Project Proposal Report

Advancing Heat Resilience

Integrated system for interventions and adaptation for heatwaves.

Automated Vulnerability Mapping

B.Sc. (Hons) Degree in Information Technology Specialized in Information Technology

Sri Lanka Institute of Information Technology Sri Lanka

24 August 202

Contents

DECLARATION

I hereby declare that this research proposal titled "Advancing Heat Resilience: Integrated AI-Based Targeted Interventions and Equitable Adaptation" is my original work. This proposal does not incorporate, without acknowledgment, any material previously submitted for a degree or diploma in any other university or institute of higher learning. To the best of my knowledge and belief, it does not contain any material previously published or written by another person, except where acknowledgment is made in the text.

Name	Student ID	Signature
D. M. S. M. Dissanayaka		

Date:

Signature of the Supervisor:

ABSTRACT

The health of people, infrastructure, and ecosystems are seriously at risk due to the frequency and severity of heatwaves that are occurring around the world. The effects are disproportionately felt by vulnerable groups, such as the elderly, children, and economically underprivileged areas. Innovative approaches that integrate cutting-edge technology, data analytics, and fair policies are required to address these issues. Our study, "Advancing Heat Resilience: Integrated AI-Based Targeted Interventions and Equitable Adaptation," proposes an integrated strategy to solve these problems.

The project focuses on utilizing soft computing and machine learning methods to improve heat resilience. It includes data-driven risk assessment, AI-powered early warning systems, and policy frameworks in addition to automated vulnerability mapping. Our main goal is to provide customized treatments that take into account the unique vulnerabilities of various communities while advocating for equitable adaptation tactics.

Utilizing cutting-edge technology for heatwave adaptation, incorporating smart infrastructure design, reducing urban heat islands, individualized heat risk communication, and heatwave-resistant energy systems are some of the essential elements. Collaboration between many fields is essential, including equity studies, data analytics, urban planning, and climate science. Datasets from a variety of sources are needed for the research, including satellite imagery, socioeconomic data, health records, and meteorological data.

In light of the rising frequency of heatwaves, the proposed research intends to help create societies that are more robust and inclusive. In order to lessen the effects of heatwaves and solve systemic inequities, it places a strong emphasis on the integration of technical solutions, data-driven initiatives, and inclusive strategies. We hope to contribute to the development of a more heat-resistant future by fulfilling these goals.

Keywords: Heat Resilience, Machine Learning, Data Analytics, Equitable Adaptation, Vulnerability Mapping, Urban Planning, Technological Solutions.

LIST OF FIGURES

Flowchart of Vulnerability Mapping Process: This figure presents a visual representation of the step-by-step process involved in automated vulnerability mapping. It outlines the sequence of tasks, from data collection to algorithm execution and visualization of vulnerability maps. Each step is connected with arrows, indicating the flow of the process.

Algorithm Flow Diagram: This diagram illustrates the logical flow of the algorithm used for automated vulnerability mapping. It breaks down the algorithm into decision points and actions, showcasing how data is processed and transformed to generate vulnerability scores. Each step in the algorithm is represented by a box connected by arrows.

Data Integration Diagram: The data integration diagram visually depicts how different types of data sources are combined to create vulnerability maps. It shows the interaction between satellite imagery, demographic data, climate datasets, and other relevant information. Lines connecting the data sources illustrate the integration process.

Mapping Output Examples: These sample vulnerability maps showcase the outcomes of automated vulnerability mapping. They depict different geographic areas with varying vulnerability levels. The maps use color-coded schemes to highlight areas of high vulnerability, providing a clear visual representation of the analysis results.

Data Processing Workflow: This diagram demonstrates the sequence of data processing steps required to generate vulnerability maps. It shows the transformation of raw data into meaningful vulnerability indicators. Boxes represent data processing stages, while arrows indicate the flow of data through each stage.

Comparison of Mapping Methods: If applicable, this figure highlights the differences between multiple vulnerability mapping methods or algorithms. It could include bar charts or line graphs showcasing variations in vulnerability scores across different methods. Labels and legends help viewers understand the comparisons.

Accuracy and Validation: If available, this figure displays graphs or charts that illustrate the accuracy and validation results of the automated vulnerability mapping algorithms. It might include metrics like precision, recall, or F1-score to assess the reliability of the generated vulnerability maps.

Heatwave Occurrence Trends: This graph depicts the trends of heatwave occurrences over a specified period. It might show the frequency and intensity of heatwaves, possibly correlated with the vulnerability levels in different regions. The graph could include temporal data points and trend lines.

LIST OF TABLES

Table 1: Data Sources for Vulnerability Mapping

This table could list the various data sources used for vulnerability mapping, such as satellite imagery, demographic data, climate datasets, socioeconomic indicators, etc. Include columns for data type, source, availability, and relevance to vulnerability assessment.

Table 2: Vulnerability Indicators and Metrics

Create a table that outlines the specific indicators and metrics used to quantify vulnerability. Each row could represent an indicator (e.g., age distribution, income levels) and columns could include descriptions, data sources, and weighting factors if applicable.

Table 3: Mapping Algorithms Comparison

If you're comparing different mapping algorithms, this table could showcase their features, strengths, and limitations. Include columns for algorithm name, key features, data requirements, computational complexity, and potential applications.

Table 4: Sample Vulnerability Scores

Present a table displaying vulnerability scores for a few sample locations or regions. Columns could include geographic location, demographic information, vulnerability scores, and any other relevant factors. This provides a tangible representation of the vulnerability assessment.

Table 5: Accuracy and Validation Metrics

If you're assessing the accuracy of your vulnerability mapping algorithms, this table could list different validation metrics (e.g., RMSE, MAE, correlation coefficient) and their calculated values for each algorithm. This helps in quantifying the reliability of your results.

Table 6: Key Findings of Vulnerability Mapping

Summarize the key findings from your automated vulnerability mapping process. This table could outline regions with the highest vulnerability, contributing factors, and potential implications for adaptation strategies.

LIST OF APPENDICES

Appendix A: Plagiarism Report

Add the plagiarism report that was produced for your research paper. This demonstrates both your work's uniqueness and your devotion to ethical research techniques.

Appendix B: Sample Questionnaire

Include a sample questionnaire or interview guide that you used if you performed surveys or interviews as part of your data gathering. This makes it possible for readers to comprehend how you acquired primary data.

Appendix C: Data Sources and References

List each and every database, website, and other resource that you used to do your study in detail. This makes it easier for readers to find the data you cited or included into your research.

