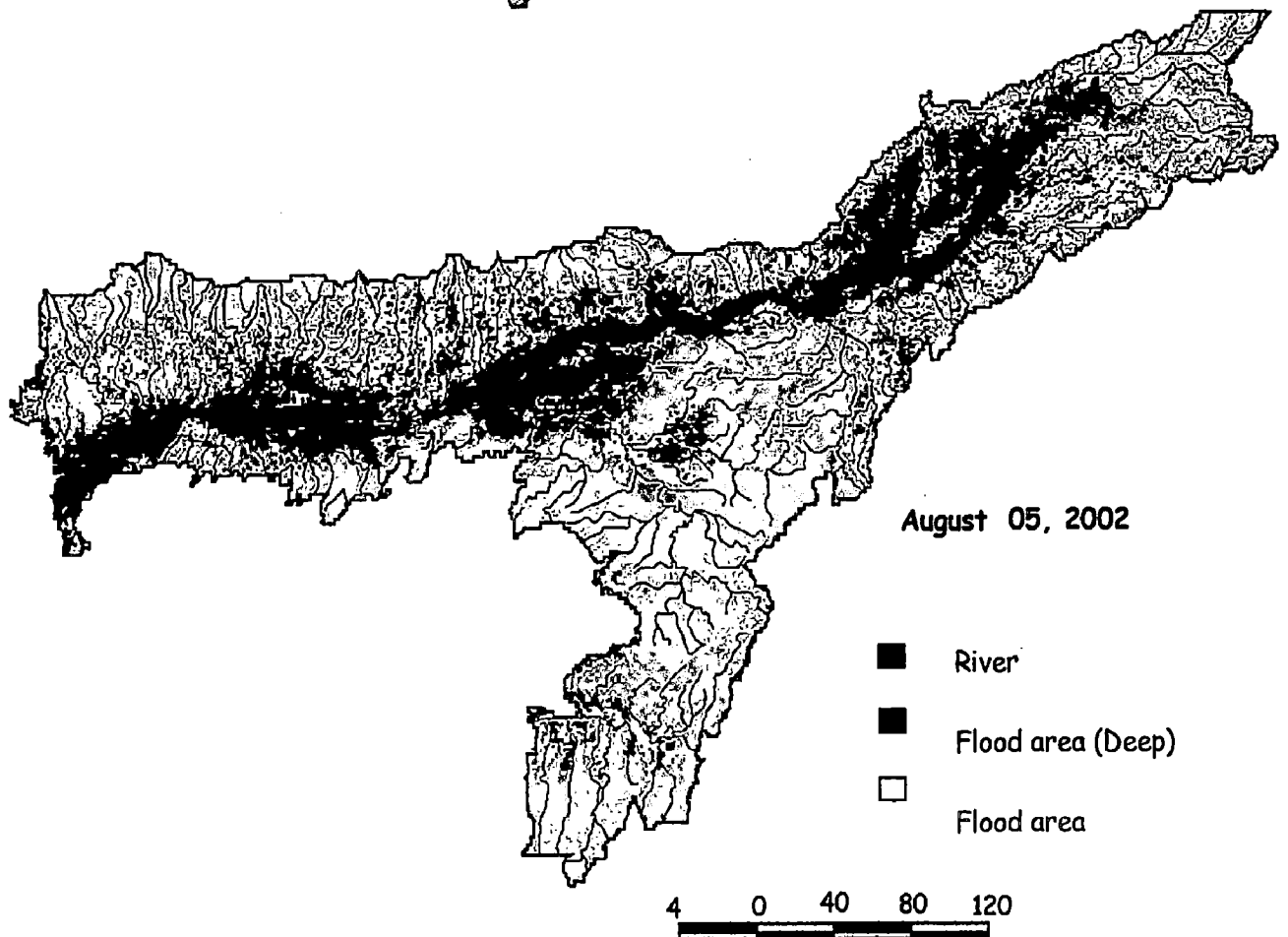
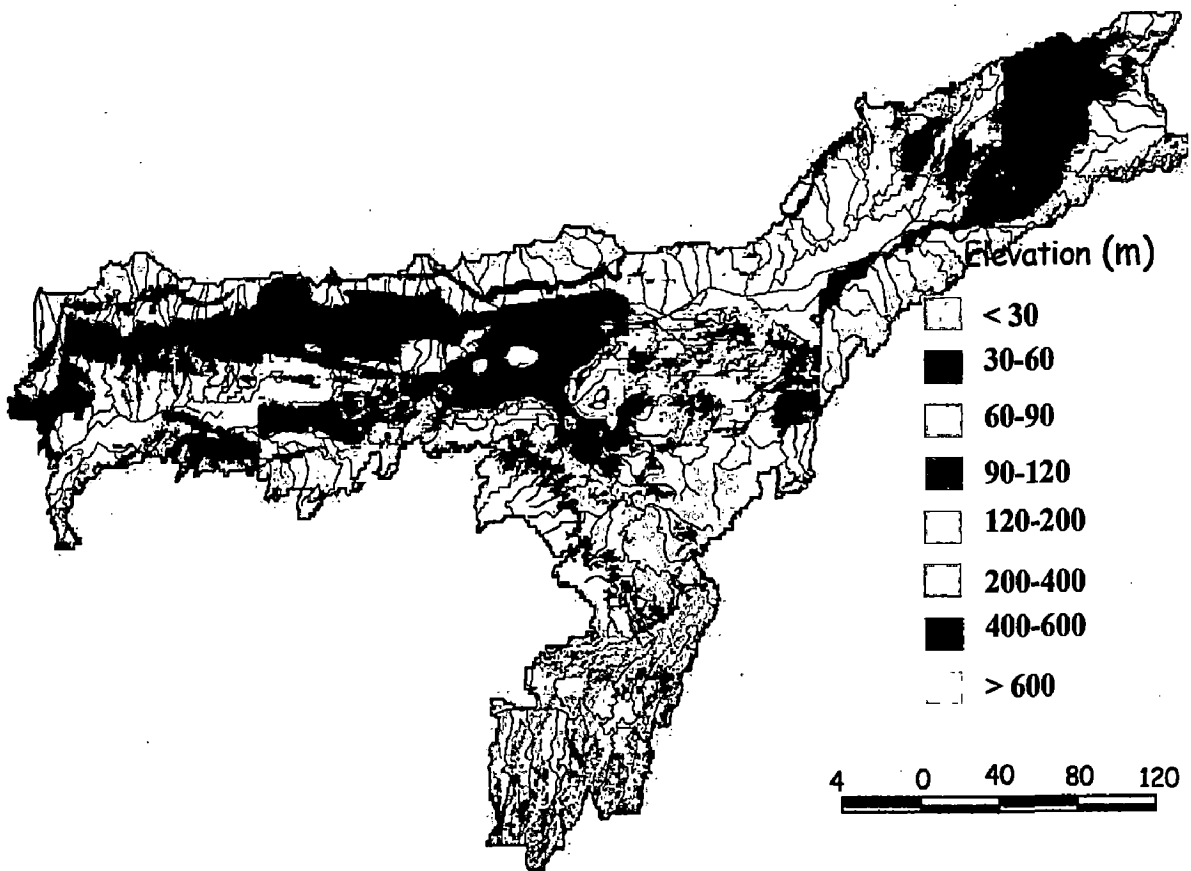
Planform & embankment locations in Reach II along the Brahmaputra, before 1990



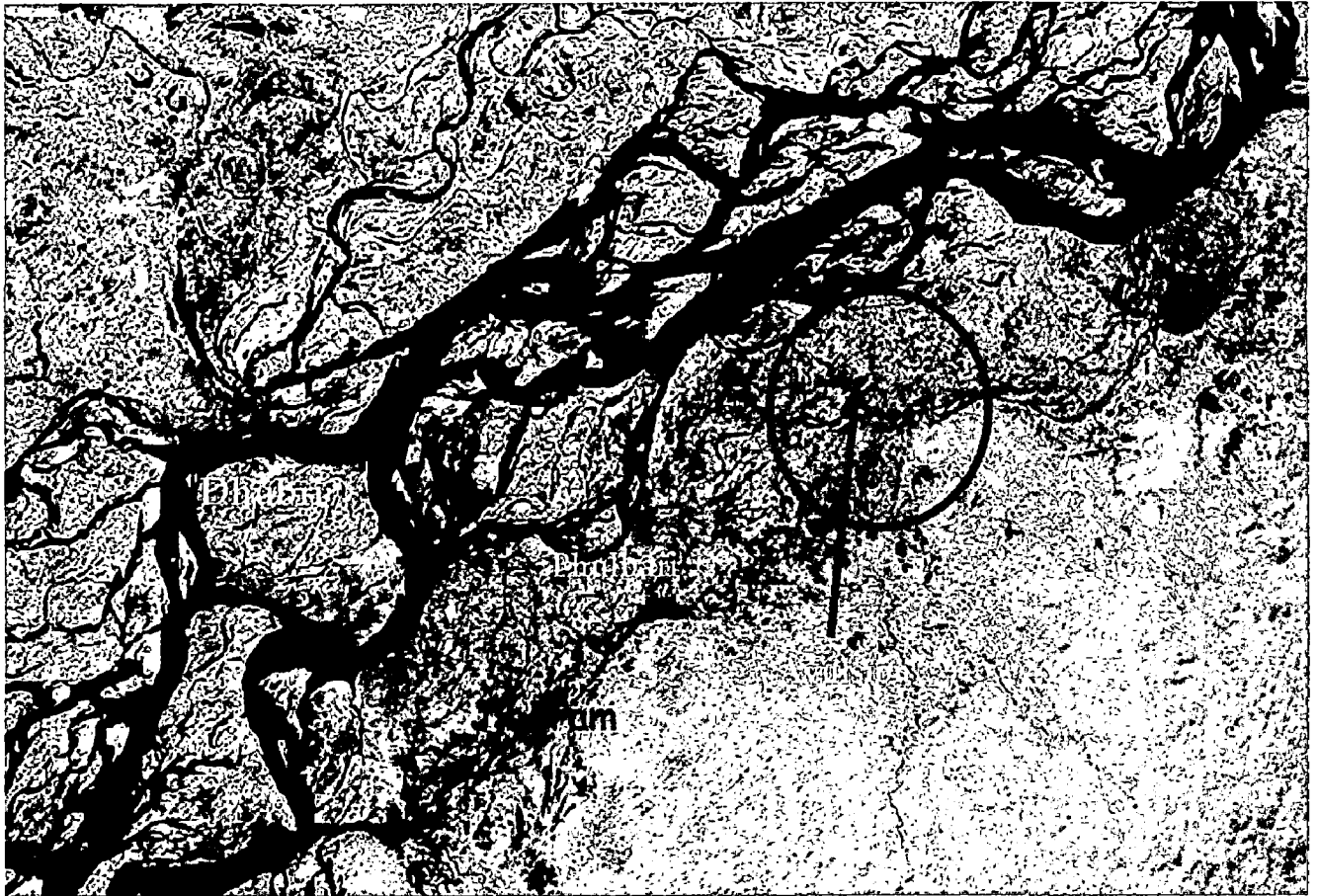
Planform & embankment locations in Reach III along the Brahmaputra, before 1990



Planform & embankment locations in Reach IV along the Brahmaputra, before 1990



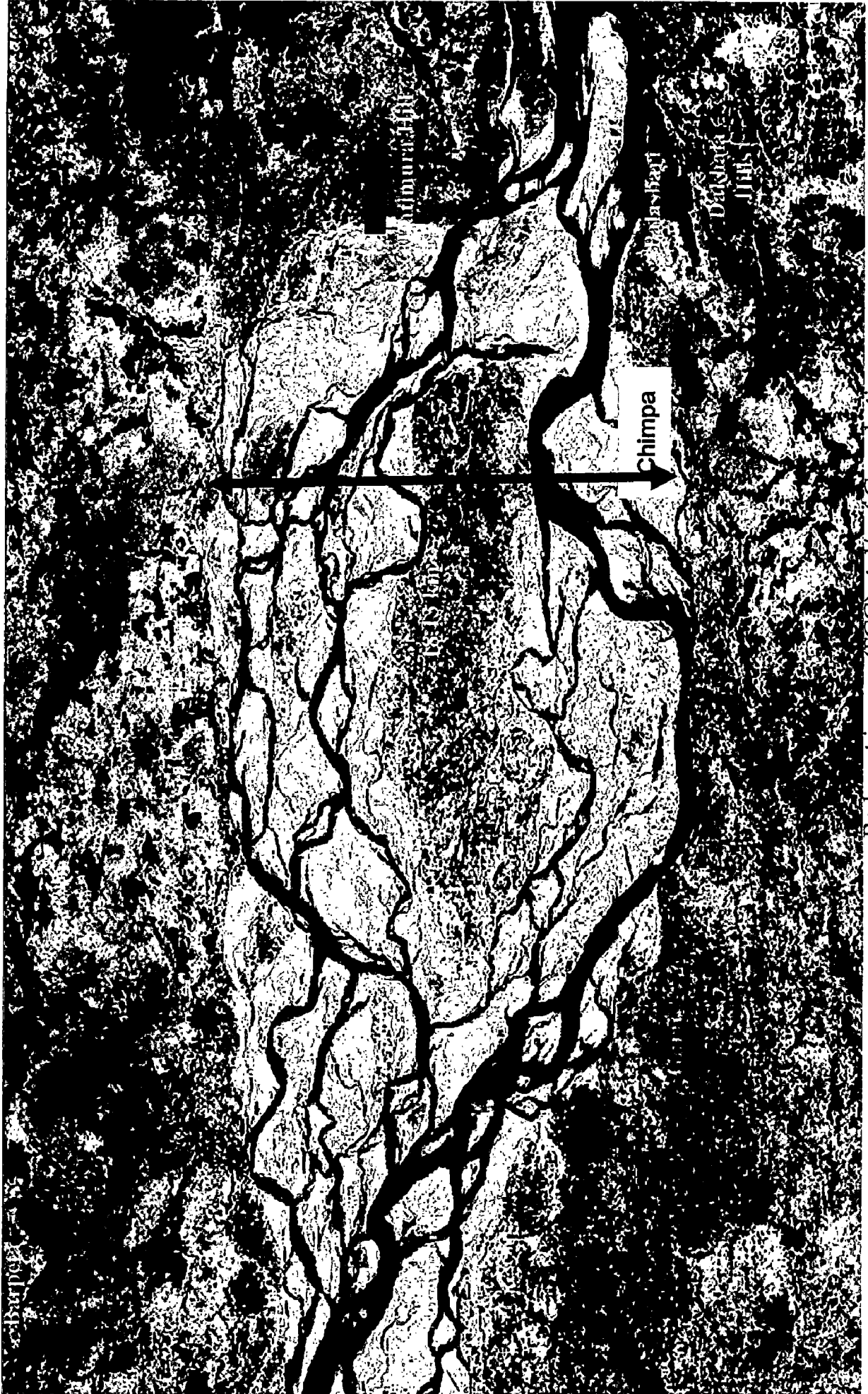
Deep and shallow flooding map of Assam valley, NOAA,



Avulsion by Jinjiram river near Dhubri, 2002



Radarsat image near Tezpur, 2002



Radarsat image (FCC) at d/s of Guwahati
91

SPATIO-TEMPORAL MORPHOLOGICAL MODELING

4.1 INTRODUCTION

The global hierarchal rank of the river Brahmaputra is recognized to be third in sediment discharge, fifth in fluvial discharge and eleventh in size of the total drainage area(17). Being one of the youngest river system with varied nature of drainage areas from snow peak mountains to lower flood valley of the Assam and the complexity exuberated by high sediment yielding geological surfaces it has been a very formidable task to quantify all the embodied "fluvio-river-morphological characteristics" to explain the ever changing characteristics of the river. The high degree of braiding(11) of the parent channel, more emphatically, when it open to the Assam valley because of still a steep valley gradient the fall in the hydraulic competency due to braiding is reflected to sediment transportation and downstream aggradation. Very unstable hydraulic geometry and hence the river channel morphology in the spatial and temporal space hinders the formulation of an idealised hydraulic models. Moreover, the researches and the literatures on braided channels are less compared to single channel in alluvium region. Due to high non linearity involved in the interdependencies of the hydrological – morphological and hydraulic parameters, majority of relationships developed relating hydrological and hydraulic parameters are empirical; eg

$$S \propto Q^{-0.4}, \quad S = \text{Slope of channel and } Q = \text{discharge} \quad 4.1$$

$$w \propto Q^{0.5}, \quad w = \text{Width of channel} \quad 4.2$$

$$\Omega \propto Q^{0.6}, \quad \Omega = \text{Stream power} \quad 4.3$$

$$Q = cA_d^n$$

A= Drainage Area,

4.4

C=Coefficient dependent on the nature of the are.

These relationships though dimensionally incompatible but are best used in the practical problems. However, suitability of an empirical expression strongly demands the idea of the hydrological region or the area under the study to be derived from acquisition of different parametric data of the area.

The river Brahmaputra is one of the river which is well under the observation of different stake holders. The sediment discharges and flood discharges at certain locations have been continuingly recorded and the river cross sections surveyed. Still, the limitation in the human capacity, instrumentation, the ambience of the measurement and the risk involved, the actual data acquisition often remain off-set by errors. The importance of the information that could be derived from the analysis of the data is very high in the design, management and future risk and hazard strategies. While, the scenario of the problems: erosion, deposition, lateral migration of channels, flood inundations in the Assam valley along the river stretch reportedly changing have been assessed in qualitative term, yet the changing of the natural environments (hydrological, morphological, seismicity...), year after year finding of solutions in quantitative terms to the alarming problems by conventional methods of idealisation of the problem often faces cost and time constraints and may not always be a witty measure.

Looking for a new avenue which is characteristically efficient, easy, less time taking, dependable and more flexible in future modification with advancement of time and changing themes of problem is the acute necessity of present time for upgradation of quality of life and environmental sustainability of the area.

Taking in to account the situation as described above, the present study is a formative attempt to implement a Neuromorphic environment utilizing the Artificial

Intelligence(AI). In the assessment of the available data, data sorting, data generation supporting further analysis, modelling and deriving inferences ANN has been known to be robust. As the technique is a data driven model requiring gamut of data patterns representing the actual phenomena to accommodate all the possibilities within the patterns of independent and dependent variables Remote Sensing and GIS Analysis have been recognized and employed tools in acquiring as much data and information in spatial and temporal scale in many of researches in hydrological discipline.

In the near future, more work with more expertise on this line would be enhancing the dependability on the strength of the technique in the more complex analysis.

The study has been carried out on the following data sets and the area.

- a) Study Stretch of the river channel (from Kobo to Dhubri) 622.37 km
- b) No. of the river cross sections (year 1957,1971,1977,1981,1988,1993&1997)65.no
- c) Hydrological Data(Dhubri-Pancharatna-Pandu) 1990 to 2002

4.2 DATA SOURCES AND DATA TYPES

The maps from the following sources have been utilized in displaying the study area and the drainage basin of the river Brahmaputra:

- (a) Topographical maps
- (b) Digital satellite images
- (c) Hydrographic and hydraulic data from surveys

4.2.1 Topographical Maps

The hydrographical area of the river including the study stretch of 622.37km is enclosed within the following Topographic Maps.

Table 4.1 Survey of India (SOI) Toposheets

Sl. No	Toposheet No.	Area	Lat/Long	Scale
1.	78 J/4	Goalpara	90° 00' X 26° 15'	1:63,000
2.	78 J/7	Gaurang	90° 15' X 26° 30'	1:63,000
3.	78 J/16	Dudhnai	90° 45' X 26° 15'	1:63,000
4.	78 J/15	Manas	90° 45' X 26° 30'	1:63,000
5.	78 J/11	Barpeta	90° 30' X 26° 30'	1:63,000
6.	78 J/3	Sankosh	90° 00' X 26° 00'	1:63,000
7.	78 J/8 & 78 K/3	Dhubri	90° 15' X 26° 15'	1:63,000
8.	78N/11	Puthimari	91° 30' X 26° 30'	1:50,000
9.	78N/16	Guwahati	91° 45' X 26° 15'	1:63,000
10.	78N/15	Guwahati	91° 45' X 26° 30'	1:63,000
11.	78N/3	Barpeta	91° 00' X 26° 30'	1:63,000
12.	78N/7	Barpeta D/S	91° 15' X 26° 30'	1:63,000
13.	78N/8	Barpeta U/S	91° 15' X 26° 15'	1:63,000
14.	78N/4	Barpeta	91° 00' X 26° 15'	1:63,000
15.	83 I/8	Sibsagar	94° 45' X 27° 30'	1:63,000
16.	83 I/15	Dibrugarh	94° 45' X 27° 30'	1:63,000
17.	83 I/11	Dihingmukh RF	94° 30' X 27° 30'	1:63,000
18.	83M/6	Dihang	95° 15' X 27° 45'	1:50,000
19.	83M10	RH of Dihang	95° 30' X 27° 45'	1:50,000
20.	83M/14	Noa Dihing	95° 45' X 27° 45'	1:50,000
21.	83M/13	Lohit	95° 45' X 28° 00'	1:50,000
22.	83M/9	Dibang	95° 30' X 28° 00'	1:50,000
23.	83M/2	Dibru RF	95° 00' X 27° 45'	1:50,000

24.	83I/14	Siemen River	94° 45'X27° 45'	1:50,000
25.	83I/10	NEFR	94° 30'X27° 45'	1:50,000
26.	83F/10	Dhansiri (S)	93° 30'X26° 45'	1:50,000
27.	83F/2	Kaziranga	93° 00'X26° 45'	1:50,000
28.	83F/6	Tezpur	93° 15'X26° 45'	1:50,000
29.	83F/14	Dhansiri (N)	93° 45'X26° 45'	1:50,000
30.	83B/13	Jia Bhareli	92° 45'X27° 00'	1:50,000
31.	83J/1	Subansiri	94° 00'X27° 00'	1:63,000
32.	83J/2	Jorhat	94° 00'X26° 45'	1:63,000
33.	83B/10	Gabhru	92° 30'X26° 45'	1:63,000
34.	83B/2	Dhansiri(N)	92° 00'X26° 45'	1:63,000
35.	83B/6	Dhansiri	92° 15'X26° 45'	1:63,000
36.	83B/3	Noa Nadi	92° 00'X26° 30'	1:63,000
37.	83B/7	Mangladoi	92° 15'X26° 30'	1:63,000
38.	83B/14	Jia Bhareli	92° 45'X26° 45'	1:63,000
39.	83F/10	Dhansiri	93° 30'X26° 45'	1:63,000

4.2.2 Digital Satellite Images

The satellite index maps of the river Brahmaputra as covered by the Indian Remote Sensing Satellite (IRS) 1A, 1C and 1D have been presented in Figure 4.1 and Figure 4.2 respectively.

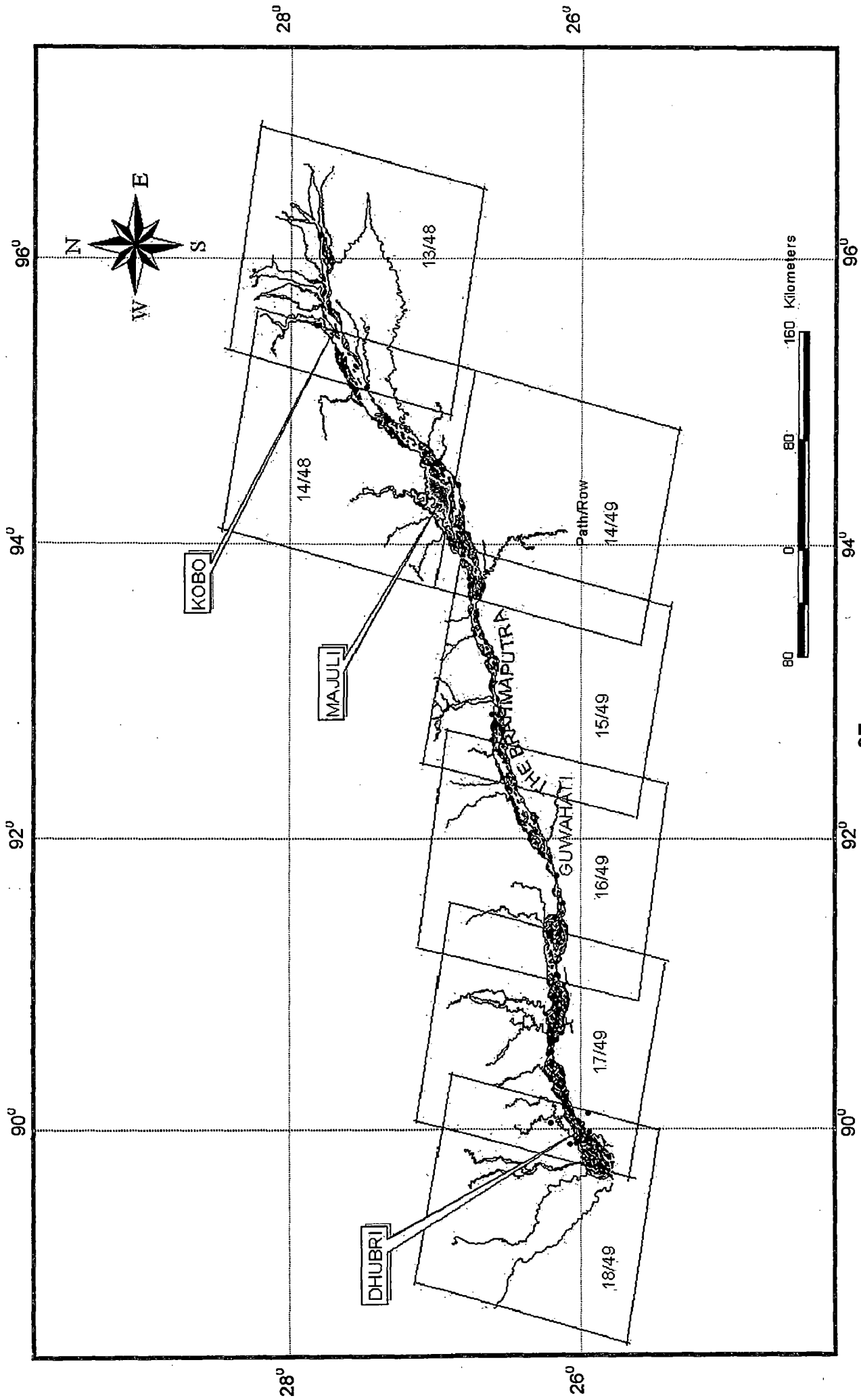


Figure 4.1 Index to IRS 1A coverage 97

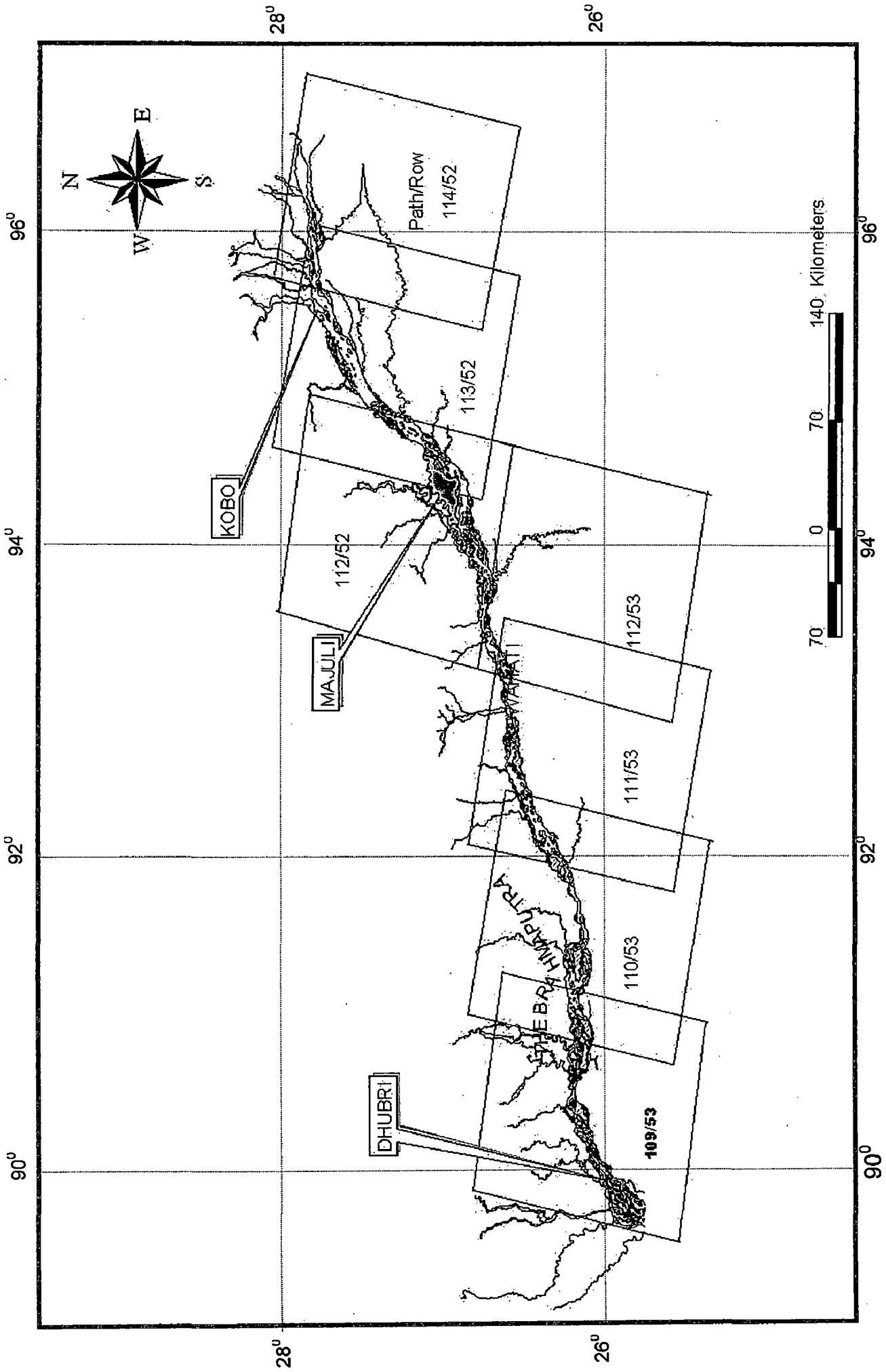


Figure 4.2 Index to IRS 1C/1D coverage

4.2.3 Observed Hydrographic and Hydraulic Data

4.2.4.1 Hydrographic data

Morphometric data: the reduced levels of the river cross-sections of post-monsoon period for the years 1957, 1971, 1977, 1981, 1988, 1993 and 1997 have been collected in respect of all the 64 pre-defined river cross-sections from the Brahmaputra Board, Government of India.

