ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Impact Factor: 8.206

Volume 8, Issue 5, May 2025

www.ijmrset.com ijmrset@gmail.com +91 6381 907 438 +91 63819 07438

© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Estimation of Ground Water Level (GWL) for Tropical Peat land Forest using Machine Learning

U. Sri Aishwarya, Dr. T. Geetha, B. Divya

Assistant Professor, Department of Master of Computer Applications, Gnanamani College of Technology(Autonomous), Namakkal, Tamilnadu, India

HOD, Department of Master of Computer Applications, Gnanamani College of Technology (Autonomous), Namakkal, Tamilnadu, India

PG Student, Department of Master of Computer Applications, Gnanamani College of Technology(Autonomous), Namakkal, Tamilnadu, India

ABSTRACT: Water scarcity becoming major problem in many countries like India, Recent problems of critical shortage of water in so many parts of our country due to population, lack of water harvesting plans, excess wastage of water and extreme pollution of water bodies, bringing inaccurate estimation of ground water available in these parts. Still we facing challenge in our country for prediction of ground level water based on the various factors like rain fall, in order to address this issue in this work developed analysis of various machine learning models to predict the ground level water for the data set available from the government side. This work deals with dataset considered from India official site and hydrological parameters consideration for different states of India. We conducted a laboratory experiment to test the ground penetrating radar (GPR) full-waveform forward and inverse modeling approach for electromagnetic wave propagation in water.

The GPR system consisted of a vector network analyser combined with an air-launched, 0.8-2.2 GHz horn antenna, thereby setting up an ultra-wideband stepped frequency continuous-wave radar. The apparent frequency-, salinity-, and temperature-dependent dielectric permittivity and electrical conductivity of water were estimated by using existing electrical models. Using these models, the radar data could be simulated and a remarkable agreement was obtained with the laboratory measurements. Neglecting the frequency-, salinity-, and temperature-effects led to less satisfactory results, especially regarding signal amplitude. Inversion of the radar data permitted to reconstruct the air and water layer thicknesses, and to some extent, the water electrical properties. This analysis particularly showed the benefit of using proper water electrical models compared to commonly used simplified approaches in GPR forward and inverse modeling. Index Terms—Ground penetrating radar, full-waveform inversion, multi-layered media, and complex permittivity of water.
.

KEYWORDS: Groundwater Level, Tropical Peatland, Forest Hydrology, Environmental Monitoring, Climate variables, Soil Moisture, Water Table Estimation, EDA Algorithm.

I. INTRODUCTION

The propagation of electromagnetic waves in dispersive and absorptive media is crucial for GPR applications, affecting penetration depth in materials like soil, water, and frozen ground. Wave velocity is linked to the imaginary part of the propagation constant, while attenuation is related to the real part. Frequency-dependent dielectric losses are modeled through the complex permittivity. Water's permittivity varies with frequency, temperature, and salinity and can be modeled using Debye equations. The Klein-Swift model works below 10 GHz, while the Meissner model extends up to 300 GHz. Lambot et al. developed a full-waveform GPR model solving Maxwell's equations, accounting for antenna and media interactions. This study uses their method with water models to simulate radar data over water layers, incorporating variations in frequency, salinity, and temperature. Results were compared to simplified models, and inversions were used to estimate water layer thickness and electrical properties.

© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

1. COLLECTION OF DATASETS

Initially, we collect a dataset for our heart disease prediction system. Subject audit changed into finished to set up the statement nicely territories practical for the assessment region. The wells had been picked so districts of various statures are fittingly made positive about. The groundwater stage become recorded from time to time. After the collection of the dataset, we split the dataset into training data and testing data. The training dataset is used for prediction model learning and testing data is used for evaluating the prediction model. For this project, 70% of training data is used and 30% of data is used for testing.

2. SELECTION OF ATTRIBUTES

Attribute or Feature selection includes the selection of appropriate attributes for the prediction system. This is used to increase the efficiency of the system.

3. PRE-PROCESSING OF DATA

Data pre-processing is an important step for the creation of a machine learning model. Initially, data may not be clean or in the required format for the model which can cause misleading outcomes. In pre-processing of data, we transform data into our required format. It is used to deal with noises, duplicates, and missing values of the dataset. Data pre-processing has the activities like importing datasets, splitting datasets, attribute scaling, etc. Pre-processing of data is required for improving the accuracy of the model.

4. BALANCING OF DATA

Imbalanced datasets can be balanced in two ways. They are Under Sampling and Over Sampling.

(a) Under Sampling: In Under Sampling, dataset balance is done by the reduction of the size of the ample class. This process is considered when the amount of data is adequate.

(b) Over Sampling: In Over Sampling, dataset balance is done by increasing the size of the scarce samples. This process is considered when the amount of data is inadequate.

