Simulating Groundwater levels in Pune

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Introduction

- Groundwater is the most useful resource in nature.
- Over 50% of urban water usage is dependent on groundwater.
- Pune, a fast-growing city, faces challenges in groundwater depletion and contamination.
- Simulation models help in understanding trends and predicting future scenarios for effective management.

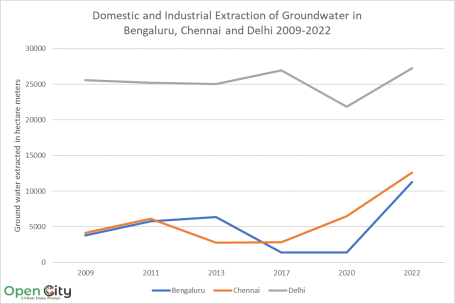


Figure: Usage of Groundwater in Major Urban Cities[1]

Study Area: **Pune I**

Physiographic Divisions

- **Western Ghats (Sahyadri Hills):** The western part of Pune district consists of rugged terrain with steep slopes and high rainfall. Major peaks include Torna, Sinhagad, Rajgad, and Purandar.
- **Deccan Plateau:** The eastern part of the district is relatively flat, with gently sloping terrain formed by basaltic lava flows. It has fertile black soil suitable for agriculture.
- **River Valleys:** The district has several rivers, including the Mula, Mutha, Pavana, Bhima, and Indrayani, which have carved out valleys over time.

Major rivers:

1. Bhima River (flows towards the east)
2. Mula-Mutha Rivers (flow through Pune city)(tributaries of Bhima)
3. Indrayani and Pavana Rivers (draining the northern part)

Study Area: **Pune II**

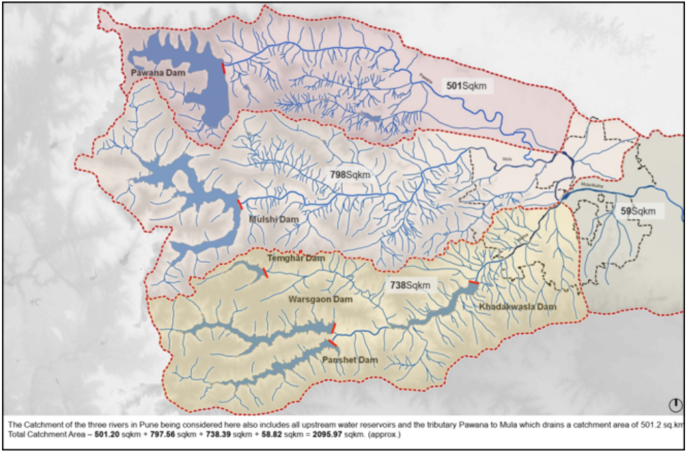


Figure: River network in Pune

Problem Statement

- **Declining Groundwater Levels:** Over-extraction due to urbanization and agriculture.
- **Pollution Concerns:** Industrial waste, sewage, and agricultural runoff affecting groundwater quality.
- **Lack of Real-time Monitoring:** Limited data availability for accurate prediction and decision-making.
- **Climate Variability Impact:** Unpredictable rainfall patterns influencing groundwater recharge.
- **Need for Sustainable Management:** Efficient policies and strategies require predictive analysis.

Objectives

1. **To simulate groundwater level fluctuations** based on historical and climatic data.
2. **To assess groundwater pollution trends** using available quality parameters.
3. **To provide predictive insights** for sustainable groundwater management in Pune.

