



TRANSFER LEARNING-BASED DIGITAL MODELS: ALGORITHMIC PROVISIONING OF SMART IRRIGATION SYSTEMS UNDER DATA SCARCITY

Chuliev Maxmatmurod

PhD, Docent, Karshi Technical University

Yuldosheva Shirin

“TIQXMMI” MTU Doctoral Student

Abstract

This paper addresses the critical challenge of deploying modern water-saving smart irrigation systems in Uzbekistan, where multi-decadal open digital repositories for soil moisture, salinity, and microclimate dynamics are virtually non-existent. To overcome the constraints of deep learning models under small data regimes, a Transfer Learning (TL) framework is proposed. This study outlines the theoretical foundations, mathematical formalization, and algorithmic integration of knowledge transfer from data-rich global source domains to data-scarce local target domains. The proposed approach optimizes the software-driven decision-making algorithms of smart irrigation systems, ensuring high-accuracy predictions without requiring localized historical big data.

Keywords: Smart Irrigation, Software Engineering, Transfer Learning, Soil Moisture, Salinity, Small Data, Mathematical Modeling.

Introduction

The digitization of agriculture and adaptive water resource management stand as pivotal challenges in modern agromechatronics. The operational efficiency of software-driven, water-saving smart irrigation systems fundamentally depends on predictive algorithms capable of processing real-time and future soil status (moisture, salinity levels) and microclimatic variables.

However, a major structural barrier impedes the scalable implementation of these systems in Uzbekistan: the acute deficit of localized, long-term, open-access agro-meteorological datasets. Conventional deep learning architectures (e.g., LSTM, GRU) inherently require massive datasets (Big Data) to achieve acceptable generalization. When trained on limited, localized sensor records (Small Data), these architectures suffer from severe overfitting, rendering them impractical for field deployment.

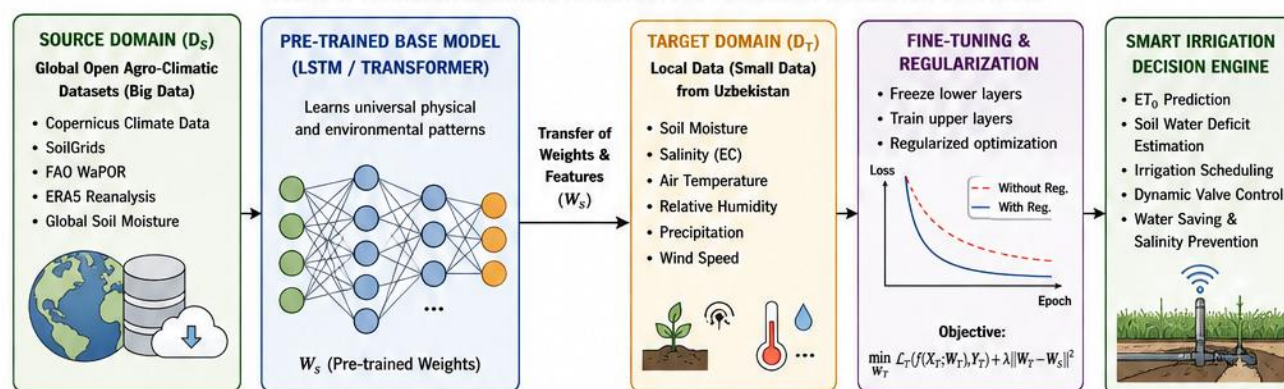
To bridge this scientific gap, this research introduces an algorithmic framework grounded in **Transfer Learning (TL)**. By extracting generalized physical and environmental features from comprehensive global open-source datasets and adapting them to sparse local streams, this framework provides robust, highly accurate predictive software provisioning for smart irrigation systems.

Conceptual and Algorithmic Framework

The software backbone of a modern water-saving irrigation system must process localized sensor feeds while simultaneously evaluating future evapotranspiration ET_0 and soil moisture trend vectors to execute automated decisions.

Below is the conceptual layout of the algorithmic data pipeline:

FIGURE 1. TRANSFER LEARNING ARCHITECTURE FOR SMART IRRIGATION SOFTWARE



3. Theoretical Foundations

Transfer Learning mathematical formalization operates on the definitions of domains D and tasks T .