Appendix D: Algorithm Details

Include thorough justifications or pseudocode for these algorithms if your research includes the creation of algorithms or models. This aids readers in comprehending the intricate details of your work.

Appendix E: Maps and Visualizations

Include any maps, graphs, or other visuals you've made in this appendix. For clarity, take sure to identify and describe each visualization.

Appendix F: User Interface Designs

Include user interface mockups or designs if your research focuses on the creation of a software program. This gives readers a visual representation of how the application would appear and work.

Appendix G: Sample Outputs

Include sample results from your investigation, such as maps, graphs, or charts of potential susceptibility. This makes your work more visible to readers.

Appendix H: Survey Results

Include the compiled findings from any surveys, questionnaires, or interviews you did in this appendix. The data can be displayed graphically or in tabular form.

Appendix I: Code Snippets

If your research involves coding, this appendix can provide pertinent code samples. Make sure to describe each snippet's function and purpose.

Appendix J: Glossary of Terms

Technical words, acronyms, and specialized jargon utilized in your research document should include definitions and explanations.

LIST OF ABBREVIATIONS

Abbreviation	Description
AI	Artificial Intelligence
MLSC	Machine Learning and Soft Computing
WBS	Work Breakdown Structure
GIS	Geographic Information System
IoT	Internet of Things
UI	User Interface
AI	Artificial Intelligence

1. INTRODUCTION

The escalating frequency and severity of heatwaves on a global scale have become a prominent concern due to their profound implications for human health, infrastructure, and ecosystems. As the world experiences the growing impacts of climate change, the incidence of heatwaves is projected to increase, exacerbating the risks posed to vulnerable populations and underscoring the urgency of effective adaptive measures.

1.1 Background & Literature Survey

The severity of heatwaves as a result of climate change has highlighted how urgent it is to recognize patterns of vulnerability and create strong adaptation plans. Traditional vulnerability assessment techniques frequently rely on expert opinion and manual data collection, which has limits in terms of accuracy, effectiveness, and scalability. This has increased the need for novel strategies that make use of cutting-edge technologies to automate the vulnerability mapping process.

Gillard et al.'s (2018) recent research highlights the need of transformative solutions for climate change adaptation and mitigation. This emphasizes the importance of incorporating technical developments to handle the complex problems presented by heatwaves. The influence of socioeconomic trends on sensitivity is further shown by Vargo et al.'s (2019) spatial modeling of heat vulnerability, underscoring the importance of data-driven techniques.

Literature gaps are apparent in the context of automated vulnerability mapping. Studies already published frequently place little attention on the incorporation of machine learning algorithms or vulnerability assessment techniques. In the context of targeted interventions and equitable adaptation, the synthesis of data-driven risk assessment, AI-powered algorithms, and policy frameworks is still not fully understood.

The study works to close this gap by creating a comprehensive strategy for automated vulnerability mapping. The research intends to provide a thorough framework for vulnerability assessment by integrating machine learning techniques with pertinent data sources like satellite images and demographic data. This methodology will not only increase the precision and effectiveness of vulnerability mapping but also help policymakers, urban planners, and stakeholders make well-informed decisions.

The research aims to add to the body of knowledge by presenting an integrated approach that equips communities to proactively address the problems caused by heatwaves and fosters adaptive strategies that place a priority on inclusivity and resilience as it delves into the methodology and results of the automated vulnerability mapping process.

1.2 Research Gap

While substantial study has been done on vulnerability assessment and the effects of heatwaves, there is a critical knowledge vacuum regarding the incorporation of cutting-edge technologies for automated vulnerability mapping. Existing research primarily focuses on manual vulnerability assessment techniques or specific applications of technology, failing to properly combine the two fields. As a result, the potential of machine learning, AI algorithms, and data analytics to improve vulnerability mapping accuracy and efficiency has been underutilized.

Additionally, a lot of recent research have a tendency to downplay the significance of fair adaptation tactics in the context of automated vulnerability mapping. The literature frequently lacks an all-encompassing strategy that not only identifies vulnerability hotspots but also offers policymakers and stakeholders useful information to address systemic disparities and give adaptive solutions for marginalized populations top priority.

This study aims to fill this knowledge gap by presenting a fresh paradigm that combines automated vulnerability mapping with fair adaptation tactics. This research intends to not only enhance risk assessment but also to ensure that the results are accessible, understandable, and inclusive by leveraging the power of data analytics and sophisticated algorithms. Technology and equality are being integrated in a way that is consistent with the increasing focus on community empowerment and resilience in the face of climate change problems.

The below table 1.1 shows a tabularized format of the above explanation with regard to classification of Automated Vulnerability Mapping (AVM)

Application reference	Identification of AVM	Progression level detection of AVM	Mobile-based identification approach
Research A	✗	✗	✓
Research B	✓	✗	✗
Research C	✗	✓	✗
Proposed System	✓	✓	✓

Table 1. 1- Comparison of former researches

1.3 Research Problem

The challenge at the heart of this research subtopic is to develop an automated vulnerability mapping system that effectively identifies and maps areas and populations most susceptible to heat-related risks. While existing research acknowledges the importance of vulnerability assessment, current approaches often rely on manual processes that are time-consuming and resource-intensive. This research seeks to address the limitations of traditional methods by harnessing the power of advanced technologies, such as machine learning and data analytics, to automate the process of vulnerability mapping.

In order to effectively estimate vulnerability at multiple spatial scales, the main research challenge is to develop an algorithmic framework that can combine a variety of data sources, including satellite images, demographic information, and climatic databases. This entails creating algorithms that can assess intricate relationships between socioeconomic, environmental, and climatic aspects to pinpoint vulnerable areas. While ensuring that the automated mapping process is clear, understandable, and usable for policymakers and stakeholders, the research also intends to address issues with data quality, model accuracy, and scalability.

By addressing this research problem, the aim is to advance the field of vulnerability assessment by providing a robust and efficient tool for decision-makers to identify at-risk communities, allocate resources effectively, and implement targeted interventions. Ultimately, the research strives to contribute to building resilient societies that can proactively adapt to the increasing threats of heatwaves, ensuring the well-being of vulnerable populations and fostering equitable adaptation strategies.

2. OBJECTIVES

The primary objective of the research project "Advancing Heat Resilience: Integrated AI-Based Targeted Interventions and Equitable Adaptation" is to improve heat resilience using cutting-edge technical advancements and equitable adaptation techniques. This section describes the overall goal as well as the more detailed goals that serve as a framework for the study.