4.2.4.2 Discharge and stage data

Discharge and stage data of the river Brahmaputra collected for various cross-sections from Central Water Commission (CWC), Assam Flood Control Department and Brahmaputra Board have constituted main data resource to the ANN implementation. The length of data record was from year 1990 to 2002. The data file comprised hourly and daily monsoon stage data for Pancharatna and Pandu for the period from 1990 to 2002. The details of data collected have been tabulated in Table 4.2. Water Year Books in respect of 1999, 2000, 2001 and 2002 of the river Brahmaputra, too, from CWC have been incorporated.

Table 4.2 Discharge and stage data

Sl. No	Cross-section	Type of data	Duration/Year
1	Pancharatna	Average monthly water level v/s average monthly discharge	1990 - 2002
2	Pancharatna	Daily water level v/s discharge	Monsoon period (June to October) (1993 -2002)
3	Pancharatna	Hourly water level v/s discharge	(June to October) (1990 -2002)
4	Pandu	Average monthly water level v/s average monthly discharge	1990 - 2002
5	Pandu	Daily water level v/s discharge	(June to October) (1993 -2002)
6	Pandu	Hourly water level v/s discharge	(June to October) (1990 -2002)
7	Dhubri	Average monthly water level	(1990 -2002)
8	Dhubri	Daily water level	(June to October) (1999 -2003)

9	Bessamora	Daily water level v/s discharge	2000
10	Bessamora	Average monthly water level	1990 - 2002
11	Bhomoraguri	Daily water level	1997 - 2002
12	Palasbari C/S 20	Average monthly water level	1990 - 1999
13	Bhomoraguri C/S 26	Average monthly water level	1990-2002
14	Ganeshghat C/S 35	Average monthly water level	1997-2002
15	Tezpur C/S 36	Average monthly water level	1990 - 2002
16	C/S 38	Average monthly water level	1990 - 2002
17	C/S 40	Average monthly water level	1990 - 2002
18	C/S 47	Average monthly water level	1990 - 1992
19	Neamatighat C/S 49	Average monthly water level	1990 - 2002
20	C/S 52	Average monthly water level	1990 - 1992
21	Dibrugarh C/S 59	Average monthly water level	1990 - 1992

4.2.4.3 Sediment data

Sediment data obtained from the daily suspended sediment data in respect of Pancharatna and Pandu for the years from 1990 to 2002 and ten days total and average monthly discharge (m^3/sec) and monthly average suspended sediment yield of major tributaries, such as the Manas, the Jia Bhareli at Bhalukpong, the Subansiri at Chouldhowaghat, the Dhansiri (N), the Dhansiri (south) at Golaghat the Kopili at Jagibhakatgaon, the Dikhow at Sibsagar (daily), and the Buri Dehing at Chenimari processed for all the years from 1999 to 2002 have been used in the study. Characteristic sediment particle size distribution at the cross-sections was collected from CWC. Tables 4.3 and 4.4 show the of sediment data details.

Table: 4.3 Sediment load data of the Brahmaputra

Sl. No	Cross-section	Type of data	Duration/Year
1.	Pancharatna	Average monthly discharge v/s sediment	1990 -2002
2.	Pandu	Average monthly discharge v/s sediment	1990 -2002

Table: 4.4 Discharge and sediment data of tributaries

Sl. No	Site	Type of data	Duration/Year
1	Buri Dehing	Average monthly discharge v/s sediment	1999 - 2002
2	Subansiri	Average monthly discharge v/s sediment	1999 - 2002
3	Kopili	Average monthly discharge v/s sediment	1999 - 2002
4	Dikhow	Average monthly discharge v/s sediment	1999 - 2002
5	Dhansiri (North)	Average monthly discharge v/s sediment	1999 - 2002
6	Dhansiri (South)	Average monthly discharge v/s sediment	1999 - 2002
7	Jia Bhareli	Average monthly discharge v/s sediment	1999 - 2002
8	Manas, Beki	Average monthly discharge	1999 - 2002
9	Puthimari	Average monthly discharge	1999 - 2002
10	Champamati	Average monthly discharge	1999 - 2002
11	Pagladiya	Average monthly discharge	1999 - 2002

4.3 PROCESSING OF HYDROGRAPHIC DATA

4.3.1 *Generation of Hydraulic/Hydrologic Data*

Hydrologic Engineering Center (HEC-6) program (devised by the US Corps of Engineers May, 2004) generated values (multirate discharges, corresponding water levels, sediment discharges and the average bed levels) for ungauged stations have been employed as the input data in the ANN.

The discharge at Pancharatna (cross-section 9), and Pandu (cross-section 22), Bhomoraguri (cross-section 36) and Bessamara (cross-section 50) and the stage data at 14 number of cross-sections were simulated as input and the discharges were generated at all 64 cross-sections. The average monthly discharges from the major tributaries were included in corresponding computer runs to have realistic data in the simulation.

4.4 METHODOLOGY

4.4.1 *Plotting of the Cross Section Profiles for the Data Years and Average Bed Level*

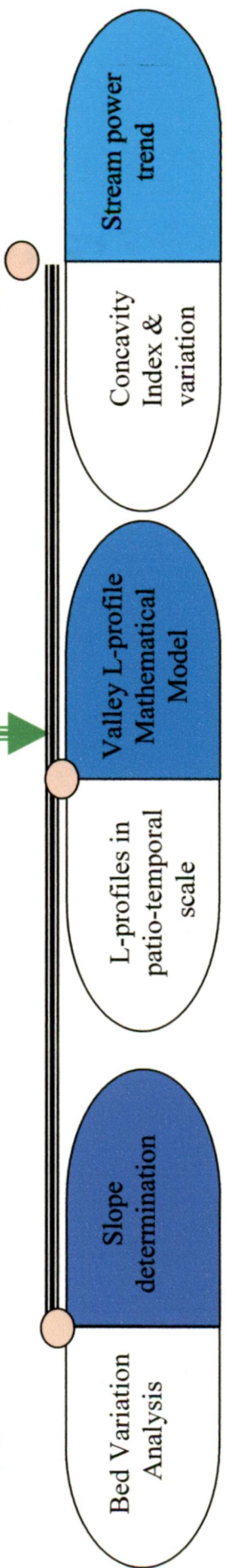
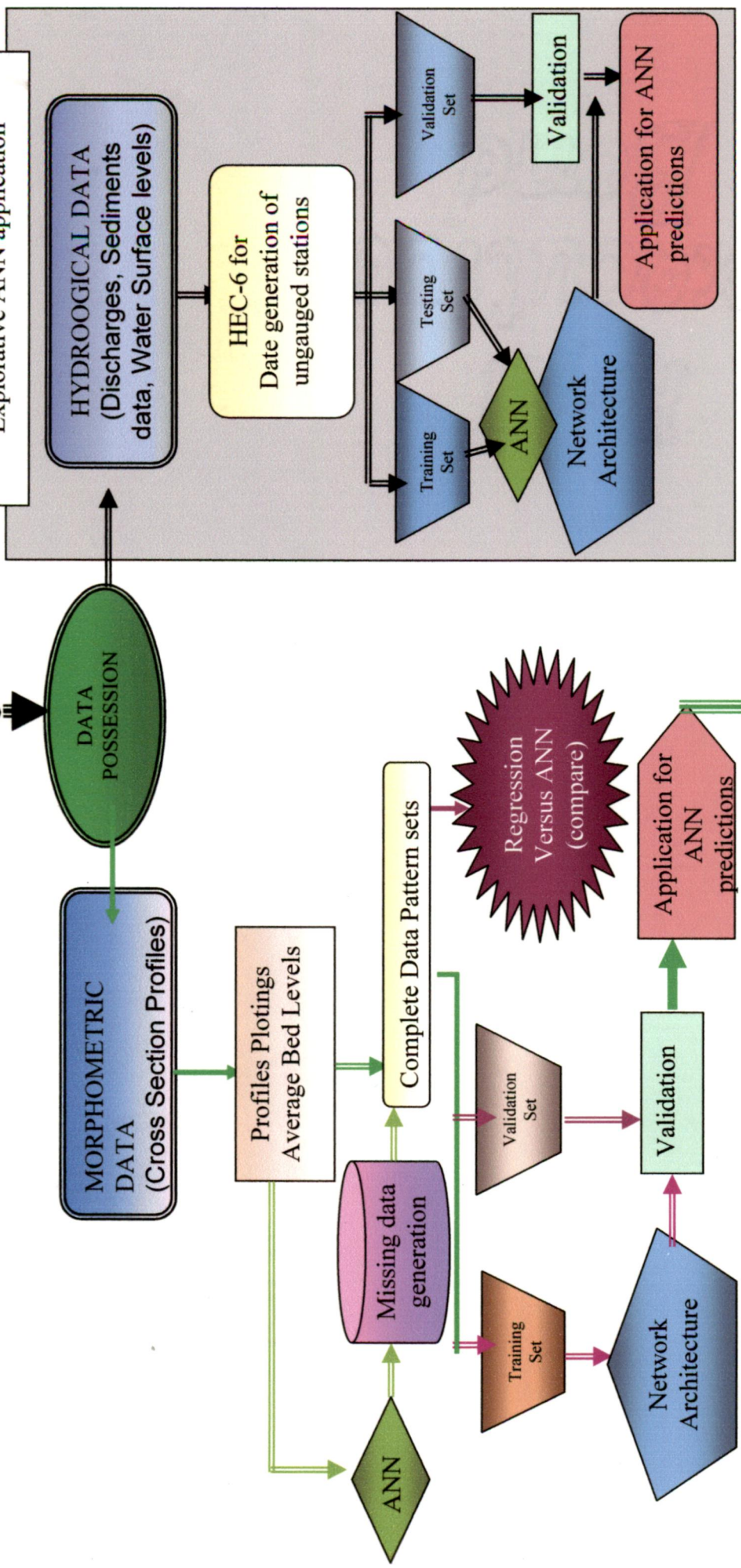
The hydraulic geometry data of 65 number of cross section for the seven data years(1957,1971,1977,1981,1988,1993 & 1997) were plotted to view the general tendencies of variation of the cross section profile in the temporal increments. The plottings have revealed a very drastic changes in the cross profiles for some of the sections. Since, the successive stations along a cross section are very widely apart compared to the vertical variation of the ground levels the non submergible banks are not easily discernible.

4.4.2 *Missing Data and generation with ANN*

The tabulation of the averaged data revealed the vacancies in the data cells for some of the cross sections and years. The missing data were generated both by Regression and ANN soft computation. Comparatively, ANN results have been found better than the regression prediction. The ANN for prediction of the missing data applied the upstream and downstream cross sections values having relatively strong

SCHEMATIC action FLOW

START



Concavity Index & variation

4.4.3 Generation of ANN Network

The frame work of ANN architecture is governed by number of Input variables and Output variables and the corresponding Hidden Layers with customised numbers of neurons. The technique of ANN soft computing as referred in the literatures have confirmed that the most dependable architecture could only be reached after multiple number of trials in ascertaining addition of Hidden Layers, selection of the competent Input Output combinations, fixing of stopping criteria, Learning Algorithms as well as Momentum and Learning rates.

The objective of the application of the ANN, here, is to track the pattern of the variation trend of the average bed levels in the study reach. Then, predict all the intermediate values of the Average Bed Levels for none survey years.

4.4.4 Strategies ANN Input Output Trials

4.4.4.1 For the Morphometric data

The hydraulic geometric data of the cross sections are available for 1957 to 1997 (seven data survey years) but for the corresponding years, other relevant hydrological data; discharge, sediment data are not available. However, the trend of the variation could be traced with ANN model utilizing the pattern of the available sets to observe the past situation along temporal scale.

4.4.4.2 For Hydrological data

The hydrological data comprised of water discharge, sediment discharge, water surface levels, average bed levels for the year 1990 to 2002. The data which are available for some of the cross sections for the given years were employed in to HEC-6 model to generate the data for remaining ungauged cross sections. The discharge data, water surface level and sediment data have been identified to be the Independent variables and average bed level as dependent variable.

The independent variables were trailed with their different combinations to observe the most reliable combination to obtain better performance of the models.

4.4.5 Learning Algorithms

Depending upon the type of the data pattern, it is a crucial task to have selected a suitable Learning Algorithms to follow the problem trend more closely. The trials were performed with all possible Learning Algorithms and identified the learning skill of the Algorithms. From many, Back Propagation Algorithm and Quick Propagation Algorithm have been found mostly tracking the non linearity of the input-output relationship. In the mean time it has been observed that some of the cross section variation patterns were very erratic that none of the Algorithms could trace the underlying trend. This may be reasoned that there might have been some flaws in data measurement itself or the location is under the influence of very erratic forces.

4.4.6 Hidden Layers

In the texts single hidden layer is said to be adequate to represent a reliable NN architecture in the majority of problems. Accordingly, it has been found that, a single input (year) and 64 outputs (average bed levels) best worked with single hidden layer consisting of 44 neurons. The trial with two hidden layers with equal number of neurons, 44, did not improve the performance of the NN network.

4.4.7 Transfer functions

$$\text{Sigmoid } f(x) = \frac{1}{(1+e^{-x})} \text{ for } 0 < x < +1 \text{ and Tan-hyperbolic } f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \text{ for}$$

$-1 < x < +1$ functions have been claimed to be very adaptable to many problems. The similar conditions prevailed in the present implementation of ANN. However, Tan-hyperbolic function has seen to be a bit superior to recognize the present problem. Since, the pattern of variation of different cross sections at different reaches have different trends and magnitude due to local conditions for some of the sections Sigmoidal function has been found to be suitable to the situation.

4.4.8 Learning and Momentum rates

Learning rate and Momentum rate are the two distinct variables in the ANN application which are applied for controlling the speed of learning of the data and their values are so adjusted that the network reach to the global minimum of error

space. In the present work, often the Learning Rate is fixed to 0.1 and Momentum Rate to 0.4 for Back Propagation Algorithm and both at 0.8 for Quick Propagation Algorithm.

4.4.9 Stopping Criteria

The tool used for the ANN implementation is provided with three different stopping criteria: Root Mean Square Error (RMSE), Iteration Number and Determinant Coefficient (DC). Since, there are only 7 number of patterns for seven years the learning process ended instantly which risked the chances of over training of the Network. The RMSE criteria with very small value close to zero required more iterations but encountered weak in prediction capability due to memorizing of the data pattern. Therefore, after a numerous attempt, it has been found that for the less number of data pattern, a small figure of iteration, say, 100 be appropriate to start with initially and keep increasing until a reliable correlation value R and DC of the training stage is attained. The iterations were increased turn by turn until no further improvement in the learning was observed.

4.4.10 Training of the Neural Net Works

4.4.10.1 For the Morphometric data

In the Artificial Intelligence environment, training of the designed Neural Network architecture takes the most leading procedural stage and importance. The data incorporated in the training set is required to be representative of most likely patterns of the inputs-outputs relationships of the problem domain. Higher is the number of different pattern sets exposed to the Network more stronger will be the prediction or generalization capacity of the Network on its application. Hence, the technique of ANN is named to be a data driven modelling technique.

In the present study, even the seven sets of data pattern has yielded encouraging result in tracing the bed level variation. The training set of the data was included with five patterns and two set were kept used for the validation.

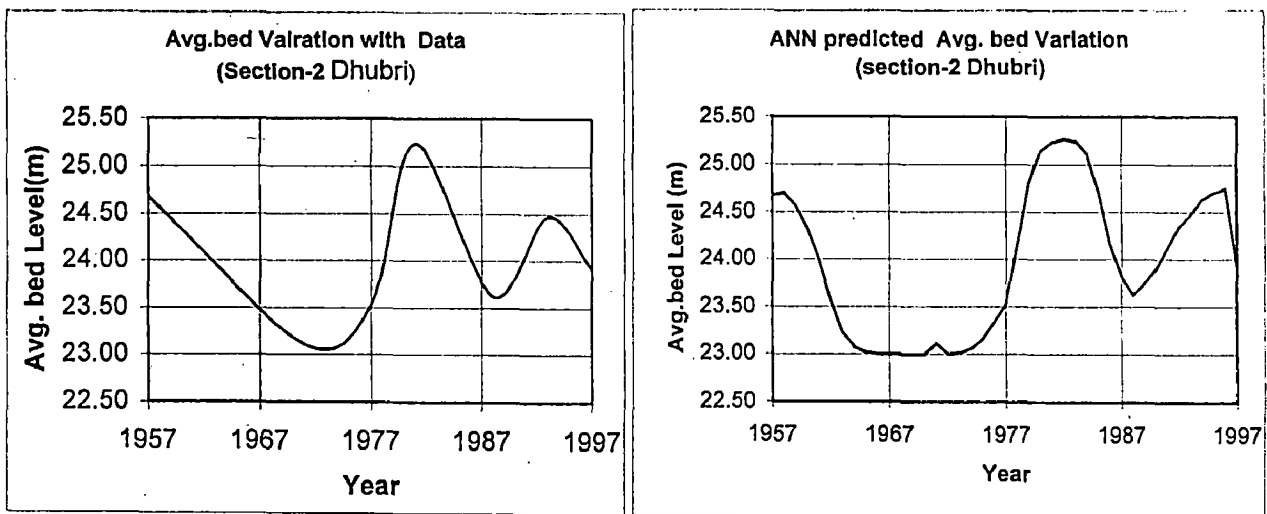


Figure:4.3

The Average Bed Level Variation Pattern (with data alone and with ANN predicated data)

The plot of the Average bed variation with initial data is a simple plot while the plot corresponding to the ANN predicated data displays an interesting variation. The lowering of the first segment of the curve is abrupt in the profile with ANN. Possibly, there had been a mojour hydrological events in the mean time of the period. Further, the drop in the trend for 1997 is drastic with ANN which might indicates the inconsistency in the measurement procedure. Similar observation have been made with other cross sections.

Training attempt was made with the Network for 64 outputs and also with segment wise in a group of six cross section. In the both the cases, the prediction response have been observed similar.

4.4.10.1.1 Validation

Since, the only two sets of the data pattern were available for the validation of the predicted values of the designed network structure the correlation R between the observed and predicted data for the total reach is found to be close to unity. However, the Nash-Sutcliffe coefficient could not be use as the measure of the Network strength due very less number of validation set.

In the expression, if the numerator in the second term is higher than the denominator by small difference the coefficient becomes "negative". The cross section with smaller deviation of the predicted values have positive value representing the efficiency of the network.

$$\text{Nash-Sutcliffe coefficient Nash} = 1 - \frac{\sum_i^N (Y_o - Y_p)^2}{\sum_i^N (Y_o - \bar{Y}_o)^2} \quad 4.5$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_i^N (Y_o - Y_p)^2} \quad 4.6$$

The prediction with single Network for all the sections the RMSE value is as low as 0.002m for cross section no 33 and as high as 2.81m for the cross section no. 42. The RMSE values explain the accuracy of the network in learning the trend of each cross section's variation.

4.4.10.2. For Hydrologic Data Set

The data set comprised of monthly averages of Discharge data, Sediment data, Water surface elevation data and Average bed level data in FPS units extracted from the outputs of HEC-6 program running. The set of the data included 156 patterns.

The training data set was framed with 90 sets of the patterns from 1 to 90. The next 44 number of data sets from 91 to 134 constituted validation set and the rest from 135 to 156 (22 no.) was left to be the testing set.

Different training set were developed with different combinations of the input Independent variables for Average bed level as output variable. The data were applied directly (in FPS) unit. The training of the Neural Networks were carried through different algorithms of learning. The trials have been found performing with encouraging results with both Sigmoidal and Tanhyperbolic transfer functions and Bach back Propagation Learning Algorithms.

4.4.10.2.1 Validation

The validation of the prediction of the Neural Network structured have been observed to be very encouraging when measured with RMSE, Correlation Coefficient R and Nash-Sutcliffe (DC) coefficients.

The RMSE of most of the Neural Networks have shown values lower than unity and the other two coefficients R and DC have been found above 0.90. The measure of validations of the ANN models developed will be dealt in the following sections.

4.5 ANN MODELS DEVELOPED FOR AVERAGE BED LEVELS

4.5.1 *Morphometric ANN Model*

The models have been developed with morphometric data (Averaged bed levels of the cross sections). The model fairly incorporates the observed average bed levels as the Training and Validation parameters. The temporal dimension in year has been the input. The model traces the variation trend of the Longitudinal profile in time scale. The model presume that the observed values of the average bed levels themselves encapsulate other unknown parameters responsible for the average bed level to take the given value in the given period and the time exhibits a reference scale of trend observation.

4.5.1.1 *Model-1*

Since, the average bed levels determined for the cross section in the survey years lacked few data, thus first attempt of ANN model structuring was started with prediction of the missing values. Number of ANN Networks were created to fill the missing data. The procedure followed involves the selection of the cross section upstream and downstream of the target cross section based on the higher value of correlation coefficient. All together 10 different Networks were used to generate the missing data presented in the table 4.5.

Table:4.5 Generated Missing Data (average bed levels) with ANN

The bold Italic figures are the predicted data

Data yrs.		1957	1971	1977	1981	1988	1993	1997
X-section	Ch. Km	Average Bed Levels Deduced from the RL of X-s Stations						
		24.68	23.11	23.52	25.23	23.63	24.47	23.91
2	17.34	24.68	23.11	23.52	25.23	23.63	24.47	23.91
3	28.05	27.17	27.24	27.67	27.37	26.08	26.76	26.14
4	38.25	27.65	26.96	27.57	28.10	27.87	27.81	27.59
5	46.92	27.92	29.15	28.98	28.28	28.35	29.26	28.81
6	56.61	30.34	28.83	28.91	28.87	27.66	27.71	28.17
7	66.3	29.59	30.33	30.36	29.86	27.53	29.56	28.51
8	73.44	30.70	31.31	30.46	28.08	28.98	29.41	30.19
9	82.62	25.72	29.58	26.90	27.27	26.02	26.46	24.56
10	92.82	30.53	28.52	32.36	30.60	30.37	29.83	29.97
11	100.98	33.30	33.24	33.80	32.79	33.37	32.67	32.79
12	109.65	34.99	35.72	34.77	34.49	33.19	33.57	33.60
13	119.85	36.08	37.93	37.42	36.80	36.34	35.93	35.47
14	128.01	36.64	36.64	37.08	36.64	35.43	37.66	36.92
15	137.7	37.55	39.01	36.13	36.13	36.98	38.04	37.62
16	146.37	37.36	39.18	38.94	38.08	37.86	38.14	38.71
17	156.06	41.02	41.87	42.68	40.56	41.14	40.82	41.29
18	167.28	42.06	41.97	41.86	40.30	41.28	41.52	40.74
19	175.95	37.33	39.87	42.20	41.32	42.28	41.48	42.37
20	182.5	42.02	41.36	40.82	39.98	39.87	42.67	40.94
21	189.21	44.40	44.40	44.55	43.60	42.37	41.86	43.42
22	197.37	43.55	36.97	42.78	42.23	41.71	42.39	44.74
23	206.55	44.13	44.73	40.94	44.03	45.20	44.00	46.49
24	213.18	45.04	42.95	43.77	44.37	43.83	44.92	44.95
25	218.79	44.65	44.45	45.46	46.39	46.03	46.48	45.50
26	224.91	49.32	48.50	50.17	48.07	48.38	48.62	49.60
27	234.6	49.28	50.10	48.40	49.25	48.65	48.79	47.76
28	241.23	50.27	50.35	50.88	50.61	49.69	50.95	51.00
29	251.95	47.73	47.42	49.09	48.46	50.84	52.23	50.35
30	262.15	55.10	53.03	49.63	51.70	51.55	52.13	51.84
31	272.35	53.90	52.14	53.59	53.00	52.31	54.16	52.46
32	284.08	55.87	56.65	55.60	55.39	55.83	56.56	56.66
33	296.83	58.04	58.30	58.55	58.62	56.55	58.22	58.64

Data yrs.		1957	1971	1977	1981	1988	1993	1997
X-section	Ch. Km	Average Bed Levels Deduced from the RL of X-s Stations						
		310.1	62.00	61.48	58.35	60.78	58.75	59.71
34	310.1	62.00	61.48	58.35	60.78	58.75	59.71	60.68
35	325.9	60.90	60.88	60.71	59.21	63.40	60.47	59.23
36	341.21	63.67	63.68	60.13	58.75	62.34	62.54	62.35
37	352.94	66.16	65.39	64.02	64.42	63.88	61.96	64.42
38	365.18	67.63	65.15	68.08	65.82	65.46	63.47	69.66
39	371.81	69.86	69.48	69.32	68.39	66.92	68.93	70.00
40	383.03	70.01	72.38	71.85	71.30	71.07	70.22	71.73
41	389.66	72.05	70.75	69.58	69.86	70.91	71.56	71.26
42	398.33	73.39	68.57	68.58	69.54	73.37	72.01	74.08
43	412.09	72.30	72.24	71.86	70.84	73.95	74.05	75.30
44	423.31	73.44	73.55	73.55	74.60	76.83	76.06	78.34
45	439.63	75.02	79.18	78.46	78.90	78.64	78.44	78.35
46	453.91	78.58	80.72	79.89	79.87	77.57	77.40	77.93
47	465.13	80.24	80.35	80.59	81.13	81.39	81.52	81.58
48	474.82	82.92	80.57	80.58	81.36	82.62	81.87	81.61
49	483.49	82.01	83.02	82.25	83.17	83.54	82.79	82.54
50	490.63	82.26	83.49	83.71	83.27	81.85	83.16	83.48
51	498.8	85.35	86.16	85.76	85.55	85.91	86.25	86.29
52	505.94	87.14	86.29	87.62	86.96	87.45	88.58	88.57
53	513.08	88.82	88.52	88.46	88.44	91.64	91.08	90.89
54	522.77	90.46	90.65	91.00	89.50	92.47	93.57	93.36
55	531.95	93.96	91.82	92.07	91.92	94.03	94.63	94.50
56	541.13	94.37	93.86	91.71	91.48	97.97	91.32	91.32
57	558.98	97.02	97.71	96.65	99.51	99.99	99.67	99.67
58	570.2	98.75	100.23	99.43	100.28	102.48	100.41	98.70
59	579.38	101.93	102.23	101.94	101.82	104.32	103.25	102.59
60	589.07	106.71	105.28	105.37	103.18	106.08	106.18	106.23
61	601.82	107.37	108.14	109.77	108.66	109.00	108.81	108.76
62	613.04	108.59	111.42	112.41	113.05	110.00	113.19	113.20
63	626.3	113.65	116.24	116.16	115.73	112.30	114.00	113.88
64	634.46	115.90	118.34	117.95	115.89	113.91	115.75	115.75
65	640.07	117.62	120.37	121.03	120.92	121.08	121.10	121.11

4.5.1.2 Model -2

This model has been structured for the ANN architecture with 6 successive data patterns (1957,1971,1977,1981,1988 &1993) and 1 data pattern as validation (1997).

The salient feature of the models are summarized in the table 4.8.

4.5.1.3 Model -3

Model-3 is an alternative of the previous Model-1. Model-3 has 5 sets of the training pattern from 1957 to 1988 with 2 set of validation patterns 1993 and 1997. The observation with Model -2 has been that the validation performance measure is lower in general trend but for some of the cross sections the Validation has improved.

The salient feature of the models are summarized in the table 4.8

4.5.1.4 Model-4

Model-4 is one another alternative of the previous two models with 4- training patterns and 3 validation patterns. These models help to explore the deterioration in the performances of the validation due to decrease in variation patterns in the training sets.

The salient feature of the models are summarized in the table 4.8

Here, it is pointed out that, since, the validation set patterns are very small ;1, 2&3 in the three models the correlation in the observed and predicted values of each cross section varies from +0.99 to -0.99 testifying the strong correlation. The correlation values entered in the tables refer to the correlation of the observed and predicted values taking values for 64 sections as one pattern.

The criteria of Nash Sutcliffe does not suit applicable for the reason that the validation pattern set is very small to be applied for each cross sections observed and prediction pattern.

The ANN models structured are identified to be optimum after many trials performed keeping the track of average RMSE, Correlation R and DC of the trainings.

4.5.1.5 Model-5

The experience with the previous model development, the RMSE, R and DC for each cross section showed that the individual cross sections has different trend

of variation which could not be simulated by a single Neural Network. The idea evolved from the former models

has helped to look for individual Neural Networks. The table 4.6 below consists of the series of Neural Networks evaluated as the optimum for the individual sections.

