Slide 1

Hello, my name is Naveed Jamal, and welcome to my research proposal presentation Climate-Adaptive Agriculture: A Global Predictive Platform for Sustainable Farming.

This project explores how advanced data science and artificial intelligence can be applied to address one of the most pressing global challenges today — the increasing instability of agricultural systems due to climate change.

Unpredictable rainfall, shifting temperature zones, and prolonged droughts are disrupting planting cycles and threatening food security worldwide. In developing regions, these changes can mean the difference between a successful harvest and severe economic hardship. Even in developed nations, farmers are facing reduced yields and new pests due to shifting climate patterns.

My proposed solution involves developing a predictive model that uses global climate, soil, and satellite data to recommend optimal seed planting times for different regions. This platform would empower farmers and agricultural agencies to make data-driven decisions, improving food production resilience and efficiency.

Although the idea was inspired by events in South Asia, my focus for this proposal is on creating a **globally scalable solution** — one that can adapt to diverse climates across continents, from Africa and South America to Europe and the United States.

Over the next twenty minutes, I’ll outline the significance of this research, its methodology, ethical framework, and the steps toward building a real-world predictive system that supports sustainable agriculture worldwide.

Slide 2

The research problem at the heart of this project stems from a critical global reality — our food systems are under threat.

According to the United Nations Food and Agriculture Organization, climate change has already reduced global agricultural productivity by more than twenty percent over the past sixty years. Extreme weather events such as droughts in sub-Saharan Africa, floods in South Asia, and wildfires in North America are further intensifying these losses.

Farmers today are often forced to make planting decisions based on outdated or generalized climate information. Localized decision-support systems are either unavailable or too complex to access, especially for smallholder farmers who represent the majority of the agricultural workforce in developing regions.

In the computing discipline, this gap represents an opportunity to integrate climate science, artificial intelligence, and big data analytics to create more adaptive agricultural systems. Predictive AI can process vast amounts of global environmental data — from temperature and soil moisture to historical crop yield patterns — to deliver tailored insights at the regional level.

Therefore, the core research problem can be summarized as follows: there is a global need for a unified, AI-driven predictive framework that helps farmers and agricultural institutions make accurate, location-specific planting decisions in response to changing climate conditions.

Addressing this issue contributes not only to data science and sustainability research but also to global food security and economic stability.

Slide 3

This slide highlights the projected global impact of climate change on agricultural yields by 2050.

The map, based on data from the IPCC and FAO, shows that many of the world’s major crop-growing regions are expected to experience significant yield losses as temperatures rise and weather patterns become more erratic.

Under the higher-emission scenario, known as RCP 8.5, regions in South Asia, Sub-Saharan Africa, and parts of Latin America could face yield losses of up to 30–50%, especially for staples like corn, rice, and wheat.

Even in developed regions such as North America and Europe, the effects are uneven — some northern zones might see short-term yield gains due to warmer temperatures, while southern regions could experience sharp declines due to drought and heat stress.

This global pattern illustrates a key problem: climate change will not affect agriculture equally, and many vulnerable areas are those already facing food insecurity.

These trends reinforce the importance of developing predictive systems that help optimize planting times, reduce losses, and improve resilience for farmers everywhere — not just regionally, but at a global scale.

Slide 4

The significance of this research lies in its intersection between food security, sustainability, and data science.

According to the latest projections from the IPCC and FAO, global food demand is expected to rise by more than 50% by 2050. Yet, the same period will see major yield reductions in key crops due to climate change — especially in regions like Sub-Saharan Africa, South Asia, and Latin America.

The research problem we’re tackling is how to **leverage data and predictive modeling to support smarter, more adaptive farming decisions** in the face of this growing instability.

While large agribusinesses may have access to technology-driven forecasting, **smallholder and independent farmers worldwide often do not**.

Our goal is to reduce this digital divide by developing a globally scalable, data-driven application that helps farmers determine **optimal planting times and crop strategies** based on changing environmental conditions.

By doing this, the project contributes not only to agricultural data science but also to broader goals in **climate adaptation and sustainable development.**

Slide 5

This slide presents the core of my research proposal — the guiding question, the project aim, and its specific objectives.

The world map on the left shows projected yield changes for key crops under future climate scenarios, using data from NASA’s Scientific Visualization Studio and AgMIP. It reminds us that while the patterns differ by region, nearly every agricultural zone on Earth is expected to experience some degree of stress or yield loss as temperatures rise.