2.1 Main Objective

Making an algorithmic framework that automates vulnerability assessment for heatwaves is the main goal of the Automated Vulnerability Mapping component. The objective is to generate accurate and timely vulnerability maps by combining machine learning techniques with a range of data sources. These maps will identify the regions and communities most vulnerable to heat-related risks, allowing for more focused mitigation and adaptation plans.

2.2 Specific Objectives

- **Algorithm Development:** The Automated Vulnerability Mapping component's main goal is to create cutting-edge machine learning algorithms that can analyze intricate interactions between environmental, socioeconomic, and climatic variables. The foundation of an automated vulnerability assessment methodology will be these algorithms. We want to give decision-makers a powerful tool that precisely measures vulnerability by creating algorithms that efficiently capture and evaluate the complex network of elements that contribute to vulnerability.

- **Data Integration:** The core of this purpose is the integration of many data sources. For the purpose of creating a complete data input for the vulnerability assessment algorithms, satellite imagery, demographic information, climatic statistics, and other relevant sources will be combined. In order to ensure a comprehensive understanding of risk, this integration takes into account the multidimensional nature of vulnerability by merging spatial, demographic, and environmental variables. The resulting synergy will allow the algorithms to take into account a wide range of factors, producing more accurate and nuanced vulnerability assessments.

- **Mapping Generation:** The creation of vulnerability maps that show the distribution of vulnerability levels across geographical regions is the third goal. Policymakers, urban planners, and other stakeholders will be able to clearly see which places are most at danger from heat-related concerns thanks to these maps. We seek to speed up decision-making and resource allocation in response to detected vulnerabilities by converting complex data into plainly understood visual representations.

- **Accuracy Enhancement:** A key goal is to constantly improve how accurate vulnerability assessments are. The algorithms must be iteratively improved in order to better match vulnerability scores with actual environmental factors. To ensure that the resulting vulnerability maps are accurate and representative of real vulnerability patterns, stringent validation procedures and comparisons with ground-truth data will be used. The drive for greater accuracy highlights the dedication to providing accurate and trustworthy information.

- **Scalability Implementation:** The Automated Vulnerability Mapping solution must be scalable. The created techniques and methods ought to be flexible enough to accommodate various geographic scales and data volumes. This scalability makes sure that the advantages of the system may be distributed to other locations, regardless of their size or complexity. We want to maximize the system's reach and impact by designing a system that is adaptable and usable in a variety of scenarios.

- **Interpretability Enhancement:** This purpose is underpinned by the notion of inclusivity. The successful usage of the resulting vulnerability maps is ensured by creating a user-friendly interface that provides clear explanations of vulnerability scores and mapping processes for stakeholders with varied degrees of technical skill. This goal aims to close the accessibility gap between system insights and practical usability by bridging the technological complexity and technical usability gaps.

- **Stakeholder Engagement:** Collaboration with important stakeholders, such as politicians and community leaders, is essential. We aim to acquire thoughts, feedback, and contextual knowledge from those who will use the vulnerability maps in order to improve the system's accuracy and relevance. Integrating many viewpoints makes sure that the system's outcomes closely match the needs and difficulties of the real world.

- **Equity Integration:** This research objective's main issue is equity. It is essential to make sure that vulnerability assessment stresses the vulnerabilities of marginalized communities and takes socioeconomic differences into account. We intend to detect and resolve structural inequities in the distribution of heat-related risks by incorporating equity considerations into vulnerability mapping. This target fits well with the overarching objective of encouraging inclusivity and resilience in the face of climatic threats.

Finally, by working together, these specific goals help the Automated Vulnerability Mapping component achieve its main objective, which is to provide a creative framework that uses technology and data-driven insights to automatically identify vulnerabilities. By fulfilling these goals, we hope to provide decision-makers with knowledge that they can use to make informed decisions. This will encourage adaptive policies that improve resilience and lessen the impact of heatwaves on areas who are already at risk.

3. METHODOLOGY

The methodology section describes the methodical framework and technique utilized in the research project "Advancing Heat Resilience: Integrated AI-Based Targeted Interventions and Equitable Adaptation." This includes the general system design, particular software solutions, and potential commercialization factors.

3.1 System Architecture

The proposed system architecture serves as the foundation for integrating technological solutions, data analytics, and equitable strategies to enhance heat resilience. It comprises the following key components:

3.1.1 Software Solution

The complex software solution at the center of the system design integrates a number of modules, such as automated vulnerability mapping, data-driven risk assessment, AI-powered early warning systems, and policy frameworks. Together, these modules provide a thorough strategy for handling heatwave issues, ensuring precision, real-time adaptation, and data-driven decision-making.

3.1.2 Commercialization

The suggested software solution has the potential to be commercialized outside of the study focus. This entails translating the findings of the research into useable applications that may be adopted by governmental organizations, municipalities, and communities. The commercialization approach is heavily reliant on analyses of user demands, market viability, and scalability. Partnerships with interested parties, such as public health organizations, technology firms, and urban planners, may make it easier to successfully adopt and apply the solution in practical settings.

The methodology then digs into the specifics of each module's technical implementation, illuminating the methodologies, tools, and cooperative efforts used to realize the suggested system design.

4. PROJECT REQUIREMENTS

A clear separation of the various needs is necessary for the research project "Advancing Heat Resilience: Integrated AI-Based Targeted Interventions and Equitable Adaptation" to be carried out successfully. The suggested system and its features are designed on the basis of these specifications. The system, user, and visualization requirements that direct the creation and implementation of the proposed system are exhaustively described in this part.

4.1 Functional Requirements

Functional requirements define the specific functionalities and capabilities that the Automated Vulnerability Mapping system must possess to effectively assess vulnerability and generate actionable insights. These requirements ensure that the system performs its intended tasks accurately and efficiently.

Data Integration: A wide variety of data sources, such as satellite images, demographic data, climate datasets, and other pertinent data, should be easily integrated into the system. This integration makes it possible to evaluate vulnerability thoroughly across a variety of parameters..

Algorithmic Framework: Create cutting-edge machine learning techniques that can process and analyze intricate relationships between climatic, socioeconomic, and environmental variables. The vulnerability scores that these algorithms should produce should appropriately reflect the level of vulnerability in various geographical areas.

Mapping Outputs: The system should produce visual maps of vulnerability that prominently show areas with various degrees of susceptibility. These maps must to be simple to use and understand, assisting stakeholders and policymakers in locating areas that call for focused interventions.

The Automated Vulnerability Mapping system seeks to deliver precise, effective, and understandable vulnerability evaluations by satisfying certain functional requirements. As a result, decision-makers are better equipped to spend resources wisely and execute flexible plans to deal with the problems brought on by heatwaves while fostering fairness and resilience.