Table:4.6

NEURAL NETWORKS WITH minimum RMSE FOR INDIVIDUAL SECTIONS

Neural Network	The cross section	X's	RMSE	X's	RMSE	X's	RMSE	
1	BBP(200)sig	6,12,14,26,28,35,39,49,53,56,57,58,63,64,	2	0.30	23	1.18	44	1.08
2	BBP(500)sig	2,3,17,37,44,48,	3	0.27	24	0.22	45	0.06
3	BBP(700)sig	42,	4	0.05	25	0.50	46	0.29
4	BBP(1000)sig	9,22,38	5	0.29	26	0.79	47	0.03
5	BBP(1500)sig	13,23,45	6	0.28	27	0.50	48	0.39
6	BBP(2500)sig	10,18,30,36,60	7	0.86	28	0.73	49	0.78
7	QP(200)sig	65,	8	0.26	29	0.95	50	0.50
8	QP(500)sig	15,34	9	0.90	30	0.13	51	0.07
9	QP(700)sig	19,25	10	0.07	31	0.99	52	0.83
10	QP(1000)sig	61,	11	0.06	32	0.09	53	0.23
11	QP(1500)sig	47,	12	0.08	33	0.37	54	0.64
12	QP(2500)sig	20,27,29,43,52,54,55,59	13	0.31	34	1.01	55	0.27
13	BBP(200)Tanh	5,62	14	1.48	35	2.03	56	3.56
14	BBP(500)Tanh	4,16,41,51	15	0.39	36	0.48	57	0.12
15	BBP(700)Tanh	8,21	16	0.25	37	1.33	58	2.64
16	BBP(1500)Tanh	40,	17	0.33	38	3.27	59	0.65
17	BBP(2500)Tanh	46,	18	0.38	39	2.38	60	0.03
18	QP(200)Tanh	7,31,33,50	19	0.47	40	0.75	61	0.05
19	QP(700)Tanh	11,	20	2.08	41	0.21	62	0.10
20	QP(1000)Tanh	24,	21	0.84	42	0.88	63	0.43
21	QP(1500)Tanh	32,	22	1.08	43	0.71	64	0.50
22							65	0.01

BBP=Batch Back Propagation, QP=Quick Propagation, Sig=Sigmoid Function ,
Tanh= Tanhyperbolic Function, (200)=No. of iteration performed.

The improvement in RMSE of the model could be observed as the arithmetic average of the single Neural Network prediction(for 2-validation set) dropped from 1.19m to 0.68m with the individual Neural Networks. The inference that can be drawn from the individual networks is that the cross sections with same Neural Network have the similar condition of morphological environment.

But it has been noted that some of the sections:56,35,38 could not improve even with the individual Neural Networks. Thus, on the way to ANN implementation it has been borne the additional knowledge that the process which is encountered difficult to be learned by the Neural Network while the similar process has been successfully traced advocates the erratic ness in that process or short comings in the observations and information collection.

Table:4.7

Average RMSE, Correlation R and Determinant Coefficient(From the Program)

No.	NN structure	Average RMSE	Correlation R	DC
1	BBP(200)sig	0.83584	0.49925	0.29789
2	BBP(500)sig	0.7252	0.69	0.45972
3	BBP(700)sig	0.61833	0.76027	0.58984
4	BBP(1000)sig	0.56076	0.78138	0.63826
5	BBP(1500)sig	0.50717	0.81667	0.6872
6	BBP(2500)sig	0.34093	0.91249	0.83739
7	QP(200)sig	0.3252	0.92042	0.85271
8	QP(500)sig	0.26628	0.93551	0.88549
9	QP(700)sig	0.24744	0.94437	0.89653
10	QP(1000)sig	0.23979	0.95182	0.90487
11	QP(1500)sig	0.22744	0.95372	0.91115
12	QP(2500)sig	0.49077	0.99804	0.99245
13	BBP(200)Tanh	1.4541	0.80689	0.21416
15	BBP(700)Tanh	0.37453	0.95309	0.81793
16	BBP(1500)Tanh	0.40002	0.97633	0.89755
17	BBP(2500)Tanh	0.23018	0.98761	0.94885
18	QP(200)Tanh	1.8549	0.70144	0.32966
19	QP(700)Tanh	1.4982	0.80046	0.1088
20	QP(1000)Tanh	1.3801	0.84534	0.24673
21	QP(1500)Tanh	1.3344	0.85963	0.30412

The RMSE, R and the DC are given by the NN program.

Table:4.8

Model No.	Purpose	Input Variables (input Neurons)	Output variables (output Neurons)	No. of Hidden Layer (neurons)	Transfer Function	Learning Algorithm	Learning rate	Momentum rate	Stopping Criteria (Value)	RMSE	Correlation Coeff.	Nite Cliffe Coeff.	Validation RMSE Nash-Coeff. R	Remarks
1	Missing data Prediction (10 networks were developed) for total missing data)	US & DS Xs-With high R values	Missing Avg.Bed Level	1 (varied)	Both Tanh & Sigmoid	BBP & QBP	for BBP=0.1 &	for BBP=0.8 &	Iteration) 50,000 to 100,000)	< 0.1	> 0.8	> 0.8	The total data pattern fed for learning	
2	Prediction of all inter mediate data for non survey years of the study period with 1997 as the validation data year.	Years	Av. Bed. Levels	1 (44)	Tanh	BBP	0.1	0.4	500	0.44m	0.96	0.82	Avg RMSE=1.07m R=+0.99 to -0.99 Nash-Poor<0	for less validation data it is very likely
3	Prediction of all inter mediate data for non survey years of the study period with 1993 and 1997 as the validation data year.	Years	Av. Bed. Levels	1 (44)	Sigmoid	BBP	0.1	0.4	1500	0.38m	0.96	0.83	Avg RMSE=1.19m R=+0.99 to -0.99 Nash-Poor<0	for less validation data it is very likely
4	Prediction of all inter mediate data for non survey years of the study period with 1988, 1993 and 1997 as the validation data year.	Years	Av. Bed. Levels	1 (44)	Sigmoid	BBP	0.1	0.4	1500	0.31m	0.98	0.92	Avg RMSE=1.19m R=+0.99 to -0.99 Nash-Poor<1	for less validation data it is very likely
5	Identification of the Individual Networks to each cross sections (21 no. of networks)	Years	Av. Bed. Levels	1 (44)	Both Tanh & Sigmoid	BBP & QBP	for BBP=0.1 & for QBP=0.8	for BBP=0.4 & for QBP=0.8	200 to 2500	0.22 to 1.85m	0.49 to 0.99	0.1 to 0.99	Avg RMSE=0.68m R=+0.99 to -0.99 Nash-Poor<2	

4.5.2 Validation Plots

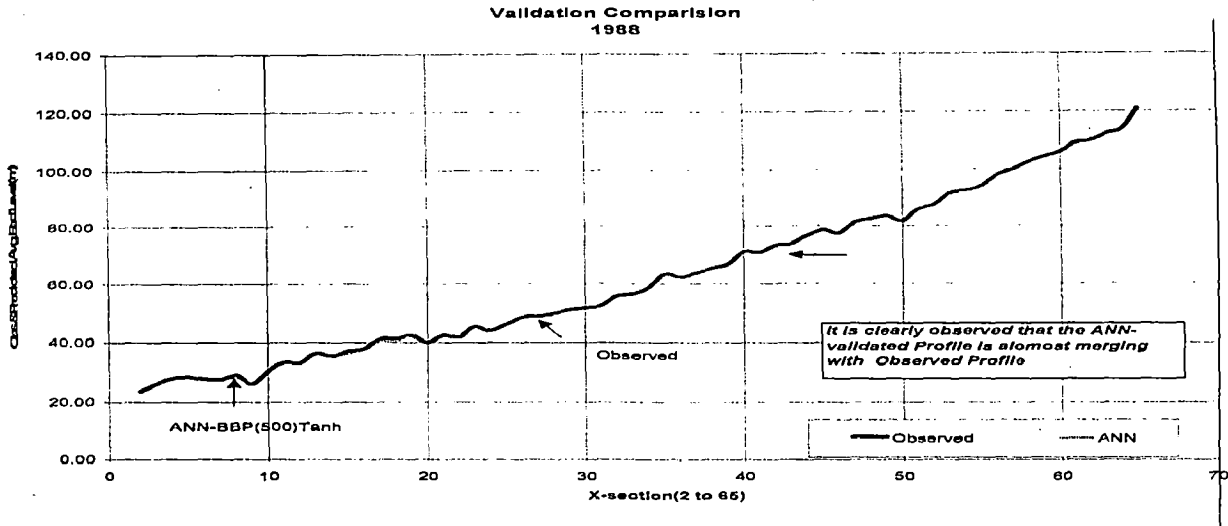


Figure:4.4(a)
Validation plot of Observed Avg. bed Levels and ANN predicted values for 1988

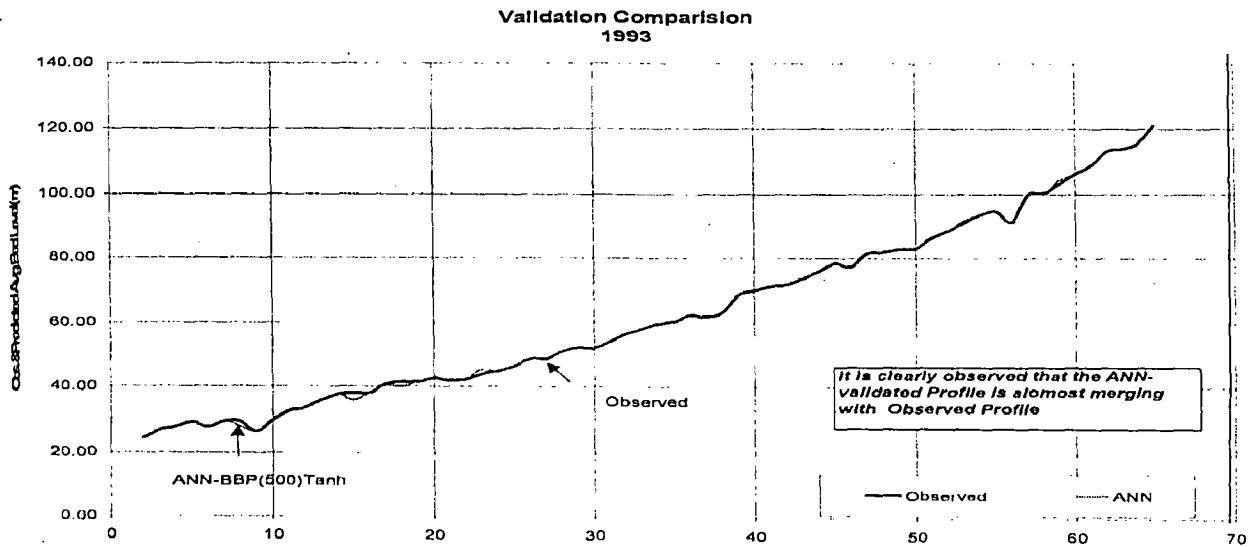


Figure:4.4(b)
Validation plot of Observed Avg. bed Levels and ANN predicted values for 1993

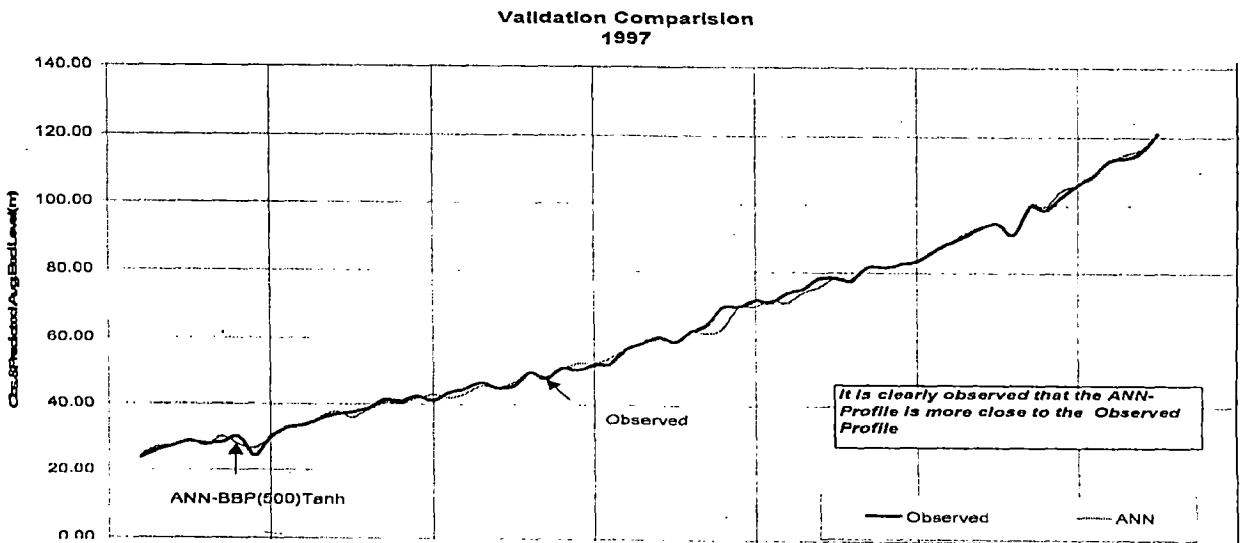


Figure:4.4(c)
Validation plot of Observed Avg. bed Levels and ANN predicted values for 1997

The validation is very encouraging for the years 1988 and 1993 but it is degraded for the year 1997.

4.6 REGRESSION MODELS ON THE MORPHOMETRIC DATA

Since, regression models have been in use in many fields, to realise the appreciation of ANN environment in data driven techniques, following Regression Models have been developed and applied to predictions. As the every individual cross section represents a single entity, regression have been performed on the set of seven data of average bed levels. First four data were regressed over the corresponding years and rest three were predicted and validated.

The table 4.11 shows the regression parameters and the validation performances in terms of Correlation R, Nash-Sutcliffe Coefficient (DC) and RMSE.

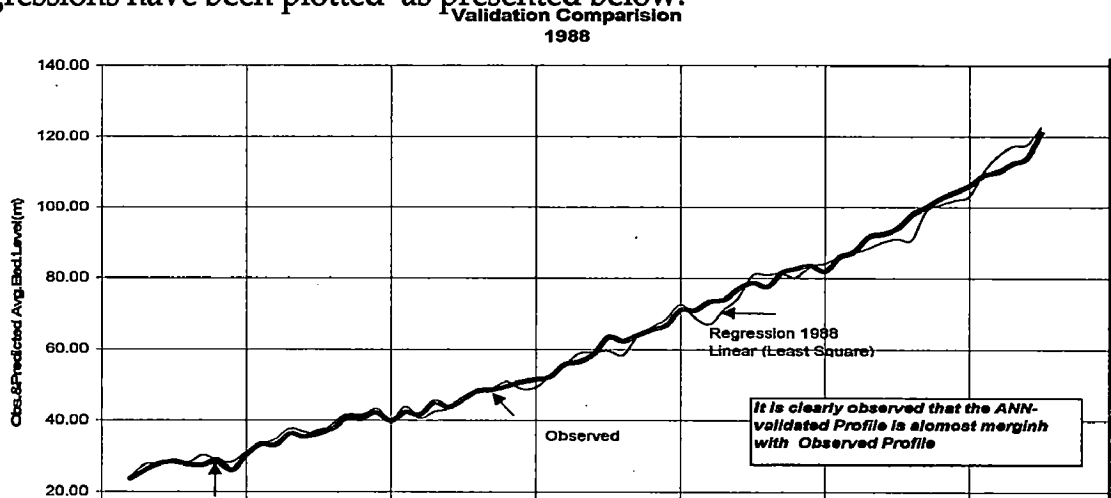
The average of the RMSE values of all the 64 cross section for regression has been 2.40m while it is 1.19m only with the single Neural Network and further 0.68m with individual Neural Networks.

Table 4.9

Cross Section	Intercept	Slope	Validation		
			Correlation R	Nash Coeff	RMSE
2	25.969	-0.001	-0.39	0.105	0.45
3	-0.493	0.014	0.15	0.940	1.67
4	2.880	0.013	-0.93	0.662	0.22
5	-23.267	0.026	0.56	-0.559	0.57
6	154.424	-0.063	-0.87	0.704	0.56
7	-8.153	0.019	0.54	0.669	2.53
8	187.518	-0.080	-0.97	0.876	1.64
9	-87.610	0.058	-0.69	0.946	3.77
10	-39.875	0.036	-0.76	0.957	1.53
11	45.926	-0.006	0.82	0.141	0.43
12	72.356	-0.019	-0.92	0.948	1.43
13	-41.708	0.040	-1.00	0.968	2.51
14	21.963	0.008	0.70	-4.990	1.15
15	168.293	-0.066	-0.65	0.931	2.28
16	-48.448	0.044	0.96	0.765	1.35
17	15.569	0.013	0.24	0.920	0.92
18	147.556	-0.054	0.63	0.723	0.99
19	-337.040	0.191	0.03	0.964	2.85
20	193.751	-0.077	-0.44	0.634	2.68
21	84.297	-0.020	-0.61	0.706	1.76
22	121.085	-0.040	-0.93	0.845	3.44
23	155.742	-0.057	-0.46	0.898	3.90
24	117.145	-0.037	-0.90	0.873	1.80
25	-80.671	0.064	-0.49	0.753	0.99
26	89.234	-0.020	-0.92	0.361	0.81
27	81.958	-0.017	0.76	0.513	0.80
28	11.698	0.020	0.91	0.183	0.82
29	-38.583	-0.044	-0.19	0.869	2.69
30	417.720	-0.185	-0.56	0.995	4.28
31	109.061	-0.028	-0.13	0.231	1.18
32	94.619	-0.020	-0.94	0.859	1.22
33	9.137	0.025	0.96	0.565	1.68

Cross Section	Intercept	Slope	Validation		
			Correlation R	Nash Coeff	RMSE
34	248.184	-0.095	-1.00	0.745	1.92
35	162.292	-0.052	0.99	0.425	2.82
36	456.028	-0.200	-0.13	1.000	6.30
37	231.827	-0.085	-0.15	0.176	1.42
38	147.336	-0.041	-0.61	0.090	3.31
39	168.838	-0.051	-0.99	0.296	1.86
40	-54.868	0.064	0.38	0.885	2.23
41	271.196	-0.102	-0.59	0.992	3.55
42	430.743	-0.183	-0.28	0.985	8.72
43	169.156	-0.049	-0.87	0.973	4.60
44	5.236	0.035	0.60	0.877	3.31
45	-241.553	0.162	-0.99	0.998	3.59
46	-29.947	0.056	0.61	0.996	4.06
47	19.056	0.031	0.99	0.906	0.32
48	239.640	-0.080	0.98	0.967	2.91
49	11.996	0.036	-0.98	0.627	0.85
50	-17.292	0.051	0.96	0.785	1.86
51	63.532	0.011	0.93	0.509	0.30
52	79.330	0.004	0.89	0.812	1.50
53	120.993	-0.016	0.98	0.989	3.68
54	127.511	-0.019	-0.80	0.977	3.89
55	263.186	-0.087	-0.79	0.995	4.68
56	342.500	-0.127	0.90	0.176	5.30
57	-28.944	0.064	-0.90	0.964	0.96
58	-4.679	0.053	-1.00	0.229	2.16
59	108.663	-0.003	1.00	0.811	2.00
60	344.415	-0.121	-0.99	1.000	4.45
61	-40.802	0.076	-0.96	0.994	1.58
62	-257.238	0.187	0.90	0.796	4.08
63	-77.138	0.098	0.87	0.965	5.08
64	57.372	0.030	0.90	0.892	3.23
65	-170.065	0.147	1.00	1.000	2.54

The predicted values of the average bed levels for 1988,1993 and 1997 with regressions have been plotted as presented below.



with ANN
Figure:4.5(a)
Validation Plot of Regression and ANN for the year 1998

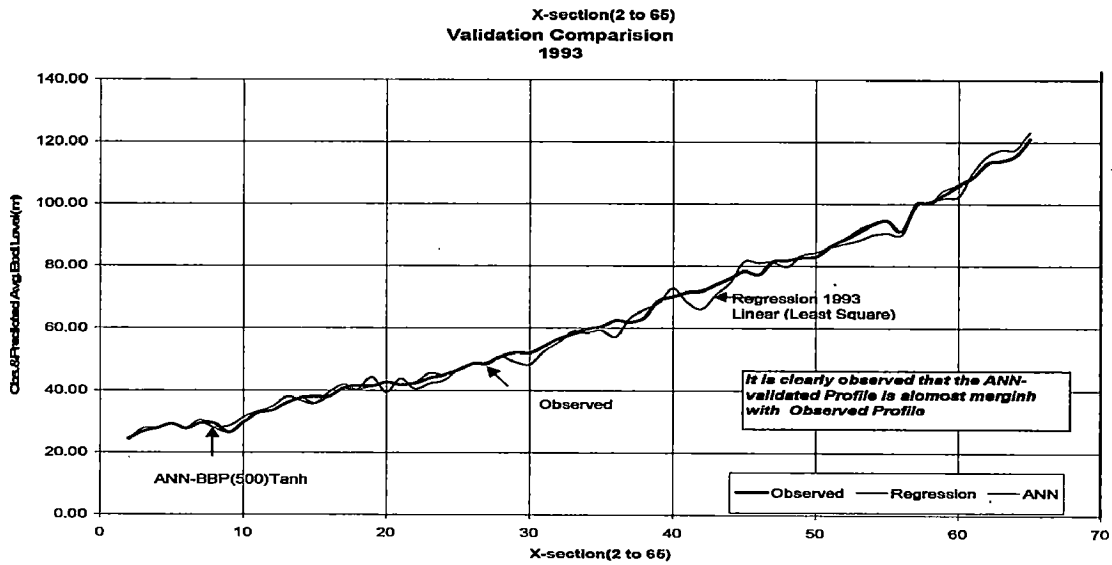


Figure:4.5(b)
Validation Plot of Regression and ANN for the year 1993

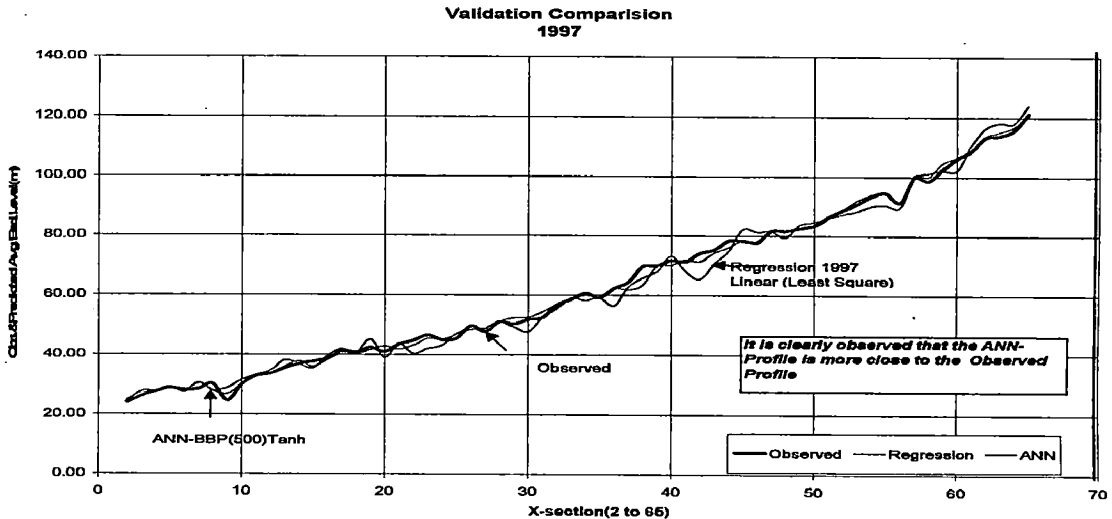


Figure:4.5(c)
Validation Plot of Regression and ANN for the year 1993

The three plots show that the validation ANN prediction is far superior than regression model for all the three years. However, the validation deteriorates for both the models from 1988 to 1997. This indicates that both the models hold competency in predicting for immediate next lead period and its strength goes down for long lead forecasting. Therefore, ANN is more suggestable in real time forecasting.

4.7 HYDRO-MORPHOLOGICAL MODELS

Conceptually, river longitudinal morphology is subjected to influence of many hydrological parameters like, flood discharges, characteristic dimension and nature of the sediment transported and the rate of the transportation and, to some extent, the stage of the river location and the age of the river. In laboratories flumes as well as in the prototype channels the bed level variation mechanism have been studied and numerous mathematical approaches have already been proposed which utilizes the under lying physical laws of fluvial dynamics. The physically based deterministic approaches demand high understanding of the river hydraulics. The analysis of river hydrodynamic problems have been eased by fast computing environment of present generation of computers. There are numerous software readily available in use. Yet the modeller is required to be very competent to handle the problem with these packages. Again, the observed data in hand form the foundation of the success of the model performance. In the modelling process, calibration becomes more important which is equivalent to training stage in Neural Network. The validation of the model performance and the acceptability of the results depend upon the nature of the problem and extent of the acceptable error limit. But, often mathematical modelling are cost and time consuming.

Searching for an easy way out of assessing such problems ANN is expected to be a robust alternative requiring less time and efforts without compromising the quality of the results. In this present study the significant hydrological parameters; discharge(one major parameter of Stream Power), Water surface level (depth parameter to the tractive force), and sediment rate (the constituent ingredient of the bed material) have been selected to be independent variables. The average bed level of the river channel has been the targeted output to observe the process of

aggradation and degradation phenomena. The study has been carried out for selected cross sections for which the all the three mentioned data are available. Among the 64 cross sections following 4 cross sections were chosen.

Cross Section	Location	Chainage	Data Period
2	Dhubri	17.34 km	1990 to 2002
9	Pancharatna	82.62 km	1990 to 2002
10	Goalpara	92.82 km	1990 to 2002
22	Pandu(Gauhati)	213.18 km	1990 to 2002

4.7.1 Model -6,7&8 (Cross Section No.-2)

Model -6, 7 and 8 corresponds to the cross section no -2. The average bed levels have been simulated with the mean monthly average discharges (Model-6), Water surface Level (Model-7) and mean monthly Sediment discharge. The 90 data pattern set was used for training, 22 data pattern as testing and the middle 44 data pattern were used for the validation. The results of training and the validation both have been very well for all three models. In the following table 4.10 the salient details of the models have presented along with performance measures.

4.7.2 Model -9&10(Cross Section No.-9)

4.7.3 Model -11,12,13&14(Cross Section No.-10)

4.7.4 Model -15,16&17 (Cross Section No.-22)

Table:4.10 (Salient Features of the Hydromorphic Models)

data a

All the data are Mean Monthly
 Training set-Jan-1990 to June 1996

Teasting set-Mar,2001 to Dec, 2002

Validation set-July,1996 to Feb,2001

Model No.	Purpose	Input Variables (input Neurons)	Output variables (output Neurons)	No. of Hidden Layers (neurons)	Transfer Function	Learning Algorithm	Learning rate	Momentum	Stopping Criteria (Value)	Validation RMSE, Nash Coeff., & R=	Remarks
6	For Average bed Cross section no -2 (Dhubri)	1 (Dis-cft/sec)	1(Av. Bed. Levels)	1(2)	Tanh	BBP	for BBP=0.1	for BBP=0.4	700	0.527 0.65 0.9827	
7	For Average bed Cross section no -2	Water Level (m)	1(Av. Bed. Levels)	1(2)	Tanh	BBP	for BBP=0.1	for BBP=0.4	1900	0.552 0.615 0.948	
8	For Average bed section no -2	Sediment discharge	1(Av. Bed. Levels)	1(2)	Sigmoid	BBP	for BBP=0.1	for BBP=0.4	4500	0.552 0.9635 0.9816	
9	For Average bed section no -9 (Pancharatna)	Water Level (m)	1(Av. Bed. Levels)	1(2)	Tanh	QBP	for QBP=0.8	for QBP=0.8	500	0.0 0.0 0.0	Fixed Control Point
10	For Average bed section no -9 (Pancharatna)	Year and Month	3(Av. Bed+WS+Sediment)	1(2)	Sigmoid	QBP	for QBP=0.8	for QBP=0.8	600	211390. 0.0 cft/sec 0.0 0.7882 0.0 0.9371 0.9371	
11	For Average bed section no -10	1 (Dis-cft/sec)	1(Av. Bed. Levels)	1(2)	Tanh	BBP	for BBP=0.1	for BBP=0.4	700	0.991 ft 0.97	

All the data are Mean Monthly

Training set-Jan-1990 to June 1996

Teasting set-Mar,2001 to Dec, 2002

Validation set-July,1996 to Feb,2001

data at

Model No.	Purpose	Input Variables (input Neurons)	Output variables (output Neurons)	No. of Hidden Layer (neurons)	Transfer Function	Learning Algorithm	Learning rate	Momentum rate	Stopping Criteria (Value)	Validation RMSE= Nash-Coeff. & R=	Remarks
12	For Average bed Cross section no -10	Water Level (m)	1(Av. Bed. Levels)	1(2)	Sigmoid	QBP	for QBP=0.8	for QBP=0.8	10000	0.763 ft 0.97 0.99	
13	For Average bed Cross section no -10	Sediment discharge	1(Av. Bed. Levels)	1(2)	Sigmoid	QBP	for QBP=0.8	for QBP=0.8	10000	1.74 ft 0.92 0.82	
14	For Average bed Cross section no -10	1(Year, Month & Ws. Level	1(Av. Bed. Levels)	1(4)	Tanh	QBP	for QBP=0.8	for QBP=0.8	500	0.871ft 0.950 0.980	
15	For Average bed Cross section no -22(Pandu-gauhathi)	1 (Dis-cft/sec)	1(Av. Bed. Levels)	1(2)	Tanh	BBP	for BBP=0.1	for BBP=0.4	1100	2.034ft 0.797 0.94	
16	For Average bed Cross section no -22(Pandu-gauhathi)	Water Level (m)	1(Av. Bed. Levels)	1(2)	Sigmoid	QBP	for QBP=0.8	for QBP=0.8	40000	0.398ft 0.988 0.994	
17	For Average bed Cross section no -22(Pandu-gauhathi)	Sediment discharge	1(Av. Bed. Levels)	1(2)	Sigmoid	QBP	for QBP=0.8	for QBP=0.8	700	2.795ft 0.616 0.907	

Observation: The correlation of the observed and the predictions is $R=0.9842$ & $DC=0.65$

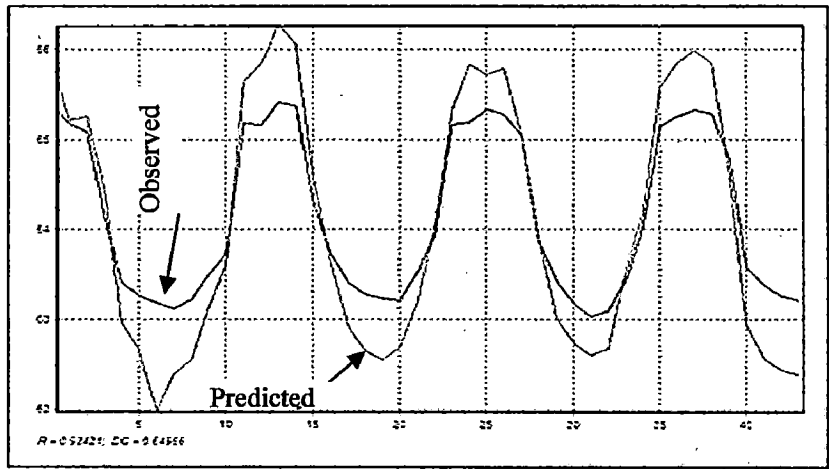


Figure:4.6(a)
Model-6 Validation Profile of Discharge vs Avg.bed.