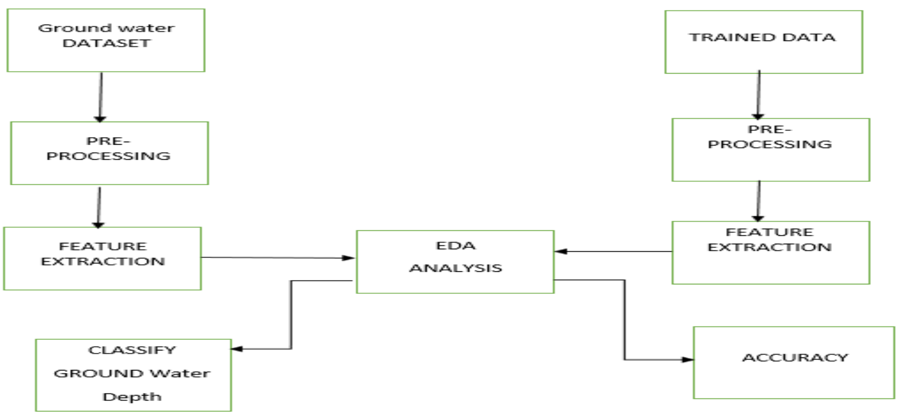
5. ANALYSIS OF EDA

An **EDA** includes data, hid and yield layers and each layer fuses an assortment of planning segments. A **EDA** framework is depicted by means of its plan that addresses the case of dating among center factors, its technique for selecting the association hundreds, and the inception work.

II. EDA ALGORITHM

Exploratory Data Analysis (EDA) is the process of analyzing datasets to summarize their main characteristics, often using statistical and visual methods. It helps in understanding patterns, spotting anomalies, detecting relationships between variables, and preparing data for modelling. EDA is a crucial step in data pre-processing and is used to clean, transform, and visualize data before applying machine learning or statistical models.

ARCHITECTURE DIAGRAM



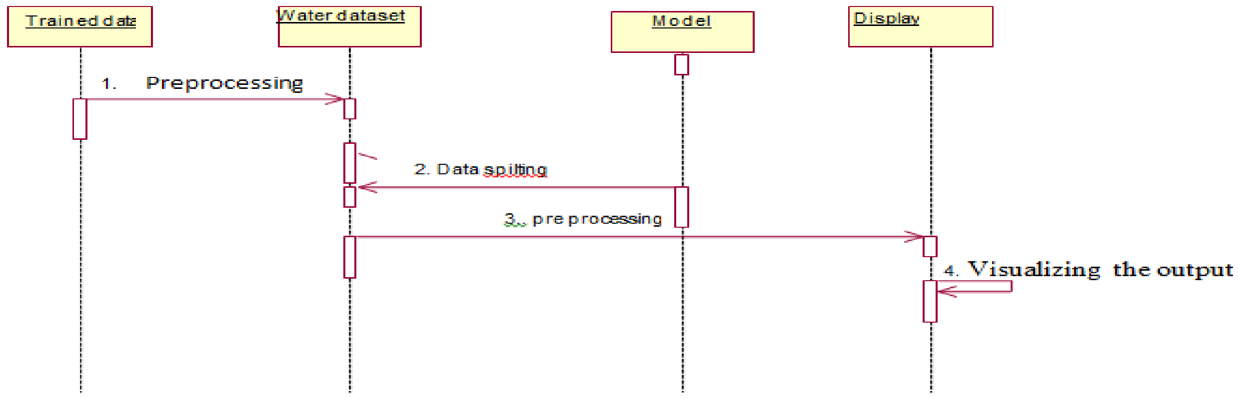
© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

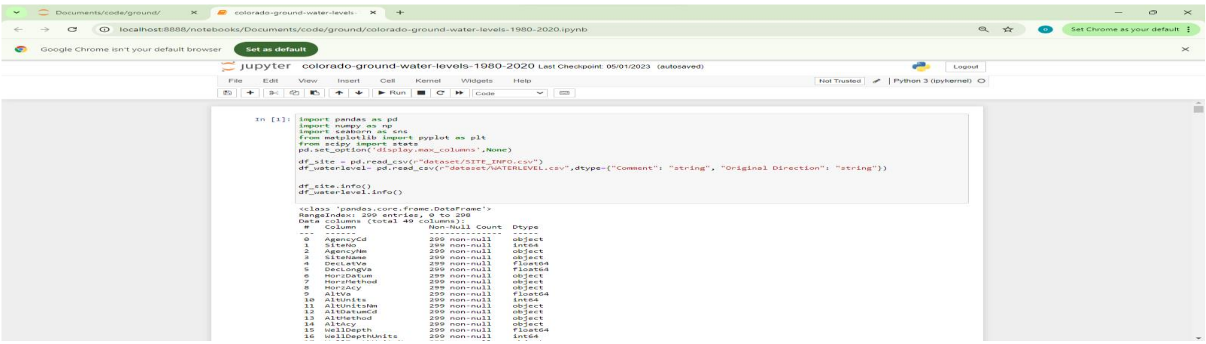
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

