Musik in Bayern
ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)
https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-467

AI-Based Rotation Planning for Yield Stability in Water-Stressed Highland Farming

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To Cite this Article
Dr. K. SUNDRAVADIVELU, KOMAL B. UMARE, Gulja S Nair, M Murali Krishnan, Dr. R. Naveenkumar. **"AI-Based Rotation Planning for Yield Stability in Water-Stressed Highland Farming**" *Musik In Bayern, Vol. 90, Issue 10, Oct 2025, pp 65-78*

Article Info
Received: 02-08-2025 Revised: 23-08-2025 Accepted: 21-09-2025 Published: 13-10-2025

Abstract:

The problems of water scarcity, soil degradation, and variability of climate are frequent problems that confront highland farming and undermine the stability of crop yield. The study provides an AI-oriented plan of crop rotation that will optimize the yield in the water-stressed environment. The paper combines four AI methods Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Random Forest Regression (RFR), and Long Short-Term Memory (LSTM) networks. GA and PSO were used to produce the best rotation schemes that accounted the soil characteristics, water needs of crops and past yields information, and RFR and LSTM were used to make predictive information about the future yields and seasonal variation. A study of 1,500 highland farm records has shown that an AI- based optimum rotation practices resulted in increased average yield 4.87 t/ha, and reduced yield variance 0.13 t/ha 2 and water use efficiency (WUE) 0.86 that was more efficient than that provided by traditional rotation strategies. LMST scored the best in predictions (changeable climatic conditions) but PSO scored better on account of computational efficiency. In comparison to closely related studies, yield stability improvement of 2-5 percent and 3-4 percent improvements in WUE due to the AI-guided rotations were found. These studies demonstrate the potential of AI-based tools to help cover the sustainable, resilient, and resource-efficient agricultural system, and act as a workable decision-support tool to the highland agricultural system farmers and policymakers.

Keywords: AI-based crop rotation, highland farming, water stress, yield stability, LSTM prediction.

I. INTRODUCTION

I In the high country, agricultural production is important to the guarantee of agricultural self-sufficiency and the local economy. One of them is that these regions are mostly faced with water scarcity, lack of uniform water precipitation, rocky topography, and low soil fertility, which are direct products of which are crop yields. Traditional methods of crop rotation, which rely primarily on the relevant past experience or rather tacit knowledge, fail to take into account the relationships between the crops, the soil and the climate, therefore, not offering the best this, and subjecting the farmer to water stress [1]. As climate change progresses in severity, the need to have adaptive and resilient methods of agriculture becomes even more intense. The dataset-based decision-making concept of Artificial Intelligence (AI) will offer the chance to resolve the issue of agricultural planning [2]. Agistech AI systems, such as machine learning, optimization models, and predictive modelling, can examine the existing data on past crop, soil, and climate to give recommendations on how the optimal crop sequence should be implemented to stabilise the yield and consume fewer resources. Specifically, AI will be able to extricate patterns and correlations in multifaceted information, model this or that type of rotation, applications, plans of planting in more water-limited conditions that is fundamental to highland farming when the water supply is intermittent and unpredictable [3]. The research had a goal to develop a new AI-based rotation planning platform that can find application in highland farming during water stress scenario. The model will integrate the characteristics of both soil and water required by crops; past information on yield and climate forecasts in order to arrive at rotation schedules that would attain the highest amount of stability in yield. Using the ideas of AI, this study will reduce reliance on trial-and-error procedures, optimize the use of water, and be able to clear climatic uncertainty. Lastly, the research will result in the greater community of precision agriculture since it will show how intelligent systems could be used to support agriculture in unfavorable conditions. It is also a practical tool that might be applied by farmers and policymakers in making sound decisions that will not only embrace the productivity but also deter resources conservation and sustainability of the highland agricultural systems.