Observation: The correlation of the observed and the predictions is $R=0.9479$ & $DC=0.615$

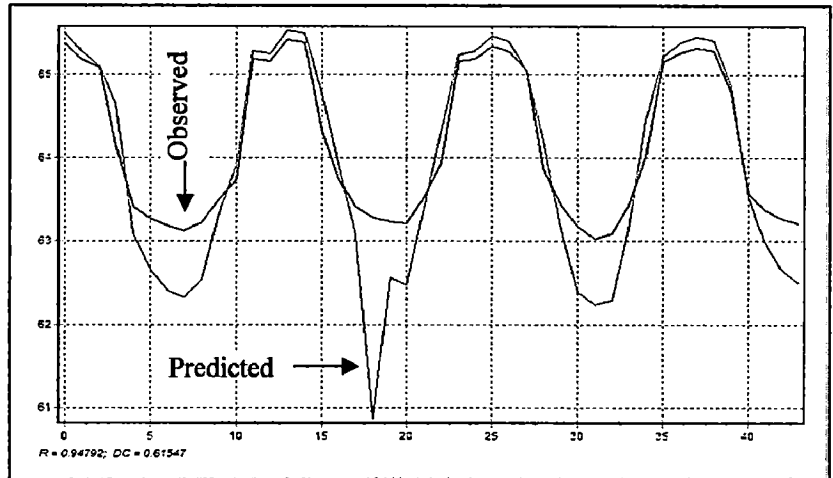


Figure:4.6(b)
Model-7 Profile of Water Surface Level vs Avg.bed.

Observation: The correlation of the observed and the predictions is $R=0.9816$ & $DC=0.9635$

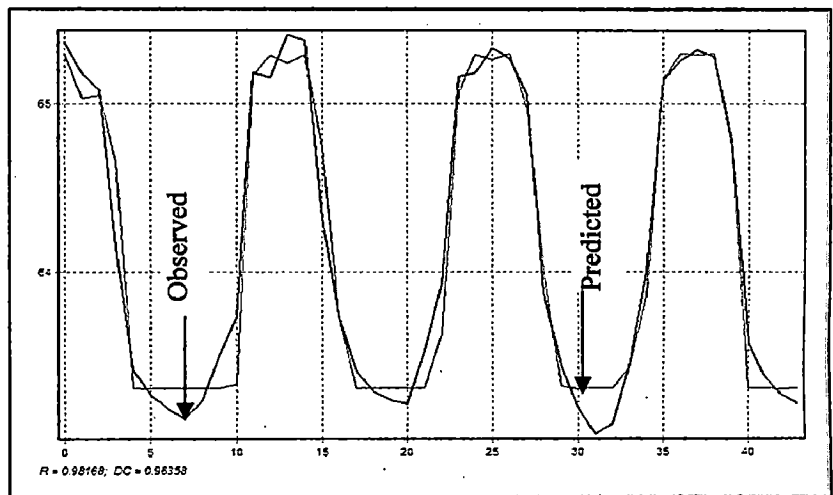


Figure:4.6(c)
Model-8 Profile of Sediment vs Avg. bed. Levels

Observation: The observed Avg. bed levels are almost constant but due variation in the Input the predicted Levels have also fluctuate.

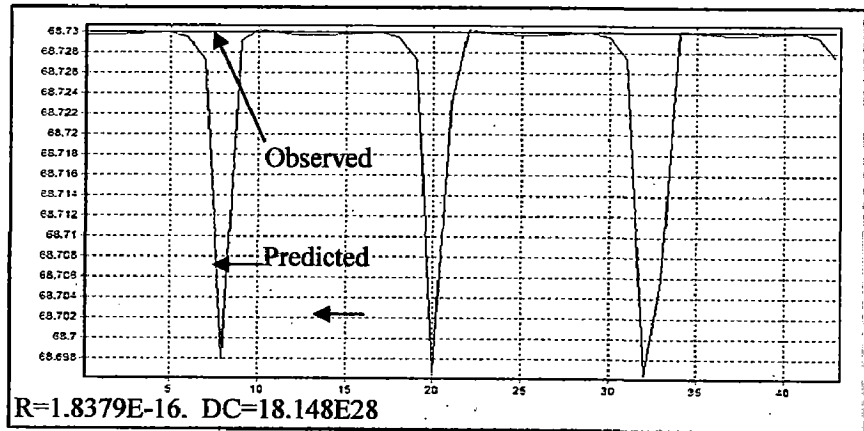


Figure:4.7(a)
Model-9 Profile of Year & Months vs Avg.bed. Level

Observation: The observed discharge profile has high variation compared to predicted which is of uniform peaks.

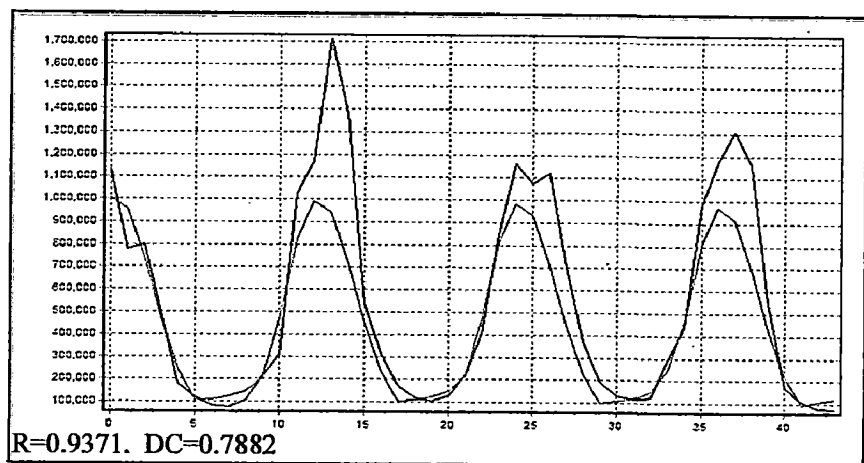


Figure:4.7(b)
Model-10 Profile of Year & Months vs Discharge

Observation: The observed water surface profile has high level of variation compared to predicted which is of uniform peaks. The R and DC values are satisfactory.

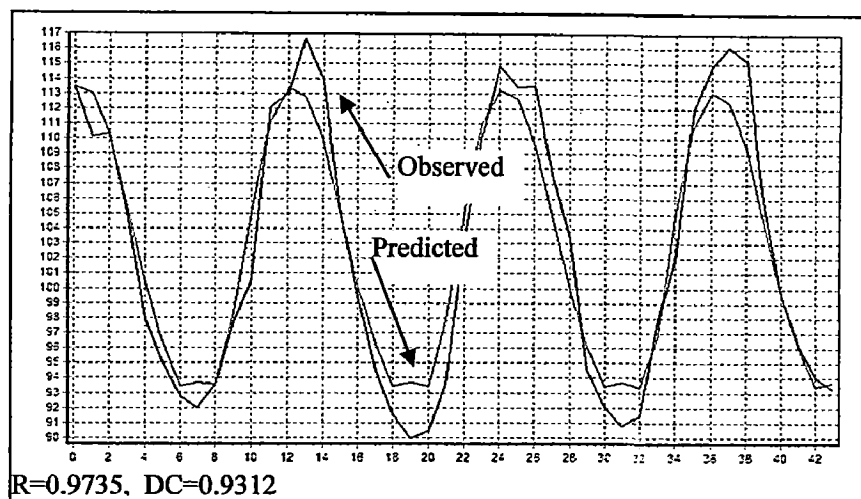


Figure:4.7(c)
Model-10 Profile of Year & Months vs Water Surface

Observation: The observed water surface profile has lower minimum compared to predicted which is of uniform peaks. The R and DC values are satisfactory.

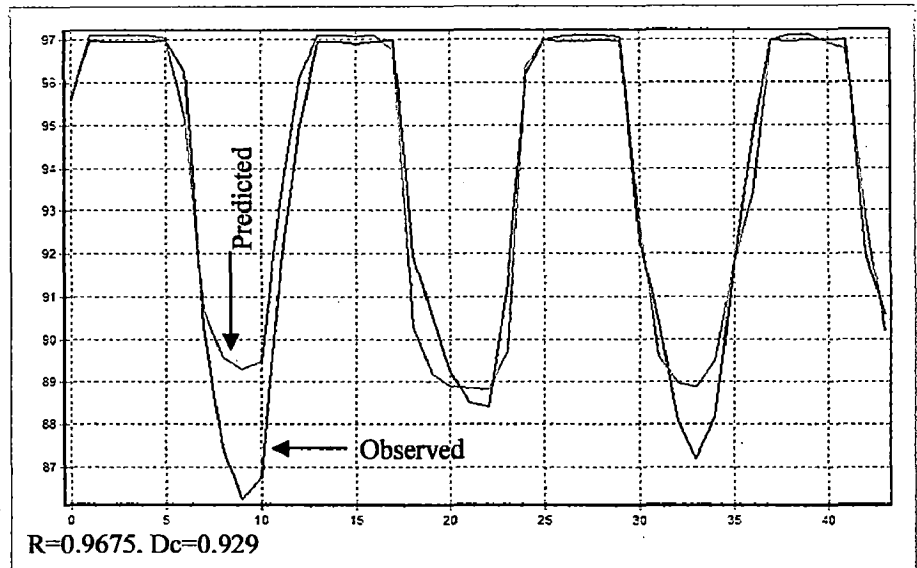


Figure:4.8 (a)
Model-11 Validation Profile of Discharge vs Avg. bed levels

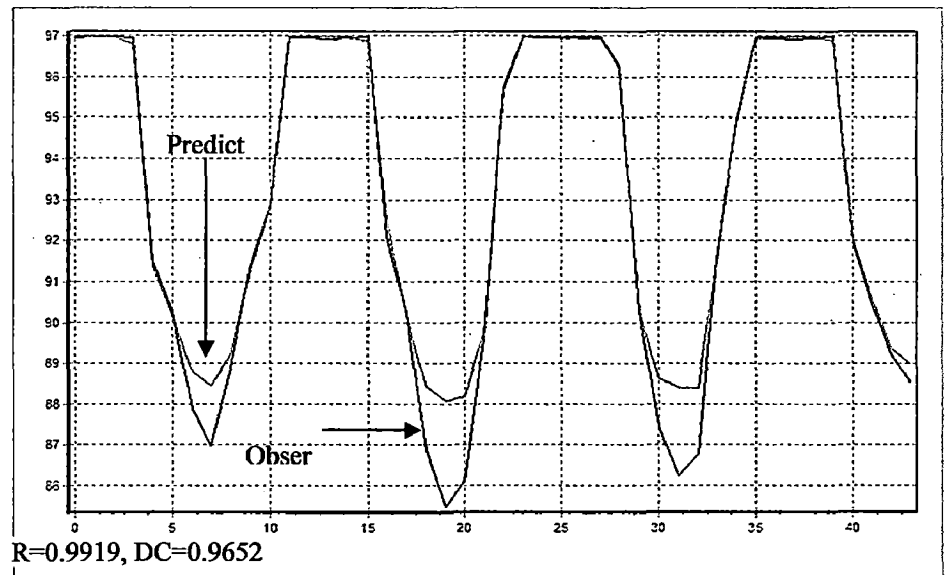


Figure:4.8(b)
Model-12 validation Profile of Water Surface vs Avg. bed Levels

Observation: The predicted Profile is merging with the observed profile on the higher level but takes upper level on the lower side.

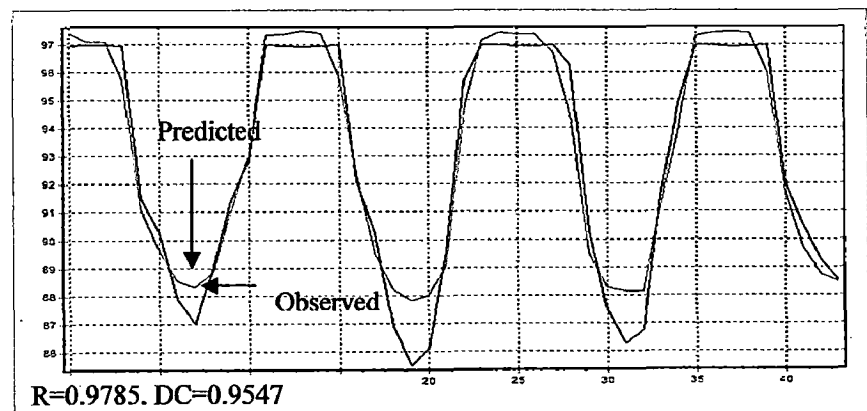


Figure:4.8(c)
Model-13 validation Profile of Sediment discharge vs Avg. bed Levels

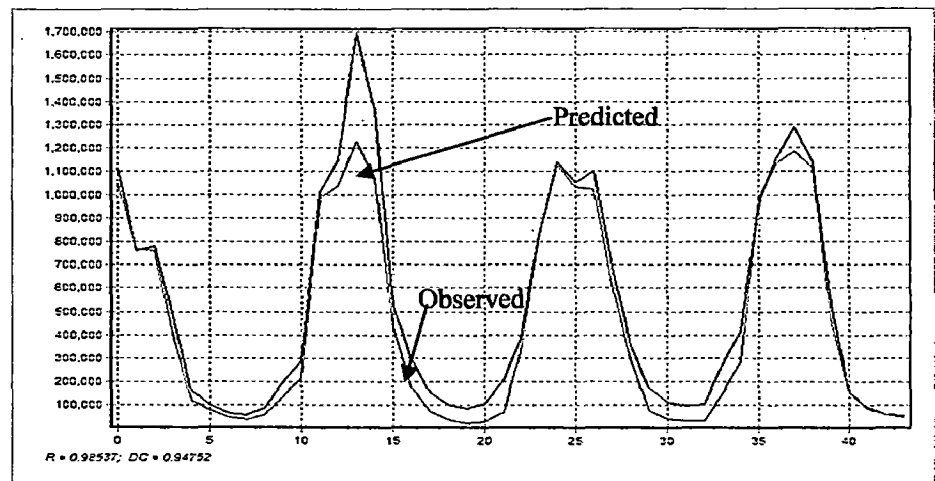


Figure:4.8(d)
 Model-14 validation profile Discharge vs Avg.bed Levels

Observation: The predicted Profile as in the case of Water surface is closely with the observed profile on the higher level but takes upper level on the lower side.

In the above three models for the cross section-22 (at Pandu) the Average bed Level variation is very closely simulated with water surface as input. The RMSE is very small and the R and DC are also significantly high. Since, the numerical figure of Discharge value and Sediment discharges are large and correspondingly the discrepancy in observed and predicted values differ by large. However, in the physical sense, discharge intensity and the sediment per unit width more important that the total rate across the section.

Observation: Unlike in the models 11 to 14 the predicted profile is rising above the observed profiles

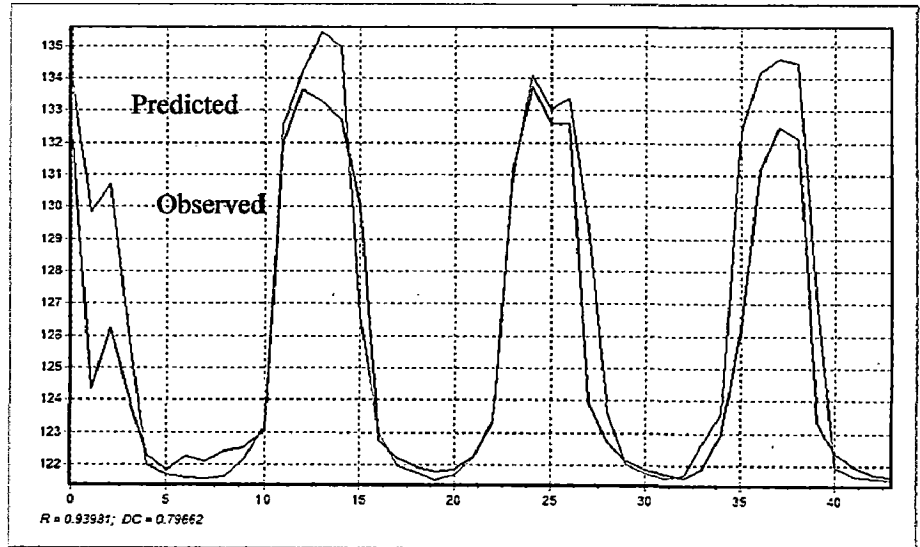


Figure:4.9(a)
Model-15 Validation Profile of Discharge vs. Avg. bed Levels

Observation: The simulation is superior with Water Surface than Discharge

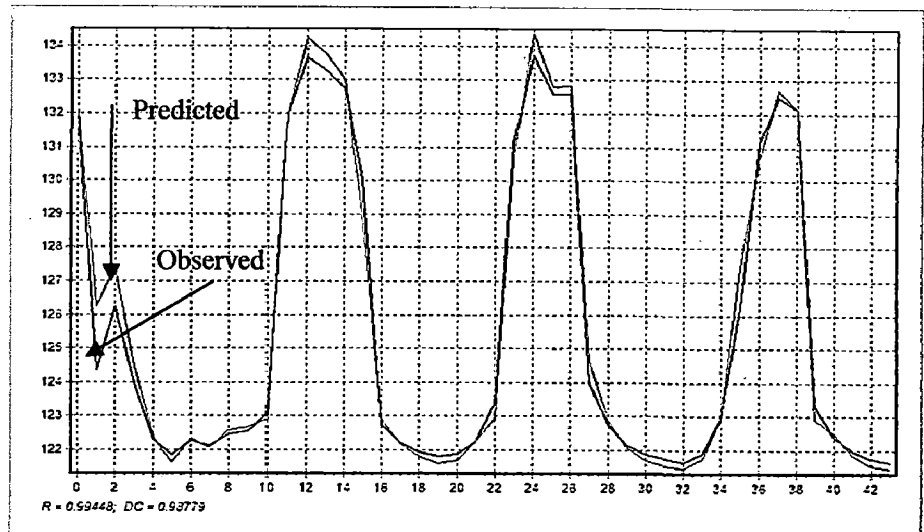


Figure:4.9(b)
Model-16 Validation Profile of Water Surface vs. Avg. bed Levels

Observation: The predicted profile with sediment discharge is more crooked than the observed AVG. bed Levels

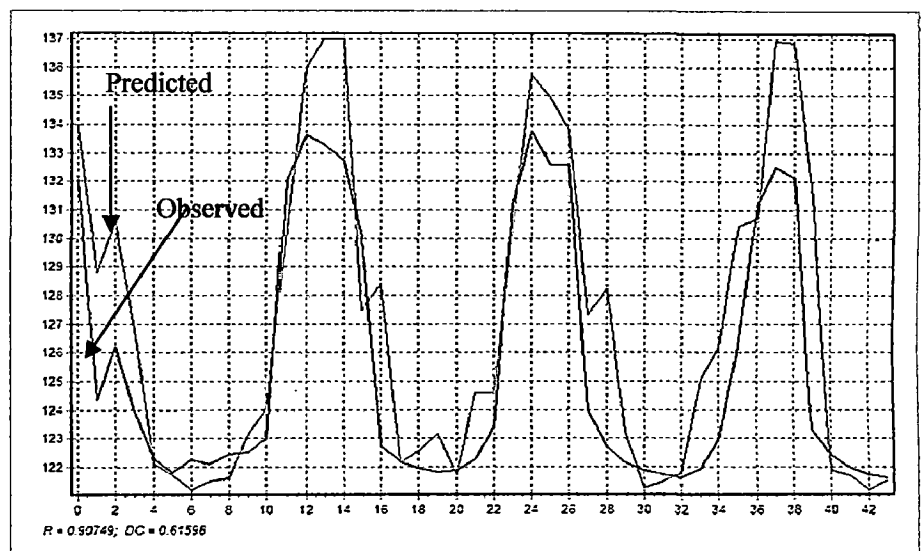


Figure:4.9(C)
Model-17 Validation Profile of Sediment discharge vs. Avg. bed Levels

The optimum connection weights of the model architectures are presented in the Appendices.

4.8 THE AGGRADATION AND DEGRADATION OF THE RIVER CHANNELS

The ANN Models- 1 to 5 (Morphometric models) have been applied to generate the average bed levels of all the intermediate values from 1957 to 1997 and further up to 2005 as forecast presented in the table 4.16(a) to ©.

The values of the average bed levels obtained from the ANN has been plotted and compared with the original plots.

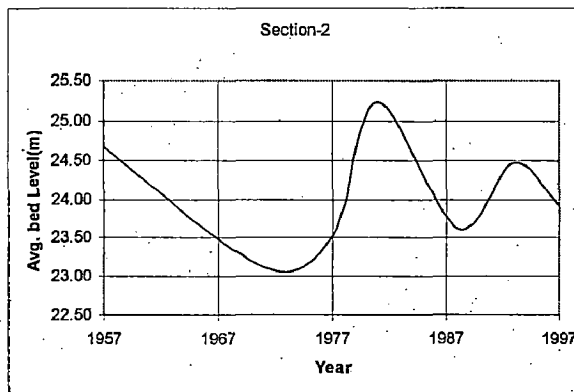


Figure:4.10(a)

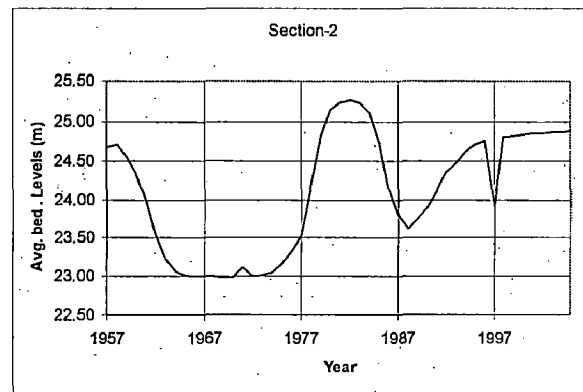


Figure 4.10(b)

The Figure 4.10 (a and (b) show that the ANN predicted average bed levels profile differs from that of the original plot. The second profile has higher steepness in the variation trend in the beginning with a small kink in the saddle. This abruptness in the variation could be related with the nature and the magnitude of the flood incident in the mean period for which the survey was not conducted. Further more, the drop in the bed level in 1997 is very distinctly differing from the trend of rising after 1988. In the later year after 1997 the trend of bed rise is smooth with flatter slope which is very convincing. So, the reliability of the data of the year 1997 has been observed inconsistent which has been further supported by following more cross section.

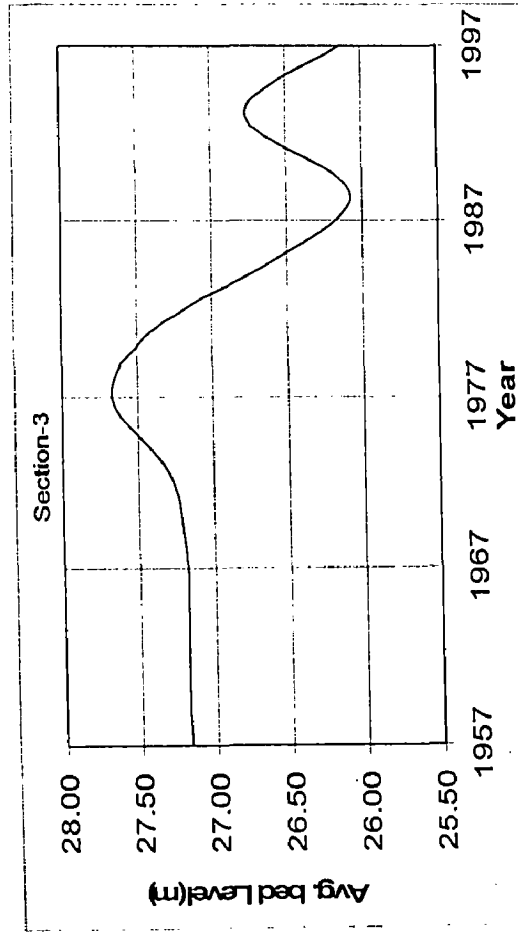


Figure 4.11(a)
Cross Section-3

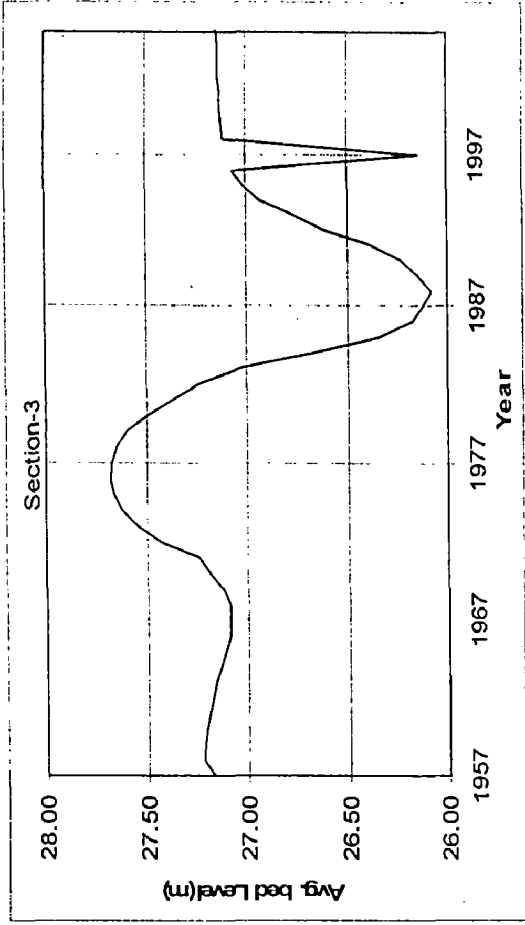


Figure 4.11(b)
Cross Section-3

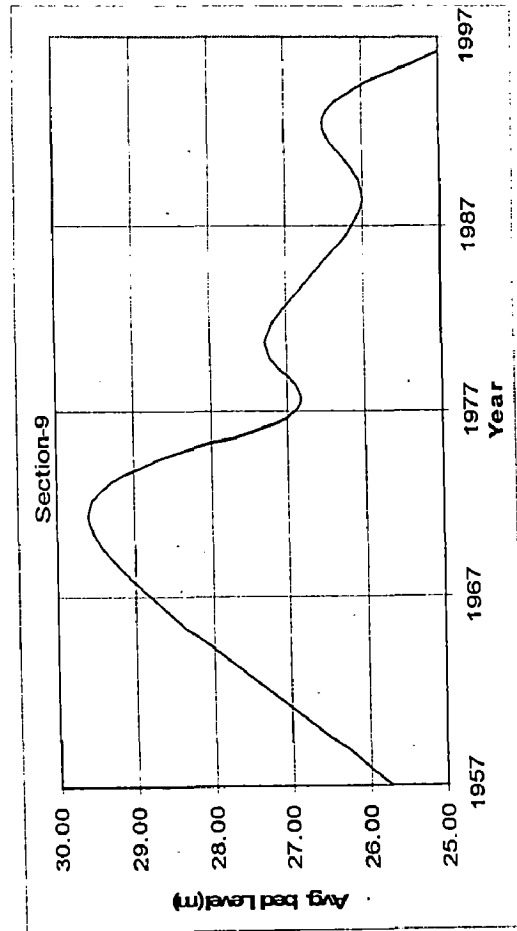


Figure 4.11(c)
Cross Section-9

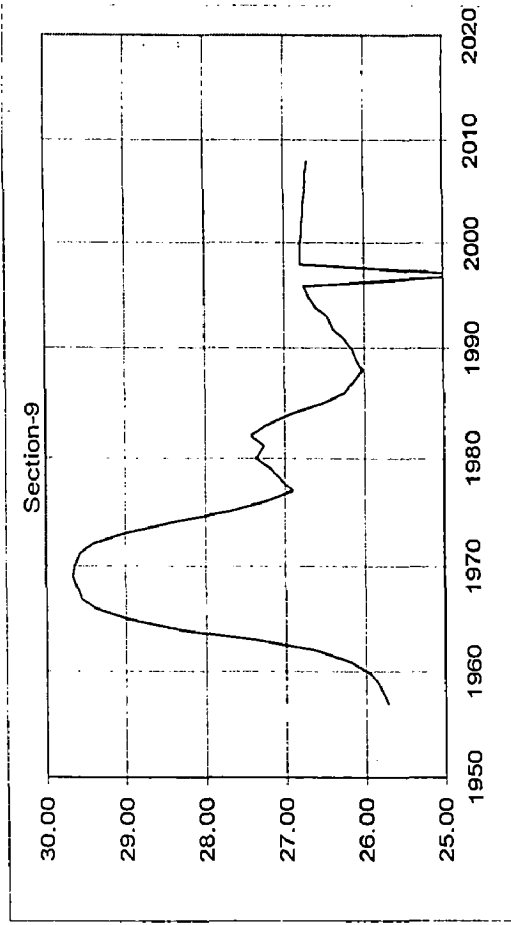


Figure 4.11(d)
Cross Section-9

Table 4.11(b)