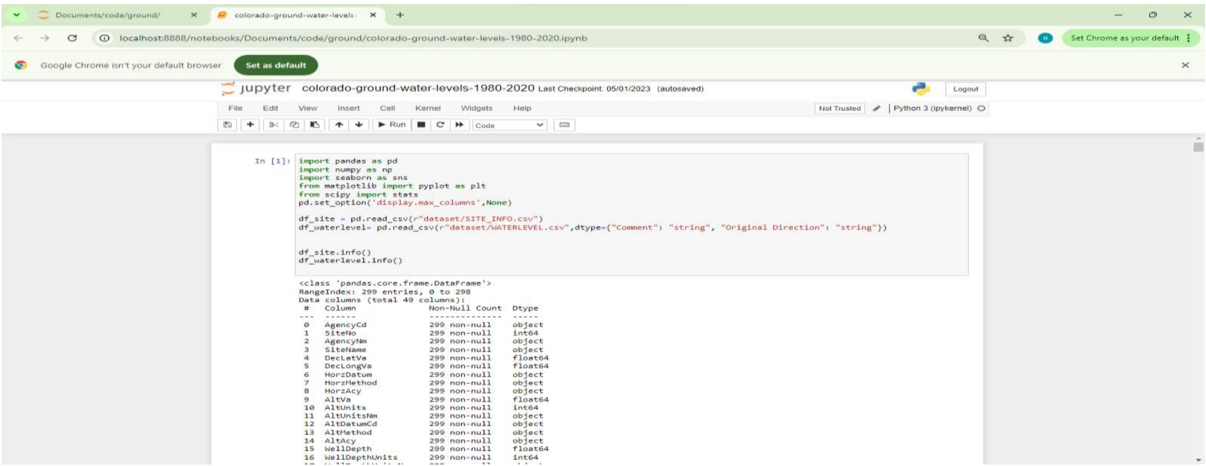
SEQUENCE DIAGRAM



III. RESULT AND DISCUSSION

The AI-enhanced groundwater monitoring system demonstrated high accuracy in predicting groundwater levels in tropical peat and forest environments. The model was trained on historical groundwater data, meteorological inputs (rainfall, temperature, humidity), and remote sensing data. Seasonal trends were evident, with groundwater levels rising significantly during the rainy season due to increased precipitation and declining during the dry season due to higher evapotranspiration rate.