Datasets I

1. Groundwater Levels Data collected from 2000-2023.

Station Ground Water Level Information 2004			
Jan-04	**Range-jan**	May-04	Range-may
Ane	7.1 - 7.1	Ane	11.32 - 11.32
Bhadalwadi	7.8 - 7.8	Bhadalwadi	0.45 - 0.45
Bukum	0.72 - 0.72	Bukum	4.1 - 4.1
Dhumalwadi	11.65 - 11.65	Dhumalwadi	12.15 - 12.15
Dorlewadi	7.31 - 7.31	Dorlewadi	6.74 - 6.74
Jejuri	6.9 - 6.9	Jejuri	7.46 - 7.46
Junnar	4.5 - 4.5	Junnar	5.1 - 5.1
Karanje	7.3 - 7.3	Karanje	7.47 - 7.47
Khutbhav_Pz	11.08 - 11.08	Khutbhav_Pz	12.21 - 12.21
Kolwan	1.25 - 1.25	Kolwan	3.4 - 3.4
Lonawala	1.6 - 1.6	Lonawala	2.02 - 2.02
Loni (Ambegaon)	9.65 - 9.65	Loni (Ambegaon)	9.65 - 9.65
Mulshi	1.72 - 1.72	Mulshi	2.13 - 2.13
Narayangaon	6.9 - 6.9	Narayangaon	6.92 - 6.92
Narayanpur	8.1 - 8.1	Narayanpur	8.72 - 8.72
Nimbgaon-Ketke	13.54 - 13.54	Nimbgaon-Ketke	13.54 - 13.54
Otur	20.3 - 20.3	Otur	19.1 - 19.1
Pangre Sailar Basti	8 - 8	Pangre Sailar Basti	8 - 8
Parne	7.57 - 7.57	Parne	9.27 - 9.27
Patas	1.65 - 1.65	Patas	1.32 - 1.32
Pimpri (Kh) Malvasti	4.95 - 4.95	Pimpri (Kh) Malvasti	6.82 - 6.82
Pune	2.4 - 2.4	Pune	2.92 - 2.92
Rajgurnagar (Khed)	1.57 - 1.57	Rajgurnagar (Khed)	2.28 - 2.28
Sakurde	9.6 - 9.6	Sakurde	7.82 - 7.82
Shivpur Khed	6.43 - 6.43	Shivpur Khed	10.45 - 10.45
Undavri Kade Pathar	8.8 - 8.8	Undavri Kade Pathar	8.8 - 8.8
Wehle	1.5 - 1.5	Wehle	2.5 - 2.5

Figure: Snapshot of Groundwater level Dataset

Datasets II

2. Rainfall Data in Pune from 2000-2023.

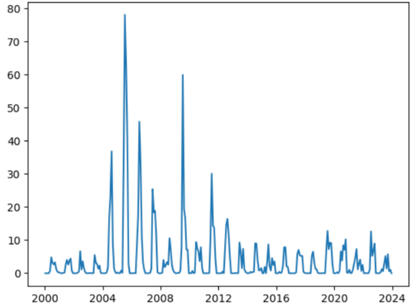


Figure: Snapshot of Rainfall Dataset

Datasets III

3. Water Quality data in Bhima river basin from 2012-2023.

Months	pH	Dissolved Oxygen (mg/l)	B.O.D. (mg/l)	C.O.D. (mg/l)	Nitrate (mg/l)	Fecal Coliform (MPN/100 ml)	WQI
YEAR : 2023							
January	7	4.3	10.4	39.5	1.63	25	61.76
February	7.5	4.3	18.8	59.8	N/A	25	60.07
March	7.7	4.3	19	60	1.33	140	53.14
April	7.2	3.8	21	64	1.36	175	51.67
May	7.8	3.3	22	68	0.89	200	45.05
June	7	3.8	23	72	2.11	250	48.58
July	7.4	4.1	19	56	1.22	38	58.21
August	7.6	3.4	20	52	0.3(BDL)	45	52.21
September	7.3	4.5	12	44	3.45	80	60.95
October	7.1	4	19	56	0.3(BDL)	170	52.61
November	7.5	4.4	17	48	2.06	200	54.33
December	6.9	4.1	17	48	2.86	250	50.92

TOTAL	pH MIN	pH MAX	pH AVG	DO MIN	DO MAX	DO AVG	B.O.D. MIN	B.O.D. MAX	B.O.D. AVG	C.O.D. MIN	C.O.D. MAX	C.O.D. AVG	Nitrate MIN	Nitrate MAX	Nitrate AVG	Fecal Coliform MIN	Fecal Coliform MAX	Fecal Coliform AVG
	6.9	7.8	7.33	3.3	4.5	4.03	10.4	23	18.18	39.5	72	55.61	0.3(BDL)	3.45	1.46	25	250	133.17