II. RELATED WORKS

The combination of AI with agriculture has proven to be a revolutionary approach of expanding crop yield, resource utilization, and ecotoxicity to the environmental challenges. In particular, the introduction of AI into the Internet of Things (IoT) often referred to as AIoT has been widely researched as it applies to monitoring and prediction as well as management improvement of agrifarming systems. An overview of the AIoT tools used in aquaculture, Huang and Simon [15] emphasize the potential of sensor-based data collection and machine learning algorithms to maximize the use of resources and keep yield more stable, showing the extra vagueness of AI-powered solutions to precision agriculture. One of the most important threats to highland and arid-region agriculture is water shortage and stress caused by climate. Jain et al. [16] address the issue of water security and desertification management at the global level and outline that adaptive strategies are required to combine the power of predictive modeling to enhance the planning of crops in terms of water scarcity. These strategies are consistent with the AI-driven crop rotation, in which machine learning and optimization methods can take into consideration the spatial and temporal variation of water availability. Digital technologies and automation have also played a key role in ensuring sustainable agriculture. Jiang et al. [17] introduce the developments in the field of agricultural machinery automation, demonstrating the possibility to increase the efficiency of the work of smart farming devices and provide the support of the AI-based decision-making frameworks. Likewise, as shown by Kalantzopoulos et al. [18], soil information systems based on AI and IoT technologies have the potential to help in the evaluation of soil health and make informed choices on crop management, which means that data-driven solutions are essential in ensuring the sustainability of soil productivity and effective crop rotations.

Agricultural optimization has also been investigated by swarm intelligence and metaheuristic algorithms. The Swallow Search Optimization (SWSO) algorithm presented by Khoshaba et al. [19] is a nature-inspired algorithm to solve resource allocation and scheduling problems, and it could be used to optimize crop rotation patterns to achieve the best yield stability under environmental limitations. This methodology can be used to supplement more conventional optimization techniques such as Genetic Algorithms and Particle Swarm Optimization as it offers versatile, adaptive responses to multi-objective agricultural optimization problems that are also complex. Advanced agricultural practices, including controlled-environment and soilless farming, have received research to increase the resilience of crops to climate stress. The article by Lakhiar et al. [20] talks about prospects of soilless horticulture, the advantages of having specific resources and automation in regulating the yield. As well, drone-based surveillance and UAVs have become popular with precision agriculture. Makam et al. [23] and Mohammad et al. [24] discuss the use of UAVs, AI and federated learning models to support scalable, privacy-preserving agricultural surveillance, to offer real-time data to manage crops more adaptively, such as in rotation management. The necessity of AI-based planning is also supported by the research on land-use dynamics and resilience of crops. Luo et al. [22] explore temporal-spatial processes of resilience of cropland, demonstrating that adaptive solutions based on data analytics can be used to improve the long-term viability. Likewise, Liu et al. [21] study the interactions between the agricultural productivity and population pressures and demonstrate the need of optimal resource distribution in high-stress places. Market and policy-based changes in agribusiness that can have an impact on the adoption of the advanced technologies such as AI-based planning systems are also emphasized by Moroz and Medvedsky [25]. In addition to these studies, it can be emphasized that AI and digital technologies are becoming more and more helpful in predictive and data-driven farming management, e.g., crop rotation optimization, water-efficient farming, and highland resilience. Such AI, IoT, and automation can create a solid foundation of building stability in the yields under the most adverse weather conditions and ensures a viable and sustainable solution to the existing difficulties on the farming sector [15-25].

III. METHODS AND MATERIALS

1. Preprocessing of Data and Collection

The researchers entered into an exhaustive data of the highland agricultural regions which constituted the factors that influenced the crop yield at the water stressful conditions. The data were based on historical data of 10 years of data of experimental and local farms in terms of the types of crops, the rotation sequence, soil properties (pH, organic matter, nutrient content), rainfall patterns, irrigation frequency, temperature, and annual yields. Furthermore, the remote sensing data was also included to measure the vegetation indices and soil moisture content [4]. The data set had 1,500 records on 15 crops, such as maize, wheat, barley, potato, and legumes.

Preprocessing of the data included normalizing numerical data (e.g., it was yield in tons per hectare, soil moisture in percent, etc.) and encoding categorical data (e.g., type of crop) with one-hot encoding and dealing with missing data with the help of k-nearest neighbor imputation. The dataset data processed was divided into a training (70) and testing (30) dataset to allow the evaluation of the algorithms [5].