THE PREDICTED INTERMEDIATE DATA with ANN MODEL-2

Year	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	
1-BBP(500)tanh	Predicted non survey data Values																					
	(Bolds: Original data	and the <i>Italic Bold</i> : Predicted non survey data Values)																				
1957	44.18	45.07	44.36	49.30	50.19	50.29	47.69	55.10	53.86	55.32	58.21	62.02	60.95	63.95	66.13	67.46	69.83	70.02	72.05	73.60	70.67	
1958	44.23	45.05	44.36	49.24	50.19	50.28	47.68	55.08	53.79	55.32	58.21	62.02	60.96	63.95	66.12	67.38	69.82	70.05	72.04	73.58	70.67	
1959	44.31	45.01	44.36	49.16	50.19	50.27	47.65	55.05	53.68	55.32	58.21	62.01	60.96	63.94	66.10	67.25	69.82	70.11	72.02	73.55	70.67	
1960	44.43	44.93	44.36	49.05	50.19	50.26	47.62	55.01	53.49	55.32	58.20	62.01	60.95	63.94	66.08	67.05	69.80	70.22	71.99	73.49	70.67	
1961	44.58	44.76	44.37	48.90	50.19	50.25	47.57	54.95	53.21	55.32	58.17	62.01	60.94	63.94	66.04	66.73	69.78	70.42	71.94	73.34	70.67	
1962	44.74	44.45	44.37	48.73	50.19	50.23	47.52	54.87	52.86	55.32	58.14	62.01	60.91	63.94	65.99	66.28	69.75	70.79	71.88	72.99	70.67	
1963	44.89	43.97	44.38	48.56	50.19	50.21	47.47	54.75	52.53	55.32	58.10	62.02	60.88	63.93	65.93	65.75	69.71	71.30	71.78	72.29	70.68	
1964	45.01	43.50	44.39	48.42	50.19	50.20	47.43	54.62	52.31	55.32	58.06	62.02	60.85	63.92	65.86	65.22	69.67	71.78	71.67	71.21	70.69	
1965	45.09	43.20	44.40	48.31	50.19	50.19	47.40	54.47	52.19	55.32	58.03	62.01	60.83	63.91	65.78	64.80	69.62	72.09	71.54	70.16	70.70	
1966	45.14	43.05	44.42	48.25	50.18	50.18	47.38	54.30	52.13	55.32	58.03	62.00	60.81	63.90	65.71	64.52	69.59	72.25	71.41	69.44	70.71	
1967	45.15	42.98	44.43	48.23	50.18	50.19	47.37	54.12	52.10	55.32	58.05	61.98	60.81	63.89	65.64	64.38	69.56	72.33	71.29	69.04	70.72	
1968	45.12	42.95	44.44	48.25	50.17	50.21	47.38	53.88	52.10	55.32	58.12	61.93	60.83	63.87	65.56	64.37	69.54	72.36	71.17	68.82	70.73	
1969	45.01	42.95	44.47	48.32	50.15	50.27	47.41	53.49	52.11	55.32	58.24	61.91	60.86	63.84	65.45	64.54	69.52	72.37	71.01	68.69	70.74	
1970	44.93	42.95	44.45	48.50	50.10	50.35	47.42	53.03	52.14	56.65	58.30	61.48	60.88	63.68	65.39	65.15	69.48	72.38	70.75	68.57	70.74	
1971	43.97	42.93	44.59	49.00	49.98	50.52	47.64	51.87	52.25	55.32	58.55	60.86	60.96	63.56	65.04	65.79	69.49	72.32	70.50	68.56	70.77	
1972	42.69	43.15	44.72	49.62	49.67	50.68	47.93	50.85	52.51	55.32	58.65	59.76	61.02	63.07	64.72	66.80	69.47	72.25	70.19	68.52	70.80	
1973	41.63	43.34	44.91	50.00	49.19	50.80	48.33	50.17	52.93	55.32	58.69	58.90	61.06	62.18	64.37	67.51	69.44	72.14	69.96	68.50	70.83	
1974	41.17	43.56	45.10	50.14	48.81	50.86	48.74	49.85	53.32	55.32	58.71	58.53	61.04	61.21	64.09	67.85	69.41	72.03	69.82	68.48	70.86	
1975	41.03	43.74	45.28	50.17	48.62	50.89	49.00	49.74	53.53	55.32	58.72	58.42	60.92	60.47	63.93	67.95	69.37	71.92	69.75	68.49	70.88	
1976	40.94	43.77	45.46	50.17	48.40	50.88	49.09	49.63	53.59	55.60	58.55	58.35	60.71	60.13	64.02	68.08	69.32	71.85	69.58	68.58	71.86	
1977	41.02	44.07	45.65	49.90	48.50	50.86	48.98	49.94	53.53	55.32	58.71	58.70	60.16	59.51	63.95	67.70	69.14	71.69	69.72	68.62	70.94	
1978	42.05	44.25	45.88	49.18	48.47	50.80	48.77	50.38	53.37	55.32	58.70	59.39	59.68	59.15	64.09	67.16	68.89	71.53	69.74	68.87	70.98	
1979	43.25	44.40	46.06	48.38	48.46	50.71	48.57	51.09	53.17	55.32	58.66	60.42	59.38	58.93	64.24	66.31	68.60	71.37	69.77	69.28	71.02	
1980	44.03	44.37	46.39	48.07	49.25	50.61	48.46	51.70	53.00	55.39	58.62	60.78	59.21	58.75	64.42	65.82	68.39	71.30	69.86	69.54	70.84	
1981	44.82	44.50	46.23	48.01	48.40	50.47	48.46	52.14	52.84	55.32	58.53	61.29	59.28	58.85	64.41	65.19	68.11	71.19	69.87	70.24	71.18	
1982	45.17	44.44	46.24	47.98	48.36	50.27	48.62	52.23	52.68	55.32	58.35	61.17	59.48	58.98	64.41	65.09	67.82	71.16	69.96	70.88	71.38	
1983	45.36	44.30	46.24	47.96	48.33	49.98	48.98	52.10	52.48	55.33	57.85	60.69	60.24	59.38	64.38	65.18	67.45	71.16	70.13	71.81	71.80	
1984	45.42	44.10	46.22	47.96	48.31	49.77	49.53	51.87	52.31	55.36	57.09	59.92	61.85	60.25	64.30	65.36	67.14	71.17	70.38	72.68	72.47	
1985	45.43	43.93	46.22	47.96	48.31	49.69	50.09	51.66	52.23	55.48	56.69	59.27	62.94	61.30	64.19	65.51	66.99	71.17	70.65	73.14	73.11	
1986	45.43	43.87	46.26	47.93	48.31	49.67	50.54	51.55	52.22	55.69	56.59	58.95	63.26	61.99	64.02	65.50	66.94	71.13	70.87	73.50	73.52	
1987	45.20	43.83	46.03	48.38	48.65	49.69	50.84	51.55	52.31	55.83	56.55	58.75	63.40	62.34	63.88	65.46	66.92	71.07	70.91	73.37	73.95	
1988	45.44	44.10	46.41	47.96	48.31	49.75	51.29	51.60	52.54	56.11	56.67	58.89	63.17	62.47	63.32	64.88	67.08	70.88	71.15	73.24	73.98	
1989	45.44	44.37	46.49	47.97	48.31	50.01	51.66	51.73	53.14	56.28	56.90	59.04	62.80	62.55	62.81	64.35	67.36	70.66	71.27	73.05	74.11	
1990	45.44	44.65	46.54	48.03	48.31	50.54	51.96	51.88	53.83	56.43	57.38	59.28	62.03	62.57	62.37	63.90	67.90	70.45	71.39	72.73	74.18	
1991	45.43	44.84	46.57	48.26	48.31	50.87	52.14	52.02	54.14	56.53	57.94	59.55	61.07	62.56	62.11	63.63	68.56	70.30	71.50	72.33	74.20	
1992	44.00	44.92	46.48	48.62	48.79	50.95	52.23	52.13	54.16	56.56	58.22	59.71	60.47	62.54	61.96	63.47	68.93	70.22	71.56	72.01	74.05	
1993	45.43	45.00	46.58	49.07	48.31	50.99	52.28	52.24	54.25	56.63	58.50	59.89	59.94	62.44	61.91	63.42	69.36	70.15	71.67	71.68	74.22	
1994	45.43	45.03	46.59	49.31	48.31	51.00	52.31	52.31	54.26	56.65	58.58	59.94	59.72	62.38	61.88	63.39	69.52	70.15	71.73	71.49	74.22	
1995	45.43	45.04	46.59	49.44	48.31	51.01	52.33	52.38	54.26	56.67	58.62	59.93	59.60	62.33	61.86	63.37	69.61	70.14	71.77	71.37	74.22	
1996	46.49	44.95	45.50	49.60	47.76	51.00	50.35	51.84	52.46	56.66	58.64	60.68	59.23	62.55	64.42	69.66	70.00	71.75	71.26	74.08	75.30	
1997																						

Table: 4.12

In the table the aggradations and degradations, in single successive reaches have been presented. The table presents the variations corresponding to the ANN

predicted average bed levels both in the spatial and temporal sections of the study
THE VARIATION OF THE AVG, BED IN EACH REACHES(With ANN Predicted Data)

X-section	Change (km)	Variation (1957 to 1967)	Avg variation	Variation (1967 to 1977)	Avg variation	Variation (1977 to 1987)	Avg variation	Variation (1987 to 1997)	Avg variation	Variation (1997 to 2005)	Avg variation	Variation (1990 to 2005)	Avg variation	Observation remarks
2	17.34	-1.68		0.53		0.28	-0.64	0.11		0.97		1.14		
3	28.05	-0.08	-0.88	0.59	0.56	-1.56	-0.64	0.03	0.07	1.00	0.99	1.00	1.07	
4	38.25	-0.71	-0.40	0.63	0.61	0.33	-0.62	-0.31	-0.14	0.06	0.53	-0.20	0.40	
5	46.92	0.94	0.12	0.12	0.38	-0.69	-0.18	0.52	0.10	0.51	0.29	0.73	0.26	
6	56.61	-1.15	-0.10	-0.28	-0.08	-1.16	-0.92	0.42	0.47	-0.65	-0.07	-0.11	0.31	
7	66.30	0.79	-0.18	-0.02	-0.15	-2.83	-1.99	0.98	0.70	1.88	0.61	2.75	1.32	
8	73.44	0.79	0.79	-1.03	-0.52	-2.56	-2.69	2.29	1.63	-2.29	-0.21	0.00	1.37	
9	82.62	3.83	2.31	-2.65	-1.84	-0.78	-1.67	-1.56	0.36	2.18	-0.05	0.64	0.32	
10	92.82	-2.11	0.86	3.94	0.64	-2.13	-1.46	-0.26	-0.91	0.21	1.20	-0.02	0.31	
11	100.98	-0.38	-1.25	0.88	2.41	-0.48	-1.31	0.53	-0.39	-0.16	0.03	-0.59	-0.31	
12	109.65	0.75	0.18	-0.97	-0.04	-1.50	-0.99	0.33	-0.10	-0.03	-0.10	0.29	-0.15	
13	119.85	1.73	1.24	-0.40	-0.68	-1.07	-1.29	-0.87	-0.27	0.41	0.19	-0.31	-0.01	
14	128.01	-0.11	0.81	0.55	0.08	-1.69	-1.38	1.53	0.33	0.86	0.63	2.23	0.96	
15	137.70	1.62	0.76	-3.04	-1.25	-0.16	-0.92	1.65	1.59	-1.65	-0.40	0.00	1.11	
16	146.37	1.76	1.69	-0.18	-1.61	-1.09	-0.62	0.85	1.25	-0.44	-1.05	0.35	0.17	
17	156.06	1.74	1.75	-0.08	-0.13	-2.24	-1.66	0.85	0.85	-0.85	-0.64	0.00	0.17	
18	167.28	0.10	0.92	-0.30	-0.19	-1.65	-1.95	0.54	0.69	-0.54	-0.69	0.00	0.00	
19	175.95	1.40	0.75	3.46	1.58	-0.05	-0.85	0.23	0.38	-0.52	-0.53	-0.24	-0.12	
20	182.50	-0.65	0.37	-0.55	1.46	-1.06	-0.56	1.18	0.70	1.89	0.68	2.83	1.30	
21	189.21	-0.04	-0.34	0.19	-0.18	-2.08	-1.57	0.94	1.06	-1.62	0.13	-0.44	1.20	
22	197.37	-6.44	-3.24	5.67	2.93	-0.96	-1.52	2.91	1.93	-1.29	-1.46	1.49	0.52	
23	206.55	1.00	-2.72	-4.20	0.74	4.50	1.77	1.06	1.98	-1.06	-1.17	0.00	0.74	
24	213.18	-1.99	-0.49	0.72	-1.74	0.10	2.30	1.08	1.07	0.10	-0.48	0.95	0.47	
25	218.79	-0.23	-1.11	1.04	0.88	0.80	0.45	-0.76	0.16	1.09	0.60	0.18	0.56	
26	224.91	-1.06	-0.65	1.91	1.48	-2.21	-0.71	1.65	0.45	-0.12	0.48	1.52	0.85	
27	234.60	0.90	-0.08	-1.78	0.07	-0.10	-1.16	-0.54	0.55	0.54	0.21	0.00	0.76	
28	241.23	-0.09	0.41	0.70	-0.54	-1.21	-0.65	1.33	0.39	0.01	0.28	1.26	0.63	
29	251.95	-0.35	-0.22	1.71	1.21	1.44	0.12	-0.19	0.57	2.02	1.02	1.08	1.17	
30	262.15	-0.79	-0.57	-4.67	-1.48	1.92	1.68	0.29	0.05	0.85	1.44	1.08	1.08	
31	272.35	-1.77	-1.28	1.46	-1.61	-1.37	0.27	0.24	0.26	1.81	1.33	1.73	1.40	
32	284.08	-0.55	-1.16	0.28	0.87	0.09	-0.64	0.98	0.61	0.04	0.93	0.60	1.16	
33	296.83	-0.01	-0.28	0.52	0.40	-1.96	-0.94	2.06	1.52	0.06	0.05	2.03	1.32	
34	310.10	0.00	-0.01	-3.65	-1.56	0.60	-0.68	1.73	1.89	-1.24	-0.59	0.56	1.29	
35	325.90	-0.09	-0.05	-0.11	-1.88	2.55	1.57	-4.03	-1.15	0.18	-0.53	-3.76	-1.60	
36	341.21	0.23	0.07	-3.78	-1.94	1.87	2.21	0.36	-1.84	-0.09	0.05	-0.21	-1.98	
37	352.94	-0.45	-0.11	-1.69	-2.74	0.01	0.94	0.40	0.38	-2.56	-1.33	-1.47	-0.84	
38	365.18	-3.11	-1.78	3.56	0.93	-2.58	-1.29	4.16	2.28	-6.31	-4.44	-1.53	-1.50	
39	371.81	-0.27	-1.69	-0.26	1.65	-2.38	-2.48	3.06	3.61	-0.18	-3.24	2.75	0.61	
40	383.03	2.25	0.99	-0.41	-0.33	-0.72	-1.55	0.61	1.83	-1.60	-0.89	-0.74	1.00	
41	389.66	-0.63	0.81	-1.84	-1.12	1.29	0.29	0.40	0.50	0.65	-0.48	0.76	0.01	
42	398.33	-3.95	-2.29	-0.86	-1.35	4.72	3.00	0.79	0.59	-3.59	-1.47	-2.74	-0.99	
43	412.09	-1.60	-2.77	1.15	0.15	1.66	3.19	1.78	1.28	-1.08	-2.33	0.25	-1.25	
44	423.31	0.00	-0.80	0.11	0.63	3.22	2.44	1.58	1.68	-2.27	-1.67	-0.67	-0.21	
45	439.63	3.81	1.91	-0.38	-0.13	0.15	1.68	-0.25	0.66	0.04	-1.11	-0.14	-0.41	
46	453.91	2.06	2.94	-0.75	-0.56	-2.19	-1.02	0.23	-0.01	-0.61	-0.28	-0.19	-0.17	
47	465.13	0.07	1.07	0.28	-0.23	0.79	-0.70	0.20	0.21	-0.03	-0.32	0.12	-0.03	
48	474.82	-2.31	-1.12	-0.03	0.13	2.05	1.42	-1.02	-0.41	-0.42	-0.23	-1.37	-0.62	
49	483.49	0.97	-0.67	-0.73	-0.38	1.31	1.68	-1.02	-1.02	-0.29	-0.36	-1.26	-1.32	
50	490.63	0.91	0.94	0.53	-0.10	-1.85	-0.27	1.62	0.30	0.21	-0.04	1.75	0.25	
51	498.80	0.76	0.83	-0.35	0.09	0.09	-0.88	0.43	1.03	-0.01	0.10	0.27	1.01	
52	505.94	-0.85	-0.04	1.32	0.49	-0.25	-0.08	1.19	0.81	0.05	0.02	0.83	0.55	
53	513.08	-0.56	-0.70	0.20	0.76	3.01	1.38	-0.58	0.31	0.93	0.49	0.04	0.44	
54	522.77	0.20	-0.18	0.35	0.28	1.25	2.13	1.10	0.26	0.41	0.67	0.72	0.38	
55	531.95	-1.94	-0.87	0.05	0.20	1.82	1.54	0.61	0.85	0.20	0.30	0.43	0.58	
56	541.13	0.23	-0.85	-2.89	-1.42	6.36	4.09	-6.75	-3.07	-0.34	-0.07	-6.73	-3.15	
57	558.98	-0.56	-0.17	0.18	-1.35	3.53	4.94	-0.51	-3.63	0.51	0.08	0.00	-3.37	
58	570.20	1.27	0.35	-0.59	-0.20	2.99	3.26	-3.72	-2.12	0.91	0.71	-2.69	-1.35	
59	579.38	-0.25	0.51	0.26	-0.16	2.36	2.67	-1.70	-2.71	1.87	1.39	0.02	-1.34	
60	589.07	-1.34	-0.79	0.00	0.13	0.42	1.39	0.44	-0.63	0.32	1.09	0.38	0.20	
61	601.82	0.12	-0.61	2.28	1.14	-0.86	-0.22	-0.15	0.15	-0.04	0.14	-0.23	0.08	
62	613.04	2.38	1.25	1.43	1.86	-2.20	-1.53	2.99	1.42	0.21	0.08	2.61	1.19	
63	626.30	2.24	2.31	0.27	0.85	-3.81	-3.00	1.53	2.26	1.51	0.86	2.98	2.79	
64	634.46	2.41	2.32	-0.36	-0.04	-3.93	-3.87	1.74	1.63	1.17	1.34	2.79	2.88	
65	640.07	1.75	2.08	1.66	0.65	0.00	-1.96	0.07	0.90	0.07	0.62	0.12	1.46	

The reaches between the successive cross sections had both aggradation & degradation in the former periods. Later, from 1987 onward the trend of variation turned to more aggradation side. In the time span from 1990 to 2005 the ANN predicted data of Average Bed Levels have displayed very good compliance with the Observed aggradation of the river, Brahmaputra.

The arithmetical calculations over the data ANN predicted average bed level data coupled with the observed data has determined aggradations and degradations scenario as given in the table no 4.17(a) &(b)

Table 4.13(a)

Period (5 years)	No. of Cross section in Aggradations No.	Average Aggradation rate in the Total Study Period (cm)	Average Aggradation rates in the period (cm)	Maximum Aggradation rates observed in the period (cm)
57-67	28	11.12	11.92	37.1
67-77	31	11.12	9.94	35.92
77-87	24	11.12	18.56	44.59
87-97	48	11.12	10.27	54.42
97-2005	34	11.12	6.34	16.42
90-2005	42	11.12	9.67	35.33

Table 4.13(b)

Period (5 years)	No. of Cross section in Degradations No.	Average Degradation rate in the Total Study Period (cm)	Average Degradation rates in the period (cm)	Maximum Degradation rates observed in the period (cm)
57-67	35	10.0	-9.0	-40.0
67-77	32	10.0	-9.0	-26.0
77-87	39	10.0	-14.0	-47.0
87-97	15	10.0	-11.0	-33
97-2005	29	10.0	-9.0	-49.0
90-2005	21	10.0	-9.0	-34.0

The aggradation is more pronounced in the lower reach and the upper most reach while the degradation is the most general phenomena in the middle reach. The reason could be the confluences of more northern tributaries in to the main stream which bring higher discharges with high sediment concentration. The analysis has also shown clearly that the slopes in the middle reach has increasing trend as oppose to declining trends of upper reach and lower reach.

Thus, the results of the analysis for the quantification of aggradation /degradation and the slopes have been in close agreement with the physically based conceptual models.

TRENDS OF DIFFERENT ASPECTS OF AGGRADATIONS
 Agg Rates cm/km

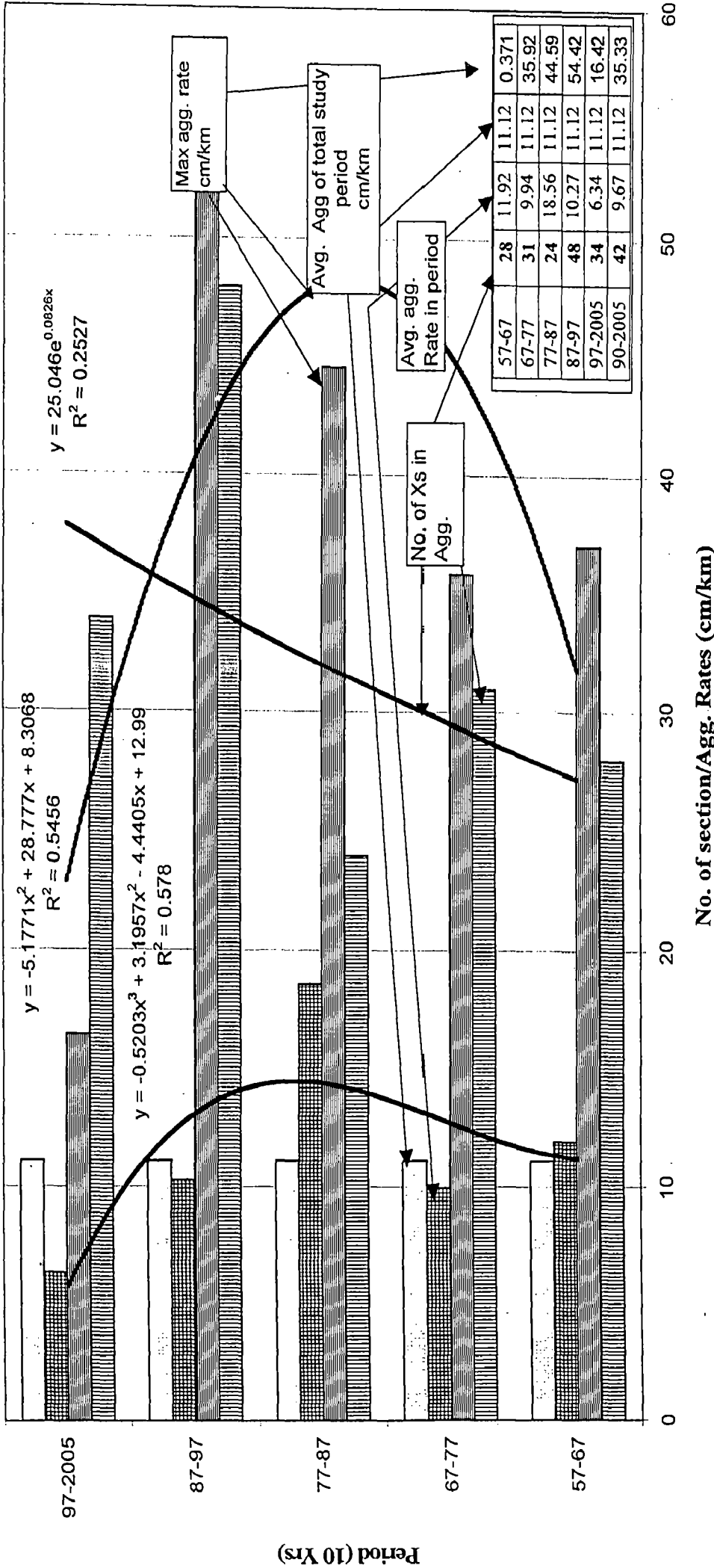


Figure:4.12

Analytical Trend Profiles of the max. aggradations/ no. of Sections./ avg, bed aggradation

Observation: Curve-1:-The number of cross sections in aggradations has increasing trend

Curve-2: The maximum aggradations rate has oscillatory trend, now, in declining phase.

Curve:3- The average bed level variation rate in each period has also an oscillatory trend, now, in declining phase.

4.9 LONGITUDINAL SLOPES AND THE CONCAVITY

Besides, the assessment of the aggradations and degradations, longitudinal slopes and further the concavity of the study reach in total have also been the other morphological parameters taken under the objective of the study. The longitudinal profiles drawn with the average bed levels corresponding to their predicted values within the bound of the temporal time segments have provided ample idea on the slopes in segments as well as in total length which has been found to be under going adjustment.

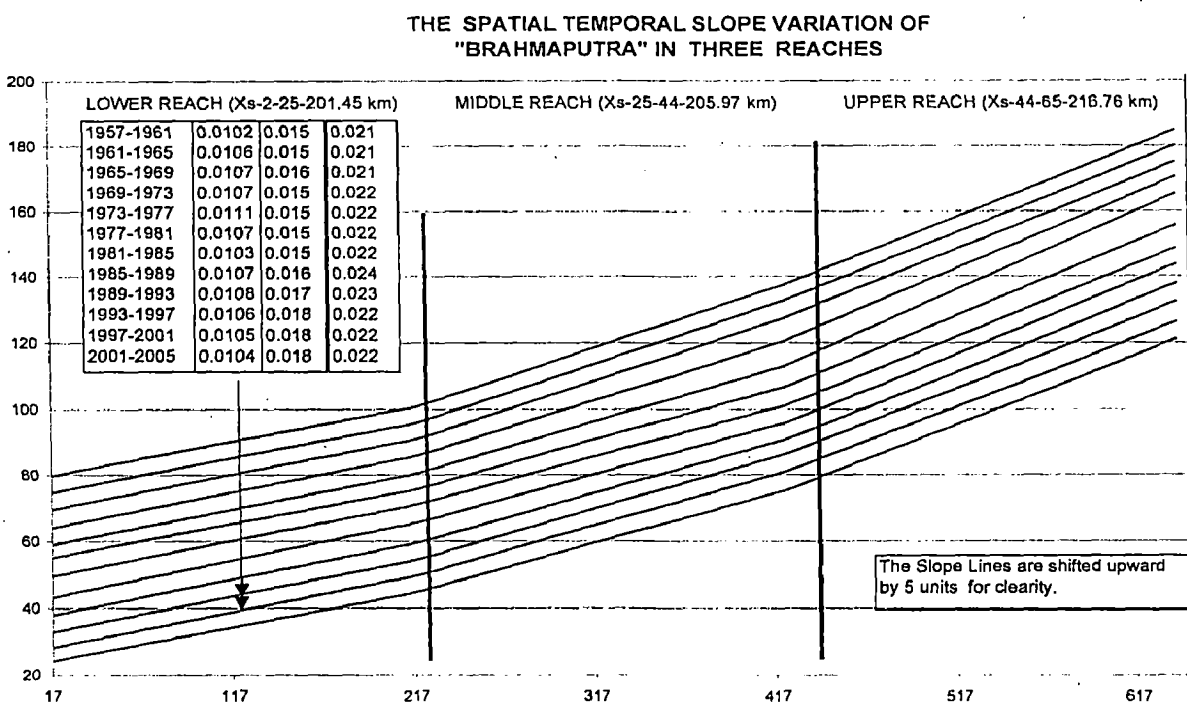


Figure:4.13
The Longitudinal Slopes in Spatial –Temporal Variation

The figure: 4.13 the slopes have been determined for three segments and 12 no. of time segments. Also visually, the slopes could be observed having different values. The steepness is higher in the upper reach but has tendency to become flatter as shown in the figure :4.14. The middle reach has the slope in increasing trend. This explains the influence of the tributaries joining the main stream with high sediment discharges in the middle reach.

Table:4.14

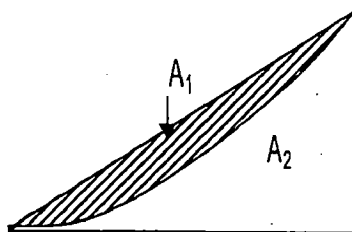
Slopes of the three reaches

Period	L-Reach	M-Reach	U-Reach
1957-1961	0.0102	0.015	0.021
1961-1965	0.0106	0.015	0.021
1965-1969	0.0107	0.016	0.021
1969-1973	0.0107	0.015	0.022
1973-1977	0.0111	0.015	0.022
1977-1981	0.0107	0.015	0.022
1981-1985	0.0103	0.015	0.022
1985-1989	0.0107	0.016	0.024
1989-1993	0.0108	0.017	0.023
1993-1997	0.0106	0.018	0.022
1997-2001	0.0105	0.018	0.022

The slopes in the total reach has also been presented in the figure: 4.14. These slope profiles are the fitted polynomials to the plotted data.

The profiles have been further analysed to determine the concavity index of the valley profiles. The concavity, too, has also been found to exhibit mild changes. In general, study of river morphology and the valley profile concavity spans over a period of thousands of years following the historical background of the changes. In the literatures, the concavity of the valley profiles are referred as the shape of the total river channel length from the point of origination to the point of its outfall in to the sea. The longitudinal profiles mostly have concave upward shape due to abrupt then gradual decrease in the slope. For the rivers, which have slope increasing in the downstream direction take convexity upward. The concavity values of the river, Brahmaputra, determined in the temporal scale of the study period has been presented in the table 4.20.