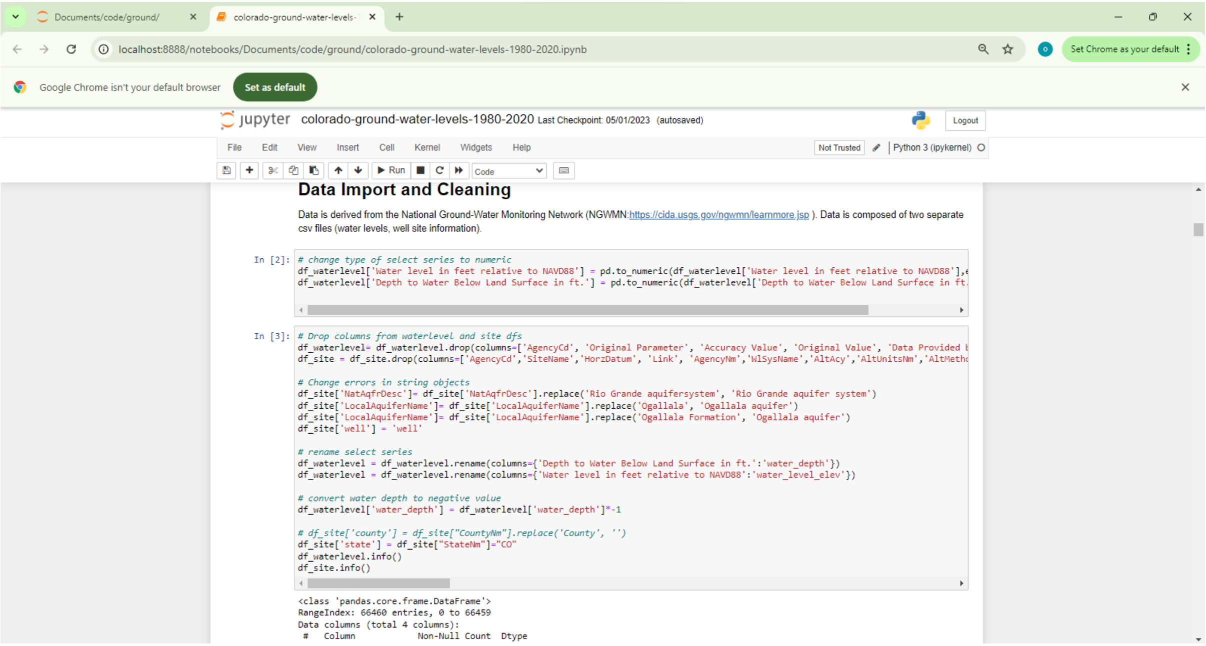


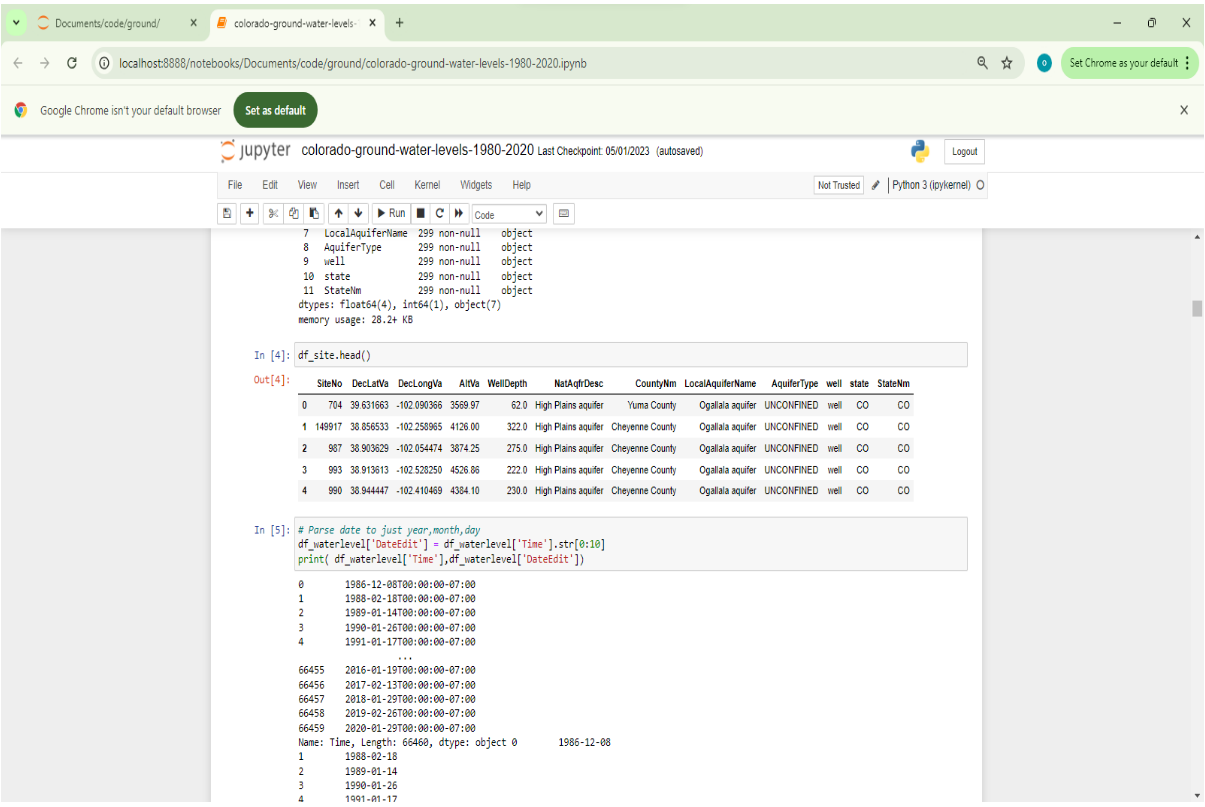
© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