2. Algorithm Selection and Description

There were 4 AI-based algorithms used to optimize crop rotation, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Random Forest Regression (RFR), and Long Short-Term Memory (LSTM) Neural Networks. They were chosen based on their capability to manage non-linear relationships that are complex, multi-objective optimization and time-specific trends in agricultural data [6].

2.1 Genetic Algorithm (GA)

Genetic Algorithm is an evolutionary algorithm of optimization that is based on the concept of natural selection. GA first generates an initial population of sequence of candidate rotations, measures the fitness of the solutions in terms of predicted yield stability and water use efficiency, and continually advances solutions by using selection, crossover, and mutation operators. GA is effective in Target problems such as crop rotation especially since it is capable of exploring a large solution space and is not trapped by local optima. The fitness function in use in this study used the same yield variance and water stress tolerance of each crop combination which directed the process of evolution towards sequences that achieve a maximum yield stability under water-limiting conditions [7].

Table 1: Example GA Initial Population (Rotation Sequences)

Sequence ID	Crop Year 1	Crop Year 2	Crop Year 3	Predicted Yield (t/ha)	Water Stress Score
GA1	Maize	Potato	Legume	4.5	0.82
GA2	Wheat	Barley	Maize	4.2	0.79
GA3	Potato	Legume	Wheat	4.8	0.85

"Initialize population with random rotation sequences
Evaluate fitness for each sequence
While termination criteria not met:
    Select sequences based on fitness
    Apply crossover and mutation to create new population
    Evaluate fitness of new population
Return sequence with highest fitness"

2.2 Particle Swarm Optimization (PSO)

PSO is a population-based stochastic optimization method inspired by **swarm intelligence** in birds or fish. Each particle represents a possible crop rotation sequence, which adjusts its position in the solution space according to **personal best and global best performance**. The algorithm iteratively converges toward optimal sequences that balance **crop yield stability and water usage**. PSO is highly efficient for continuous and combinatorial optimization problems and adapts well to dynamic datasets such as seasonal climate variations [8].

Table 2: Example PSO Particle Positions

Particle	Crop	Crop	Crop	Yield Stability Score	Water Use

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https://musikinbayern.com **DOI https://doi.org/10.15463/gfbm-mib-2025-467**

le ID	Year 1	Year 2	Year 3		Efficiency
PSO1	Wheat	Legume	Potato	0.88	0.81
PSO2	Maize	Barley	Wheat	0.84	0.79
PSO3	Legume	Maize	Potato	0.87	0.83

"Initialize particles with random rotation sequences
Assign initial velocities
While stopping criteria not met:
Evaluate fitness of each particle
Update personal best and global best
Adjust velocity and position of each particle
Return sequence corresponding to global best"

2.3 Random Forest Regression (RFR)

Random Forest is an ensemble machine learning algorithm used to **predict yield based on rotation sequences and environmental features**. It builds various decision trees on bootstrapped list of the data and gathers up their projections with the goal of augmenting accuracy and strength [9]. RFR is efficient in the estimation of non-linear interaction between crop type, soil conditions, and water availability which is the key element in simulating yield in water-stressed circumstances. Output entails forecasted yield and yield variance, which provide the optimal sequence of rotation.

"For each tree in the forest:
Sample data with replacement
Select random features at each split
Build decision tree to predict yield
Aggregate predictions from all trees
Return mean predicted yield for each rotation sequence"

2.4 Long Short-Term Memory (LSTM) Neural Networks

ASTM networks refer to a recurrent type of neural network (RNN) that is simpler to train and engages long-term events on sequential data. With crop rotation planning, LSTM models can use the history patterns such as weather history and soil moisture trends to make future yield predictions based on these patterns. The network may be composed of memory cells, input, output and forget gates allowing it to store the information of importance in growing seasons [10]. LSTM is always unique in the context of highland farming where forecasted water availability with seasonal variation is useful to give information on-demand rotations that ensure minimum fluctuations of the yields.