Table:4.15



Concavity Index = A_1/A_2
 A_1 = Shaded Area
 A_2 = Area of the Triangle

Period	Concavity Index	Percent Change
61-65	0.150	
65-69	0.149	0.88
69-73	0.152	2.19
73-77	0.155	2.24
77-81	0.155	0.45
81-85	0.149	4.00
85-89	0.141	4.76
89-93	0.143	0.75
93-97	0.146	2.31
97-2001	0.144	1.59
2001-2005	0.147	2.62

The concavity index of the river Ialomita(tributary of Danube) is reported to be 0.86.The Longitudinal profiles of the rivers all over the world are observed to be fitting to Exponential, Power and Logarithmic curves due to high concavity value for the total length of the rivers starting from their origination at higher mountainous altitudes. However, if the total longitudinal profile is observed in segmented stretches the nature of the curve varies. The present study length of the river Brahmaputra constitutes the lower flood plain region of the river valley profile, the best fit curve has been found to be a second degree polynomial with the R^2 value over 0.99 and 0.98 for exponential curve fit.

POLYNOMIAL GENERATED AVG. BED PROFILES ADJUSTMENT IN TEMPORAL SCALE

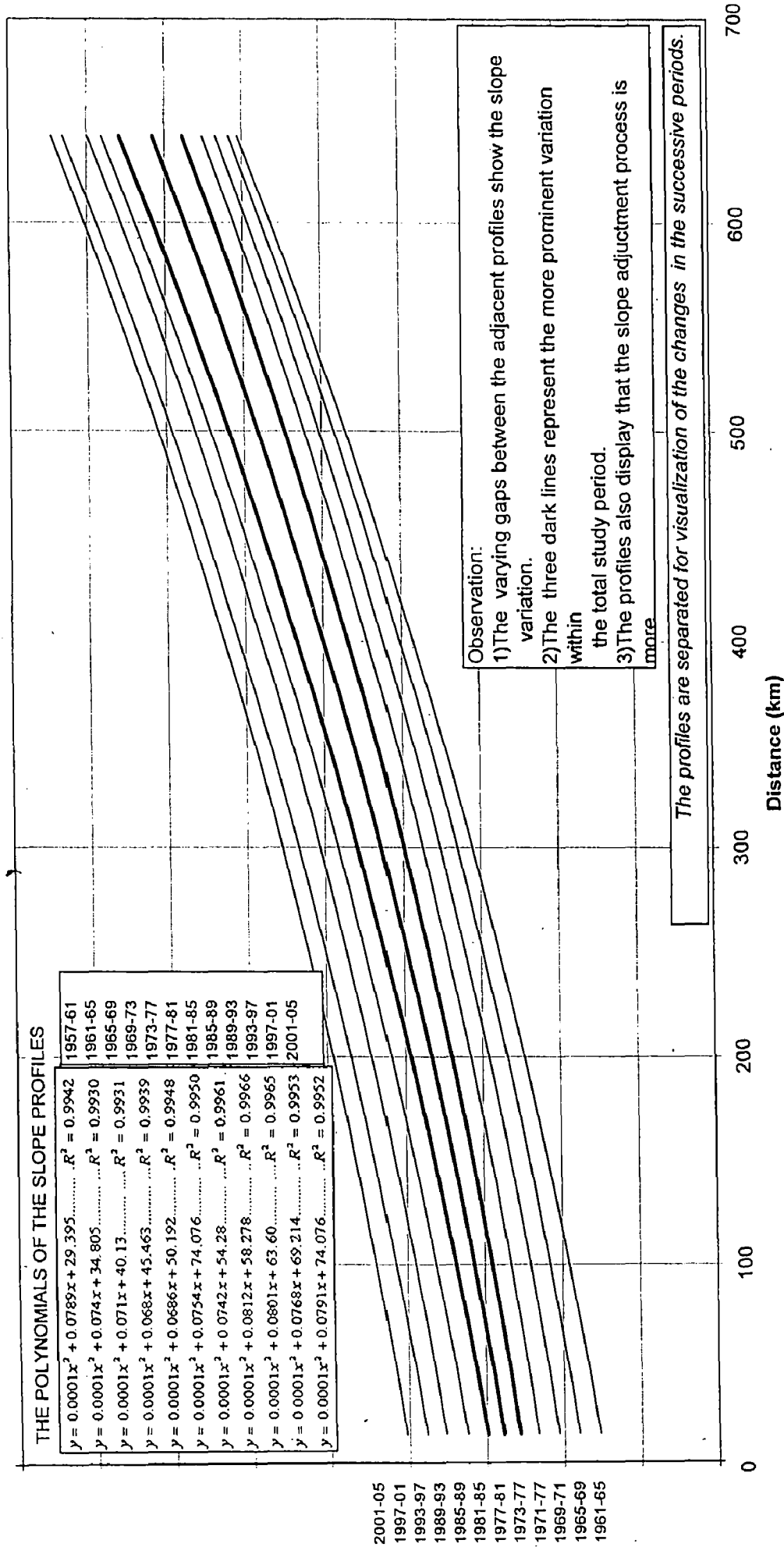
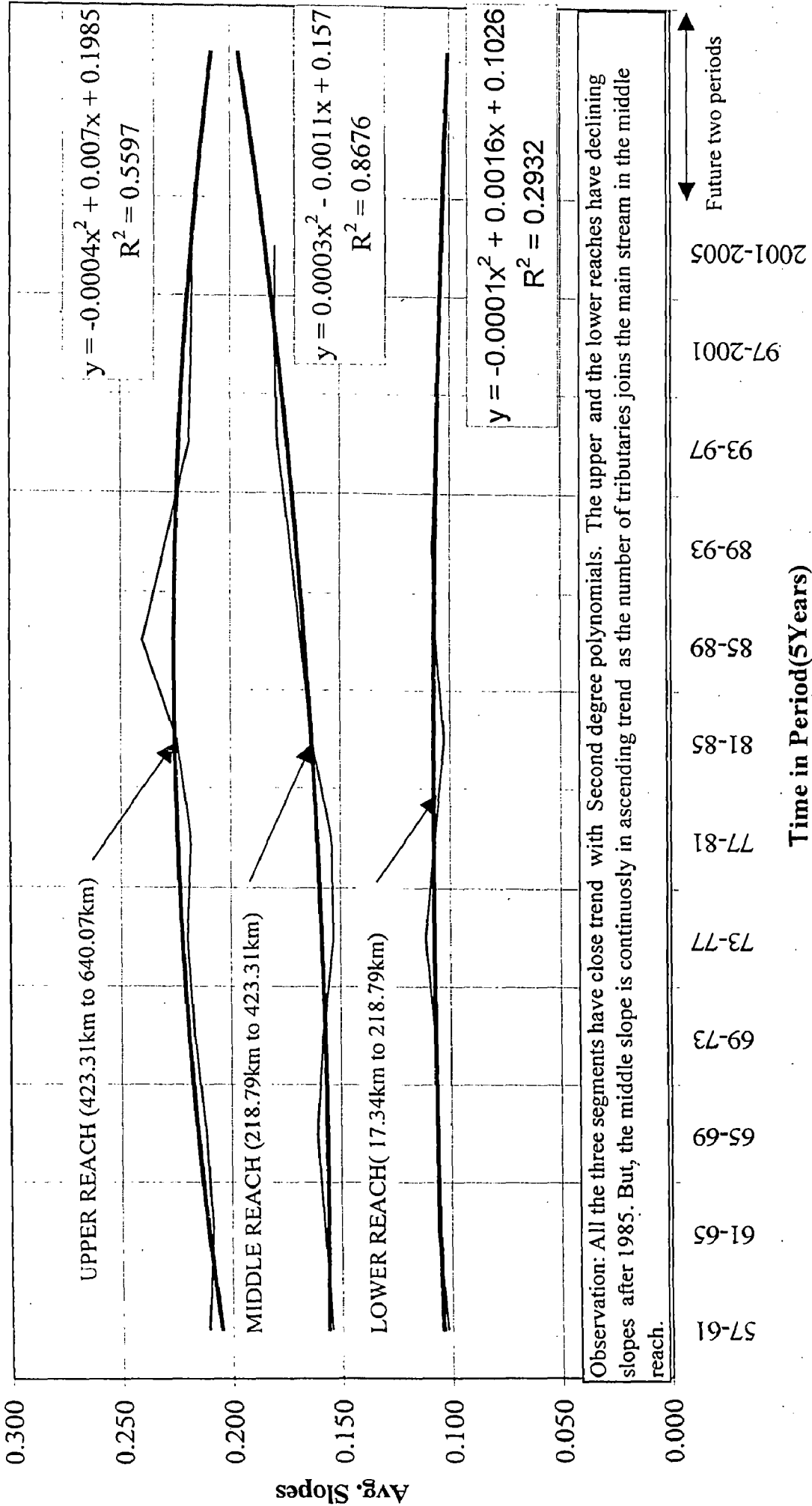


Figure:4.14
Polynomial generated Slope profiles of the river Brahmaputra

SLOPE ADJUSTMENT OF SEGMENTED REACHES OF RIVER
BRAHMAPUTRA WITH TIME



Observation: All the three segments have close trend with Second degree polynomials. The upper and the lower reaches have declining slopes after 1985. But, the middle slope is continuously in ascending trend as the number of tributaries joins the main stream in the middle reach.

Time in Period(5Y years)

Figure:4.15

RELATIVE VARIATION(%) OF CONCAVITY INDEX OF THE RIVER " Brahmputra "

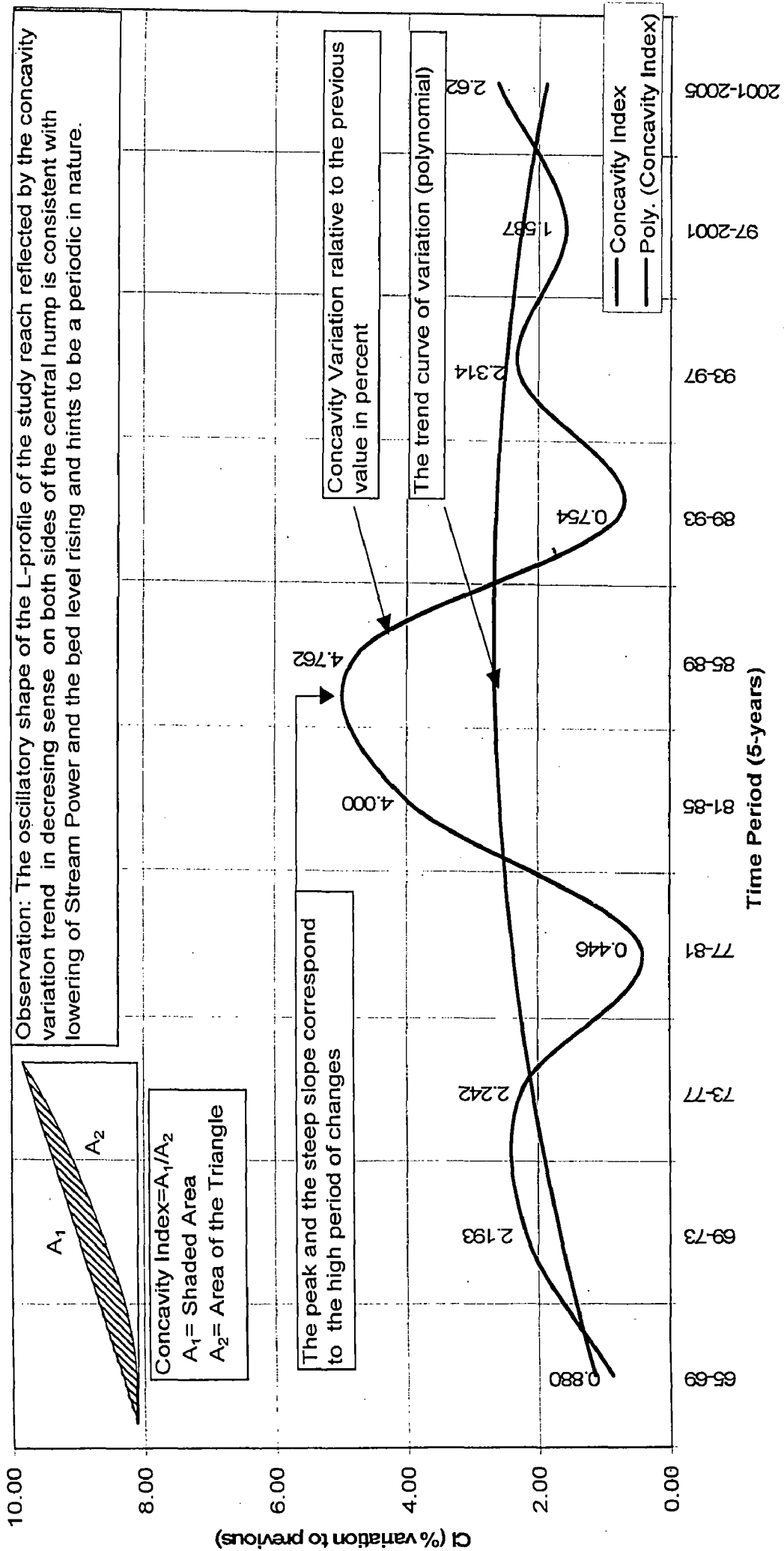


Figure:4.16
Relative variation of Concavity Index in Percentage(%)

4.10. THE STREAM POWER AND CORRELATION TO THE SLOPE VARIATIONS

The flow hydraulic parameters of an open channel flow such as hydraulic mean depth, wetted perimeter, flow area, slopes and the hydrological parameter discharge and the physical properties, $\gamma (= \rho g)$ of the fluid (water) are related to express the stream power of the flow at a point along the direction of flow(1).

$$\text{Stream Power is given as } \Omega = \gamma QS \quad 4.7$$

The stream power of a flow quantifies the kinetic energy of the flow encapsulated in the mass of the fluid. The stream power concept has been applied in the prediction of sediment transportation capacity of the flow. The discharge and the slopes in the expression 4.7 directly proportional to the Stream Power and γ is nearly constant.

The magnitude of stream power is one of the deterministic parameters of erosion of the bed and banks of a stream. The stream power is the function of location of the section in the river reach and slope has very significant contribution in the stream power, it has been found relevant to correlate the temporal changes in the slopes of the river Brahmaputra in different reaches of the study stretch and the stream power to explain the aggradation process of the lower reach.

In the figure 4.16, the dominant discharge profile is increasing in the downstream direction due to more and more augmentation of flow by tributaries, however, the stream power is decreasing because of the flatter slopes in the downstream. Therefore, discharge can not singly enhance the stream power. In the mountainous reaches, the discharge is low, still the stream power is higher due to steep slopes.

The observed aggradation of the lower reach, the decreasing slope trend is justified further by the falling of the stream power profile which is more prominently observed during the later periods of the time segments from 1985 to 2005.

STREAM POWER WEAKING IN THE DOWNSTREAM DUE TO FLATTENING OF L-SLOPE

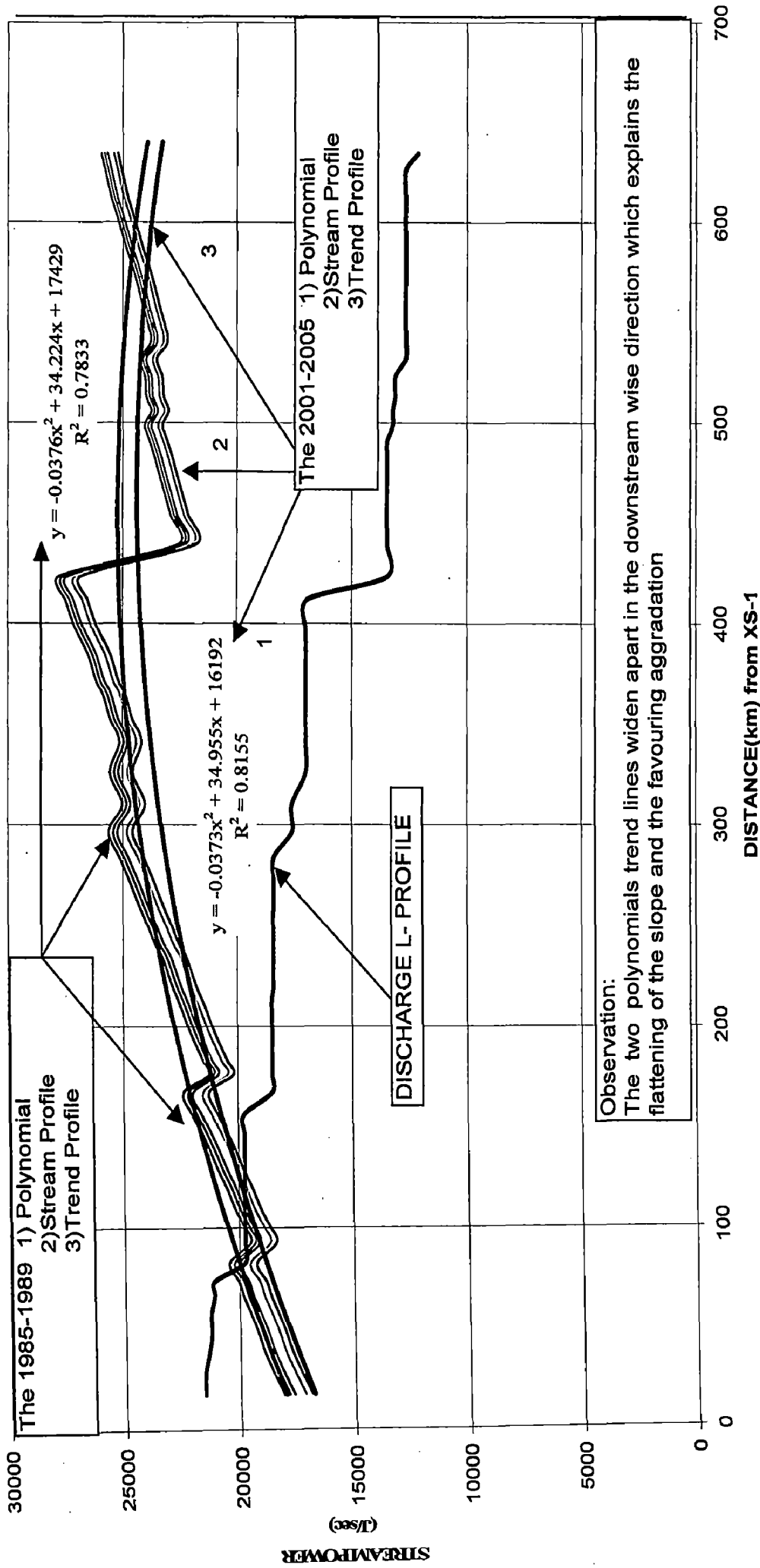


Figure:4.17

Stream Power Profiles from 1985 to 2005 and the falling trend

4.10 CONCLUDING REMARKS

The application of the Artificial Neural Network in the prediction of the geomorphological dimensions with the limited observed data have been realised competently useful in further analysis to describe existing and the near future probable trend of the morphological features under the interest.

5

CHAPTER

WIDTHS AND THALWEGS

5.1 INTRODUCTION

River active channel width and flood coverage within and beyond the permanent banks holds important consideration in the river management work. In the study of river morphology, river width has important contribution in predicting the Braided Index(BI) (Brice;1960,19664), Plan Form Index(PFI) & Flow Geometric Index(FGI) (Sharma,1995), Bed Relief Index(BRI)(Smith; 1970).

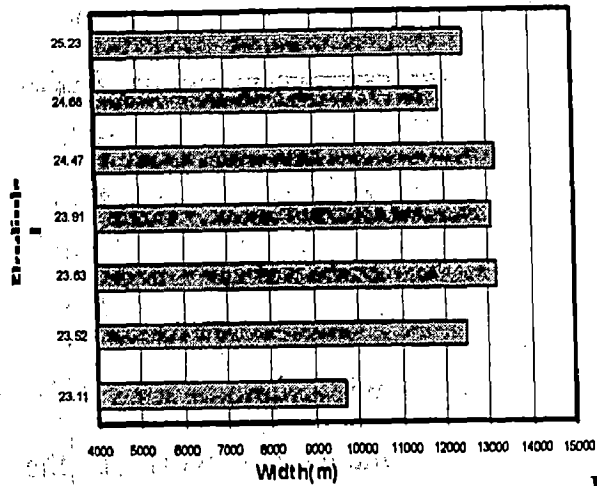
The same morphometric data base availed for the previous model development have been assessed for width variation through the period 1957 to 1997. The general consciousness of the dwellers of the Assam valley is that the river bed is rising because of drainage congestion due to fast urbanization of the valley surrounding the out fall point. The effect of bed level rising would be in turn widening of top width during the flood incidences. However, the widths variation does not comply with the trend of bed level variation and for some of the cross sections the trend is even opposite.

5.2 RIVER CHANNEL WIDTHS OF THE RIVER BRAHMAPUTRA

5.2.1 Width Profiles and the Average bed Levels

The Figure:5.1 below show the typical situation of the river width variation of the river, Brahmaputra,

**X-section -2
Width Variations(m)**



**X-section -3
Width Variations(m)**

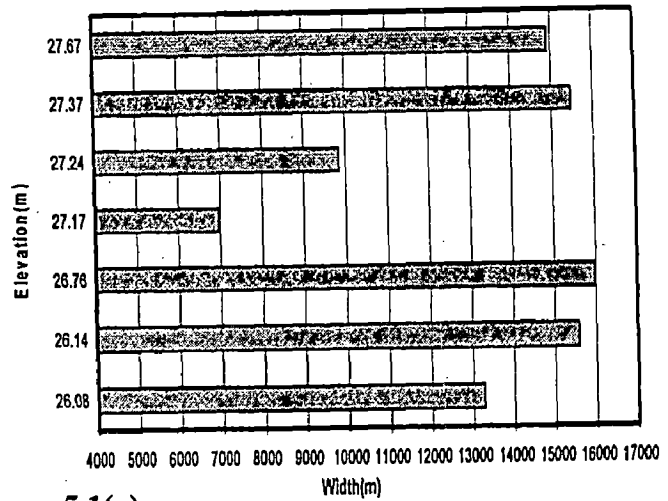
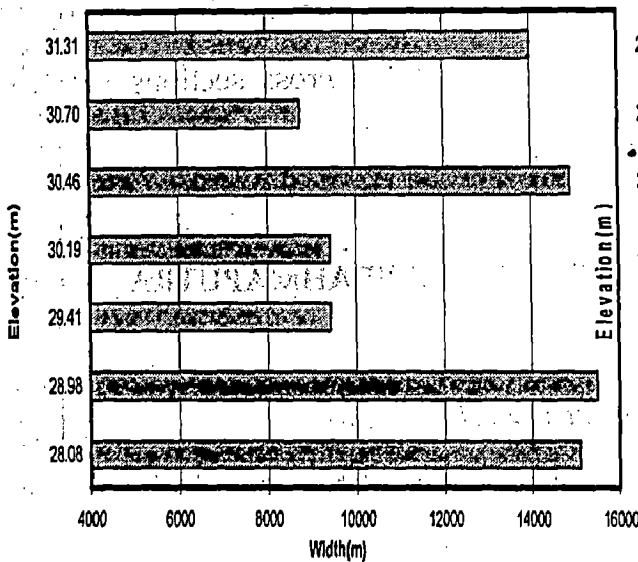


Figure:5.1(a)

River Widths vs the Avg. bed variation

The Figure:5.1, the cross section-2 has width increasing with the rise in the Average bed levels but in the later period the width tended to shrink but in the cross section -3 the variations of the width is not compatible with bed level rising. Under the free natural condition and for a constant discharge the width is anticipated to be expanded for rise in bed level. But the flood embankment would have restricted it in the present case..

**X-section -8
Width Variations(m)**



**X-section -9
Width Variations(m)**

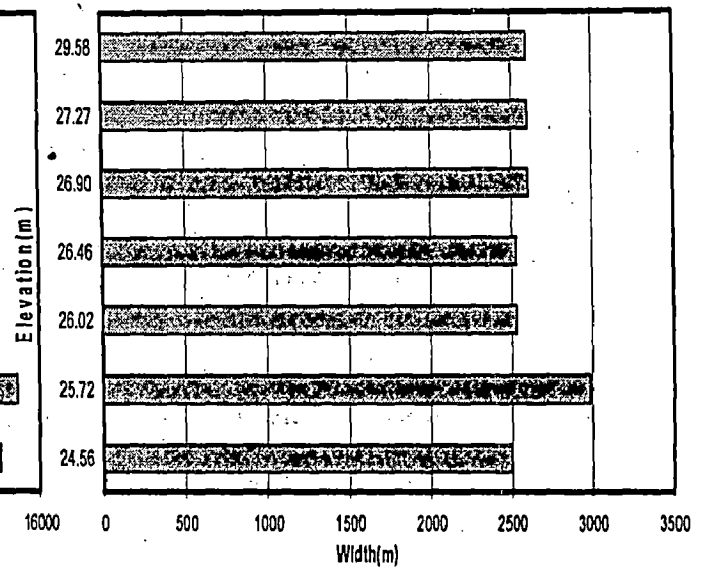


Figure:5.1(b)

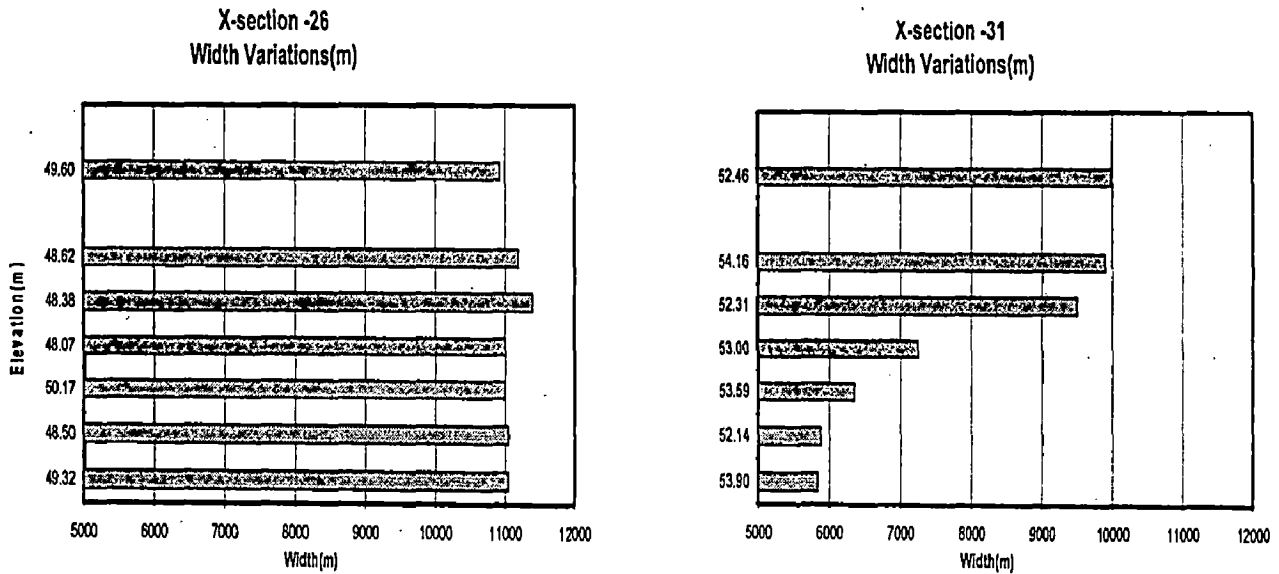


Figure5.1(c)

In the figure 5.2(b), the cross-8 exhibits very drastic variation with no compatibility with the river bed rising. This suggest the existence of the different conditions in that mean period. The cross section-9 shows a nearly equal widths above 25.72m of the average bed level which could be concluded as the impact of the embankment.

Like the previous situation in the cross section-9, cross section-26 has fairly constant width while the cross section, 31, shows a natural condition of width expansion with the bed level rise.

5.2.2 Correlation Of Width And Average Bed Levels.

The present study also encompasses the width variation and the average bed levels variation to search a possible conclusion. The hydrodynamics of river fluvial process put emphasis on both width and the longitudinal slope. The discharge intensities and the sediment concentration distribution across a channel width varies significantly. In steep gradient channels, widths tends to be widen in downstream reaches due to drop in the slopes. If width is restricted for safety against flood hazards in flood plains the slope tends to adjust to pass the discharge and the sediments. In bends, the velocity of flow is higher on the concave outer bend than the convex inner

bend impelling to evolve secondary flow in bends and consequently sediments are deposited on the lower velocity zone and erosion progress on the high velocity zone. In the section 5.1, the example of the river width and river bed variations could be explained based on their correlation with the local conditions such as of flood mitigation measure works and other natural and artificial controls. A study may be envisaged for study to explore the impact of river control measures on the river morphology implemented in the area.

The available data base for the present study have been used to quantify the statistical correlation between widths and corresponding the average bed levels of each cross sections. The variation of the width along streamwise direction is plotted parallel to the average bed variation in the Figure 5.2. The close study of the profiles has shown that the total width variation from 1957 to 1997 in majority of the reaches is positive i.e expansion. The reasons could be of following origin:

- The magnitude of the flood discharges is in ascending trend, or
- The river channels flow areas at different sections are shrinking due to shallowing of the channels and the same time bank erosion is extensive.

Both the reasons bear significant validity. As the travel time of flood discharge is shortening due to decrease in vegetative cover over the drainage basin which in effect is increasing instantaneous flood peaks. Next, the shallowing of the channels and more braiding in the due course of time has decreased the fluvial capacity in terms of discharge passing because of increase in resistance by braiding.