My central research question asks how we can use data-driven predictive models to optimize planting times and strengthen agricultural resilience worldwide. In other words, how can computing help farmers make better, more adaptive decisions in the face of uncertainty?

The project’s aim is to design and evaluate a globally scalable predictive system that combines machine-learning algorithms with environmental and climate data.

To achieve this, I’ll begin by compiling and analysing multi-regional datasets. The next step will be identifying the most influential variables — temperature, precipitation, soil moisture, and so on — that determine planting success.

Using these insights, I’ll build and validate predictive models capable of recommending optimal planting windows, then visualize the outputs through a user-friendly prototype. Finally, I’ll evaluate the system’s potential impact on sustainability and resilience.

This slide captures how the project moves from a global challenge — illustrated by this map — to a structured, evidence-driven plan for technological intervention.

Slide 6

This slide summarises the key body of literature that informs my research proposal.

The first body of work examines machine learning in agriculture, which has achieved major successes in yield prediction, disease detection, and precision irrigation. For instance, Liakos and Shahhosseini and their respective teams, demonstrated how supervised learning and ensemble models can predict crop outcomes more accurately than traditional statistical methods.

The second stream of research, drawn from climate science and agronomy, highlights how climate change has already suppressed agricultural productivity. Studies such as that performed by Lobell and his team (2011) as well as the IPCC (2022) show that rising global temperatures and altered rainfall patterns have reduced yields of staples such as corn and wheat, especially in tropical and semi-arid regions.

The third theme involves spatio-temporal data integration. Zhong et al. (2019) demonstrated that advanced deep-learning architectures can combine remote-sensing and time-series data to capture local environmental variation. However, these methods are often computationally intensive and difficult to scale globally.

Another emerging theme is explainable artificial intelligence — particularly relevant for agriculture. Farmers are less likely to trust a system that acts as a ‘black box’. Therefore, modern interpretability frameworks such as SHAP or LIME should be integrated into any agricultural decision-support model.

Across these strands, one critical gap remains: despite rapid progress in agricultural machine learning, there is no global predictive framework focused on determining the optimal time to plant. Most current research looks at yield prediction or crop monitoring after planting. My proposal aims to address this early-stage decision gap by combining predictive analytics, climate modeling, and human-centric design.

This synthesis forms the theoretical foundation of my research — where data science meets climate resilience and practical agricultural decision-making.

Slide 7

This slide outlines the proposed methodology and overall research design.

The project adopts a quantitative, mixed-methods approach combining environmental data analysis with machine learning model development.

The process begins with data collection, drawing on open global repositories such as the Food and Agriculture Organization (FAO), NASA EarthData, the Copernicus Climate Data Store, and NOAA. These sources provide critical inputs including temperature, precipitation, soil moisture, and historical yield data.

Next, the data will undergo preprocessing and normalization to handle missing values, outliers, and differences in scale across regions. Feature engineering will include the creation of variables such as average growing-degree days, rainfall variability, and soil temperature thresholds.

For model development, I plan to evaluate several algorithms — Random Forests and Gradient Boosting for structured data, and Convolutional Neural Networks for spatio-temporal patterns. The model will predict the optimal planting window for specific crop–region combinations, integrating both historical and forecasted data.

Importantly, this research prioritizes interpretability. Many AI models function as black boxes, but for agricultural applications, transparency is essential. Therefore, I’ll use explainable AI techniques such as SHAP and LIME to highlight which environmental features most influence a recommendation.

The evaluation phase will involve cross-validation using region-specific test sets and standard performance metrics like Root Mean Square Error and Mean Absolute Error. The model’s robustness will also be tested under varying data quality conditions to ensure it performs reliably even in low-data environments.

Finally, I plan to develop a prototype interface — potentially a web dashboard or lightweight mobile application — that visualizes the model’s recommendations in a way that is understandable to non-technical users, such as farmers or agricultural planners.

This methodology ensures a rigorous, transparent, and scalable foundation for building a truly global climate-adaptive agricultural decision-support system.

Slide 8

The tangible outcome of this research will be the development of a prototype artefact — a climate-adaptive predictive platform that supports agricultural decision-making.

The artefact will integrate multiple data sources, including global climate records, soil information, and satellite imagery. These data streams will feed into the machine learning model developed earlier, producing localized recommendations on the optimal time to plant for specific crops.