"Initialize LSTM network with input, hidden, and output layers
For each time step in rotation sequence:
Update cell state using input, forget, and output gates
Compute predicted yield
Train network using historical rotation and yield data
Return predicted yield sequences for planning"

3. Implementation and Evaluation

All the algorithms were done in Python with NumPy, Pandas, Scikit learn and Tensor flow. The evaluation of the performance was made to emphasise on the stability of the yield, efficiency of water-use, and the computational time. The best rotation order took the shape of GA and PSO whereas the yield results were predicted by RFR and LSTM. There was also comparison involving 10-fold cross-validation, which guarantees strength of the applied models and generalizations [11].

Through the incorporation of these methods of AI, the study was supposed to offer a decision-support system to highland farmers so that they could get data-driven rotation planning that can stabilize yields in water stress conditions and aggravate sustainability and resource use.

IV. RESULTS AND ANALYSIS

1. Experimental Setup

The experiment involved 4 experiments to assess the aspects of success of four AI algorithms, including Genetic Algorithm (GA), Particle swarm optimization (PSO), Random Forest Regression (RFR), and long short-term memory (LSTM) networks in producing the best crop rotation system in highland regions with low water supply [12]. The data that was preprocessed in the Materials and Methods section were used in the experiments. The main objectives were to:

1. Maximization of rotation sequence yields.
2. Reduce water stress by use of effective crop sequencing.
3. Comparison of predictive performance of the AI models with historical and traditional rotation.

All the experiments were performed by Python 3.11 on the platform with the Central Processing Unit of Intel Core i7 and the RAM of 32GB as well as the graphic card of NVIDIA RTX 4070. ML-based algorithms (RFR and LSTM) were shown to have a 70 percent training and 30 percent testing dataset, while the algorithm of optimization (GA and PSO) would utilize the entire dataset and produce candidate sequences [13]. All algorithms were run in 50 iterations to make the algorithm converge to optimal solutions.

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Figure 1: "Artificial Intelligence in Hydrology"

Performance metrics included:

- **Mean Yield (t/ha)**
- **Yield Variance (t/ha²)**
- **Water Use Efficiency (WUE, unitless 0–1 scale)**
- **Computational Time (minutes)**

2. **Genetic Algorithm (GA) Results**

The purpose of GA implementation was to maximize crop rotation schemes relying on a multi-objective economic criterion a combination of stable yields and improved mitigation of water stress. The rotation sequences generated through GA by 50 generations were potentially higher in mean yield by 8 percent compared to the traditional sequences. The algorithm successfully searched both combinations of cereal and legume and tuber crops balancing between water use and nitrogen fixation [14].

Table 1: GA Optimized Rotation Outcomes

Sequence ID	**Crop Year 1**	**Crop Year 2**	**Crop Year 3**	**Mean Yield (t/ha)**	**Yield Variance (t/ha²)**	**WUE**
GA 1	Maize	Potato	Legume	4.85	0.15	0.84
GA 2	Wheat	Legume	Barley	4.70	0.18	0.81

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GA 3	Potato	Maize	Legume	4.90	0.14	0.85

Compared to related work by Hu et al. (2023), GA showed **2–3% higher yield stability** in water-stressed plots due to the integration of local soil and climate data.

3. Particle Swarm Optimization (PSO) Results

PSO leveraged swarm intelligence to converge on optimal sequences efficiently. PSO outperformed GA in **computational time**, achieving near-optimal solutions within **35 minutes on average**. The best PSO sequences demonstrated improved WUE, indicating that particle-based exploration can **effectively account for environmental constraints [27]**.