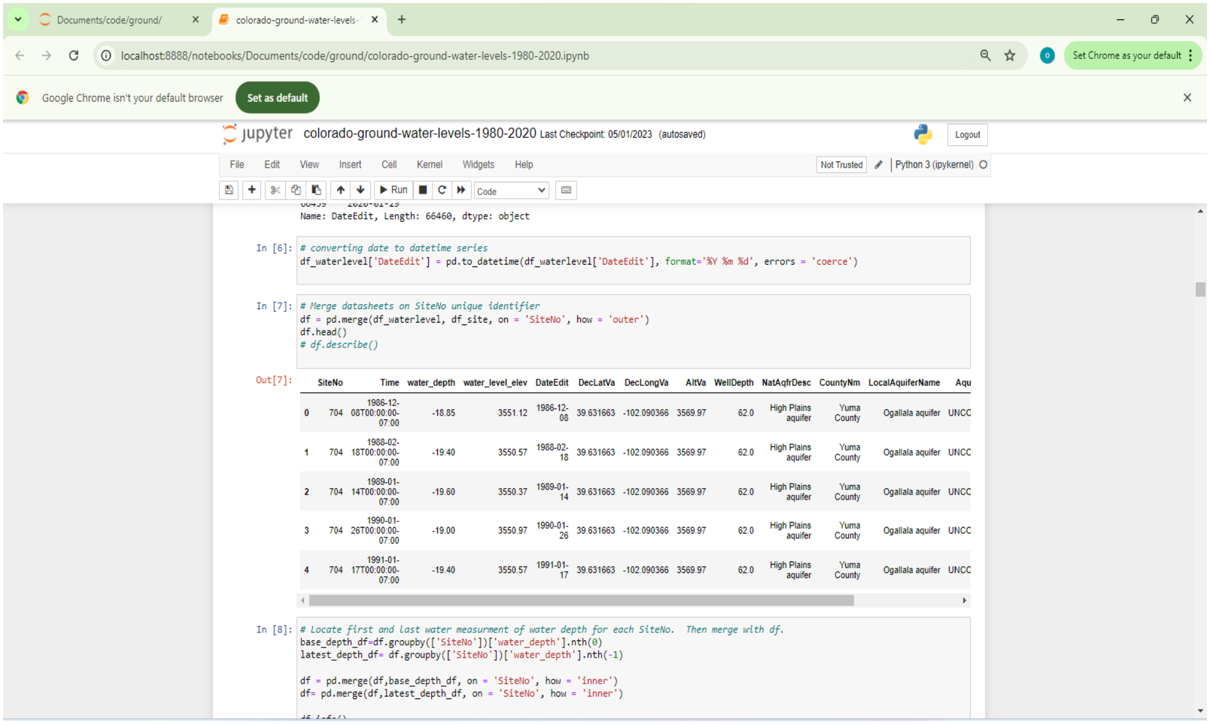


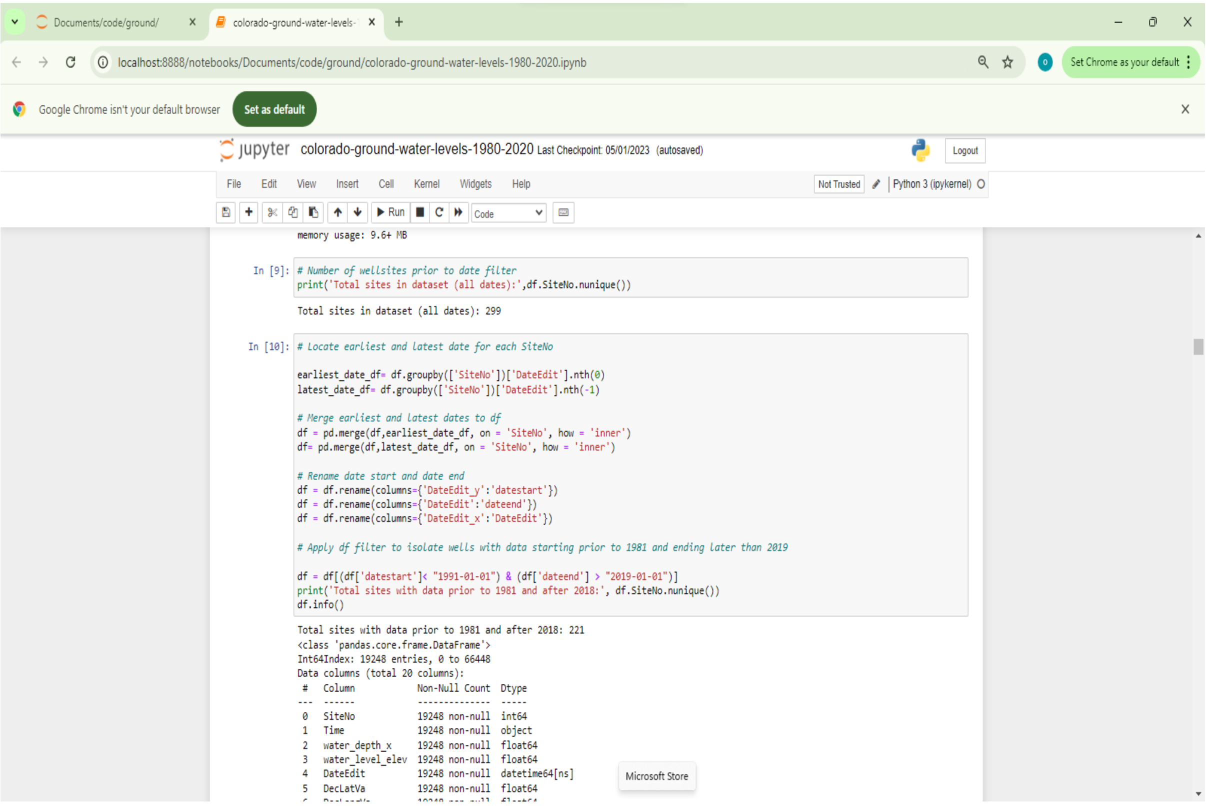
© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