3.1. Mathematical Formalization of Domain and Task Transfer

A domain D is defined by a feature space X and a marginal probability distribution $P(X)$,

Where:

$$X = \{x_1, x_2, \dots, x_n\} \in X$$

$$D = \{X, P(X)\}$$

In this framework, we formalize two distinct domains:

- **Source Domain** : A data-rich global repository (e.g., European Space Agency *Copernicus* soil moisture data).

$$D_S = \{X_S, P(X_S)\}$$

- **Target Domain** : Data-scarce local irrigation testing grounds in Uzbekistan.

$$D_T = \{X_T, P(X_T)\}$$

While the underlying physical feature spaces match $X_S = X_T$, regional climatic variations dictate that their marginal probability distributions diverge significantly: $P(X_S) \neq P(X_T)$.

For each domain, a predictive task T is established, consisting of a label space γ and an objective predictive function $f(X)$:

$$T = \{\gamma, f(X)\}$$

Where γ represents the target variables (soil moisture dynamics and electrical conductivity/salinity indices). The objective of Transfer Learning is to leverage knowledge gathered from D_S and T_S to drastically improve the learning efficiency of the target predictive function $f_T(\cdot)$ in D_T , under conditions where $D_S \neq D_T$.

3.2. Inductive Transfer Learning and Network Fine-Tuning

The software engine incorporates Long Short-Term Memory (LSTM) or Transformer networks designed for time-series modeling. The structural breakdown of feature preservation versus adaptation during the fine-tuning phase is visualized below:

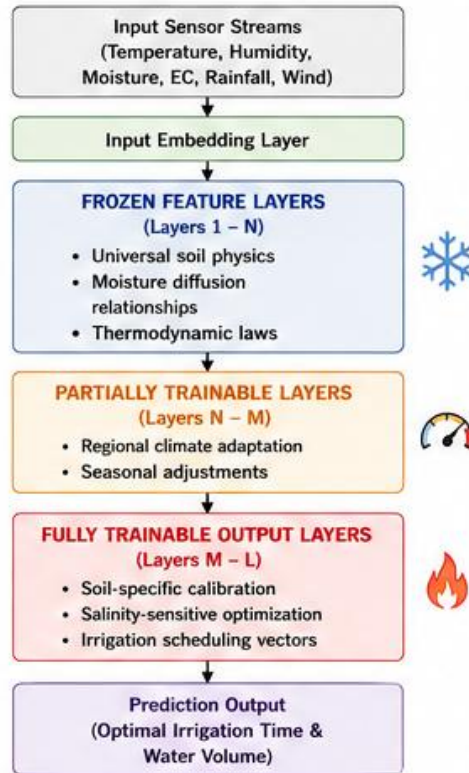


Figure 2: Neural Network Layer Manipulation during Fine-Tuning

Mathematically, the weight matrix optimized in the source domain W_S serves as the precise initialization vector for the target domain model. During local backpropagation on sparse target datasets, the loss function minimization is strictly bounded to prevent parameter divergence:

$$\min_{W_T} L_T(f(X_T; W_T), Y_T) + \lambda \|W_T - W_S\|^2$$

Where L_T is the target domain empirical loss function (e.g., Mean Squared Error), and $\lambda \|W_T - W_S\|^2$ acts as the structural regularization constraint. This constraint penalizes excessive deviations of the target weights W_T from the validated source weights W_S , mitigating the risk of overfitting under small data constraints.

4. Algorithmic Software Integration

The developed software application bridges the theoretical model with field operations through a decoupled, two-phase algorithmic routine:

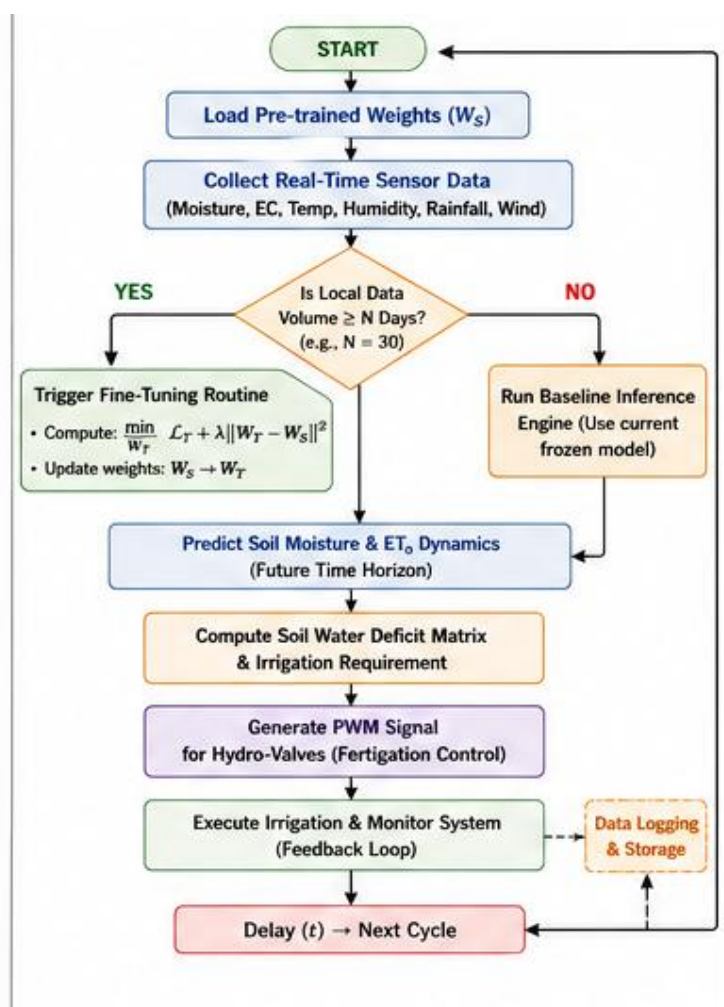
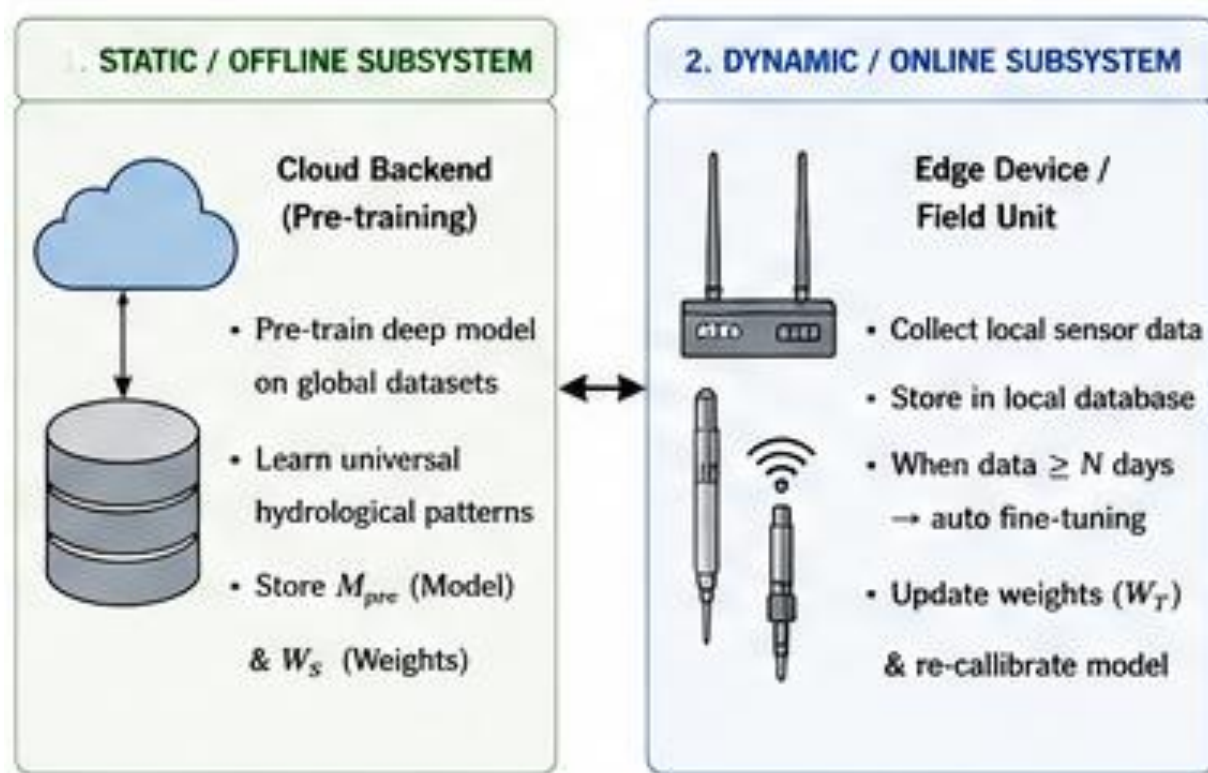