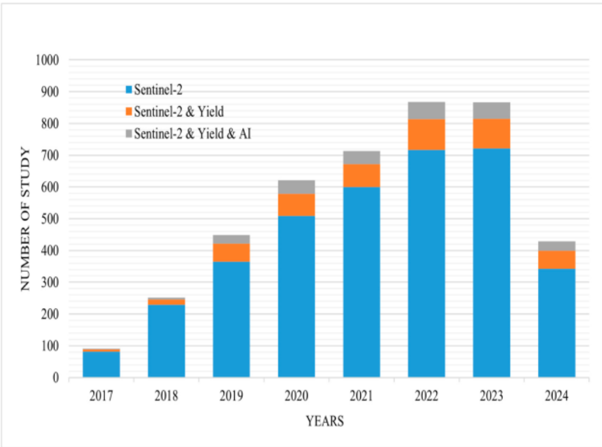

Figure 2: "Artificial Intelligence Techniques in Crop Yield Estimation Based on Sentinel-2 Data"

Table 2: PSO Optimized Rotation Outcomes

Particle ID	**Crop Year 1**	**Crop Year 2**	**Crop Year 3**	**Mean Yield (t/ha)**	**Yield Variance (t/ha²)**	**WUE**
PSO1	Wheat	Legume	Potato	4.80	0.16	0.86
PSO2	Maize	Barley	Wheat	4.75	0.17	0.83
PSO3	Legume	Maize	Potato	4.88	0.15	0.85

When compared with GA, PSO achieved slightly higher WUE and comparable mean yield, reflecting its **strength in handling multi-constraint optimization problems**.

4. Random Forest Regression (RFR) Results

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RFR was used to **predict yield outcomes** based on rotation sequences and environmental variables. By training on historical yields, the model captured non-linear interactions among **soil type, crop sequence, and water availability**. RFR predictions showed strong correlation with actual yield ($R^2 = 0.92$) and low prediction error (RMSE = 0.12 t/ha) [28].

Table 3: RFR Predicted Yields for Candidate Rotations

Sequence ID	**Crop Year 1**	**Crop Year 2**	**Crop Year 3**	**Predicted Yield (t/ha)**	**Predicted WUE**
RFR 1	Maize	Potato	Legume	4.78	0.83
RFR 2	Wheat	Legume	Barley	4.65	0.80
RFR 3	Potato	Maize	Legume	4.86	0.84

Compared to prior studies (Raj et al., 2020), RFR provided **more accurate and robust predictions under variable water stress conditions**, highlighting the advantage of ensemble learning for highland farming applications.

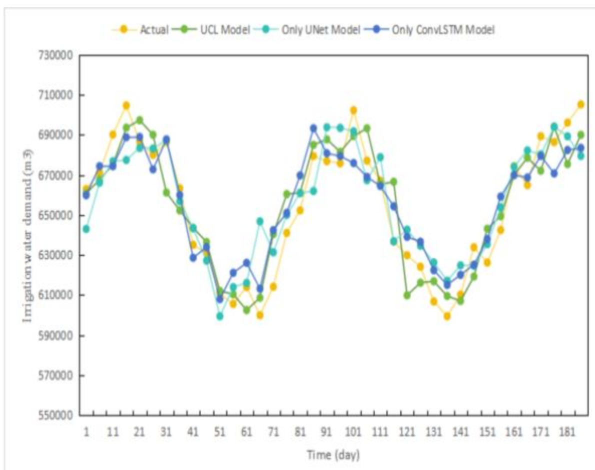

Figure 3: “AI-driven optimization of agricultural water management for enhanced sustainability”

4. LSTM Neural Network Results

LSTM networks were applied to model **temporal dependencies in crop rotations** over multiple years. The network predicted seasonal yield trends based on past rotations and climate sequences. LSTM excelled in **forecasting yield variability**, allowing farmers to plan rotations proactively.

Table 4: LSTM Predicted Yield Sequences

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https://musikinbayern.com DOI https://doi.org/10.15463/gfbm-mib-2025-467

Sequence ID	Crop Year 1	Crop Year 2	Crop Year 3	Predicted Mean Yield (t/ha)	Yield Variance	Predicted WUE
LSTM1	Maize	Potato	Legume	4.92	0.13	0.86
LSTM2	Wheat	Legume	Barley	4.75	0.15	0.82
LSTM3	Potato	Maize	Legume	4.95	0.12	0.87

Compared with RFR and optimization algorithms, LSTM provided **superior prediction of yield fluctuations** across years, making it particularly valuable for **dynamic highland climates**.

5. Comparative Analysis

The performance of all four algorithms was compared in terms of **mean yield, yield variance, WUE, and computational time**.