Figure: Snapshot of Water Quality Dataset

Data Imputation I

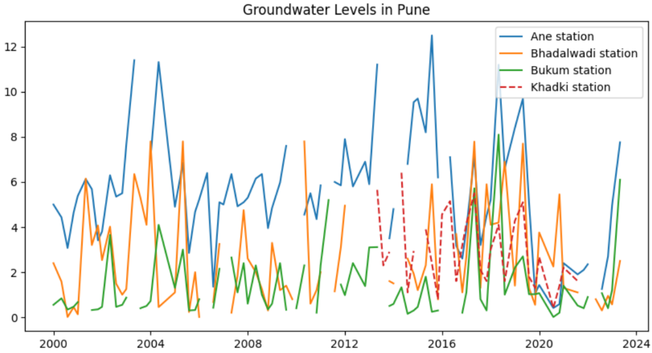


Figure: Groundwater Levels at Different stations (has missing values)

Data Imputation II

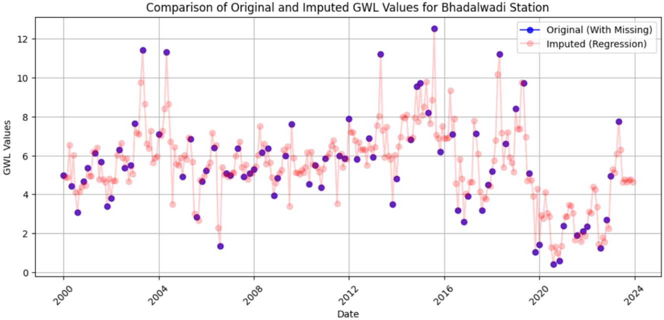


Figure: Missing values filled with Predictive Imputation (Bhadalwadi Station)

Data Imputation III

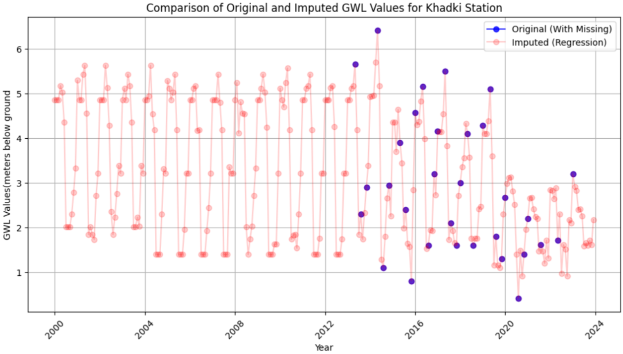


Figure: Missing values filled with Predictive imputation(Khadki Station)

Data Imputation IV

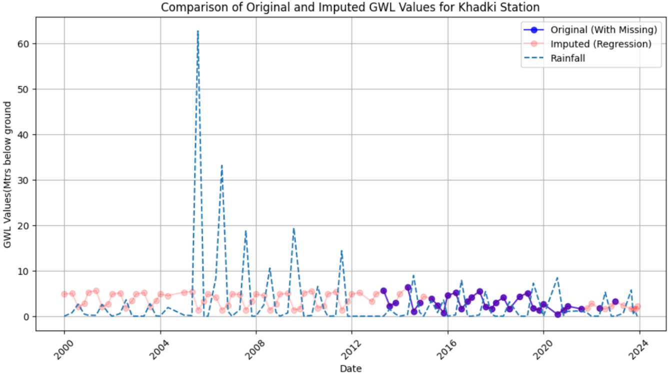


Figure: Relationship between rainfall and imputed values(Khadki Station)

Data Imputation V

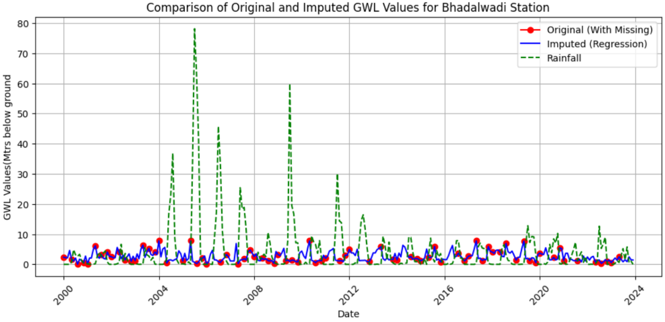


Figure: Relationship between rainfall and imputed values(Bhadalwadi Station)