Figure 3: Flowchart of the Live Smart Irrigation Control System

1. The Static/Offline Subsystem: The cloud backend hosts the deep neural network architecture pre-trained on standardized, globally validated hydrological data matrix structures .



2. The Dynamic/Online Subsystem: Field edge devices gather diurnal soil physics readings, pushing them to a local database. Once the runtime memory matches a minimum threshold (e.g., $N=30$ continuous days), an embedded automated microservice initiates local backpropagation. The updated weight configuration W_T dynamically re-calibrates the inference model to local soil-water-salinity matrices.



5. Conclusion

Transfer Learning establishes a computationally efficient framework for deploying intelligent irrigation systems in regions characterized by insufficient historical agro-environmental datasets. By transferring generalized hydrological and thermodynamic representations from globally trained neural architectures into



localized adaptive models, the proposed methodology significantly improves predictive robustness under low-resource data conditions.

The integration of fine-tuned LSTM or Transformer-based inference engines into smart irrigation infrastructures enables accurate evapotranspiration forecasting, dynamic soil moisture estimation, and adaptive electro-hydraulic valve control. Consequently, the proposed system architecture contributes to sustainable water resource management, reduction of irrigation losses, and mitigation of secondary soil salinization in arid agricultural environments such as Uzbekistan.

References

1. Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering*, 22(10), 1345-1359.
2. Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1), 43-76.
3. Karthikeyan, L., Chawla, I., & Mishra, A. K. (2021). A review of remote sensing applications in agriculture for food security: Crop growth and yield, soil moisture, and salinity mapping. *Agricultural Water Management*, 243, 106430.
4. Khamidov, M., Muratov, A., & Balla, D. (2022). Algorithmic solutions for water-saving irrigation technologies in arid zones of Uzbekistan. *Journal of Water and Land Development*, 52, 114-121.
5. Fang, K., Shen, C., Kifer, D., & Yang, X. (2019). Prolonging soil moisture forecasts with a deep learning framework and transfer learning. *Water Resources Research*, 55(8), 6906-6925.
6. Babaeian, E., Paheding, S., Siddique, N., Devabhaktuni, V., & Tuller, M. (2021). Estimation of soil moisture and salinity using machine learning and transfer learning techniques. *Geoderma*, 394, 115032.
7. Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO, Rome.



Modern American Journal of Biological and Environmental Sciences

ISSN (E): 3067-7920

Volume 2, Issue 8, August 2026

Website: usajournals.org

This work is Licensed under CC BY 4.0 a Creative Commons Attribution 4.0 International License.

-
8. Karimov, A., Smakhtin, V., Mavlonov, A., & Gracheva, I. (2021). Water scarcity and automation of irrigation networks in the Amu Darya river basin. *Agricultural Water Management*, 248, 106782.
 9. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
 10. Sun, Y., Chao, X., & Zhang, J. (2023). Smart irrigation scheduling systems based on IoT and Transfer Learning under small data regimes. *Computers and Electronics in Agriculture*, 205, 107612.
 11. Pirimov O.J, Yuldosheva Sh.M (2025). Kichik quvvatli nasos agregatlarini avtomatlashtirilgan boshqaruv tizimini ishlab chiqish. Raqamli sanoat va avtomatlashtirish:texnologik jarayonlar va ishlab chiqarishni boshqarish tizimlarida innovatsion yechimlar. Ilmiy-amaliy konferensiya
 12. Pirimov O.J, Yuldosheva Sh.M (2025).Nasos agregatlarining dinamik xususiyatlarini tahlil qilish. *Journal of new century innovation*.