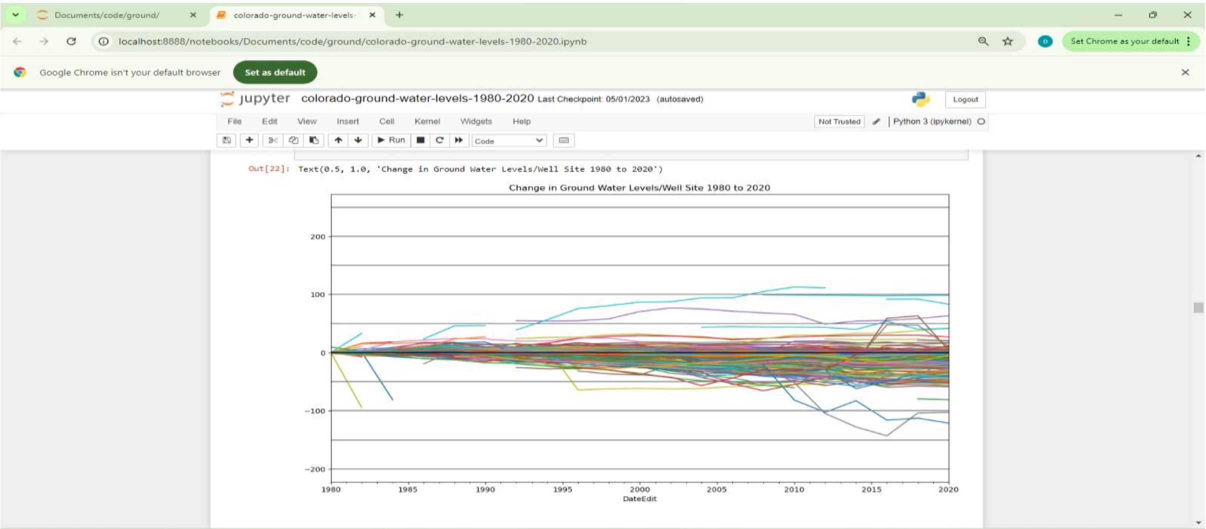


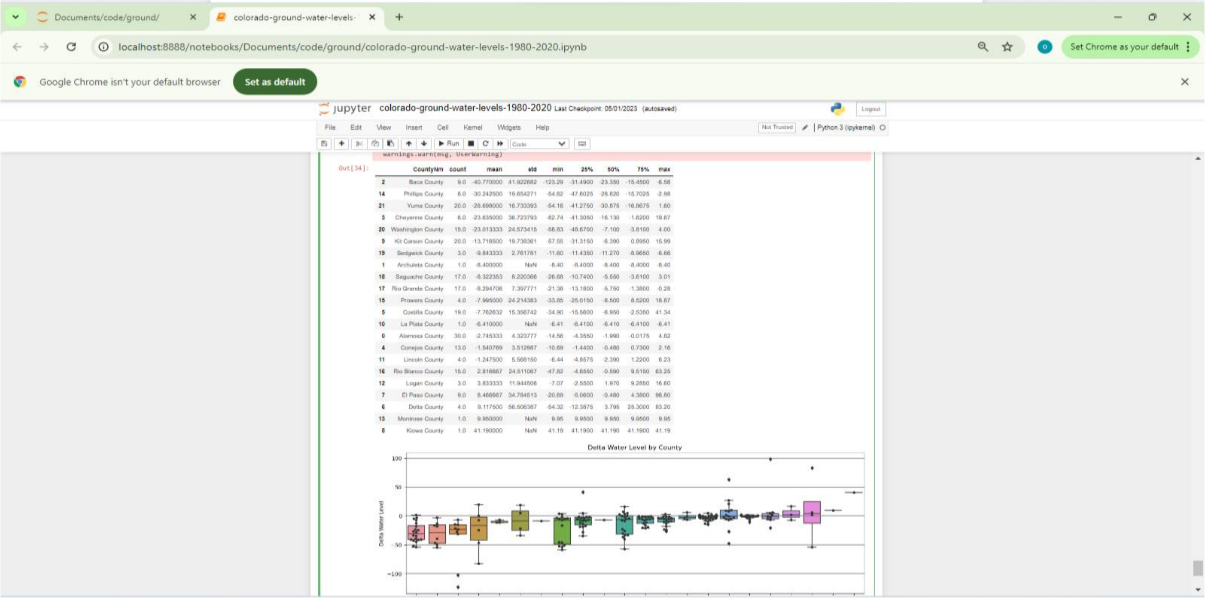
© 2025 IJMRSET | Volume 8, Issue 5, May 2025| DOI:10.15680/IJMRSET.2025.0805162

