

## **MS THESIS**

# **ESTIMATION OF EVAPOTRANSPIRATION (ET) FOR MAJOR CROPS USING SURFACE ENERGY BALANCE ALGORITHM FOR LAND (SEBAL) MODEL, AND ASSESSMENT OF THE WATER ENERGY AND FOOD NEXUS (WEFN) IN PAKISTAN**



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**Estimation of Evapotranspiration (ET) for Major Crops  
Using Surface Energy Balance Algorithm for Land  
(SEBAL) Model, and Assessment of the Water Energy  
and Food Nexus (WEFN) in Pakistan**



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**CERTIFICATE OF APPROVAL**

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**"ESTIMATION OF EVAPOTRANSPIRATION (ET) FOR MAJOR CROPS USING SURFACE ENERGY BALANCE ALGORITHM FOR LAND (SEBAL) MODEL, AND ASSESSMENT OF WATER ENERGY AND FOOD NEXUS (WEFN) IN PAKISTAN"**

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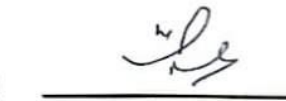
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# DEDICATION

All praise is due to Almighty Allah, the Most Merciful and the Most Compassionate, whose infinite blessings, guidance, and strength have illuminated every step of this journey. Without His divine grace, this achievement would have remained beyond reach.

I dedicate this work to my beloved parents, whose unconditional love, sacrifices, and ceaseless prayers have been the foundation of my life. Their unwavering faith in me has consistently given me the strength to move forward, and their encouragement has carried me through the most challenging moments. Whatever I have achieved today is a reflection of their endless support and silent prayers.

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This thesis stands as a testament to the values of faith, love, perseverance, and dedication that each of you has instilled in me. May Allah reward you abundantly and bless you all.

**Murad Ali**

# **DECLARATION**

I hereby declare that the work presented in this thesis is the result of my own efforts and research, except where explicit acknowledgment has been made. This thesis is entirely my original composition and has not been submitted, in whole or in part, for the award of any other degree or qualification at this or any other institution.

**Murad Ali**

**43FET/MSCE/F23**

**Date: 16/12/2025**

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## List of Abbreviations

| Abbreviation | Full Form                                                      |
|--------------|----------------------------------------------------------------|
| ALARM        | Automated Land and Resource Monitoring                         |
| ALEX         | Atmosphere-Land Exchange                                       |
| ARS          | Agricultural Research Service                                  |
| ASCE         | American Society of Civil Engineers                            |
| CA           | Catchment Area                                                 |
| CHIRPS       | Climate Hazards Group InfraRed Precipitation with Station data |
| CROPWAT      | FAO Crop Water Requirement Model                               |
| CSA          | Climate Smart Agriculture                                      |
| DEM          | Digital Elevation Model                                        |
| DOY          | Day of Year                                                    |
| DTW          | Depth to Water                                                 |
| EI           | Energy Intensity                                               |
| ERA5         | ECMWF Reanalysis Version 5                                     |
| ET           | Evapotranspiration                                             |
| ETA          | Actual Evapotranspiration                                      |
| EUE          | Energy Use Efficiency                                          |
| FAO          | Food and Agriculture Organization                              |
| GEE          | Google Earth Engine                                            |
| GIS          | Geographic Information System                                  |
| HEC          | Higher Education Commission                                    |
| IIUI         | International Islamic University Islamabad                     |
| ISPRS        | International Society for Photogrammetry and Remote Sensing    |
| IWMI         | International Water Management Institute                       |

| Abbreviation | Full Form                                                                   |
|--------------|-----------------------------------------------------------------------------|
| KP           | Khyber Pakhtunkhwa                                                          |
| LAI          | Leaf Area Index                                                             |
| LE           | Latent Heat Flux                                                            |
| METRIC       | Mapping Evapotranspiration at High Resolution with Internalized Calibration |
| MODIS        | Moderate Resolution Imaging Spectroradiometer                               |
| NDVI         | Normalized Difference Vegetation Index                                      |
| NRPU         | National Research Program for Universities                                  |
| OLI          | Operational Land Imager                                                     |
| PET          | Potential Evapotranspiration                                                |
| PM           | Penman–Monteith                                                             |
| PMD          | Pakistan Meteorological Department                                          |
| QGIS         | Quantum Geographic Information System                                       |
| RL           | Outgoing Longwave Radiation                                                 |
| RMSE         | Root Mean Square Error                                                      |
| RS           | Remote Sensing                                                              |
| SAVI         | Soil Adjusted Vegetation Index                                              |
| SDG          | Sustainable Development Goals                                               |
| SEBAL        | Surface Energy Balance Algorithm for Land                                   |
| SRTM         | Shuttle Radar Topography Mission                                            |
| SSEB         | Simplified Surface Energy Balance                                           |
| TIRS         | Thermal Infrared Sensor                                                     |
| TRMM         | Tropical Rainfall Measuring Mission                                         |
| TSEB         | Two Source Energy Balance                                                   |
| USA          | United States of America                                                    |

| Abbreviation | Full Form                               |
|--------------|-----------------------------------------|
| USDA         | United States Department of Agriculture |
| WEF          | Water–Energy–Food                       |
| WEFN         | Water–Energy–Food Nexus                 |
| WEFNI        | Water–Energy–Food Nexus Index           |
| WF           | Water Footprint                         |
| WP           | Water Productivity                      |
| WRVI         | Water Related Vegetation Index          |
| WUE          | Water Use Efficiency                    |

## Abstract

Accurate field-scale estimation of crop water use is essential for sustainable irrigation management and for addressing trade-offs within the water–energy–food (WEF) nexus in semi-arid regions. This study applies the Surface Energy Balance Algorithm for Land (SEBAL) implemented in Google Earth Engine (GEE) to determine hourly, daily and seasonal actual evapotranspiration ( $ET_a$ ) for eleven wheat fields in Swabi District, Pakistan, during the 2023–2024 growing season. The main objectives were to (i) calibrate SEBAL-derived  $ET_a$  with FAO-56 Penman–Monteith estimates ( $ET_c$ ) processed in CropWat 8.0 using the double-crop-coefficient approach, (ii) quantify field-scale water consumption and energy use, and (iii) integrate SEBAL-derived  $ET_a$  with measured yields and groundwater-pumping energy to calculate water productivity (WP), energy productivity (EP), energy intensity (EI), normalized indicators (NWP, NEP, NYI), and a composite WEF Nexus Index (WEFNI). Landsat-8 imagery, ERA5-Land meteorological data, and locally collected irrigation, and yield, records were combined to execute SEBAL and compute productivity metrics.