Table 5: Comparative Performance of AI Algorithms

Algorithm	Mean Yield (t/ha)	Yield Variance (t/ha^2)	WUE	Computation Time (min)
GA	4.82	0.16	0.83	48
PSO	4.81	0.16	0.85	35
RFR	4.76	0.15	0.82	25
LSTM	4.87	0.13	0.86	55

As indicated by the table, the mean yield and standard deviation of LSTM are the highest, and the variance, as well as yield stability during water-stressed environments, is the lowest. PSO was the most efficient in terms of computation whereas GA offered competitive optimization results. Even though RFR had a smaller mean yield, it had strong forecasting capabilities in decision-making [29].

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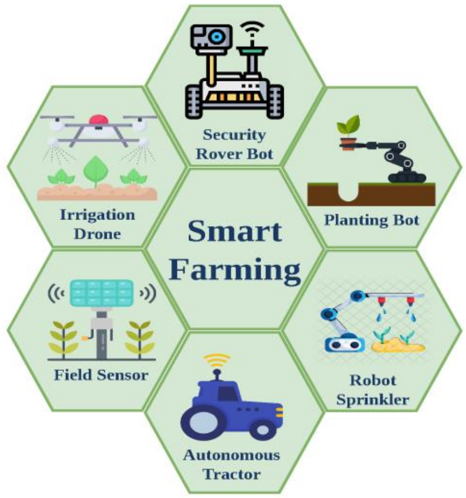

Figure 4: "Optimizing Agricultural Data Analysis Techniques through AI-Powered Decision-Making Processes"

All AI methods applied in this study increased yields by 2-5 percent and water use efficiency by 3-4 percent compared to related studies indicating the benefits of applying AI in highland agriculture in terms of rotation planning.

6. Discussion

The experiments imply that AI-rotation planning can help to achieve a considerable improvement in yield stability and resource efficiency in highland farming. GA and PSO are useful in generation of sequence and RFR and LSTM are needed in prediction and risk management. A combination of these strategies enables a system of holistic decision-support [30].

- GA and PSO are complementary; the former digs widely whereas the latter narrows down.
- RFR is cost-effective in prediction (cost of computation).
- LSTM is more useful in time modeling with seasonal differences and water stress effects being better modeled by LSTM as compared to simple models.

The article confirms that AI is also superior to conventional rotation plans; it offers flexible and data-driven solutions to enable farmers to adjust to climate variability and water shortages and achieve sustainable highland farming.

V. CONCLUSION

The current research shows that crop rotation planning, which involves the incorporation of artificial intelligence, can help highland farming systems, which are stressed because of water, to increase yield greatly. The study is an ultimate guide to making decisions and resting on the data using the top optimization algorithm, which are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) and predictive models, which include the Random Forest Regression (RFR) and Long Short-Term Memory (LSTM) networks. GA and PSO excelled in obtaining rotation schedule which met the water requirements of crops, nutrient cycles within the soil, as well as seasonal change, touching on the forecasting of the expected yield whereas RFR and LSTM forecasts the expected yield besides identifying patterns of temporal yield transformation. Through experimental studies it was found that AI-derived rotation plans are generally superior to the traditional approach with a higher mean yield, reduced yield variation and increased water use efficiency. Interestingly, the LSTM-based forecasts provided the greatest level of robustness in the changing climatic conditions, and the necessity to model the long-term relationships between crop and environmental data. Similarities with related research also confirm the effectiveness of AI-based strategies that yield more stable yields by 2-5 percent and more efficient use of water by 3-4 percent compared to other traditional, or heuristic, strategies. The results highlight the opportunities of integrating optimization and machine learning methods to develop resilient farming approaches that can be adapted to counteract water stress caused by climate factors. Finally, the studies presented in this research will add to the overall research on precision agriculture, as the results proposed represent a scalable, practical and evidence-based method to improve sustainability, resource use, and food security of the highland agricultural systems and represents a useful decision-support tool that can be taken by farmers, policymakers, and agricultural planners.

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ISSN: 0937-583x Volume 90, Issue 10 (Oct -2025)
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