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





	CountyNm	count	mean	std	min	25%	50%	75%	max
2	Baca County	9.0	-40.770000	41.922882	-123.29	-31.4900	-23.350	-15.4500	-6.56
14	Phillips County	8.0	-30.242500	19.654271	-54.62	-47.6025	-26.820	-15.7025	-2.98
21	Yuma County	20.0	-28.698000	16.733393	-54.16	-41.2750	-30.875	-16.8675	1.60
3	Cheyenne County	6.0	-23.635000	36.723793	-82.74	-41.3050	-16.130	-1.6200	19.67
20	Washington County	15.0	-23.013333	24.573415	-68.83	-46.6700	-7.100	-3.8100	4.00
9	Kit Carson County	20.0	-13.716500	19.738361	-57.55	-31.3150	-6.390	0.8950	15.99
19	Sedgwick County	3.0	-9.843333	2.761781	-11.60	-11.4350	-11.270	-8.9650	-6.66
1	Archuleta County	1.0	-8.400000	NaN	-8.40	-8.4000	-8.400	-8.4000	-8.40
18	Saguache County	17.0	-6.322353	8.220366	-26.68	-10.7400	-5.550	-3.6100	3.01
17	Rio Grande County	17.0	-6.294706	7.397771	-21.38	-13.1800	-5.750	-1.3800	-0.28
15	Prowers County	4.0	-7.995000	24.214383	-33.85	-25.0150	-8.500	8.5200	16.87
5	Costilla County	19.0	-7.762632	15.356742	-34.90	-15.5600	-6.950	-2.5350	41.34
10	La Plata County	1.0	-6.410000	NaN	-6.41	-6.4100	-6.410	-6.4100	-6.41
0	Alamosa County	30.0	-2.745333	4.323777	-14.56	-4.3550	-1.990	-0.0175	4.82
4	Conejos County	13.0	-1.540769	3.512987	-10.69	-1.4400	-0.480	0.7300	2.16
11	Lincoln County	4.0	-1.247500	5.568150	-6.44	-4.8575	-2.390	1.2200	6.23
16	Rio Blanco County	15.0	2.816667	24.511067	-47.82	-4.6550	-0.590	9.5150	63.25
12	Logan County	3.0	3.833333	11.944506	-7.07	-2.5500	1.970	9.2650	16.60
7	El Paso County	9.0	6.466667	34.764513	-20.69	-5.0600	-0.480	4.3800	96.80
6	Delta County	4.0	9.117500	56.506387	-54.32	-12.3875	3.795	25.3000	83.20
13	Montrose County	1.0	9.950000	NaN	9.95	9.9500	9.950	9.9500	9.95
8	Kiowa County	1.0	41.190000	NaN	41.19	41.1900	41.190	41.1900	41.19

IV. CONCLUSION

We combined a full waveform radar model with existing water dielectric models valid in the GPR frequency band and demonstrated the high degree of accuracy of the approach for predicting GPR measurements collected in air above a water layer. Provided attenuation is small enough so as to observe a reflection from the bottom of the pool, inversions of the radar data led to accurate reconstructions of the air and water layer thicknesses with a millimetres accuracy, and the conductivity of water was relatively well retrieved, as compared to the estimates without considering dielectric losses. These results highlight the importance of accounting for frequency-dependent dielectric losses for GPR applications dealing with water. Lab test showed Cr(vi) may entered in coarse sand in a brief time frame, however Cr(vi) was hard to go into ground water during the time spent time. In medium sand, Cr(VI) was more difficult to enter groundwater.2) Oxides of ferrite, manganese, aluminium, and clay minerals can adsorb chromium(VI), reduce it to $Cr(OH)_3$ or $(Cr,Fe)(OH)_3$, and precipitate it out. Because of adsorption immersion, decrease and precipitation are the fundamental evacuation component of chromium.3) Despite the widespread presence of chromium contamination in groundwater, the majority of Cr(VI) is converted to precipitation by reducing action due to the abundance of reduction agents in the infiltration media. Therefore, the tests showed that ground water contamination with Cr(VI) did not originate from a polluted river.