Calibration results demonstrated strong agreement between SEBAL-estimated and FAO-56  $ET_c$  values, with field-level  $R^2$  ranging from 0.54–0.93, RMSE from 0.44–0.87 mm day<sup>-1</sup>, bias from –0.069 to 0.446 and pooled regression ( $SEBAL = 0.698 ET_c + 1.22$ ;  $R^2 = 0.63$ ). This shows SEBAL’s suitability for field-scale  $ET_a$  estimation. Hourly, daily, and seasonal  $ET_a$  ranged between 0.2–0.9 mm h<sup>-1</sup>, 2.0–7.5 mm day<sup>-1</sup>, and 456–668 mm, respectively, across the fields. WP varied from 0.45 – 0.73 kg m<sup>-3</sup>, EP from 31 – 106 kg kWh<sup>-1</sup>, EI from 0.009 – 0.032 kWh kg<sup>-1</sup>, and WEFNI ranged from 0.04–0.90 indicating strong spatial variability in resource use. Fields 7, 8, and 11 achieved the highest WEFNI, reflecting balanced water and energy use with high yields, whereas Fields 5 and 6 performed poorly due to inefficient resource use and suboptimal irrigation.

The results suggest that the calibrated SEBAL approach is a robust and scalable method for mapping crop-specific  $ET_a$  and evaluating the interconnections among water, energy, and crop productivity. Integrating SEBAL outputs with WEF Nexus indicators provides a practical framework for diagnosing field-level inefficiencies and supporting sustainable agricultural water management. Future research should emphasize multi-season and multi-crop calibration, automated end-member selection, integration of ground-based validation data, and the development of decision-support dashboards and capacity-building programs to operationalize this approach for farmers and irrigation managers.

# 1 Introduction

Agriculture is the largest sector of Pakistan's with about 24% share to gross domestic product (GDP), engaging approximately half of the work force and providing livelihood to 67% of the population [1]. More than 93% of the available water is used for irrigation and to operate water pumps and tractors for agriculture purposes consumes 1.5% of the nation's total energy usage [2], [3]. Therefore, optimizing water and energy usage is essential for environmental and economic sustainability. Mostly the conventional methods of irrigation are used, and crops are irrigated according to the local rotation-based water distribution system without considering the ET based irrigation scheduling, real-time crop water requirements and soil moisture content [4]. This reduces soil fertility, lowering ground water levels, and causes more water loss resulting from surface runoff and deep percolation of water beyond the root zone of the crops. While increasing water and energy requirements and decreasing food production. Excessive pumping of water from deep wells causes high consumption of energy [5]. Worldwide, farming is by far the biggest user of freshwater resources, using around 70% of annual water withdrawal [6]. Pakistan ranks as the fourth-largest user of groundwater for irrigation globally. Because surface water sources are sufficient to irrigate only around 27% of the total cultivated area, the remaining 73% relies either directly or indirectly on groundwater extraction to meet irrigation demands. [7]. It is projected that approximately 40% of irrigation water in developing nations is lost through surface runoff, evaporation, and percolation beyond the effective root zone [8]. Pakistan's Water Resources Vulnerability Index (WRVI) has reached 77%, indicating a severe level of water stress and scarcity [9]. This challenge is further aggravated by climate change and unpredictable weather patterns that have severely impacted the country over recent decades. Consequently, water resources are rapidly depleting, and glacial melt is accelerating at a concerning pace. The below-average storage levels in reservoirs have further reduced the availability of water for both irrigation and ecological flow requirements [10].

Water management in agriculture is increasingly acknowledged as a major problem closely tied to broader development concerns. Agricultural practices have significantly impacted freshwater resources, leading to problems such as salinization, over-extraction,

and nutrient pollution [11]. Irrigation is the controlled application of water to farmland and is considered the backbone of agriculture. Accurately determining crop water requirements is necessary for good irrigation scheduling [12]. Over the years, various irrigation techniques have been developed to meet the specific water requirements of different crops under varying regional conditions. The four primary irrigation methods include surface, subsurface, sprinkler, and drip/micro irrigation [13], as shown in Figure 1. Globally, surface irrigation accounts for about 75% of irrigated land, followed by sprinkler irrigation at 20% and drip/trickle systems at 5% [14]. However, no single irrigation method can achieve 100% efficiency while also being suitable for all soil types, climatic conditions, and crop varieties [15]. Typical application efficiencies of different irrigation systems are shown in Table 1.

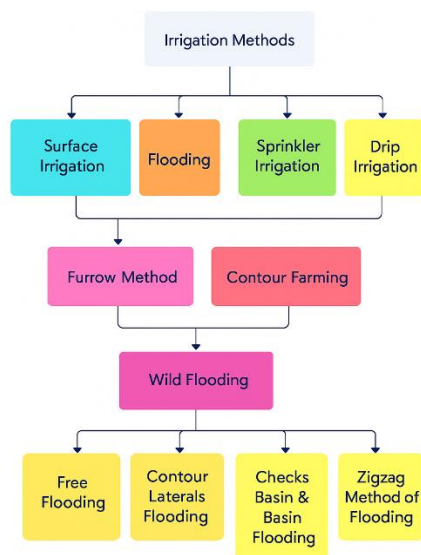


Figure 1: Different irrigation methods

Table 1: Usual application efficiencies of various irrigation systems [16].

| Irrigation methods     | Application efficiency |
|------------------------|------------------------|
| Surface irrigation     | 50-60%                 |
| Level basin irrigation | 60-80 %                |
| Border irrigation      | 60-75 %                |
| Furrow irrigation      | 50-70 %                |
| Drip irrigation        | 80-90 %                |
| Sprinkler irrigation   | 60-85 %                |
| Sub-surface irrigation | 50-80%                 |

Evapotranspiration (ET) is a combined term that encompasses transpiration, which refers to the movement of water absorbed by plants from the soil through roots and released through the leaves to the atmosphere, and evaporation from exposed surfaces such as vegetation, bare soil, and water bodies [17]. ET is a basic part of the hydrological cycle, as it describes the mechanisms and energy involved in transferring water stored within the soil, watershed, and vegetation canopy into the atmosphere as vapor [18]. Its significance is evident through its wide range of applications in hydrology, field-scale irrigation scheduling, soil and crop management, plant water stress assessment, meteorology, and climatology, as well as in forecasting extreme events such as droughts and floods [19].