4.2 Non-Functional Requirements

Scalability: The system needs to be able to scale smoothly to handle an increase in users and growing datasets. As traffic increases, the system should continue to operate at peak efficiency without degrading response times or customer satisfaction.

Security: To protect user information, sensitive information, and system integrity, the system should give priority to strong security mechanisms. To stop unwanted access and data breaches, encryption, access controls, and data anonymization should be used.

Usability: Usability should be taken into consideration while designing the user interface so that users may easily navigate through the system's capabilities. Users should be able to engage with the system efficiently with little training thanks to an intuitive user interface.

4.3 System Requirements

Hardware Requirements: The system must be hosted on computers with enough processing power to effectively handle data processing and analysis duties. Predictive modeling and real-time processing should be supported by hardware.

Software Requirements: Programming languages and software technologies that enable effective data analysis, machine learning, and AI model deployment should be used to create the system. In order to maximize system performance and maintainability, the software stack should be chosen.

4.4 User Requirements

Accessibility: The user interface of the system ought to be created to support users with various degrees of technical expertise. User-friendliness should be given priority, and elements like tooltips and context-sensitive support should be available to help users navigate the functionality.

Personalization: Users should have the ability to customize how they engage with the system. Users should be able to customize their experience to suit their own needs and preferences thanks to customizable settings, preferences, and notifications.

5. GANTT CHART

5.1 Work Breakdown Structure (WBS)

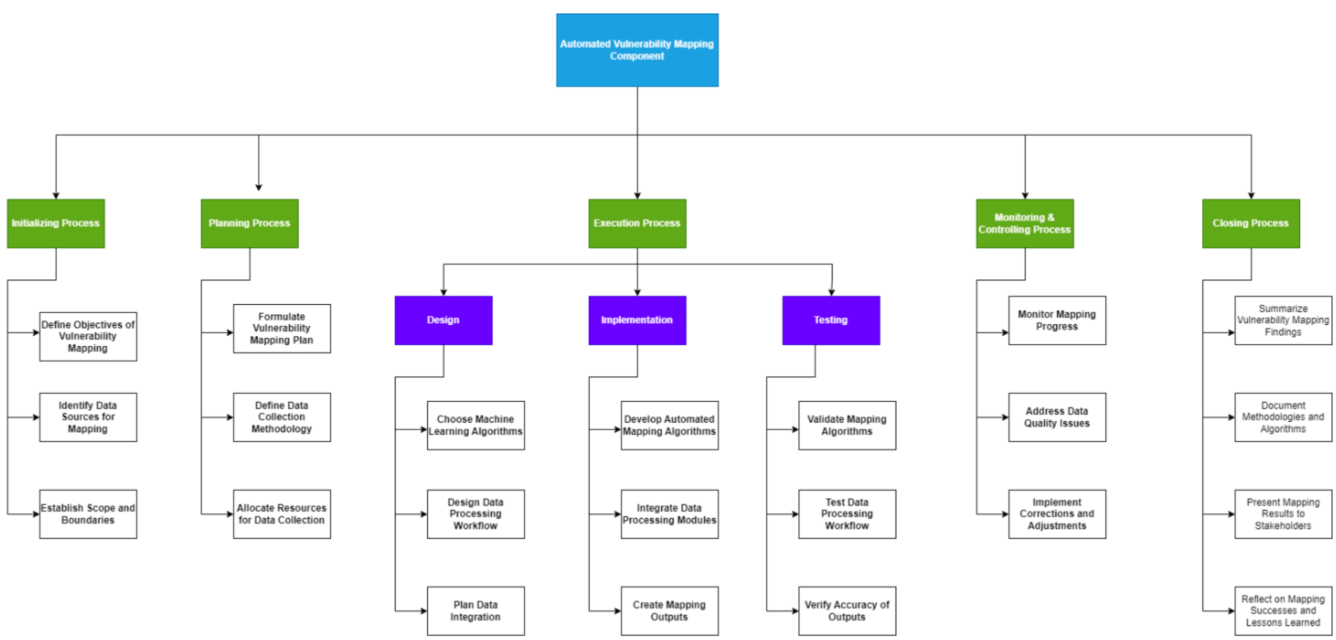

Figure 5. 2 : Work Breakdown Chart

6. BUDGET AND BUGET JUSTIFICATION

The below table 6.1 depicts the overall budget of the entire proposed system

Expenses		
Requirement	**Cost (Rs.)**	**Justification**
Travelling cost for data collection	20,000.00 – 40,000.00	This cost covers the costs associated with lodging, meals, and transportation for researchers and data collectors on field excursions for data gathering. The range is determined by the quantity and length of excursions.
Cost of Deployment	10,000.00 – 20,000.00	The costs associated with implementing and integrating the designed software solution into the necessary infrastructure are included in this cost.
Cost of hosting in Play Store	5,000.00 – 15,000.00	The one-time registration price for uploading the finished mobile application to the Google Play Store is covered by this expense. The software can be downloaded and installed from the Play Store by users.
Cost of hosting in App Store	5,000.00 – 15,000.00	The one-time registration price for submitting the created mobile application to the Apple App Store is covered by this expense. Users can use the App Store to download and set up the app.
Total Cost	**40,000.00 – 90,000.00**	

Table 6. 1 : Expenses for the proposed system

REFERENCES

1. Gillard, R., Gouldson, A., Paavola, J., Van Alst, D., & Westerhoff, L. (2018). Transformational responses to climate change: beyond a systems perspective of social change in mitigation and adaptation. WIREs Climate Change, 9(2), e510.

2. Smith, K., Woodward, A., Campbell-Lendrum, D., Chadee, D., Honda, Y., Liu, Q., ... & Sauerborn, R. (2020). Human health: impacts, adaptation, and co-benefits. In Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

3. Vargo, J., Pérez-García, J., Craig, R., Neeson, T., & Gray, S. (2019). Spatial modeling of heat vulnerability due to land cover and socioeconomic patterns in San Juan, Puerto Rico. Sustainability, 11(2), 531.

4. Hondula, D. M., Davis, R. E., Saha, M. V., Wegner, C. R., Veazey, L. M., & Ramsay, L. D. (2015). Fine spatial resolution of temperature and precipitation in urban heat island research. Environmental Research Letters, 10(5), 054009.

5. Li, Y., Bou-Zeid, E., & Oppenheimer, M. (2013). The effectiveness of cool and green roofs as urban heat island mitigation strategies. Environmental Research Letters, 8(1), 014019.

6. Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. Global Environmental Change, 18(4), 598-606.