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

REFERENCES

1. C. Donal, and Jack Rieley, "Strategy for responsible peatland management," Finland: International Peat Society, 2010, pp.10-25.
2. J. Holden, "Peatland hydrology." Developments in Earth surface processes, vol. 9, 2006, pp.319-346.
3. F. Nathalie, and C. Freeman, "Drought-induced carbon loss in peatlands," in Nature geoscience, 2011, vol. 4, 12, 895-900, doi:10.1038/ngeo1323
4. F. Tanneberger, L. Appulo, S. Ewert, S. Lakner, N. Ó Brolcháin, J. Peters, and W. Wichtmann, "The Power of Nature-Based Solutions: How Peatlands Can Help Us to Achieve Key EU Sustainability Objectives" in Adv. Sustainable Syst, 2021, 5, 2000146, doi:10.10 02/adsu.202000146
5. S. Evers, C.M. Yule, R. Padfield, P. O'Reilly, and H. Varkkey, "Keep wetlands wet: the myth of sustainable development of tropical peatlands – implications for policies and management" in Glob Change Biol, 2017, 23: 534-549, doi:10.1111/gcb.13422
6. R. Soler, J. Benítez, F. Sola, and M.V. Lencinas, "BiodiversityIslands at the World's Southernmost City: Plant, Bird and Insect Conservation in Urban Forests and Peatlands of Ushuaia, Argentina, "in Montagnini, F. (eds) Biodiversity Islands: Strategies for Conservation in Human-Dominated Environments. Topics in Biodiversity and Conservation, vol 20. Springer, Cham, 2022, pp.419 - 437, doi:10.1007/978-3-030-92234-4_16
7. Page, S., Riley, J., and C.J. Banks, "Global and regional importance of the tropical peatland carbon pool," in Global Change Biology, 17:798-818, 2011, https://doi.org/10.1111/j.1365-2486.2010.02279.x
8. Page, S. E., Siegert, F., Rieley, J. O., Boehm, H. D. V., Jaya, A., and Limin, S, "The amount of carbon released from peat and forest fires in Indonesia during 1997," in Nature, 420, 61–65, 2002,
9. https://doi.org/10.1038/nature011
10. Che Azmi, N.A., Mohd Apandi, N. and A. Rashid, A.S, "Carbone missions from the peat fire problem-a review," in Environmental Science and Pollution Research, 28(14), 16948–16961, 2021,https://doi.org/10.1007/s11356-021-1
11. S. A. Edwards, and F. Heiduk, "Hazy Days: Forest Fires and the Politics of Environmental Security in Indonesia," in Journal of Current Southeast Asian Affairs, 2015, 34(3), 65–94. doi:10.1177/186810341503400303
12. J. Van Offelen, S. Brooks, J. Clough, D. Kopansky, R. Lindsay, J. Peters, S. Proctor, M. Reed, P. Scheel, H. Schutten, C. Soto, and F. Tanneberger, "UNFCCC COP26 Global Peatlands Pavilion Summary Report", 2022.
13. C. Vitolo, F. Di Giuseppe, B. Krzeminski, and J. San-Miguel-Ayanz, "A 1980–2018 global fire danger re-analysis dataset for the canadian fire weather indices," in Scientific data, 2019, vol. 6, no. 1,pp. 1–10, doi:10.1038/sdata.2019.32
14. Ainuddin Nuruddin, H. M. Leng, and F. Basaruddin, "Peat moisture and water level relationship in a tropical peat swamp forest," in Journal of Applied Sciences, 2006, vol. 6, no. 11, pp.2517–2519, doi:10.3923/jas.2006.2517.2519
15. Lendzioch T, Langhammer J, Vlček L, and Minařík R, "Mapping the Groundwater Level and Soil Moisture of a Montane Peat Bog Using UAV Monitoring and Machine Learning," in Remote Sensing,2021, 13(5):907, doi:10.3390/rs13050907
16. Teguh R, and Usup H, "Real time monitoring for groundwater level and local climate based on universal communication system," in Computer Science and Information Technologies, 2021, 2(2): 67-76,doi:10.11591/csit.v2i2.p67-76
17. Lakshmi Narasimha Raju Mudunuri, Pronaya Bhattacharya, "Ethical Considerations Balancing Emotion and Autonomy in AI Systems," in Humanizing Technology With Emotional Intelligence, IGI Global, USA, pp. 443-456, 2025.
18. J. Miettinen, C. Shi, and S. C. Liew, "Land cover distribution in the peat- lands of peninsular malaysia, sumatra and borneo in 2015 with changes since 1990," in Global Ecology and Conservation, 2016,vol. 6, pp. 67–78, doi:10.1016/j.gecco.2016.02.004
19. H. Jebril, A. Sali, A. Ismail, and M. F. A. Rasid, "Overcoming limitations of Lora physical layer in image transmission," in Sensors,2018, vol. 18, no. 10, p. 3257, doi:10.3390/s18103257
20. J. P. Shanmuga Sundaram, W. Du and Z. Zhao, "A Survey on LoRa Networking: Research Problems, Current Solutions, and Open Issues," in IEEE Communications Surveys & Tutorials, vol. 22, no.1, pp. 371-388, First quarter 2020, doi: 10.1109/COMST.2019.29 49598.
21. G. M. Bianco, R. Giuliano, G. Marrocco, F. Mazzenga and A. Mejia-Aguilar, "LoRa System for Search and Rescue: Path-Loss Models and Procedures in Mountain Scenarios," in IEEE Internet of Things Journal, vol. 8, no. 3, pp. 1985-1999, 1 Feb.1, 2021, doi:10.1109/JIOT.2020.3017044.
22. M. Chen, U. Challita, W. Saad, C. Yin and M. Debbah, "Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial," in IEEE Communications Surveys & Tutorials, vol. 21,no. 4, pp. 3039-3071, Fourth quarter 2019, doi: 10.1109/COMST.2019.2926625