In hydrology and agro-meteorology, two key conceptual forms of evapotranspiration (ET) are widely used: reference evapotranspiration ( $ET_o$ ) and potential evapotranspiration (PET). These provide standardized benchmarks that help in estimating actual water losses under varying environmental and crop conditions.  $ET_o$  refers to the evapotranspiration from a standardized reference surface, typically a well-watered, actively growing grass of fixed height (approximately 0.12 meters) with specified surface resistance and albedo. This standardization allows  $ET_o$  to serve as a consistent baseline for comparing different crops and land covers, independent of specific plant characteristics. The fluctuations in reference evapotranspiration ( $ET_o$ ) are entirely governed by climatic variables, including air temperature, solar radiation, wind velocity, and atmospheric humidity. The most commonly adopted and globally recognized approach for estimating reference evapotranspiration ( $ET_o$ ) is presented in [20]. This paper introduced the FAO-56 PM equation, which combines energy balance and aerodynamic principles to provide a physically based estimate of reference evapotranspiration under standard conditions. This equation has become the global standard in irrigation planning, climate analysis, and water resource assessments. In data-limited regions, simplified empirical models and machine learning approaches are used [21], [22]. While Potential evapotranspiration (PET) represents the maximum possible evapotranspiration assuming unlimited water availability. Unlike  $ET_o$ , it is not restricted to a specific reference surface and thus reflects the full atmospheric demand. Classical methods for PET estimation include the Penman, Priestley–Taylor, Thornthwaite, and Hargreaves equations [23], [24], [25].

Interest understanding in the interconnections among water, energy, and food has grown significantly due to increasing population pressures, changing climate, and the limited availability of natural resources [26]. Within this context, ET plays a critical role in regulating water losses in agricultural systems through effective irrigation scheduling [27]. Field-based ET measurements obtained using traditional ground instruments such as eddy covariance systems, Bowen ratio energy balance, or lysimeters allow for precise estimation of ET at specific locations [28]. However, these techniques are often expensive, labour-intensive, and prone to equipment-related challenges [29].

Alternatively, the FAO-56 PM equation offers a reliable framework for estimating ET by integrating key weather parameters such as air temperature, relative humidity, and wind speed. This approach is well suited for conditions where only basic weather station data

are accessible, particularly in its standardized form developed by the FAO [30]. Nevertheless, single-point measurements in heterogeneous landscapes may fail to show the spatial variability of ET across larger regions [31]. In humid climates, annual ET can account for nearly 50 % of total precipitation, whereas in arid and semi-arid zones it often approaches the entire annual rainfall [32]. Although ground-based methods provide accurate ET estimates for specific sites, their applicability at broader spatial scales remains limited due to landscape heterogeneity and complex hydrological processes. Furthermore, traditional ground-based measurement methods are insufficient for accurately representing ET variability across extensive and heterogeneous regions, particularly in areas influenced by strong advection effects. [33].

Remote sensing provides an efficient, economical, and spatially consistent means of estimating evapotranspiration (ET) over regional and meso-scale areas [34]. It establishes a direct relationship between the surface's radiative characteristics and the components of the surface energy balance (SEB). Over the last thirty years, the combined use of optical and thermal infrared remote sensing data has greatly improved the accuracy and spatial coverage of ET estimation [35]. Most remote sensing-based models rely on the principles of SEB and net radiation and are widely applied in areas such as water use assessment, ecological process modeling, biophysical property analysis, and watershed-scale water resources planning and management [36]. Among these approaches, single-source SEB methods are commonly employed to derive ET from satellite observations. A prominent example is the SEBAL developed by [37]. Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) [38], and the Simplified Surface Energy Balance (SSEB) [39] are the most widely adopted approaches.

The implementation of these models necessitates the identification of “anchor points,” which are specific pixels that represent extreme thermal and vegetation conditions, particularly in the case of SEBAL. These pixels must satisfy certain selection criteria to ensure the accuracy of the energy balance estimation. First, they should be located within homogeneous agricultural fields to minimize variability. Second, they must be free from any shadow or cloud interference to avoid distortions in the satellite signal. Finally, they should exhibit uniform surface temperature ( $T_s$ ), NDVI, and albedo values, ensuring that the selected points accurately reflect the desired surface conditions [40].

The selection of an  $ET_a$  method is determined by multiple considerations, including the intended use, the needed temporal and spatial resolution, meteorological data availability, and the specific limitations advantages of each modelling approach [41]. Remote sensing (RS)-based approaches for  $ET_a$  estimation are typically categorized into two main groups. The first group consists of vegetation index-based models, which estimate  $ET_a$  using basal crop coefficients derived from spectral reflectance data [42], as exemplified by the MOD16 model [43]. The second group includes land surface temperature ( $T_s$ ) based models, which rely upon SEB framework. It may be single source models, where soil and foliage are considered as a one layer, such as SEBAL [37], and METRIC [44], or two-source models, where soil and vegetation components are evaluated separately, such as TSEB [45] and ALEX-DisALEX [46], [47, p. 1], [48].

These models typically integrate satellite imagery with meteorological datasets, and in some cases, field observations are also used to compute the key elements of the energy balance such as latent heat, sensible heat, and soil heat flux as well as  $ET_a$ . Among  $T_s$  based methods, SEBAL has emerged as one of the most widely applied models, as it calculates  $ET_a$  from a mixture of satellite and meteorological inputs through the SEB. SEBAL has demonstrated robust performance across different climatic zones and land cover types, offering reliable results for water resources planning and management [49], [50], [51], [52]. A distinctive feature of SEBAL is its internal mechanism for computing the near surface temperature gradient ( $dT$ ), which depends on accurately selecting anchor pixels representing the wet (cold) and dry (hot) ends of the  $ET_a$  range.

Energy consumption in agricultural systems can be broadly classified into direct and indirect forms. *Indirect energy* refers to the energy embedded in off-farm processes, including the production, manufacturing, packaging, and transportation of fertilizers, pesticides, and agricultural machinery. In contrast, direct energy is consumed during on-farm operations, such as water pumping, land preparation, crop management, harvesting, and transportation activities [53]. Since most of these on- and off-farm operations rely heavily on nonrenewable energy sources, improving energy efficiency and reducing excessive energy use are critical for sustainable production systems [54]. Efficient resource utilization not only reduces energy dependency but also enhances profitability, productivity, and long-term competitiveness in the agricultural sector [55].