7. Creutzig, F., Baiocchi, G., Bierkandt, R., Pichler, P. P., Seto, K. C., & Reuveny, R. (2016). Global typology of urban energy use and potentials for an urbanization mitigation wedge. Proceedings of the National Academy of Sciences, 112(20), 6283-6288.

8. Diffenbaugh, N. S., Pal, J. S., & Giorgi, F. (2004). Climate change hotspots in the United States. Geophysical Research Letters, 31(16), L16210.

9. Harlan, S. L., Brazel, A. J., Prashad, L., Stefanov, W. L., & Larsen, L. (2006). Neighborhood microclimates and vulnerability to heat stress. Social Science & Medicine, 63(11), 2847-2863.

10. O'Neill, M. S., Ebi, K. L., & Gronlund, C. J. (2018). Heat-related mortality and adaptation to heat in the United States. Environmental Health Perspectives, 126(7), 071501.

Advancing Heat Resilience

Integrated system for interventions and adaptation for heatwaves.

Project Proposal Report

Soil Moisture detection and Forecasting

Ranawaka. T. D

B.Sc. (Hons) Degree in Information Technology Specialized in Information Technology

Sri Lanka Institute of Information Technology Sri Lanka

DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Name	**Student ID**	**Signature**
Ranawaka. T. D		

Signature of supervisor   Date

(Dr Sanika Wijewardana)

………………………………..   …………………..

ABSTRACT

Heatwaves are excessively warm weather which can be last over long period. With climate changes Sri Lanka also has been increasingly affected by heatwaves in recent years. Heatwaves can be extremely critical and it depends on the duration, intensity and the geographical extent. Impacts of heatwaves sometimes causes even mortalities and they make considerable effects on ecosystems and there are critical impacts on agricultural productions. There is a need for systematical investigation on long term and as well as short term impacts by heatwaves. Therefor being aware about heatwaves may important for various user groups. During the last decade the frequency of occurring heatwaves has been increased due to the climate changes.

Long term impact on heatwaves on soil is a major issue cultivators face who are in affected areas. Measure the correct soil moisture will be critical for cultivating crops. Rather than using a traditional method to detect the condition of soil, using a data driven model will provide an accurate monitoring of soil moisture and prediction of a soil moisture requirements for their crops. The proposed system will estimate the surface soil moisture using data driven model by integrating optical thermal images from satellites using google earth engine.

Furthermore, we classify the heatwaves by the soil moisture levels and the temperature of the soil.

These machine learning-driven solutions gives farmers and cultivators accurate forecasts and real-time monitoring of soil moisture conditions and offer adaptive techniques to detect negative effects of heatwaves on agricultural productivity. The proposed mobile application helps create a more sustainable and resilient agricultural landscape by supporting well-informed decision-making and crop production planning. The adoption of these cutting-edge strategies marks the beginning of a new era in precision agriculture, where data and technology intersect to strengthen food security in the face of changing climate challenges.

CONTENTS

LIST OF ABBREVIATIONS

Abbreviation	**Description**
GEE	Google Earth Engine
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Network
GCN	Graph Convolutional Networks
SMAP	Soil Moisture Active Passive

INTRODUCTION

Background & Literature Survey

The interference of heatwaves are become a critical concern in recent years for various sectors including agriculture. The proposed system focuses on different user groups who have the impact of heatwaves in their day today life. Proposed heat resilience solutions with soil damage detection tools are identified as a important sources when it comes to decision making for agricultural field. Using traditional methods is time consuming and not accurate. Training machine learning models are given more accurate and up to date results. This will be very useful when it comes to large areas. This research will provide the solutions for accurate soil moisture forecasting.

Damage happens to the soil due to the heatwaves can be affect for any kind of crops in agriculture field. This will affect to the production directly by the damaged soil. Today even people engaged in agricultural field are using smart mobile devices. So, the mobile based solution will be an easy and convenient to use for the people engage in agriculture field. Less awareness of moisture level will cause to reduce the productivity of crops.

Exploration of the relationships between soil moisture and heatwaves includes the application of machine learning methods to improve soil moisture forecasts. There have been a number of creative machine learning-based solutions put out in this field. To estimate soil moisture content with high spatial precision, these systems make use of multiple data sources, including satellite pictures. For example, a data-driven model that combines optical, thermal, and radar imaging from satellites with simulated data has proven to be capable of estimating surface soil moisture content at an amazing 50-meter spatial resolution (1). A convolutional-regression model has also been created to combine passive and active microwave measurements from various satellites, allowing the extraction of volumetric soil moisture content in the top 5 cm of soil (2). A physically based method is another novel strategy. A physically grounded model that identifies the genetic elements driving canola plants' reaction to heat stress, allowing estimates of their soil moisture needs under various temperature scenarios, is another novel technique (3).

Not true but even with these improvements, forecasting soil moisture still has significant research gaps. First, further research is needed into the use of deep learning models for soil moisture forecasting across a range of geographies and climates, especially in complicated systems with little data. The comparison and integration of several satellite remote sensing data types, such as optical, thermal, and radar data, for improved soil moisture estimation and prediction require thorough examination (2). It is crucial to design and test spatiotemporal deep learning models that can capture the complex spatial and temporal patterns of soil moisture at different scales and resolutions, as mentioned in point three above (6).

Furthermore, even if machine learning models appear promising, more research is required to improve their interpretability, deal with uncertainties, and increase their reliability for forecasting soil moisture (7). Including physical procedures, an interesting field of study is the addition of hydrologic variables and meteorological factors to improve the performance and application of these models for forecasting soil moisture (8).