COMPARISON OF AVG. BED & WIDTH VARIATION(1957 TO 1997)

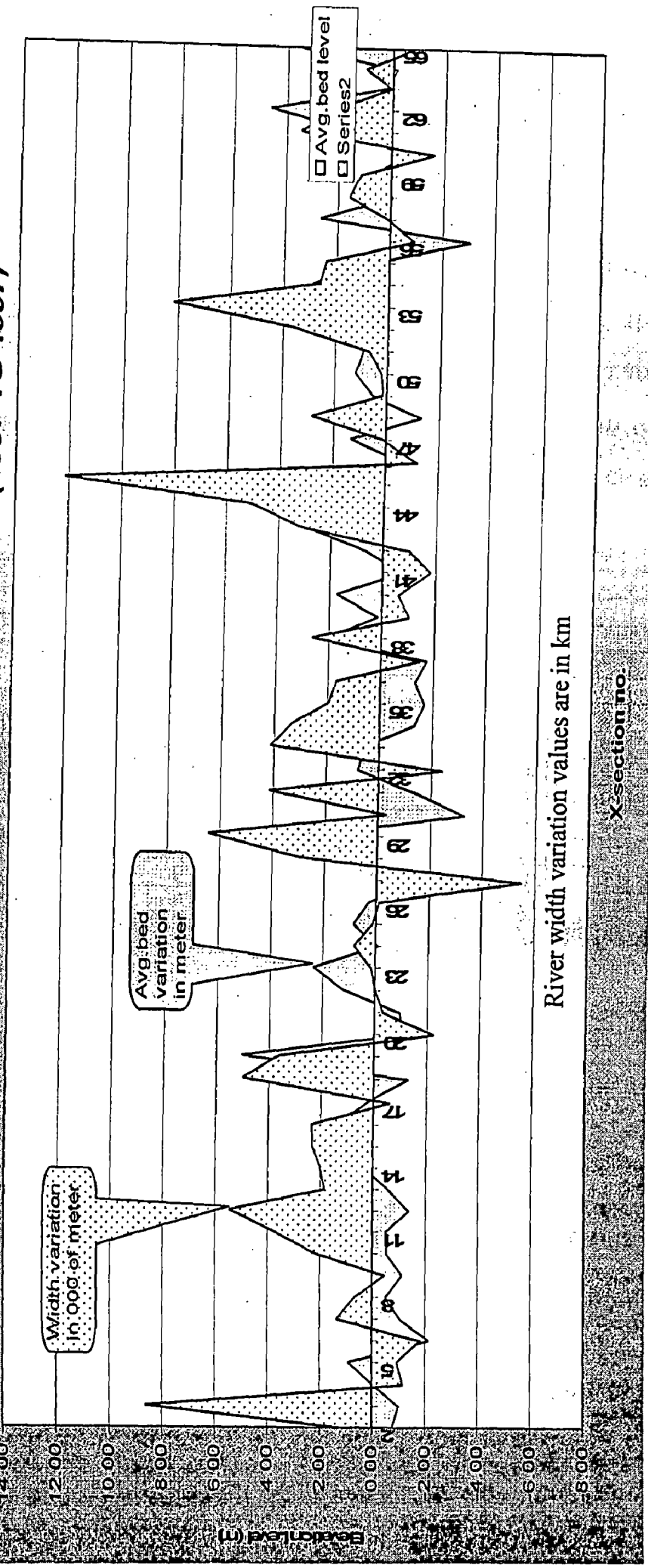


Figure 5.2
Width and Avg. bed levels variation plot

Observation: The profiles of the total widths variation and the average bed profile hold important visual scenario in the study area pertinent to the increasing severity of floods.

The figure 5.2 is a profile plot of river width variation from 1957 to 1997 against average bed levels variation for the same time period. As mentioned earlier, the width variation and average bed level variations are not always on the same sides as theoretically expected. From the plot above the reaches may be identified and the ambiguity may be unveiled.

The table 5.1 below presents the correlation values worked out

Table:5.1

Correlation R of river width and the average bed level (with 1997 data and without 1997 data) for different cross sections.

R>0.8		0.5<R<0.8		0.2<R<0.5		R>0.8		0.5<R<0.8		0.2<R<0.5	
4	0.83	19	0.66	2	0.40	4	0.84	2	0.80	6	0.46
21	0.89	25	0.72	16	0.35	19	0.87	31	0.57	14	0.23
22	0.91	27	0.53	20	0.38	21	0.95	52	0.75	22	0.37
29	0.91	43	0.64	24	0.38	25	0.97	53	0.55	28	0.24
37	0.85	46	0.60	28	0.22	29	0.97	54	0.57	39	0.26
44	0.89	47	0.78	35	0.22	37	0.90	60	0.55	42	0.26
		52	0.64	36	0.35	43	0.90	61	0.73	45	0.25
		53	0.54	39	0.34	44	0.95	62	0.72	47	0.39
		54	0.50	48	0.27	46	0.83			49	0.22
		59	0.61	49	0.33	59	0.93			50	0.20
		61	0.65	51	0.23					51	0.25
		62	0.53	58	0.23					55	0.38
										58	0.23

From the table above, it is obvious that the some of the cross sections have very good positive correlations above 0.8 and rest have medium to weak R value. The correlation computation has been done twice with 1997 data and without 1997 data.

Out of 64 cross sections being studied, nearly half of the cross sections have shown positive correlation with average bed levels which further improved when 1997 data is exempted.

5.3 THALWEGS AND AVERAGE BED LEVELS.

Thalweg is the deepest channel route within the bank of a natural river. It has been noticed that even in the straight channels the thalweg observed to be running

from one side of the bank to other side. Significance of thalweg is applied to measure the sinuosity of a meandering river(English).

$$\text{Sinuosity } P = \frac{\text{Thalweg Length}}{\text{Valley Length}} > 1.5 (\text{meandering}) \text{ and}$$

$$< 1.5 (\text{straight})$$

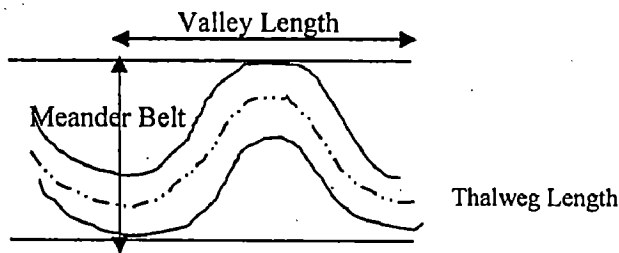


Figure:5.3

Sinusoidal river channel segment

In terms of Dominant Discharge Q and the Slope of the channel,

$$P = 0.93Q^{0.33}S^{0.048} \text{ Where } Q \text{ is given by } \frac{Q}{\sqrt{\frac{\Delta\gamma_s d^5}{\rho_f}}}$$

Of natural channels, if not restricted laterally, increase in the sinuosity reflects the base level lowering in down stream reaches and decrease (i.e becoming straight) due to base level rise.

5.3.1 Cross Section Profiles Variation And Thalweg Changes

The multiple channels with steeper slope existing upstream of meandering is one of the characteristics of a braided stream which are subjected to morphological changes in relatively short span of time because of high gradients and high sediment charged flood discharges. The Figure 5.4 saliently explains the extent of morphological dynamics of the river Brahmaputra. In the figure, changes in the cross section -2 (Dhubri) through 1951 to 1997 are depicted.

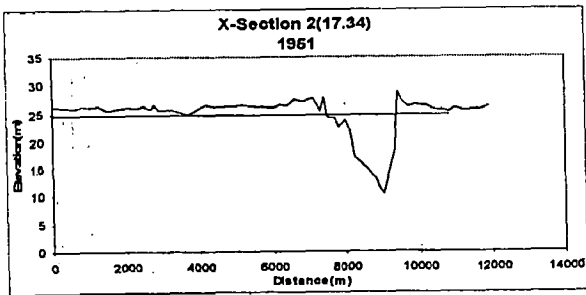


Figure:5.4 (a)1951

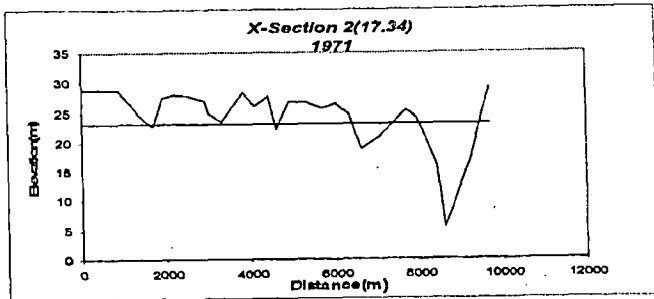


Figure:5.4 (b)1971

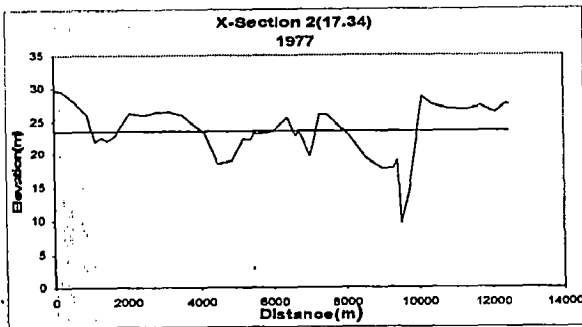


Figure:5.4 (c)1977

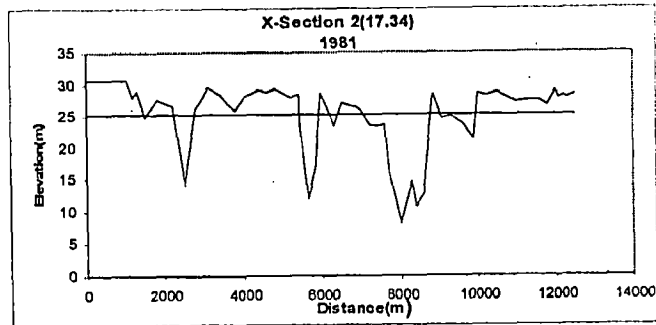


Figure:5.4 (d)1981

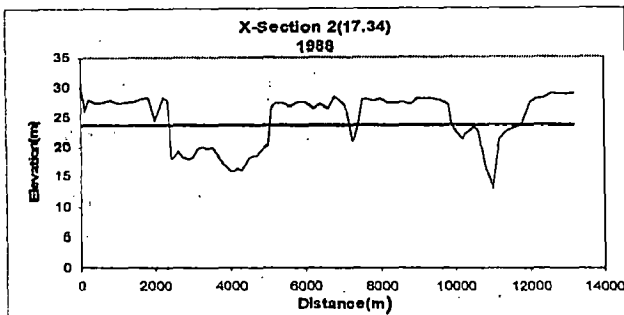


Figure:5.4 (e)1988

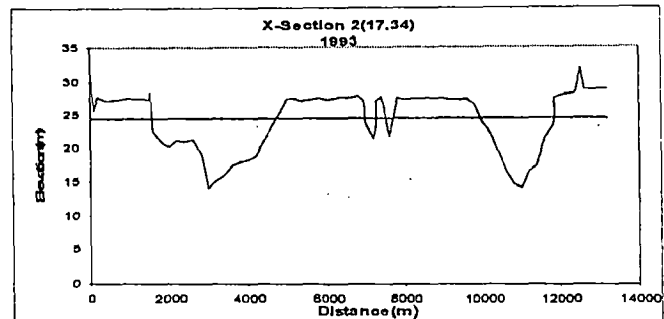


Figure:5.4 (f)1993

Observation: Changes in the cross section profile and location of the thalweg from 1951 to 1997.

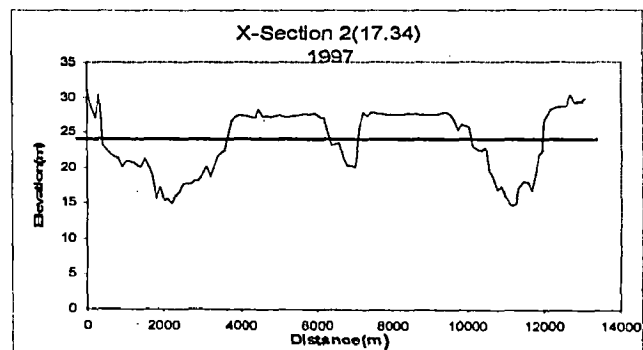


Figure:5.4 (g)1997

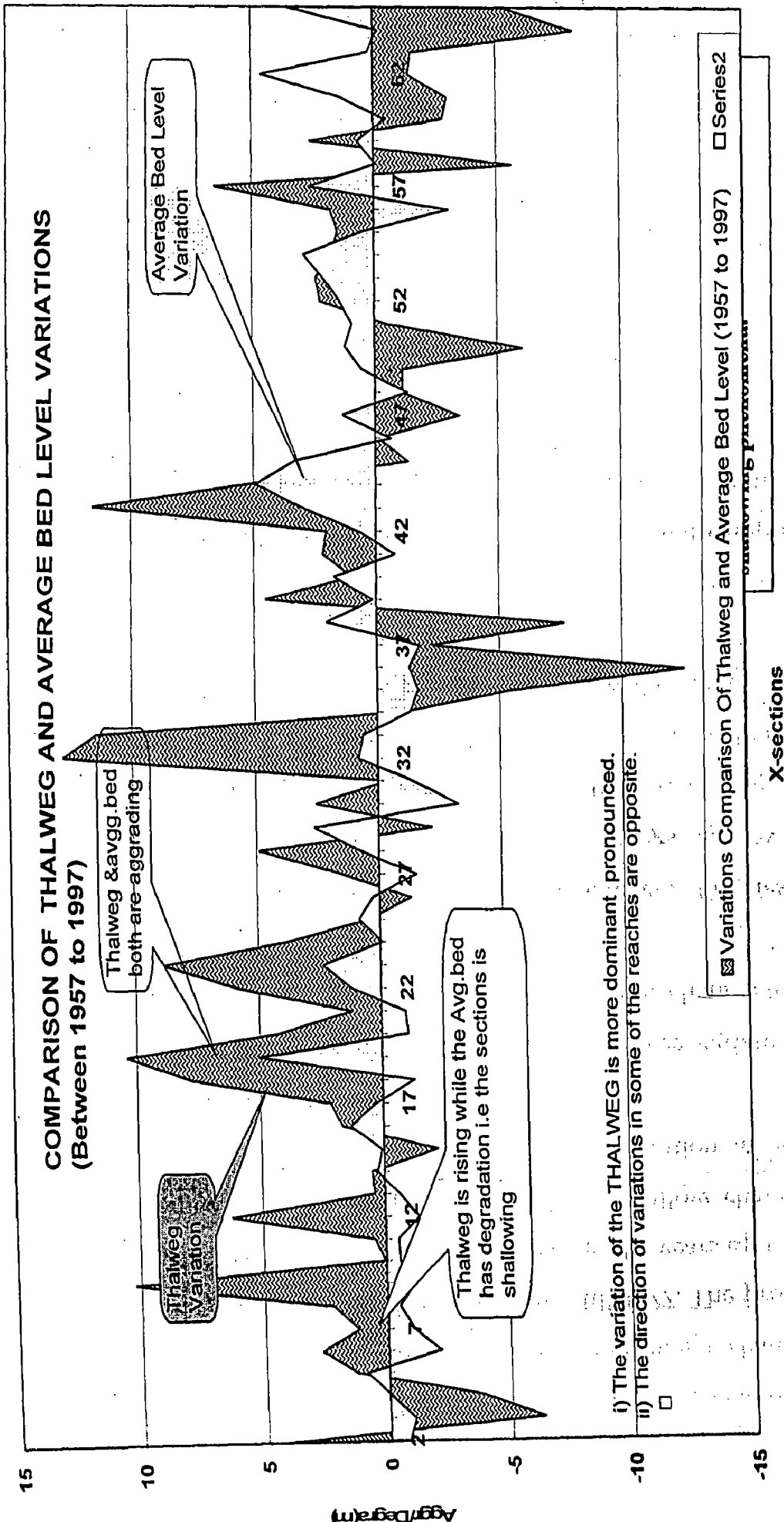
In 1951 the cross section had only one prominent channel which by 1971 developed to shallow multiple channels with same major channel. Late in 1977, shallow channels deepened and kept widening till 1977. The process of deepening and widening observed to be continued all through the years up to 1997(last survey year) accompanied with merging of the multiple shallow channels. The profiles clearly displays how the erosion and the bank migration as well as extensive widening of the river had been occurred.

As compared to the average bed level, the thalweg variation magnitude has been observed higher and changing of thalweg from one channel to another channel as seen in cross section-9(Pancharatna) as an example.

5.3.2 Thalweg L- Profile Variation And Average Bed level L-Profiles

Figure 5.5 presents idea of the variation of thalwegs and average bed levels. The profile is plotted for thalweg variation from 1957 to 1997 against the average bed level Variation for the same period. It has been observed that for most of the reaches the variation of the both parameters are on the same side while for few section they are opposite.

The higher rises of the thalweg than average bed signify the shallowing of the channel section and furthermore, for the reaches with opposite attitudes of thalweg and average bed levels variation attest the shallowing of the channels.



Observation: The mutual profiles of the thalweg and the average bed profile hold important significance in explaining the slacking of the channel competency in transporting the sediment, discharge and attest practically realized aggradation of the reaches due shallowing of the deep channels. Consequently, the vulnerability of area from flooding is scaling up.

Figure:5.5

5.3.3 Correlation Of Width And Average Bed Levels.

The correlation R i.e the trend of the variation of the widths of all the cross sections for the given periods and the corresponding average bed levels have been observed to be significantly high with almost all values close to unity. Then, it is obvious that for majority of the cross sections the variation trend from period to period is of same sign on aggradation with few exceptional cross sections. However, the correlation corresponding to extent of changes between the two is not strong as that with the bed level data it self

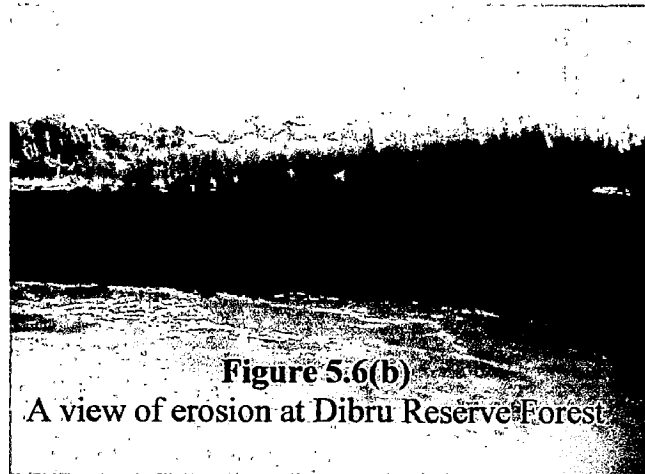
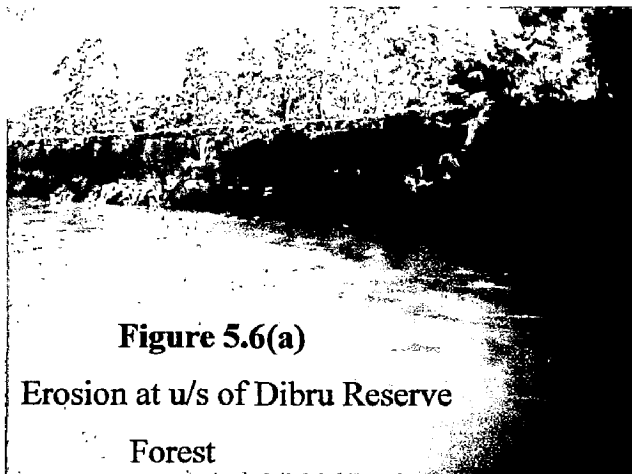
Table:5.2

THALWEG vs AVERAGE BED LEVELS		
	Corr. Of the data	Corr. of the changes
1957-1971	0.99	0.24
1972-1977	0.99	0.13
1978-1981	1.00	0.38
1982-1988	0.99	0.39
1989-1993	1.00	0.31
1994-1997	0.99	0.33

5.4 CONCLUDING REMARKS

The assessment of widths variation and thalwegs of all the cross sections of the study reaches has been found to be very reflective of the existing condition of the area. The bed level rising of the river Brahmaputra in the most of the reaches has turned out to be more in the deepest channel with this study. The rising of the average bed level of the whole flood coverage, however is 0.11m in 5 years with maximum value upto 0.54m per 5-years.

5.5 PHOTOGRAPHS OF BANK FAILURES AND EROSIONS



RESULTS AND DISCUSSIONS

6.1 NEUROMORPHIC MODELS**6.1.1 *Morphometric ANN Models***

Morphometric ANN models refer to the models structured with the hydrographic data i.e the cross section data of the river channels. The multiple models presented in the chapter-4 were aimed to gain the experience on performance of ANN models developed with different training data patterns and the Algorithms. The experience with ANN technique, which is an emerging tool of data driven procedure and has been a relatively new in the recent generation. The publications of the earlier works have appraised that ANN implementation on a problem is an iterative effort to reach to most convincing ANN architecture when validated.

- The experience with these models through 1 to 5 has been that the models for the present form of the study readily requires Sigmoidal and Tanhyperbolic transfer functions. Both have been competitively used. The number of output variables were (64 average bed levels) and the input parameter (year) was a single entity fed to the Neural Network and still the predictions have been evaluated to be competent in further extractions of the inferences out of the predicted data base. That has implied that, the prediction performance could further be enhanced with more data pattern than used in the present ANN models.
- An interesting part of the experience with ANN in the study has been that, the individual cross sections has been found specific to its location along the river reach

and best matched to to different type of NN architectures. Presented in the Table:4.10 a group of many cross sections out of 64no. showed good performance to one type of NN structure while other groups with other type irrespective of the sequence of the position of the cross section along the river reach. But surprisingly, the over all prediction of these multiple NN architectures did not surpassed that of the single NN architecture.

- When the data patterns fed to the designed NN architecture were reduced the efficiency of the models on validation of the prediction also reduced hinting the spontaneity of number of data pattern population require for better ANN model capacity. Astonishingly, some of the cross sections showed improvement in validation when one or two data patterns were drawnout.
- If the number of data patterns available for training phase is large, the training of the Networks elapses a long time depending on the learning and momentum rates chosen for the training. Very small value of RMSE, large Iteration number or high Nash Sutcliffe Coeff. assigning to the Network as stopping criteria increases the chances of over training of the network and as a result the generalization capability of the trained network falls. The experience gained with ANN here is that if the data has been a normalised pattern ranging from 0 to 1 then the assigning of RMSE value e.g 0.01 has to compared to original data value to it. If the data is a large numerical value, the normalised value of this might be very small in the range of the normalization. Therefore, it is suggestive that RMSE as stopping criteria should be used cautiously.

However, in the present study, assigning of Iteration number as the stopping criteria has been used.

- Every next trial with new stopping criteria value run with a new set of connections weights. Thus, it has been observed that it is a game of chance how one reach to a most closer to the optimum weights. Generally, the RMSE, and the Nash-Sutcliffe

Coefficient (DC) improved with increase in Iteration figure but after some value the improvement has been observed stagnated signalling the optimum learning.

- The training progress has to be necessarily monitored to spot if the learning has become unstable as shown by fluctuating RMSE and the DC values. Such situations have been rectified by adjustment of learning and momentum rates.
- Among the established algorithms in application of artificial Intelligence environment Multi Layered Feed Back Propagation(MLFBP) and Quick Propagation have been found to be adaptable to the type of the problem exposed to the Neural Networks designed in the present study.

6.1.2 *Hydro-morphological Models*

The models 6 to 17 were developed to search and assess the better combinations of Input(independent) parameters to yeild the outpur(dependent) parmeter which basically a trial error procedure. The models have been developed for three different sections to feed a varied patterns of the same type of input parameters(Flow discharge, Water levels and Sediment discharge). The developed and the presented models and the trials performed have extended the following clues to the present ANN application.

- The importance, among the input parameters in yielding the corresponding targeted output have been varying from model to model and cross section to cross section. This has borne the knowledge that same input parameters have different level of influence on the output parameters for different data patterns. Therefore, unlike the physical mathematical models ANN has exposed the reality that they are high nonlinearly related and more specific to the sites or the data patterns. This clue associated with the ANN has made it very roboust and cost and time effective in solving the problems which could not be so prompt with other approaches of modelings.
- The training of the Neural Networks were restrained from chances of getting over trained by loading a cross validation or test data patterns. It has been found that the prediction of the same data fed to it were excellent while for that test data it was poor.

That is, the Neural Network has not been over trained and would be capable in generalising the problem pattern in application. And upon the validation phase they have been prove better in prediction of the validation data.

- The success of the two transfer functions, Sigmoid and Tanhyperbolic, in tracking the patterns of the data of the present problem advocates that the variation of the output parameters corresponding to the input parameters is a continuous process and differentiable.
- The validation plots of the models 6, 7 & 8 has shown that, for model-6 the prediction ranged more up and down than the observed, for model-7 the prediction has plunged more below to the observed while for the model-8 on both side the prediction nearly merged with the observed. Similar observations could be made with other Validation profiles. In overall, it is conclusive that on steep rise or fall in the data values the ANN understands them as noisy and the prediction of the ANN could be occasionally more off for the extremities of the problem.
- ANN technique has been becoming a robust approach in Flood Forecasting of Drainage Basins which requires less attention to the under lying principles. Flood forecasting models can be developed with rainfall runoff data patterns and correspondingly the water surface levels. This would be more appropriate as a model for real time flood forecasting if the drainage basin has a reliable networks of prompt communication facilities. The rainfall in the upper regions and the corresponding water levels in the river channel in upstream in gauge stations be fed in to the model and the probable water levels and discharge be estimated in no time.
- The best advantage with the ANN models is that they could be readily updated incorporating more data patterns with time enhancing the model capability in prediction.

6.2 REGRESSION VERSUS ANN MODELS

Modeling with regression approach require the prior idea of the nature of the problem and the regression equation to the modeler or take trials with predetermined different regression equations becomes the other alternative for best fit of the data. Often, the error term in the prediction is large if the nature of the problem is more erratic and has difficulty to conclude the acceptability of the model. Regression models are good in prediction within the data period but found poor while extrapolating (forecasting).

Unlike regressions, ANN does not require to chose an expression as it is capable of tracing the pattern of the data relationship by itself though the relationship is highly non linear. In the present study regressions were performed for the individual section. Due to the small data patterns the regression predictions were found inferior to the ANN prediction.

6.3 MORPHOLOGICAL CHANGES

6.3.1 *Aggradation and Degradations*

The longitudinal profile of the river Brahmaputra has shown distinct pattern on aggradation side only after 1985 towards the later dates. It had exhibited rising and falling of the bed levels erratically. When the Average bed level profile is coupled with the corresponding thalweg levels (Figure:5.5) it has become more clear that the variations in the average bed levels correspond to the influence of dominant variations in thalweg levels which has vertical as well as lateral variation (Figure:5.4(a) to (g)). The rising of the thalwegs in most of the reaches have turned out shallowing of the river channels in effect pushing the process further to develop more braided channels.

The degradations at the locations correspond to the confluences of the high sediment laden tributaries. The confluence of a tributaries has the of influence which extend both upstream and downstream for kilometers of length.

In the recent past, the cross sections in aggradation has increased (Figure4.12) but the maximum and the average rate of the aggradation per unit of time period is decreasing.

6.3.2 Longitudinal Profiles

Longitudinal profile takes a fore most importance in the study of river morphology. The longitudinal profile of river Brahmaputra have been drawn for the study reach with the average bed levels.

Table:6.1

Period	57-61	61-65	65-69	69-73	73-77	77-81	81-85	85-89	89-93	93-97	97-2001	2001-05	Average
Slope	0.156	0.158	0.160	0.161	0.162	0.160	0.164	0.172	0.170	0.168	0.167	0.167	0.164

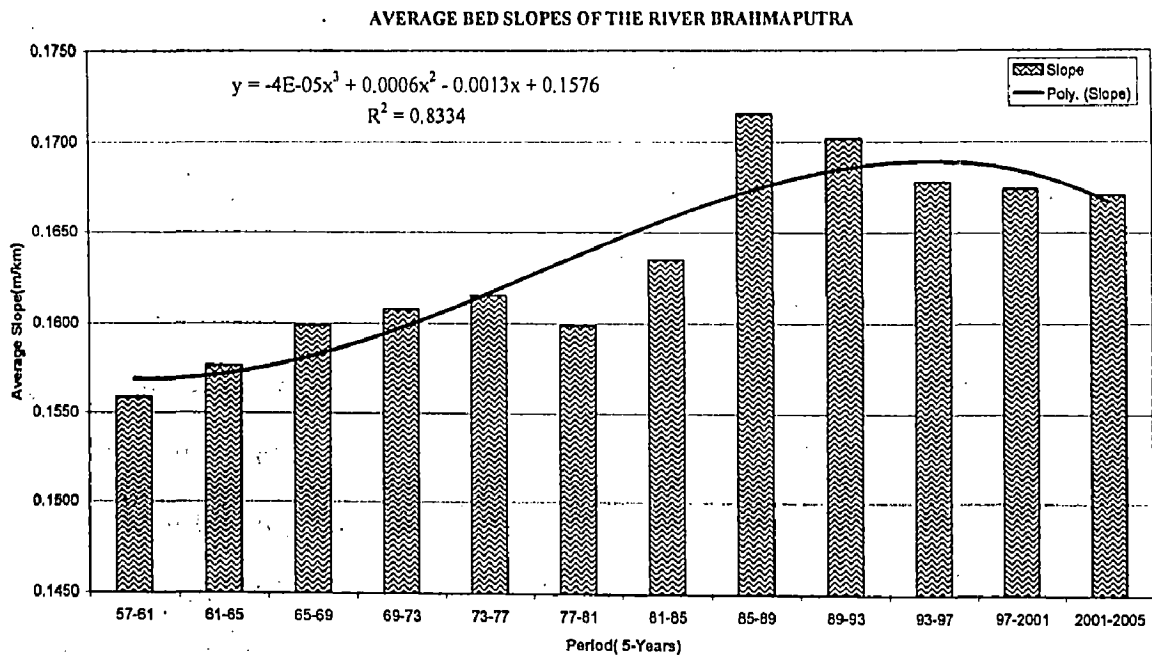


Figure:6.1
Average bed Slope of the total study reach in Temporal segments

The trend line shows the process to be an oscillating and damping but it may deviate from the present conditions.