Internationally WEFN got significant recognition after the World Economic Forum 2008, where the interdependence of these critical sectors was highlighted as a main

challenge to sustainable economic change [56]. The FAO later emphasized that the nexus framework provides a systematic method to analyze human and nature interactions, promoting integrated natural resource management across multiple sectors and scales through the creation of synergies and the careful management of trade-offs [57]. Water, energy, and food are inherently interconnected, and disturbances in one area can generate surging impacts on others. For example, extreme droughts driven by climate change intensify water scarcity, thereby undermining both food and energy security [58]. As a result, the WEF nexus emerged as a comprehensive framework for solving these interlinked global resource challenges [59].

Systematic nexus thinking is crucial, as neglecting the mutuality among water, energy, and food can result in unintended and adverse outcomes. A notable example is the rapid expansion of biofuel production, initially promoted as a climate mitigation strategy. Although intended to reduce fossil fuel dependence, it can also lead to biodiversity loss [60] and aggravate food insecurity through competition for land and water resources. Similarly, while water-saving irrigation techniques and desalination technologies can enhance water availability, they often place additional burdens on the energy sector due to their high energy demands [61].

## **1.1 Research Question**

The accurate estimation of  $ET_a$  is crucial for effective crop water management and sustainable agricultural planning. The SEBAL model has been widely applied in different parts of the globe to compute  $ET_a$  using remote sensing data. However, its performance is highly sensitive to local climatic conditions, landscape heterogeneity, and crop characteristics. To ensure reliability, SEBAL often requires calibration with ground-based reference methods such as FAO-56 PM. Despite its potential, no study has yet calibrated SEBAL for crop-specific ET estimation in Pakistan. This lack of calibration limits the accuracy of  $ET_a$  estimation and its broader application in water resources and agricultural planning at the local scale in the country.

In this context, the central research question of this study is: “How accurate are SEBAL-based actual evapotranspiration ( $ET_a$ ) estimates for wheat when calibrated and compared with FAO-56 PM  $ET_a$  in Pakistan, and how does the WEFN vary at the field level?”. This study aims to fill this gap by developing a calibration framework for SEBAL using FAO-56 ET as a reference and applying it to selected wheat fields in Pakistan. The calibrated  $ET_a$  will then be used to analyze the interconnections between water use,

energy consumption, and food production at the field level, contributing to improved irrigation management strategies and informed decision making for sustainable agricultural development.

## **1.2 Problem Statement**

In Pakistan, agriculture is the biggest user of water, while both water and energy resources are already under severe stress. Nearly 93% of the available water is used for irrigation, with approximately 40% lost through inefficient conveyance and distribution systems. This highlights the urgent need for appropriate irrigation scheduling to minimize water losses, save energy, and control groundwater depletion. Evapotranspiration (ET) is a key parameter for irrigation scheduling; however, current in-situ  $ET_a$  estimation practices are resource-intensive and rely heavily on ground-based meteorological data. Such data are scarce in Pakistan because of the smaller number of weather stations, and the use of generalized crop coefficients fails to capture spatial and temporal variability in crop water use at the field scale.

The SEBAL model provides a robust remote sensing-based approach to estimate  $ET_a$  using satellite imagery. However, its performance is highly sensitive to local climatic conditions, landscape heterogeneity, vegetation characteristics, and hot-cold pixel selection. Without proper regional calibration, SEBAL-derived  $ET_a$  can lead to significant uncertainties in crop water use estimation. Despite its global application [101], SEBAL has not been calibrated for crop-specific ET estimation in Pakistan. This gap limits its practical application for operational irrigation planning and resource optimization. Moreover, the interlinkages between water use, energy use for pumping, and crop yield at the field level remain poorly understood. Therefore, this study aims to calibrate SEBAL-derived wheat  $ET_a$  using the FAO-56 PM method as a reference and to assess the WEFN through the integration of  $ET_a$  estimates, energy consumption data, and measured crop yields. This approach will enhance the accuracy of SEBAL  $ET_a$  values and support more efficient and sustainable water and energy resource management in the agricultural sector.

## **1.3 Objectives**

1. Estimation of evapotranspiration for Wheat, crops using satellite data and SEBAL model.
2. Calibration of SEBAL based ET values with FAO-56 CropWat Model.

3. To assess the impact of ET on WEFN in the context of Pakistan's agricultural sector.
4. To propose strategies for optimizing water and energy consumption to increase food security.

## **1.4 Significance of the Research**

This research is significant both scientifically and practically. Scientifically, it contributes to the advancement of remote sensing-based evapotranspiration estimation by calibrating the SEBAL model for wheat under the local climatic and agricultural conditions of Pakistan. The study bridges a critical knowledge gap by integrating satellite-derived  $ET_a$  with the FAO-56 PM method, improving the reliability of SEBAL-derived results in data-scarce regions. Furthermore, by linking SEBAL-based  $ET_a$  estimation with the WEFN framework, the research provides an innovative approach to quantifying interdependencies among irrigation utilization of water and energy resources alongside crop production at the field scale.

From a practical perspective, the findings will support improved irrigation scheduling and energy use efficiency, contributing to water conservation and reduced energy costs in agriculture. The outcomes will help policymakers and planners in formulating sustainable strategies for integrated resource management, aligning with Sustainable Development Goals (SDGs) related to food security (SDG 2), clean water (SDG 6), and cheap clean energy (SDG 7). Ultimately, this research promotes climate-resilient and resource-efficient agricultural practices vital for Pakistan's long-term food and water security.

## 2 Review Literature:

Pakistan is predominantly an agricultural nation, with approximately 47% of its population engaged either directly or indirectly in this sector [62]. Out of the total cultivated land of 21.2 million hectares, nearly 80% is irrigated, highlighting the country's strong dependence on irrigation-based agriculture. Consequently, around 93% of Pakistan's total water resources are allocated to irrigation [63]. However, the country is projected to experience a water shortfall of about 31 MAF by 2025, posing a serious threat to both economic stability and food security [64]. Meanwhile, population growth continues to escalate water and food demands, while per person water availability has declined drastically from 5,650 m<sup>3</sup> in 1951 to 1,000 m<sup>3</sup> in 2010 indicating increasing pressure on the nation's water resources.

Table 2 [65].