The output will be presented through an intuitive interface — either a web-based dashboard or a mobile application — designed to be accessible even in low-connectivity environments.

For example, a farmer in Kenya or Argentina could input their crop type and location and instantly receive a data-backed recommendation such as: ‘Plant maize between April 12th and April 25th to avoid early-season drought risk.’

Importantly, the system won’t function as a black box. Using explainable AI techniques like SHAP and LIME, users will see which factors most influenced the recommendation — such as a sudden change in soil moisture or predicted rainfall.

From a technical standpoint, the platform will be developed using Python for model training, TensorFlow or Scikit-learn for machine learning, and a Streamlit or Power BI interface for visualization.

The artefact’s ultimate purpose is to demonstrate that predictive modeling can be transformed into actionable, user-friendly tools — bridging the gap between advanced data science and the daily decisions farmers make in the field.

Slide 9

Ethical and risk considerations are central to this research, particularly because the project involves the use of environmental and agricultural data across multiple regions.

Starting with data ethics, all datasets used — including those from FAO, NASA, and NOAA — will be open-access, anonymized, and compliant with global data protection regulations such as GDPR. Transparency in how data is sourced, processed, and interpreted will be clearly documented in the final project report.

A second critical area is algorithmic fairness. Predictive models trained on limited regional data can unintentionally introduce bias — for instance, by favoring well-documented regions while underperforming in data-scarce areas. To counter this, I will use diverse datasets and regularly test for model bias across different geographies and crop types.

The system will also include explainable AI tools, ensuring users understand the basis for each recommendation — a vital element for fostering user trust and responsible AI adoption in agriculture.

In terms of environmental and social impact, the platform promotes sustainability by helping farmers make better use of water, energy, and soil resources, while supporting smallholder farmers who are often most vulnerable to climate variability.

Lastly, risk management will address potential challenges such as inaccurate data inputs, overreliance on automated recommendations, and misinterpretation by non-technical users. These risks will be mitigated through robust model validation, clear user guidance, and continuous data updates.

Altogether, this ethical framework ensures that the proposed system adheres to professional standards of fairness, accountability, and societal benefit.

Slide 10

This slide presents the updated project timeline, condensed into a 30-week schedule running from October 2025 through April 2026.

In the first month, I will finalize the research proposal and obtain ethical approval, ensuring that all data-handling procedures comply with university and GDPR standards.

Between weeks 5 and 8, I will perform an in-depth literature review and finalize the research framework — defining the data sources, modeling approach, and performance metrics.

Data collection and preprocessing will take place from December through January, combining FAO, NASA, and Copernicus climate datasets into a unified, clean structure for machine learning.

Model development will occur during February and early March, when I’ll train and tune predictive models such as Random Forest, XGBoost, and Convolutional Neural Networks.

The following phase, evaluation and explainability, runs through March and April — I’ll validate performance using statistical metrics and apply SHAP and LIME techniques to explain the model’s decisions.

In April and May, I’ll focus on artefact development and user testing, translating the model into a functional dashboard or mobile prototype and collecting initial usability feedback.

Finally, from May through June 2026, I’ll complete the final analysis, integrate results, and prepare the dissertation for submission.

This accelerated schedule maintains methodological rigor while fitting within the 30-week capstone period, ensuring the project is both ambitious and achievable.

Slide 11

In conclusion, this project lays the foundation for a globally scalable system that bridges technology and agriculture to address one of the century’s most critical challenges — climate resilience and food security.

The proposed model, once validated, could be expanded into a multi-regional ecosystem where localized data hubs feed region-specific models. These models could continuously adapt to new weather patterns, soil conditions, and crop responses using satellite and IoT data.

Partnerships with agricultural ministries, NGOs, and global development organizations could ensure the system is tailored to local needs — for example, providing multilingual interfaces and SMS alerts in regions with limited internet connectivity.

From a long-term perspective, this research contributes directly to several United Nations Sustainable Development Goals

Zero Hunger

Climate Action

Industry, Innovation, and Infrastructure

Ultimately, the vision is not just to build a single model, but to create a sustainable, adaptive framework that empowers farmers everywhere — from the plains of Africa to the rice fields of Asia and the corn belts of the Americas.

By connecting local data, global science, and human-centered design, this project aims to transform climate uncertainty into knowledge, resilience, and opportunity.

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