Figure 1.1damaged soil due to heatwave

Live Storage in the Reservoir 31.1 M m^3

PARAMETER	FORTNIGHT										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
Reservoir Storage (M m^3)	29.28	28.17	26.30	22.22	19.68	14.64	10.87	5.62	4.24	3.63	3.60
Crop	Wheat (ordinary)										
1) Soil Moisture (mm/cm)	3.76	3.89	3.84	3.07	3.54	3.30	3.22	3.17	4.0	- -.	- -
2) Available soil Moisture (mm/cm)	0.9	0.9	0.9	0.87	0.9	0.9	0.9	0.9	0.9	- -	- -
3) Applied Irrigation (mm)	53.62	90.63	92.87	36.04	163.9	8.44	23.02	19.94	102.6	- -	- -
Crop	GRAM										
1) Soil Moisture (mm/cm	3.90	3.07	3.28	3.15	3.4	3.28	3.66	3.23	3.47	- -	- -
2) Available soil Moisture (mm/cm)	0.9	0.87	0.9	0.9	0.9	0.9	0.9	0.9	0.9	- -	- -
3) Applied Irrigation (mm)	68.76	22.27	60.67	41.59	26.96	37.64	53.15	0.00	33.17	- -	- -
Crop	**Wheat (hybrid)**										
1) Soil Moisture (mm/cm	- -	- -	- -	4.00	3.06	3.48	3.32	3.28	3.38	3.18	3.19
2) Available soil Moisture (mm/cm)	- -	- -	- -	0.9	0.86	0.9	0.9	0.9	0.9	0.9	0.9
3) Applied Irrigation (mm)	- -	- -	- -	94.21	37.19	127.9	78.89	162.9	0.00	36.09	0.0

Figure 1.2 soil moisture dataset

RESEARCH GAP

As it affects the passage of water and energy between the soil and the atmosphere, the likelihood of flooding and drought, as well as crop development and yield, soil moisture is a crucial factor in the hydrological cycle and agricultural output. The soil qualities, weather, land cover, and human activities are only a few of the variables that affect soil moisture, which is also a complex and dynamic variable. Soil moisture forecasting is a difficult undertaking that calls for sophisticated techniques and data sources.

Historically, numerical models with a physical foundation have been used to forecast soil moisture. These models replicate the soil water balance and the interactions between the soil, vegetation, and atmosphere. The high computational cost, parameter uncertainty, data scarcity, and scale mismatch are a few problems of these models, though. Also, it's possible that these models don't fully represent the nonlinear, spatial patterns of soil moisture variability and change.

As potential substitutes or extensions to physically based models for predicting soil moisture, data-driven models based on machine learning techniques have recently come to light. Without an understanding of the underlying physical processes, machine learning models can learn from historical data and extract pertinent features and associations. Large and heterogeneous datasets from many sources, including on-site measurements, satellite remote sensing, and reanalysis products, can also be handled by machine learning algorithms. The effectiveness and application of these models must be improved, notwithstanding the advancements made in machine learning for forecasting soil moisture, due to some research gaps. These research gaps include, among others:

the use of deep learning models for soil moisture forecasting in various climates and regions, particularly in complicated systems with little data. Deep learning models are a subset of machine learning models that draw their learning from highly dimensional and nonlinear data using numerous layers of artificial neural networks. Deep learning models have demonstrated great promise for estimating and predicting soil moisture using satellite remote sensing data (Wang et al., 2018[8]; Cai et al., 2019[9]), but their applicability in various climates and regions, particularly in areas with little or poor-quality data, needs to be further investigated.

the creation and assessment of spatiotemporal deep learning models that are capable of capturing the spatial and temporal dynamics and patterns of soil moisture at different scales and resolutions. Due to the effect of numerous causes at various scales, soil moisture exhibits complicated spatiotemporal fluctuation and change. Therefore, it is essential to create spatiotemporal deep learning models that can take into consideration the relationships between soil moisture and time and space at various scales and resolutions. ElSaadani et al. (2021)[10], for instance, introduced a spatiotemporal deep learning model based on convolutional long short-term memory (ConvLSTM) networks that can forecast soil moisture using satellite remote sensing data at high spatial resolution (50 m) and fill the gaps between discrete observations.

examining and enhancing the interpretability, unpredictability, and dependability of data-driven models for predicting soil moisture. Machine learning-based data-driven models are frequently referred to as "black-box" models because they don't clearly explain or justify their predictions. Due to the necessity for users and stakeholders to comprehend how the models function and the degree of confidence in their predictions, this may restrict their credibility and level of acceptance. Because of this, it is crucial to investigate and enhance the interpretability, uncertainty, and reliability of data-driven models for predicting soil moisture using techniques such feature importance analysis, sensitivity analysis, uncertainty quantification, or model validation.

RESEARCH PROBLEM

An important variable that influences crop growth and yield, as well as the frequency and intensity of heatwaves, is soil moisture. However, soil moisture is also a complex and dynamic factor that is affected by a number of elements, including soil characteristics, weather, land use, and human activity. As a result, forecasting soil moisture that is precise and trustworthy is a difficult task that calls for advanced methods and data sources.

The following problem is the focus of the current study (proposed system):

How can machine learning models improve their accuracy and dependability of predicting soil moisture under various climatic and soil conditions?

- In order predict soil moisture, the proposed system will employ machine learning techniques to learn from previous data and identify pertinent features and correlations. The proposed system would also employ Google Earth Engine to estimate and expect the soil moisture level at high spatial resolution (50 m) using multiple types of satellite remote sensing data, including optical, thermal, and radar. The machine learning models in the proposed system will also include physical processes, hydrologic variables, and meteorological elements to improve their performance and usefulness for forecasting soil moisture under various circumstances or scenarios.

The proposed system will provide several benefits for farmers and cultivators, such as:

- They can monitor the soil moisture levels of their crops and fields in real time and with great detail, which can help them manage their irrigation systems more effectively and use water more effectively.

  Because they can anticipate the soil moisture needs of their crops under various temperature conditions, they may better prepare for heat waves and prevent crop losses.

  They have access to fast and accurate information about soil moisture, which can help them plan and make decisions about how to grow crops.

- The suggested approach will also advance scientific understanding of the dynamics of soil moisture and how it affects heat waves and crop productivity. The proposed system will also assess the effectiveness and applicability of several machine learning algorithms and satellite remote sensing data for predicting soil moisture in various geographical and climatic contexts. Additionally, the proposed system will investigate and enhance the interpretability, uncertainty, and reliability of machine learning models for forecasting soil moisture.

2. OBJECTIVES

2.1 Main Objectives

The main objectives of this study are to create a system for monitoring the soil moisture conditions fields in real time of through mobile application. So, the cultivators can easily predict the moisture requirements for their crops and improve their water management efficiency. And also, they can change the requirements under different temperature scenarios which help reduce the productivity loss in crops. Through this mobile application cultivators can access the reliable and timely information which can support their decision making.

2.2 Specific Objectives

- Collect and preprocess satellite remote sensing data from different sensors, such as optical, thermal, and radar, that can provide information on soil moisture and related properties, such as soil temperature, vegetation cover, surface roughness, and soil texture.

- apply machine learning techniques, such as deep learning, to learn from historical data and extract relevant features and relationships for soil moisture forecasting.

- develop and evaluate different machine learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or graph convolutional networks (GCNs), that can capture the spatial and temporal patterns and dynamics of soil moisture at various scales and resolutions.