*Table 2: Population Wise Water Availability in Pakistan*

| <b>Year</b> | <b>Population (million)</b> | <b>Per capita water availability (m<sup>3</sup>)</b> |
|-------------|-----------------------------|------------------------------------------------------|
| 1951        |                             | 5650                                                 |
| 2003        | 146                         | 1200                                                 |
| 2010        | 168                         | 1000                                                 |
| 2025        | 221                         | 800                                                  |

Natural and anthropogenic pressures have increasingly strained global water, energy, food, and land resources. Projections indicate that by 2050, global demand may rise by 6%–55% for water, 40%–50% for energy, 60%–100% for food, and 10%–20% for land [66], [67]. These wide-ranging estimates reflect the complexity and uncertainty associated with forecasting future resource needs, which are strongly influenced by factors such as climate change and socio-economic transformations. Although approximately \$8 billion has been invested in irrigation expansion programs [68], irrigated agriculture has often fallen short of achieving its intended objectives. Such as reducing production gaps and ensuring sustainable livelihoods, largely due to linear and sector-specific attempts.

Evidence shows that while high-efficiency pressurized irrigation systems reduce water losses, they simultaneously increase energy consumption and operational costs [69].

Conventional irrigation management approaches have primarily emphasized water resources, operating under the assumption of unlimited energy supply and ideal crop growth conditions. [70]. For example, [71] provided a comparative evaluation of different water productivity indicators for major crops, while [72], [73] and [74] outlined practical guidelines, performance indicators, and case studies for evaluating the water and yield focused working of irrigation systems. Similarly, [36], [37], [38], and [39] discussed energy productivity (EP) and energy use efficiency in irrigated agriculture. However, these studies generally address each water, energy, and food resource in separately, resulting in limited understanding and quantification of their interdependencies, particularly in terms of water for food, energy for food, and energy for water linkages.

Addressing challenges within the WEFN necessitates moving beyond traditional indicators such as yield and water use efficiency as the sole indicators of success in irrigated farming. Instead, it requires a holistic assessment of trade-offs and co-benefits, considering environmental sustainability, equity considerations, and long-term resource resilience [79]. For instance, [80] found that a 1% growth in agricultural produce can result 0.6% to 1.2% more families achieving food security, underscoring the importance of understanding the linked energy water implications. This is particularly relevant in smallholder and farmer-led irrigation systems, where traditional irrigation methods are often the backbone of rural livelihoods [81].

One of the analytical tools increasingly used in WEFN assessments is the sustainability polygon, which effectively communicates and visualizes trade-offs and synergies in irrigated farming. This approach is notably applied in the Diagnostic Tools for Investment (DTI) in water for agriculture and power, where it supports the presentation of indices and indicators linked to investment priorities, institutional settings, and policy frameworks [82]. In India and Nepal, [84] employed sustainability polygons to assess the sustainability of various climate-smart agriculture practices in smallholder rice, seed cotton, and maize systems under both irrigated and rainfed conditions. Similarly, [84], [85] applied the polygon method in a WEFN framework to examine how various fertigation plans affect resource use efficiency, crop productivity, and effectiveness in Italy, Greece, and the Czech Republic. Furthermore, [86] utilized sustainability polygons under a footprint index-based WEFN approach to evaluate the sustainability of irrigation

practices in Italy, demonstrating their value in integrating multidimensional performance metrics into agricultural decision-making.

In Northern Greece, [87] assessed the effects of various irrigation methods and management plans on the water usage of cotton. Their findings revealed that drip irrigation can lower the total water usage by approximately 5% as compared to sprinkler systems, while deficit irrigation reduces water use by around 12% relative to 100% irrigation strategies. Similarly, [88] examined the combined impact of organic soil cover and drip irrigation in the Upper Litani Basin, Lebanon, and found that these practices although modest in effect led to a 5% reduction in blue water footprint. In India, a long-term field study on coconut farms by [89] demonstrated increased water productivity through the adoption of mulching and drip fertigation techniques.

Additionally, [90] and [91] introduced an innovative procedure to improve energy use in pumped irrigation systems. By applying a semi-arranged demand model, along with sector-based network management and critical point control, they optimized the performance of pumping stations. Field application of this model in an irrigation district in southern Spain indicated potential energy savings ranging from 5.6% to 25.8%. The study further showed that approximately 14.5% and 7.8% of critical hydrants can be scheduled to operate exclusively during non-peak hours, thereby reducing energy costs while maintaining adequate crop irrigation.

[92] utilized MODIS satellite imagery in combination with ground-based weather data within the SEBAL to compute ET over the Sanjiang Plain, Northeast China. Their findings indicated that SEBAL is highly suitable for ET estimation, showing only an 8.86% deviance from ground-based measurements. This demonstrates SEBAL's reliability, particularly in complex environments such as wetlands, where direct ET measurement is often challenging.

In Pakistan, several studies have been carried out at different times to determine ET for various crops using different approaches. [93] assessed the performance of four commonly applied techniques—Radiation Method, Modified Penman Method, Blaney and Criddle Formula, and the FAO PM Equation by comparing them against Pan Evaporation data. Their results showed that the FAO PM Equation provided the most accurate estimates under Pakistan's diverse climatic conditions.

Further, [94] applied the CROPWAT model to find crop water requirements and ET for rice, cotton, and wheat in Southern Punjab. The study indicated that evapotranspiration (ET) values ranged from 1.8 to 10.24 mm/day, whereas effective rainfall fluctuated between 2 and 31.3 mm. The total irrigation water requirements were calculated to be 996.4 mm for rice, 623.3 mm for cotton, and 209.5 mm for wheat. Similarly, the net irrigation depths for rice, cotton, and wheat were estimated at 72.4 mm, 67.8 mm, and 44.1 mm, respectively, while the gross irrigation amounts were 103.5 mm, 99.8 mm, and 63 mm. Based on these findings, the study inferred that the CROPWAT model serves as a reasonably effective approach for estimating crop water requirements in the study area.

[95] examined the influence of meteorological parameters on evapotranspiration (ET) across various climatic zones of Pakistan. Their study covered seasonal and annual ET trends from 1951 to 2016 at 50 weather stations situated in highly arid, and semi-arid regions, using FAO-56-PM method. The study revealed that ET is extremely sensitive and positively linked with wind speed, temperature, and solar radiation, while vapor pressure exhibits a negative correlation with ET.

In another study, [96] investigated the variability of climatic parameters from 1981 to 2010 and their influence on ET in humid zones of Pakistan. The outcomes demonstrated that a 20% gain in temperature, wind speed and solar irradiance led to an increase in annual ET demand by 11.93%, 2.83%, and 16.37% respectively. Conversely, a 20% increase in vapor pressure caused a decrease in annual ET by 2.5%. The study further highlighted seasonal variations in ET sensitivity—ET was more responsive to temperature and solar irradiance during the monsoon, to vapor pressure in winter, and to wind speed in summer.