When the profiles are closely observed to explore the total valley profile (Figure:4.14) it could be sensed that the profile as a single curve is rotating about the point in the lower reach. Further more, in three segments (Figure:4.13) the slopes increase upwardly. The slopes and their change are evaluated complying with the

predicted aggradation/degradation and have been found to be convincing. At present phase of time scale the slope of the lower and the upper reaches are flattening while in the middle reach is steepening. The situation could be reasoned as in the middle reach large number of tributaries join the main river Brahmaputra. Therefore, the changes in the behaviour of tributaries also play a great role in the management of the main river.

6.3.3 Valley Profile Concavity

The concavity, in general, represents the shape of the total river valley from the origination to the final outfall location. In the present study, the focus has been on the study reach which starts from about 1900km downstream from the point of the origination of river Brahmaputra to 2522.73km ahead. The study reach lies in the lower flood plain. The valley concavity has been determined for the study length. As explained in the previous section due to changes in the slopes correspondingly multiple concavity values have been found. The important part of the concavity for discussion would be the best fit curve for the concave shape. Logarithmic, power, Linear and exponential expressions are suggested to be the best fit to the L-profiles of river valleys. Since, the study reach, here, is only the lower river basin and has flatter concavity, second degree polynomial has found to be the best fit for the valley profile with $R^2 = 0.99$ and exponential with $R^2=0.98$

6.4 STREAM POWER CHANGES

The observed and the evaluated aggradations in the later periods (Figure:4.17) of the study period have been supported by the declining of the stream power, noticeably after 1985. This validates the concept of fall in the competency in sediment transportation. The extent of decrease is more on the lower reach. However the increasing trend of middle reach slope might be maintaining the sediment transportation capacity.

6.5 CONCLUDING REMARKS

Geo-morphology and their changes is the subject of thousand and millions of years. In the present context of the study the period spans over just about 50 years. However, the endeavour to search into the data in hand if it holds any dynamism in the river morphology at the present age of the river Brahmaputra has been reckoned to be encouraging. The results and the subsequent discussions in the previous sections have revealed that the morphological aspects of the river Brahmaputra are at the state of adjustments to maintain the hydraulic requirement of the fluvial processes.

CONCLUSIONS AND SCOPE FOR FUTURE STUDY

7.1 CONCLUSIONS

As the title of the dissertation suggests, the prime objective of the work is oriented to the river morphology of the river Brahmaputra and more specific to the Longitudinal Profile. Study of river morphology of river like Brahmaputra which is highly complex with respect to its fluvial process is due to the braided channel configuration and the huge size. The present study has endeavoured to investigate the changes of the river valley longitudinal profile in the recent past of half a century and then to indicate broadly the trend in coming years from a short term view. The salient observations of the study has been summarised as follows.

- 1) The encouraging application of ANN in the prediction of the average bed levels for entire study period (1957 to 1997 and forecast up to 2005) which meaningfully constituted the data base for the morphological analyses of the river Brahmaputra, has reaffirmed the applicability of the technique in the similar type of predictions.
- 2) The aggradation of the river bed of Brahmaputra has been the most predominant phenomenon in the recent past. In this respect the present study has been meaningful in revealing the process quantitatively in spatio-temporal scale. Visualisation of the spatial response of the morphological changes in the three discrete segments of about 200 km each of the total reach (622.74km) in Assam plains has led to the conclusion that, within the study period, the lower reach (17.34km to 218.79km) and the upper most reach (423.31 km to 640.07km) have undergone aggradations. The middle reach (218.79km to 423.31km) has exhibited degradations in local stretches probably, due to joining of the

tributaries into the main stream in this reach. The average rates of the river bed rise (in 5-years) per km of the reach length have been worked out in the entire study period as 0.05m for the lower and middle reach and for upper reach, 0.07m. The average degradation rate per km in the entire reach figured out to be 0.10m. However, in the later periods of the study from 1985 onwards, aggradation rates per km have been as high as 0.54m (in 5-years) which is quite above the average rate of the entire study period.

In the local scale, aggradation and degradation variation scenario has been seen quite high and complex to figure out a unique clue. Despite the major aggradation in the later periods, the lower reach has been observed just maintaining its level to a balance at the end of the study period. And, during the whole period the middle reach has been seen degraded by 0.44m and the upper reach has been raised by 1.35m

In over all, it could be concluded that the average bed variation has trend of changes more on the aggradation side in the later periods because of the inclusion of more cross sections into aggradation. However, the trend of the average values of the aggradation (Figure:4.12) for the periods has shown that it could lead to a cyclic process for which further research is essential with more data.

- 3) The aggradation and degradation characteristics of the bed variations in different segments for different period has shown perceptible influence of other morphological parameters; longitudinal profile and slope displaying the unsteady state of the river morphology. On quantifying this fluctuation of slopes during the span of study period it has come out to be 4.9% to 0.2% , maximum in 1985- 89 then drastically plummeting to 0.2% in 2001-05. The average slope of the entire stretch of the river has been worked out to be 0.00016.

Similarly, the three reaches : lower, middle and the upper have average slopes 0.11m /km, 0.17m/km and 0.22m/km respectively. Again , their ranges of variation for the study period have been 4.14% to 0.29%, 5.82% to 0.14% and 6.85% to 0.14% respectively. The range of the slope variations hints at the degree of instability of the slopes in the three reaches.

- 4) The longitudinal profiles of the river valley floor generated by the fitted polynomials have revealed that the total longitudinal profile has been under self adjustment to maintain the sediment and discharge flow capacity mechanised by the fluvial process. The Figure:4.14 may be closely noticed to perceive the gap variation between two successive profiles. The gaps are more on the upper reach while for the lower reach the gap variation is comparatively small. This also concludes that the morphological changes (bed variation, slopes) are more dynamic in the upper reach.
- 5) The study has also attempted quantifying the concavity index of the study stretch (17.34km to 640.07 km). In an average over the study period, it has been worked out to be 0.15. Perceptibly, the concavity index has also been analysed varying in different periods (Figure:4.16) steeply down from 4.75% in 1985-89 period to 0.75% in 1989-93 but taking an average figure of 2.41% between 1985 to 2005. Moreover, the profile of the river valley which constitutes the lower drainage basin of the river approaching to the sea has been found to best fit a second-degree polynomial with R^2 above 0.99 and exponential curve with R^2 nearly equal to 0.98 .
- 6) The influence of concavity and the longitudinal profile slope variation has made the stream power responsive to the observed bed level rising. The decrease in the stream power from 1985 to 2005 (Figure:4.17) has ultimately forced average bed levels to aggrade.

7) The total average variation of thalweg level through the entire study period has been observed to be 1.20m in the lower reach, 1.39m in the middle reach in aggradation. Unlike the average bed level, thalweg in upper most reach has shown degradation of -1.84m over the entire study period. The major variation has been found to be from the period 1981-85 to 1993-97 and then, has followed decreasing trend afterward.

The increase in braiding of the river channels observed in the recent studies could be further reasoned that the thalweg levels have exhibited high aggradation in lower and the middle reaches(Figure:5.5) which has led to shallowing of the active flow channels. This has forced the inherent channel process to develop small multiple channels to develop such that the flow area is increased to maintain the discharge and the sediment transportation capacity.

7.2 SCOPE FOR FUTURE STUDY

The complexity in understanding the interdependencies of the parameters of different origins in deciding the morphological features from one generation to next generation of highly braided rivers like Brahmaputra has been a time consuming and costly affair. However, in the present context, the study period under consideration represents a very small segment of the river life cycle but has been able to suggest following recommendations.

- The present study has identified the middle reach more susceptible to degradation. Further study on the interrelationship of tributaries and the bed variations in the vicinity and the further downstream might reveal the solution to the downstream aggradation problem.
- Aggradations and the concavity, slopes and the channel lengths are collectively responsive to base level variation. The morphological changes of the present study area can be further investigated relative to the sea level rise.

Appendix-I :Original Average bed level Data tabulations and assessments

RIVER BRAHMAPUTRA
AGGRADATION AND DEGRADATION OF LONGITUDINAL PROFILE
FROM THE YEAR 1957 TO 1997

X-section	2.00		3.00		4.00		5.00		6.00	
Km	17.34		28.05		38.25		46.92		56.61	
Ref	E (m)	Aggra/Degra(m)	Width flood plan(m)	Width variation every year(m)	Total variation(m)	E (m)	Aggra/Degra(m)	Width flood plan(m)	Width variation every year(m)	Total variation(m)
Yr.1957	24.68	referen	11887		6968	27.65		18246	27.92	
1971	23.11	1.57	9700	-2187	9850	26.96	0.69	8150	29.15	-10095
1977	23.52	1.16	12479	2779	5070	27.57	0.08	18250	28.98	10100
1981	25.23	0.55	12500	21	15475	28.10	0.44	17474	28.28	-771
1988	23.63	1.05	13200	700	13268	27.87	0.22	17230	28.35	-1015
1992										
1993	24.47	0.21	13200	0	15990	27.81	0.16	18820	29.26	1590
1997	23.91	0.77	13096	-104	15590	27.59	0.06	17070	28.81	-1175
1998										
STD	0.74		1242		3456	0.35		3720	0.50	
Max. Variation in any single period	1.71		1.28		0.69			1.24		0.90

X-section	7.00		8.00		9.00		10.00		11.00	
Km	66.30		73.44		82.62		92.82		100.98	
Ref	E (m)	Aggra/Degra(m)	Width flood plan(m)	Width variation every year(m)	Total variation(m)	E (m)	Aggra/Degra(m)	Width flood plan(m)	Width variation every year(m)	Total variation(m)
Yr.1957	29.59		14202		8765	25.72		2987	30.53	
1971	30.33	0.74	14000	-202	14000	29.58	3.86	2600	28.52	-387
1977	30.36	0.77	14900	900	14900	26.90	1.18	2608	32.36	8
1981	29.86	0.27	15100	200	15100	27.27	1.55	2606	30.60	-2
1988	27.53	2.06	15500	400	15500	26.02	0.30	2530	30.37	-457
1992										
1993	29.56	0.03	15540	40	9436	26.46	0.74	2530	29.83	-457
1997	28.51	1.08	15550	10	9436	24.58	1.16	2500	29.97	-30
1998										
STD	1.03		645		3068	1.56		166	1.15	
Max. Variation in any single period	2.33		2.85		3.86			3.84		1.01

RIVER BRAHMAPUTRA
AGGRADATION AND DEGRADATION AND WIDTH
FROM THE YEAR 1957 TO 1997

X-section km	12				13				14				15				16			
	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)
Ref Yr.1957	34.99	8529			12801	11643			37.55	12436			37.36	10348			10348	146.37		
1971	35.72	8400	-129	-129	12800	10100	-1543	-1543	39.01	11450	-986	-986	39.18	11800	1452	1452	11800	146.37	1452	1452
1977	34.77	11141	2741	2612	12831	11752	1652	109	36.13	13465	2015	1029	38.94	11800	0	1452	11800	146.37	0	1452
1981	34.49	11550	409	3021	13600	11800	48	157	36.13	13465	0	1029	38.08	11800	0	1452	11800	146.37	0	1452
1988	33.19	14000	2450	5471	14970	13873	2073	2230	36.98	14593	1118	2147	37.86	12702	902	2354	12702	146.37	902	2354
1992																				
1993	33.57	14000	0	5471	14970	13675	-198	2032	38.04	14720	137	2284	38.14	12705	3	2357	12705	146.37	3	2357
1997	33.60	14000	0	5471	14651	13662	-13	2019	37.62	14758	38	2322	38.71	12709	4	2361	12709	146.37	4	2361
1998																				
STD	0.91	2488			1036	1415			1.04	1262.3			0.65	850.4			850.4	146.37		
Max. Variation	1.30								2.23				2.88					1.82		

in any single period(in between the Bold boarder period)

X-section km	17				18				19				20				21			
	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)
Ref Yr.1957	41.02	15525			16728	17595			42.02	7210			44.25	8620			8620	189.21		
1971	41.87	15540	15	15	15630	5457	1849	1849	41.36	5199	-2011	-2011	44.40	8500	-120	-120	8500	189.21	-120	-120
1977	42.68	15540	0	15	19500	11900	6443	8292	40.82	5150	-49	-2060	44.55	8530	30	90	8530	189.21	30	90
1981	40.56	15540	0	15	19450	11900	0	8292	39.98	5150	0	-2060	43.60	8550	20	-70	8550	189.21	20	-70
1988	41.14	17833	2293	2308	20396	7225	4675	3617	39.87	4950	-200	-2260	42.37	8300	-250	-320	8300	189.21	-250	-320
1992																				
1993	40.82	18855	1022	3330	20415	7225	4785	41.48	4.14	4963	13	-2247	41.86	8160	-140	-460	8160	189.21	-140	-460
1997	41.29	14903	-3952	-622	20415	7225	4785	42.37	5.04	4949	-14	-2261	43.42	8302	142	-318	8302	189.21	142	-318
1998																				
STD	0.72	1480			1856	3100			1.02	819.6			1.04	168.91			168.91	189.21		
Max. Variation	2.12								2.80				2.54					1.56		

in any single period(in between the Bold boarder period)

X-section km	22				23				24				25				26				
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	
Ref Yr.1957	43.55	3304	197.37	306.55	213.18	206.55	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18	213.18
1971	36.97	3080	-224	4566	-8	44.13	0.60	4574	-8	45.04	-2.08	3500	-84	44.65	0.20	8166	-792	48.50	-0.81	11050	0
1977	42.78	3290	210	4800	34	44.73	-3.19	4600	34	43.77	-3.27	3635	135	45.46	0.81	7103	-271	50.17	0.85	11000	-50
1981	42.23	3290	0	4490	-110	44.03	-0.10	4490	-110	44.37	-0.67	3637	2	53	1.74	9451	2348	48.07	1.25	11012	12
1988	41.71	3250	-40	4292	-4490	44.00	-0.33	4292	-4490	43.83	-1.21	3500	-137	84	1.38	8500	-951	48.38	-0.94	11400	388
1992						44.00	-0.33	4292		44.92	-0.11	3440	-60	144	1.83	8810	310	48.62	-0.70	11200	-200
1993	42.39	3200	-50	4730	0	46.49	2.36	4730	0	44.95	-0.09	4400	960	45.50	0.85	8300	-510	49.60	0.29	10930	-270
1997	44.74	3290	90	4730	156	46.49	2.36	4730	156	44.95	-0.09	4400	960	45.50	0.85	8300	-510	49.60	0.29	10930	-270
1998						1.79		145.3		0.78		330.0		0.80		807.3		0.76		158.7	
STD	2.45	80.4		145.3		1.79		145.3		0.78		330.0		0.80		807.3		0.76		158.7	
Max. Variation	6.58									2.08				0.98				2.05			

in any single period(in between the Bold boarder period)

X-section km	27				28				29				30				31				
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	
Ref Yr.1957	49.28	13975	234.60	241.23	251.95	241.23	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95	251.95
1971	50.10	12311	-1664	12050	-50	50.27	0.08	12100	-50	47.42	-50	15780	-50	53.03	-17.6	5894	-405	52.14	-17.6	5894	45
1977	48.40	13600	1289	12050	0	50.88	0.61	12050	0	49.09	-50	15780	0	49.63	-0.31	6350	365	53.59	-0.31	6350	466
1981	49.25	13650	50	14900	2850	50.61	0.34	14900	2850	48.46	1.03	15780	0	51.70	-0.40	7254	465	53.00	-0.90	7254	904
1988	48.65	13500	-150	14300	-600	49.69	-0.58	14300	-600	50.84	3.42	21600	5820	51.55	3.55	15700	1700	52.31	1.59	9500	2246
1992	48.79	12870	-630	1105	-630	50.95	0.68	1404	-630	52.23	4.80	22100	500	52.13	2.97	12500	-3200	54.16	0.27	9900	400
1993												22000									
1997	47.76	8500	-4370	1404	-5475	0.47		1404	-5475	1.92		3956		1.81		1083.4		0.81		1917	
1998																					
STD	0.74	1909		1404		0.47		1404		1.92		3956		1.81		1083.4		0.81		1917	
Max. Variation	1.70									2.39				3.40				1.86			

in any single period(in between the Bold boarder period)

X-section km	32				33				34				35				36										
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)							
Ref Yr.1957	55.87		15201			58.04		12662			62.00		12204			60.90		7769			63.67		6440			341.21	
1971	56.65	0.77	16788	1567	1567	58.30	0.27	12750	88	88	61.48	-0.52	12924	720	720	60.88	0.02	7730	-39	-39	63.68	0.01	5750	-690	-690		
1977	55.60	0.27	15460	-1308	259	58.55	0.51	13178	428	516	58.35	-3.65	12410	-514	206	60.71	-0.20	7728	-2	-41	60.13	3.54	5780	30	-660		
1981	55.39	0.49	14996	-464	-205	58.62	0.59	13160	-18	498	60.78	-1.23	14810	2400	2606	59.21	1.69	7738	10	-31	58.75	-4.92	5760	-20	-680		
1988	55.83	0.05	12500	-2496	-2701	56.55	1.49	16600	3440	3938	58.75	-3.26	14800	-10	2596	63.40	2.49	9620	1882	1851	62.34	1.33	8000	2240	1560		
1992	56.56	0.69	13550	1050	-1651	58.22	0.19	16160	-440	3498	59.71	-2.30	15500	700	3296	60.47	-0.44	9500	-120	1731	62.54	1.13	8000	0	1560		
1993																											
1997																											
1998																											
Max. Variation	1.04					2.08				2.42						4.18											

In any single period (in between the Bold boarder period)

X-section km	37				38				39				40				41										
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)							
Ref Yr.1957	66.16		10485			67.63		9220			69.86		9900			70.01		11098			72.05		8515			389.66	
1971	65.39	0.77	10010	-475	-475	65.15	-2.48	9200	-20	-20	69.46	-0.37	9584	-316	-316	72.38	2.37	8780	-2318	-2318	70.75	-2.19	7950	-565	-565		
1977	64.02	2.15	9050	-960	-1435	68.08	0.45	8900	-300	-320	69.32	0.53	9621	37	-279	71.85	1.84	8820	40	-2278	69.58	-2.47	7900	-50	-615		
1981	64.42	1.75	9090	40	-1395	65.82	1.82	8960	60	-260	68.39	-1.47	9520	-101	-380	71.30	1.29	8820	0	-2278	69.86	-2.18	8100	200	-415		
1988	63.88	2.29	8750	-340	-1735	65.46	-2.17	8924	-36	-296	66.92	-2.94	8957	-563	-943	71.07	1.06	10050	1230	-1048	70.91	-1.13	6800	-1300	-1715		
1992	61.96	1.20	8750	0	-1735																						
1993						63.47	-4.16	11700	2776	2480	68.93	-0.93	8900	-57	-1000	70.22	0.22	10100	50	-998							
1997	64.42	1.75	9000																								
1998																											
Max. Variation	2.45					2.93				2.37																	

In any single period (in between the Bold boarder period)

X-section km	42				43				44				45				46										
	398.33				412.09				423.31				439.63				453.91										
Ref Yr.	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)							
1957	73.39		9580			72.30		11628			73.44		8400			75.02		8394			78.58			12353			
1971	68.57	32	8920	-660	-660	72.24	0.07	11600	-28	-28	73.55	0.11	8400	0	0	79.18	4.16	8400	6	6	80.72	2.14	12400	47	47		
1977	68.58	31	8800	-120	-780	71.86	0.44	13456	1856	1828	73.55	0.11	10720	2320	2320	78.46	3.43	10000	1600	1606	79.89	1.31	12340	-60	-13		
1981	69.54	34	8580	-220	-1000	70.84	1.47	13450	-6	1822	74.60	1.15	10300	-420	1900	78.90	3.88	9450	-550	1056	79.87	1.29	12270	-70	-83		
1988	73.37	02	8600	20	-980	73.95	1.65	14700	1250	3072	76.83	3.39	13200	2900	4800	78.64	3.62	9681	231	1287	77.57	1.01	12400	130	47		
1992	72.01	38	8650	50	-930	74.05	1.75	14700	0	3072						78.44	3.42	20000	10320	11606							
1993											76.06	2.62	13200	0	4800												
1997																											
1998																											
Max. Variation in any single period		32			3.12			2.24			4.16			2.30													

X-section km	47				48				49				50				51										
	465.13				474.82				483.49				490.63				498.80										
Ref Yr.	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)							
1957	80.24		13243			82.92		7634			82.01		7616			82.26		6565			85.35			10628			
1971	80.35	0.10	13200	-43	-43	80.57	2.36	7634	0	0	83.02	1.01	7600	-16	-16	83.49	1.22	6640	75	75	86.16	0.81	10096	-532	-532		
1977	80.59	0.35	13300	100	57	80.58	2.34	8320	686	686	82.25	0.24	7655	55	39	83.71	1.44	6670	30	105	85.76	0.41	10980	884	352		
1981	81.13	0.89	13300	0	57	81.36	1.57	8260	-60	626	83.17	1.16	7660	5	44	83.27	1.00	6670	0	105	85.55	0.20	10910	-70	282		
1988	81.39	1.15	13425	125	182	82.62	0.31	10045	1785	2411	83.54	1.52	7760	100	144	81.85	0.41	6773	103	208	85.91	0.55	11270	360	642		
1992																											
1993																											
1997																											
1998	81.58		13320	-105	77	81.61		10340	295	2706	82.54		7755	-5	199	83.48		6775	2	210	86.29		11260	-10	632		
Max. Variation in any single period		54			2.36			1.01			1.41			0.81													

X-section km	52				53				54				55				56			
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)
Ref Yr. 1957	87.14	9611	7700	4300	90.46	9270	93.96	11582	94.37	10581	541.13	10581	16	16						
1971	86.29	9690	12000	4300	90.65	9520	91.82	11720	138	10597	531.95	10597	16	16						
1977	87.62	12440	13800	1800	91.00	11740	92.07	13860	2140	12700	541.13	12700	2103	2119						
1981	86.96	13010	15280	1480	89.50	11610	91.92	13840	-20	12700	541.13	12700	0	2119						
1988	87.45	12380	15510	230	92.47	11713	94.03	13600	-240	9800	541.13	9800	-2900	-781						
1992																				
1993																				
1997																				
1998	88.57	12385	15465	-45	93.36	11775	94.50	13600	0	2018	541.13	2018								
Max. Variation	1.33		3.20		2.97		2.14		6.50											

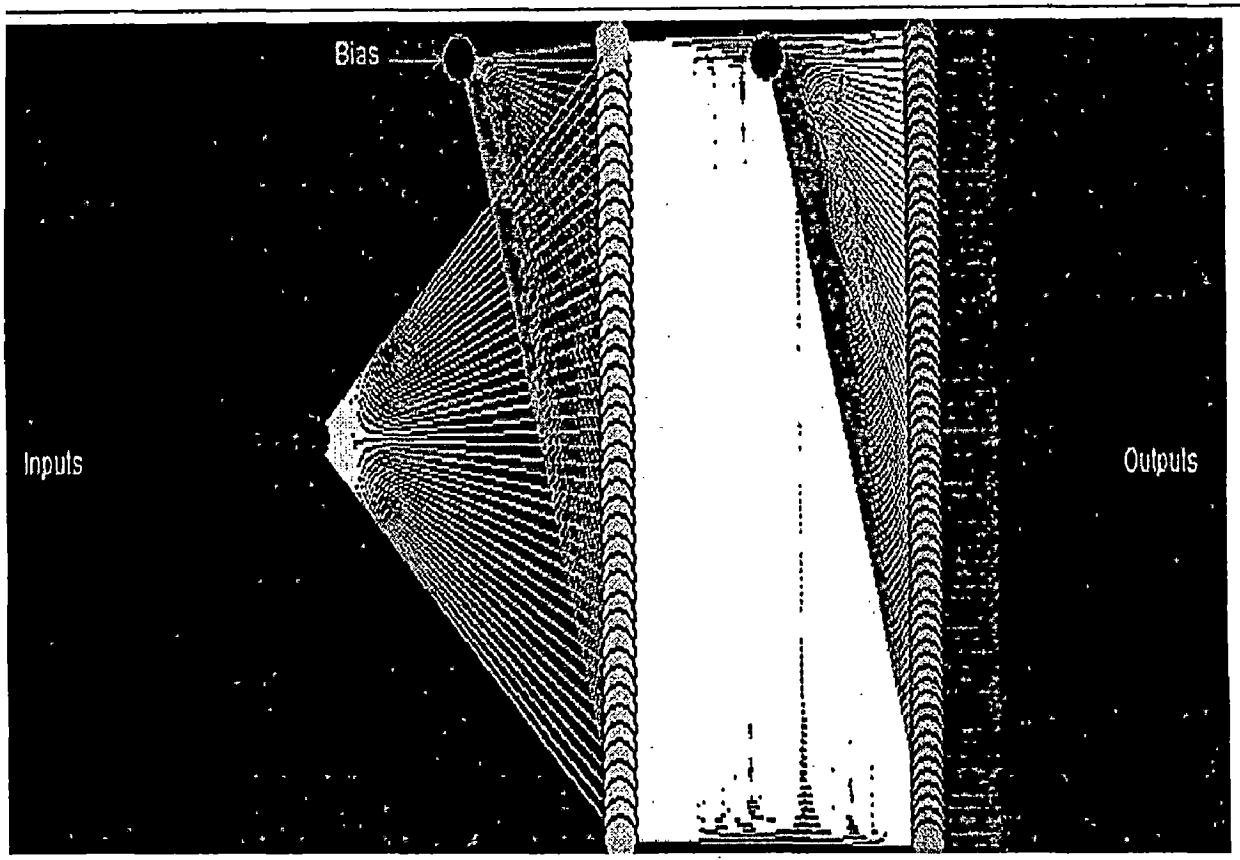
in any single period

X-section km	57				58				59				60				61			
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)
Ref Yr. 1957	97.02	8820	9158	256	101.93	9250	106.71	14264	107.37	11719	601.82	11719	3207	3207						
1971	97.71	10331	9414	1511	102.23	9253	105.28	14299	35	14926	601.82	14926	3207	3207						
1977	96.65	12850	11220	1806	101.94	9712	105.37	14200	-99	14970	601.82	14970	44	3251						
1981	99.51	10900	10340	-880	101.82	10033	103.18	13770	-430	14480	601.82	14480	-490	2761						
1988	99.99	9500	10700	360	104.32	10400	106.08	12700	-1070	13900	601.82	13900	-580	2181						
1992			10800	100	103.25	11400	106.18	15100	2400	16000	601.82	16000	2100	4281						
1993																				
1997																				
1998																				
Max. Variation	2.86		2.20		2.50		2.91		1.63											

in any single period

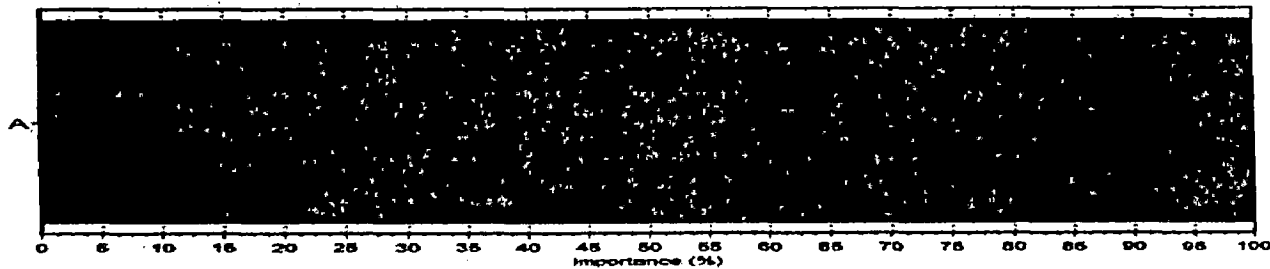
X-section km	62						63						64						65							
	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	El.(m)	Aggra/Degra(m)	Width flood plain(m)	Width variation every period(m)	Total variation(m)	
Ref Yr.1957	108.59		10200			113.65		10510			115.90		6918			117.62		7949								
1971	111.42	2.83	10180	-20	-20	116.24	2.59	10311	-199	-199	118.34	2.44	6939	21	21	120.37	2.75	8080	131	131						
1977	112.41	3.81	13243	3063	3043	116.16	2.51	10580	269	70	117.95	2.05	6900	-39	-18	121.03	3.41	8084	4	4						
1981	113.05	4.46	11941	-1302	1741	115.73	2.09	10350	-230	-160	115.89	-0.01	7536	636	618	120.92	3.30	8200	116	116						
1988	110.00	1.41	12600	659	2400	112.30	-1.35	10500	150	-10	113.91	-1.98	7900	364	982	114.24	-3.38	7200	-1000	-749						
1992																										
1993																										
1997																										
1998																										
Max. Variation in any single period		2.83					3.44					2.44														

Appendix-II ANN architecture, Importance and Optimum Connection Weights of the ANN Model.



The ANN Architecture of the model -2
BBP(500)Tanh
There are 2968 no. of connection weights.

N1L1-N1L2	0.1926	N8L2-N9L3	-0.2499	N15L2-N61L3	0.0139
N1L1-N2L2	0.0453	N8L2-N10L3	-0.4750	N15L2-N62L3	0.4130
N1L1-N3L2	0.0599	N8L2-N11L3	0.5461	N15L2-N63L3	-0.0430
N1L1-N4L2	0.0766	N8L2-N12L3	-0.5012	N15L2-N64L3	-0.7999
N1L1-N5L2	-0.1000	N8L2-N13L3	1.4639	N16L2-N1L3	-2.4738
.....Total no 2968					



There is only one input parameter (time in year) so, the importance is 100%

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Note: The references marked "" are only cross references.*