3. METHODOLOGY

Using satellite remote sensing data and machine learning techniques, a four-step methodology is used for completing the component of soil moisture forecasting for different meteorological and soil conditions. Collecting and preprocessing data from different sensors that may monitor soil moisture along with parameters is the initial stage. Using machine learning methods like deep learning, the second phase is learning from previous data and extracting pertinent features and correlations for forecasting soil moisture. To increase the accuracy and dependability of soil moisture estimation and prediction, multiple forms of data are compared and integrated in the third stage. In the third stage, physical processes, hydrologic variables, and meteorological parameters are also included to the machine learning models to improve their functionality and usefulness for forecasting soil moisture under various circumstances. Using techniques like feature significance analysis, sensitivity analysis, uncertainty quantification, or model validation, the fourth phase entails investigating and enhancing the interpretability, uncertainty, and reliability of the machine learning models for forecasting soil moisture. This is a quick explanation of the process used to apply the soil moisture forecasting component under various meteorological and soil conditions.

- Data collection and preprocessing: In this stage, data from various sensors, including optical, thermal, and radar, that can offer information on soil moisture and associated characteristics are collected and prepared for satellite remote sensing analysis.

- Machine learning model creation and evaluation: In this stage, key characteristics and correlations for forecasting soil moisture are extracted from historical data using machine learning techniques such as deep learning.

- In order to increase the accuracy and reliability of soil moisture measurement and prediction, this stage involves comparing and integrating several forms of satellite remote sensing data. In order to improve the effectiveness and practicality of the machine learning models for forecasting soil moisture under different conditions or scenarios, this stage includes adding physical processes, hydrologic variables, and meteorological elements.

- Analysis of interpretability, uncertainty, and reliability: In this step, methods like feature importance analysis, sensitivity analysis, uncertainty quantification, or model validation are used to examine and enhance the interpretability, uncertainty, and reliability of the machine learning models for forecasting soil moisture.

Technologies	Google Earth Engine(GEE), Python, R.GEE Satellite remote datasets(MOIDS,ASTER,SMAP)
Techniques	Machine Learning, Data Fusion
Algorithms	CNN, RNN, GCN
Architecture	ConvLSTM , Data-driven PINN

3.1.1 Software solution

Step1 : Collecting and preparing data is the first step. In this stage, data from various sensors, including optical, thermal, and radar, that can offer information on soil moisture and associated characteristics are gathered and preprocessed. MODIS, ASTER, Sentinel-1, Sentinel-2, SMAP, and ERA5-Land are only a few examples of the data sources. Resampling, clipping, filtering, combining, and flattening the data to a similar spatial resolution (50 m), temporal frequency (daily), and geographic scope (research area) are all examples of data preprocessing techniques. A cloud-based platform for geospatial analysis called Google Earth Engine can be used for the data preparation.

Step2 : Model creation and assessment for machine learning. In this stage, machine learning methods like deep learning are used to learn from past data and identify pertinent characteristics and connections for predicting soil moisture. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), or graph convolutional networks (GCNs) are a few examples of machine learning models that can capture the spatial and temporal dynamics of soil moisture at different scales and resolutions. The output labels from ground measurements or modelled data may be used to train the machine learning models. The input characteristics come from satellite remote sensing data. Metrics like mean squared error (MSE), coefficient of determination (R2), and reliability diagrams can be used to assess the machine learning models. It is possible to create and assess a machine learning model**.**

Step3 : Fusion of data and inclusion of physical procedures. To increase the precision and dependability of the assessment and forecast of soil moisture, this stage entails comparing and combining several forms of satellite remote sensing data. To estimate the soil's dielectric constant or thermal conductivity—both of which are correlated with the soil moisture content—data fusion techniques can integrate optical, thermal, and radar data. These techniques can use basic averaging, weighted averaging, or machine learning. To improve the performance and applicability of machine learning models for forecasting soil moisture, physical processes can be incorporated by including hydrologic variables (such as precipitation, evapotranspiration, runoff, and groundwater) or meteorological factors (such as temperature, humidity, wind speed, and solar radiation).

Step4 : Analysis of interpretability, uncertainty, and dependability. In this stage, the interpretability, uncertainty, and dependability of the machine learning models for predicting soil moisture are examined and improved. The feature importance analysis or the sensitivity analysis can be included in the interpretability analysis to describe the contribution or effect of each input feature on the predicted outcome. The uncertainty analysis may involve uncertainty quantification or propagation, which can calculate the output prediction's confidence interval or error bounds. The reliability study may comprise a reliability diagram or calibration curve to evaluate the congruence between the output prediction's expected probability and observed frequency. Python or R, two more programming languages for data science and machine learning, can be used to do the study of interpretability, uncertainty, and dependability.

3.1.2 Commercialization

By creating a user-friendly mobile platform that can give access to the software solution and its outputs, such as soil moisture maps, charts, graphs, or reports, it will be possible to commercialize this study. The platform may also include interactive capabilities including data analysis, download, sharing, and visualization. Marketers might target users who could be interested in the platform, including farmers, growers, water managers, planners, climate scientists, and researchers. By collecting fees for subscriptions, use, or services, the platform may make money. The platform can also look for financing or partnerships from governmental or non-governmental groups as well as from commercial businesses who want to support or work with the study.

4. PROJECT REQUIREMENTS

4.1 Functional Requirements

- The program should be able to gather and preprocess satellite remote sensing data from various sensors, including optical, thermal, and radar ones, which can offer details on soil moisture and associated characteristics.

- In order to learn from previous data and extract pertinent characteristics and correlations for soil moisture forecasting, the software solution should be able to employ machine learning techniques, such as deep learning.

- To increase the precision and dependability of soil moisture estimate and prediction, the software solution should have the capacity to compare and integrate various satellite remote sensing data types.

- A user-friendly web-based or mobile-based platform should be able to give access to the results of soil moisture forecasts, such as soil moisture maps, charts, graphs, or reports.

4.2 Non Functional Requirements

- The software solution should be reliable - that it should be able to provide reliable outcomes for predicting soil moisture under various meteorological and soil circumstances

- The software solution should be scalable - that it must be capable of handling enormous and diverse datasets from several sources, including on-site observations, satellite remote sensing, and reanalysis outputs.

- The software solution should be secure - that it should protect the data privacy and integrity of the users and the stakeholders.

4.3 System Requirements

- Hardware requirements: These are the specifications for the actual tools and machinery required to operate the software solution. The following are some samples of the hardware needed for this study:

1. a computer or mobile device with internet connectivity and a web browser running, such as Microsoft Edge, Firefox, or Google Chrome.