[97] applied the SEBAL model to map the spatiotemporal dispersal of evapotranspiration across various climatic zones of Pakistan. They analyzed total 48 Landsat-8 images for six representative locations: Skardu, Kalam, Peshawar, D.I. Khan, Quetta, and Tando Jam. However, despite significant advancements in evapotranspiration modeling, integrated assessments of crop energy–water interactions remain limited. To date, only one study conducted by [98] has employed an integrated approach to quantify the crop energy and water (CEW) nexus in California’s Central Valley, USA. In that study, the SSEB<sub>op</sub> evapotranspiration model was applied to compute crop water consumption (ET<sub>a</sub>), while crop energy consumption was derived from groundwater table depths, energy used per unit of water pumped, and crop yield data obtained from USDA-NASS

dataset. Therefore, there is a need to apply the SEBAL model to estimate  $ET_a$  and, based on the derived  $ET_a$ , analyze the WEFN to provide a more broad understanding of resource interactions in agricultural systems.

Furthermore, SEBAL has been widely applied for actual evapotranspiration estimation in several regions of the world, several studies have emphasized that its performance is highly sensitive to landscape heterogeneity, surface characteristics, vegetation conditions, and hot–cold pixel selection. Therefore, careful calibration against ground-based reference methods such as FAO-56-PM is essential to ensure reliable ET estimates across varying climatic and surface conditions [37], [44], [50], [99], [100]. However, to date, no study has calibrated the SEBAL model for crop-specific ET estimation in Pakistan, particularly for wheat. To address this gap, the present research aims to calibrate SEBAL-derived actual evapotranspiration for wheat fields using the FAO-56 PM method as a reference, thereby improving the accuracy and applicability of SEBAL under local conditions. This will enable researchers and water management professionals to estimate crop  $ET_a$  using remote sensing techniques and satellite data alone, without relying on extensive ground-based meteorological inputs, thereby enhancing the capacity for efficient crop water management. Furthermore, the calibrated SEBAL-based wheat actual evapotranspiration will be utilized to evaluate the efficiency of the SEBAL algorithm in analyzing variations in the water–energy–food nexus (WEFN) across multiple fields, using measured crop yield data and energy consumption for irrigation water pumping.

### 3 Materials and Methods

This study employs an integrated methodological framework to estimate and analyze actual evapotranspiration (ET<sub>a</sub>) for wheat fields using remote sensing and energy balance modeling procedures, with a specific focus on WEFN. The approach combines satellite-based modeling, ground-based meteorological observations, and analytical tools to quantify ET<sub>a</sub> and evaluate its interactions with water and energy resources in irrigated agricultural systems. The SEBAL model was implemented GEE platform to derive spatiotemporal ET<sub>a</sub> estimates for the selected wheat fields. To ensure model reliability under local climatic conditions, SEBAL outputs were calibrated and validated using the FAO-56 -PM approach as a reference. The calibrated ET<sub>a</sub> estimates were then integrated with field-level crop yield and energy use data to assess WEFN indicators. This methodological structure enables a comprehensive evaluation of irrigation water use, energy consumption, and food production, thereby supporting sustainable agricultural water management in the region

#### 3.1 Study Area

The study was conducted in Swabi District, of Khyber Pakhtunkhwa (KP), Pakistan, situated between latitudes 34°03' and 34°25' N and longitudes 72°17' and 72°55' E. The district is spread over an area of approximately 1,543 km<sup>2</sup> and lies in semi-arid subtropical climatic zone of Pakistan. It is surrounded by Mardan, Nowshera, Buner, and Haripur districts. Swabi is situated within the Peshawar Basin, characterized by fertile alluvial plains formed by the Indus and Kabul River systems, marking it one of the agriculturally rich districts of Khyber Pakhtunkhwa.

Agriculture is a major source of livelihood in Swabi, with wheat, sugarcane, tobacco, and maize being the major crops grown under in both irrigated and rainfed conditions. The region's irrigation network is developed through canal systems derived from the Indus River and supplemented by tube wells. However, rapid population growth, water scarcity, and growing energy requirements have imposed significant burden on local water resources, highlighting the need for efficient water management practices.

Swabi have hot summers and mild winters, with average annual rainfall range from 600 and 1200 mm, major portion of which happens in monsoon season (July–September) and winter rains (December–February). The mean annual temperature ranges from 10°C in

winter to 38°C in summer, contributing to high evaporative losses. The soil is generally silty loam to sandy loam, supporting high agricultural productivity when adequate water is available.

For this study, eleven agricultural fields representing diverse soil, topographic, and irrigation conditions were selected to estimate  $ET_a$  for wheat (*Triticum aestivum* L.) using the SEBAL model implemented in GEE and analyze the WEFN. The selected fields serve as representative samples of the region's wheat cultivation patterns under varying management and irrigation regimes. Particulars of the selected fields are shown in Table 3.

*Table 3: Selected fields*

| <b>Field-No</b> | <b>Soil Type</b>    | <b>Irrigation Type</b> | <b>Fertility</b> |
|-----------------|---------------------|------------------------|------------------|
| 1               | Sandy loam + Gravel | Flooding               | Medium           |
| 2               | Sandy loam + Gravel | Flooding               | Medium           |
| 3               | Loamy sand + Gravel | Flooding               | Medium           |
| 4               | Loamy sand + Gravel | Flooding               | Medium           |
| 5               | Loamy sand + Gravel | Flooding               | Low              |
| 6               | Sandy loam + Gravel | Flooding               | Medium           |
| 7               | Silty clay          | Flooding               | High             |
| 8               | Silty clay          | Flooding               | High             |
| 9               | Sandy clay          | Flooding               | High             |
| 10              | Sandy clay          | Flooding               | Medium           |
| 11              | Silt clay loam      | Flooding               | Medium           |