Model used for Rainfall

Long Short-Term Memory (LSTM) is a type of artificial neural network (ANN) that can learn and retain information over time. LSTMs are used in many applications, including speech recognition, natural language processing, and time series forecasting.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 48, 64)            16896

 dense (Dense)               (None, 48, 64)            4160

 dense_1 (Dense)             (None, 48, 128)           8320

 lstm_1 (LSTM)               (None, 128)               131584

 dense_2 (Dense)             (None, 128)               16512

 dense_3 (Dense)             (None, 64)                8256

 dense_4 (Dense)             (None, 32)                2080

 dense_5 (Dense)             (None, 1)                 33

=================================================================
Total params: 187841 (733.75 KB)
Trainable params: 187841 (733.75 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Figure: Summary of Model used for rainfall forecasting

Model used for Water Quality Forecsting

Layer (type)	Output Shape	Param #
lstm_8 (LSTM)	(None, 24, 64)	18432
dense_24 (Dense)	(None, 24, 64)	4160
dense_25 (Dense)	(None, 24, 128)	8320
lstm_9 (LSTM)	(None, 128)	131584
dense_26 (Dense)	(None, 128)	16512
dense_27 (Dense)	(None, 64)	8256
dense_28 (Dense)	(None, 32)	2080
dense_29 (Dense)	(None, 7)	231

Total params: 189575 (740.53 KB)
Trainable params: 189575 (740.53 KB)
Non-trainable params: 0 (0.00 Byte)

Figure: Model for Water quality forecasting

For water quality forecasting too, we will be using LSTM model.

Model for Groundwater levels I

For Groundwater forecasting, the we have created a model for each of the measuring stations.
Each model is an LSTM fine tuned with Attention layers and neuroplasticity methods.
Models have 2 inputs:

1. Previous groundwater level data from that station for last **12** months.
2. Average Rainfall value of the corresponding month.

Model for Groundwater levels II

Model: "model_1"

Layer (type)	Output Shape	Param #	Connected to
input_3 (InputLayer)	[(None, 13, 1)]	0	[]
lstm_3 (LSTM)	(None, 13, 64)	16896	['input_3[0][0]']
dense_15 (Dense)	(None, 13, 64)	4160	['lstm_3[0][0]']
tf.__operators__.getitem_1 (SlicingOpLambda)	(None, 64)	0	['dense_15[0][0]']
extreme_value_attention_1 (ExtremeValueAttention)	((None, 64), (None, 13, 1))	4224	['dense_15[0][0]']
input_4 (InputLayer)	[(None, 1)]	0	[]
concatenate_2 (Concatenate)	(None, 128)	0	['tf.__operators__.getitem_1[0][0]', 'extreme_value_attention_1[0][0]']
dense_16 (Dense)	(None, 32)	64	['input_4[0][0]']
concatenate_3 (Concatenate)	(None, 160)	0	['concatenate_2[0][0]', 'dense_16[0][0]']
dense_17 (Dense)	(None, 128)	20608	['concatenate_3[0][0]']
dense_18 (Dense)	(None, 256)	33024	['dense_17[0][0]']
dense_19 (Dense)	(None, 128)	32896	['dense_18[0][0]']
dense_20 (Dense)	(None, 64)	8256	['dense_19[0][0]']
dense_21 (Dense)	(None, 32)	2080	['dense_20[0][0]']
dense_22 (Dense)	(None, 16)	528	['dense_21[0][0]']
dense_23 (Dense)	(None, 1)	17	['dense_22[0][0]']

Total params: 122753 (479.50 KB)
Trainable params: 122753 (479.50 KB)
Non-trainable params: 0 (0.00 Byte)

Figure: Model summary for groundwater forecasting

What is Attention?

Definition

Attention is a mechanism that enables neural networks to selectively focus on different parts of an input sequence while processing it.
Instead of treating all input tokens equally, attention assigns different importance (or "weights") to different tokens based on their relevance to the current computation.

In this model, we have used Extreme Value Attention- a heuristic that focuses on the Extreme values (i.e. the values that deviate the furthest from the mean.)