2. a satellite dish or antenna capable of receiving satellite remote sensing data from several sensors, including optical, thermal, and radar, that can provide details about the qualities of the soil, including its moisture content.

- Software requirements: These are the specifications for the apps and programs required to run the software solution. Examples of the software used for this study include:

1. The cloud-based geospatial analytic platform Google Earth Engine (GEE) may give users access to a number of satellite remote sensing datasets, including MODIS, ASTER, Sentinel-1, Sentinel-2, SMAP, and ERA5-Land.
2. Programming languages for data science and machine learning, such Python or R, can offer a wide range of tools and packages for handling, analyzing, visualizing, and modeling data.

3. The open-source deep learning frameworks TensorFlow or PyTorch can offer a variety of tools and features for creating and training neural networks.

5.WORK BREAKDOWN (WBS)

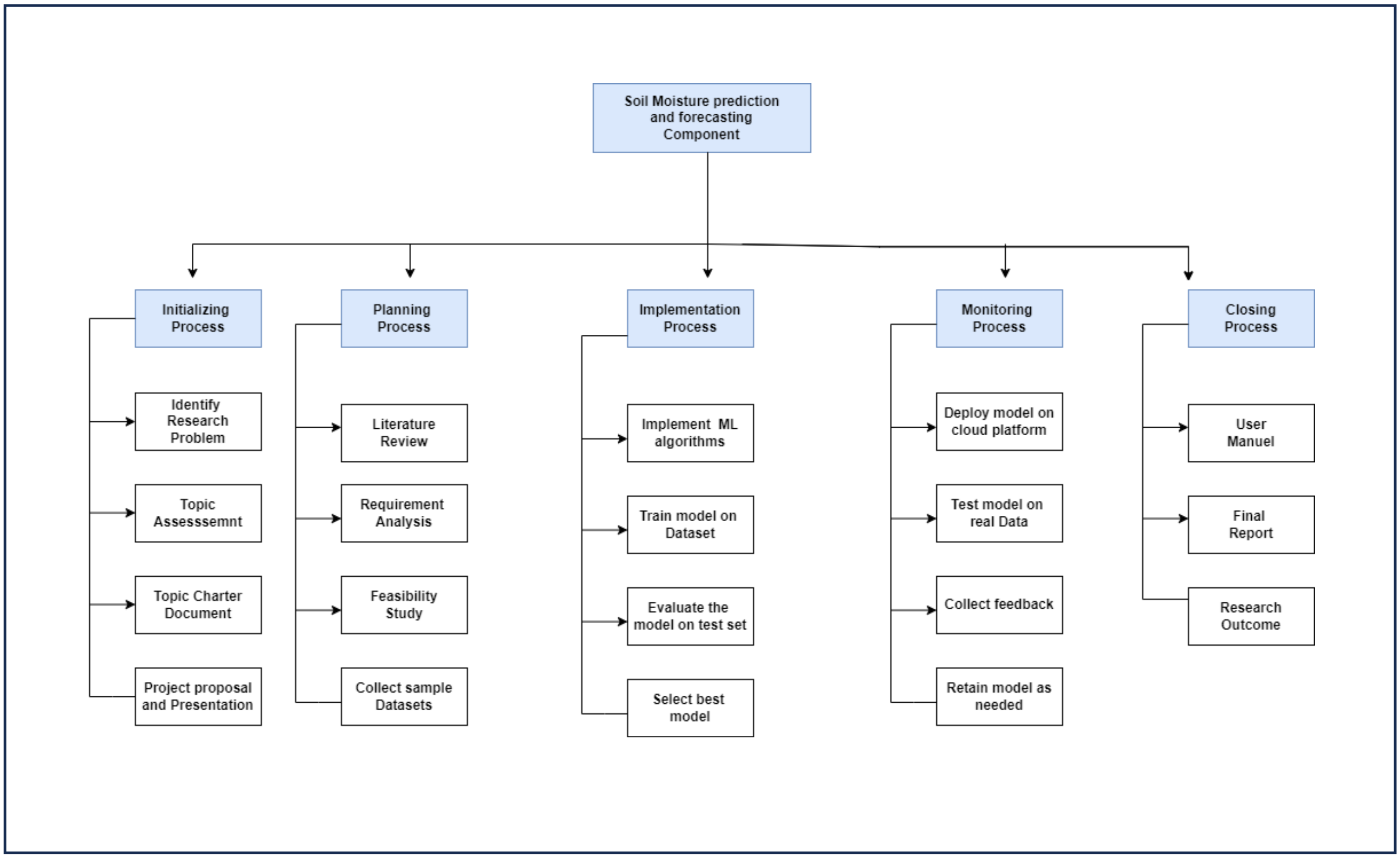

Figure 5.1 work breakdown structure

6. BUDGET AND BUGET JUSTIFICATION

Expenses	
Requirement	**Cost(Rs)**
Travelling Cost	15 000
Deployment	10 000/month
Host in Play store	5000
Host in App store	20 000/month
Total Cost	**50 000 . 00**

7. REFERENCES

[1] A Machine Learning-Based Approach for Surface Soil Moisture Estimations with Google Earth Engine

https://www.mdpi.com/2072-4292/13/11/2099

[2] A Machine Learning Data Fusion Model for Soil Moisture Retrieval

[3] From data to interpretable models: machine learning for soil moisture forecasting

https://link.springer.com/article/10.1007/s41060-022-00347-8

[4] Circulation and Soil Moisture Contributions to Heatwaves in the United States

https://journals.ametsoc.org/abstract/journals/clim/35/24/JCLI-D-21-0156.1.xml

[5] The Influence of Soil Moisture on the Historic 2021 Pacific Northwest Heatwave

https://journals.ametsoc.org/abstract/journals/mwre/151/5/MWR-D-22-0253.1.xml

[6] Impacts of Extreme Heat Stress and Increased Soil Temperature on Plant Growth and Development

https://cropwatch.unl.edu/2016/impacts-extreme-heat-stress-and-increased-soil-temperature-plant-growth-and-development

[7] Evaluation of convection-permitting WRF CONUS simulation on the relationship between soil moisture and heatwaves

https://link.springer.com/article/10.1007/s00382-018-4508-5

[8] Research on soil moisture prediction model based on deep learning - PLOS

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0214508

[9] Gap-free global annual soil moisture: 15 km grids for 1991–2018

https://essd.copernicus.org/articles/13/1711/2021/

[10] Assessment of a Spatiotemporal Deep Learning Approach for Soil Moisture ...

https://www.frontiersin.org/articles/10.3389/frai.2021.636234/full