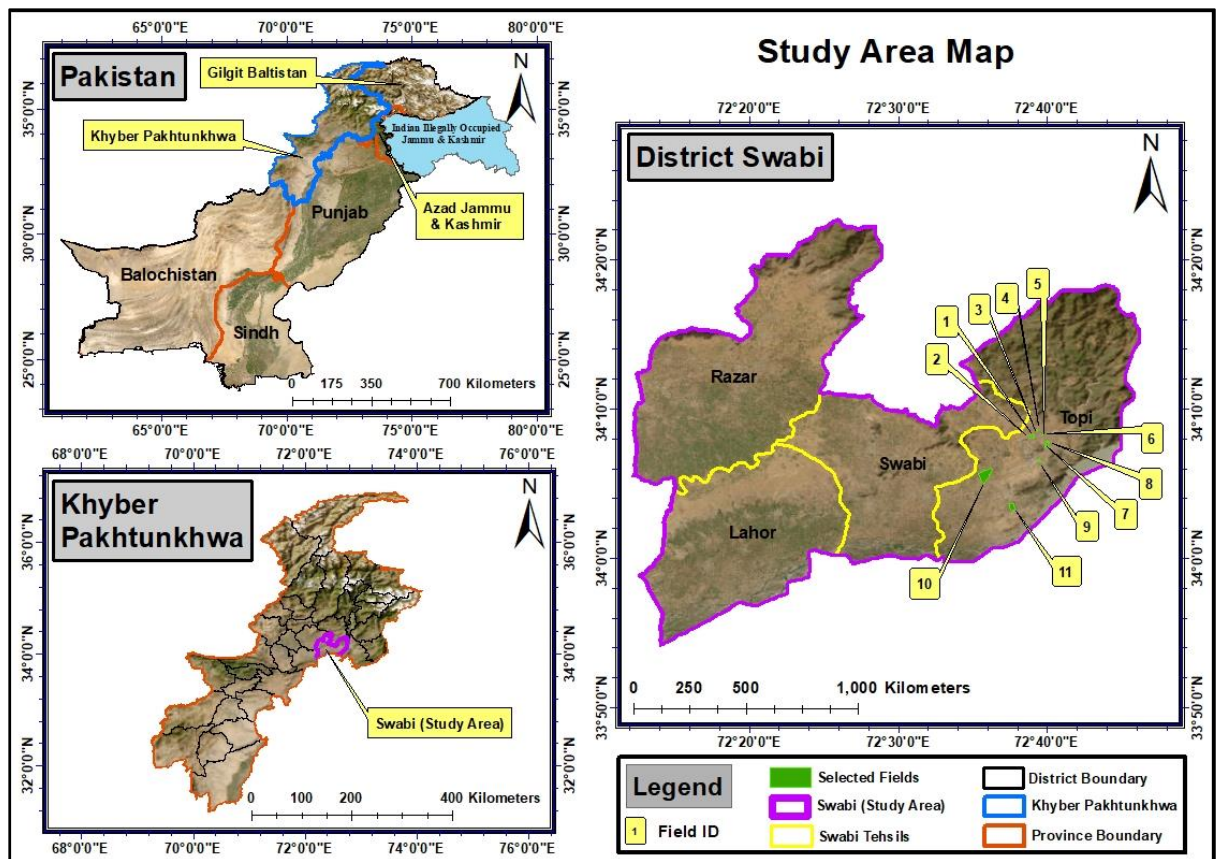


Figure 2: Study area map

### 3.2 Data Collection

The study incorporated data from several sources Table 4. For estimation of ET, using SEBAL model Landsat 8 images and ERA5-Land climate data was utilized. Precipitation data was acquired from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). These precipitation products has been commonly employed in water resources studies, environment, hydrology, meteorology, and agriculture, and has been validated by multiple projects [102]. The ground based metrological, was obtained from Pakistan Metrological Department (PMD), and crops yield, groundwater levels, and irrigation data was recorded manually. For  $ET_a$  analysis, nine Landsat 8 images with 6 cloud cover  $<10\%$  and 3 images with cloud cover  $<15\%$  were processed in GEE using the SEBAL algorithm to estimate  $ET_a$  for wheat crops in the 11 selected fields and to analyze the spatiotemporal variations in  $ET_a$  across the study area. Details of the processed images are shown in Table 5.

Table 4: Description of the data used in the study

| Data Type | Data Name | Spatial Resolution | Temporal Resolution | Source Type |
|-----------|-----------|--------------------|---------------------|-------------|
|           |           |                    |                     |             |

|                              |                          |                                   |                           |                                     |
|------------------------------|--------------------------|-----------------------------------|---------------------------|-------------------------------------|
| Precipitation                | CHIRPS                   | 0.05x0.05°                        | Monthly, Daily,<br>Pentad | Satellite/Remote<br>Sensing Product |
| Ground Water<br>Depth        | PCRWR                    | Regional                          | Yearly                    | Reports                             |
| Crop Yield                   | PBS                      | Country,<br>Province,<br>District | Yearly                    | Existing<br>Database                |
| Land Use                     | PBS                      | Country<br>Province               | Yearly/Seasonal           | Existing<br>Database                |
| Ground Based<br>Weather Data | PMD,<br>PCRWR            | Selected<br>Stations              | Daily, Monthly,           | Existing<br>Database                |
| Energy<br>Consumption        | IWMI, PSB,<br>Literature | Country and<br>Province<br>Level  | Yearly/Seasonal           | Reports,<br>Articles                |

*Table 5: Landsat 8 OLI/TIRS images used for SEBAL-based ET<sub>a</sub> estimation during the 2023–2024 wheat growing season in the study area.*

| No . | Acquisition Date | Sensor             | Path/Row | Cloud Cover (%) | Scene ID | Crop Stage       | Used For                             |
|------|------------------|--------------------|----------|-----------------|----------|------------------|--------------------------------------|
| 1    | 12 Oct 2023      | Landsat 8 OLI/TIRS | 150/036  | <10             | —        | Emergence        | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 2    | 28 Oct 2023      | Landsat 8 OLI/TIRS | 150/036  | <10             | —        | Early Vegetative | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 3    | 13 Nov 2023      | Landsat 8 OLI/TIRS | 150/036  | <10             | —        | Vegetative       | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 4    | 15 Dec 2023      | Landsat 8 OLI/TIRS | 150/036  | <10             | —        | Mid Vegetative   | ET <sub>a</sub> , NDVI, SAVI, Albedo |

|   |             |                    |         |     |   |                 |                                      |
|---|-------------|--------------------|---------|-----|---|-----------------|--------------------------------------|
| 5 | 31 Dec 2023 | Landsat 8 OLI/TIRS | 150/036 | <10 | — | Late Vegetative | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 6 | 16 Jan 2024 | Landsat 8 OLI/TIRS | 150/036 | <10 | — | Reproductive    | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 7 | 20 Mar 2024 | Landsat 8 OLI/TIRS | 150/036 | <15 | — | Flowering       | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 8 | 05 Apr 2024 | Landsat 8 OLI/TIRS | 150/036 | <15 | — | Grain Filling   | ET <sub>a</sub> , NDVI, SAVI, Albedo |
| 9 | 21 Apr 2024 | Landsat 8 OLI/TIRS | 150/036 | <15 | — | Harvesting      | ET <sub>a</sub> , NDVI, SAVI, Albedo |