What is Neuroplasticity? I

Definition

Neuroplasticity, in the context of artificial neural networks, refers to the ability of a network to dynamically adapt, reorganize, and modify its structure and connections in response to learning, experience, and external stimuli. Inspired by biological neural plasticity, this concept helps artificial networks improve learning efficiency, generalization, and adaptability.

- **Elastic Weight Consolodation:** EWC helps LSTMs retain knowledge of past time series trends while learning new ones by penalizing significant changes to important weights.
  It prevents catastrophic forgetting in continual learning, ensuring that older patterns remain useful while adapting to new data.

Results I

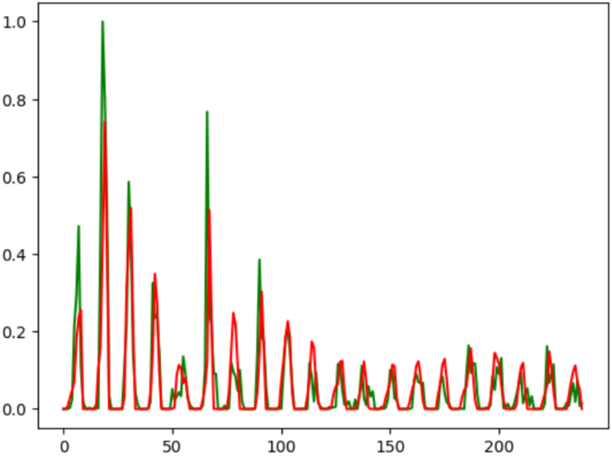


Figure: Rainfall Model

Results II

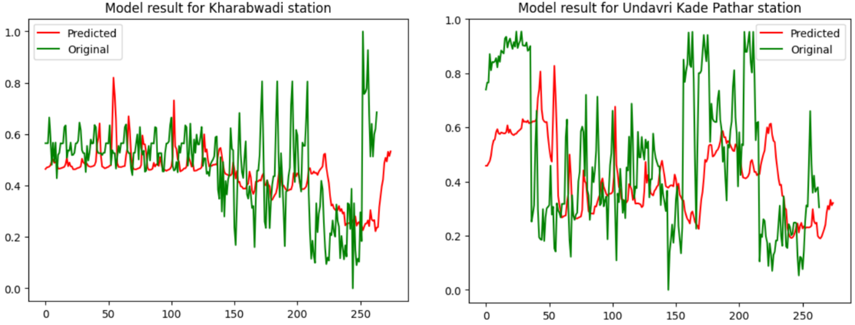
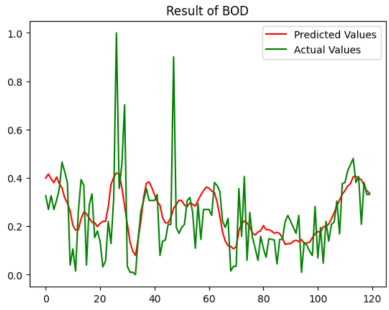


Figure: Groundwater level model

Results III



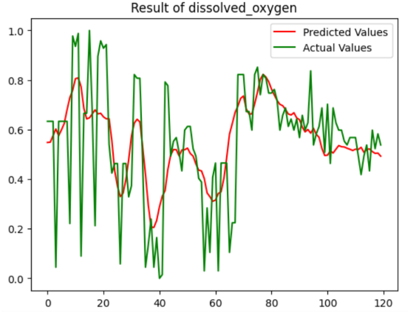


Figure: Results of Water Quality model

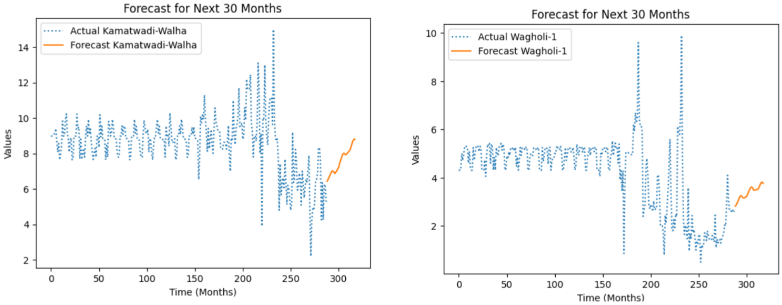


Figure: Forecasting Groundwater Levels at Various Stations

Thankyou!!