### 3.3 Evapotranspiration Estimation Using SEBAL Algorithm

Proposed by [37], the SEBAL is a remote sensing-based model designed to compute ET<sub>a</sub> and surface energy flux components, including net radiation (R<sub>n</sub>), soil heat flux (G), sensible heat flux (H), and latent heat flux (LE), at both regional and field scales. The model integrates satellite imagery with a limited set of ground-based meteorological parameters to solve the SEB. SEBAL applies an iterative, feedback-driven numerical procedure to find the distribution of radiation and heat fluxes. LE, expressed in W/m<sup>2</sup>, is approximated as the residual of the SEB equation on a pixel-by-pixel basis, using two reference or “anchor” pixels representing wet (cold) and dry (hot) conditions for the entire scene. At the dry anchor point, LE = 0 and H = R<sub>n</sub> – G, whereas at the wet anchor point, H = 0 and LE is assumed to be either R<sub>n</sub> – G or a reference ET value [103].

$$R_n = G + H + LE \quad (1)$$

Where R<sub>n</sub> is the net radiation (W/m<sup>2</sup>), representing the total heat energy available at the surface; G is the soil heat flux absorbed by the ground (W/m<sup>2</sup>); H is the sensible heat flux (W/m<sup>2</sup>), representing the convective transfer of heat between the surface and the air;

and LE is the latent heat flux (W/m<sup>2</sup>), corresponding to the energy consumed during evapotranspiration. A key component of the SEBAL algorithm is the establishment of a direct relationship between  $T_s$  and the near-surface air temperature difference ( $\delta T_a$ ) at crop height  $z$  (i.e.,  $T_s - T_a$ ). This relationship enables the calculation of  $H$  and, subsequently, the residual LE, which is directly related to evapotranspiration.

$$\delta T_a = c_1 T_s - c_0 \quad (2)$$

Where  $c_1$  and  $c_0$  are empirical coefficients derived from the anchored wet and dry conditions, specifically wet ( $\delta T_{a,wet} = 0, T_{s,wet}$ ) and dry ( $T_{s,dry}$ ) points. Under these conditions, the temperature difference is expressed as:

$$\delta T_{a,dry} = \frac{(R_n - G) r_{aH}}{\rho C_P} \quad (4)$$

These coefficients must be determined individually for each satellite scene, regardless of the surface types present within the image. Once the regression equation is established, the corresponding  $T_s$  value for each pixel is used to compute the  $H$ . The  $H$  is then calculated through following relationship:

$$H(T_s) = \frac{\rho C_P}{r_{aH}} (c_1 T_s - c_0) \quad (5)$$

### 3.3.1 Calculation of Instantaneous Latent Heat Flux ( $\lambda ET$ )

The ( $\lambda ET$ ), representing the combined effect of evaporation and transpiration at the time of satellite overpass, is estimated for each pixel using the values of net radiation ( $R_n$ ),  $G$ , and  $H$ . This estimation follows the SEB equation proposed by [49].

$$\lambda LE = R_n - G - H \quad (6)$$

where  $\lambda ET$  is the latent heat flux (W m<sup>-2</sup>),  $\lambda$  can be calculated using equation 7.

$$\lambda = \frac{LE}{R_n - G} \quad (7)$$

### 3.3.2 Calculation of Net Radiation ( $R_n$ )

$R_n$  at the Earth's surface is computed based on the energy balance between incoming and outgoing radiation at the surface-atmosphere interface. It represents the total

available energy driving evapotranspiration and other surface processes.  $R_n$  at the surface is determined using the following relationship:

$$R_n = (1 - \alpha) R_s \downarrow + R_L \downarrow - R_L \uparrow - (1 - \epsilon_0) R_L \downarrow \quad (8)$$

Where  $\alpha$  is the surface albedo,  $R_{s\downarrow}$  is the incoming shortwave radiation ( $\text{W m}^{-2}$ ),  $R_{s\uparrow}$  is the reflected shortwave radiation ( $\text{W m}^{-2}$ ),  $R_{L\downarrow}$  is the incoming longwave radiation ( $\text{W m}^{-2}$ ),  $R_{L\uparrow}$  is the outgoing longwave radiation ( $\text{W m}^{-2}$ ), and  $\epsilon_0$  is the surface thermal emissivity.

### 3.3.3 Calculation of Surface Albedo ( $\alpha$ )

In SEBAL, ( $\alpha$ ) is derived from the top-of-atmosphere albedo ( $\alpha_{toa}$ ) by correcting for atmospheric effects such as path radiance and transmissivity. It is determined through the following equation:

$$\alpha = \frac{\alpha_{toa} - \alpha_{path-radiance}}{\tau_b^2} \quad (9)$$

Where,  $\tau_b$  represents the atmospheric transmission coefficient, and  $\alpha_{toa}$  denotes the top-of-atmosphere albedo, which is calculated using Equation (5). The term  $\alpha_{path-radiance}$  refers to the deviant radiation albedo, which represents the average solar radiation in all spectral bands that is reflected to the sensor through the atmosphere before reaching the Earth's surface. Its value typically ranges between 0.025 and 0.04.

$$\alpha_{toa} = \sum (W_\lambda \times \rho_\lambda) \quad (10)$$

where  $W_\lambda$  is the weighting coefficient for each spectral band, and  $\rho_\lambda$  is the planetary reflectance for the corresponding wavelength  $\lambda$ . which is derive as follows:.

$$W_\lambda = \frac{ESUN_\lambda}{\sum ESUN_\lambda} \quad (11)$$

where  $ESUN_\lambda$  represents the mean exo-atmospheric solar irradiance for the  $\lambda$  band. This value varies with each spectral band but remains constant for a given satellite sensor. The weighting coefficients for each reflective band of Landsat 8 used in the albedo calculations are presented in Table 6.

### 3.3.4 Computation of Normalized Difference Vegetation Index (NDVI)

Vegetation indices have been significantly improved with the advent of early satellite systems developed to monitor and evaluate vegetation cover [103]. These indices are widely used to evaluate vegetation health, density, and spatial distribution. One of the most commonly applied vegetation indices is the NDVI, which is computed from the near-infrared and red bands of satellite imagery as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \quad (12)$$

where  $\rho_{NIR}$  is the surface reflectance in the near-infrared band, and  $\rho_R$  is the surface reflectance in the red band. The specific wavelengths used for these bands vary across different satellite sensors. Table 7 presents the corresponding near-infrared and red bands for the OLI sensor onboard Landsat 8.

### 3.3.5 Computation Soil Adjusted Vegetation Index (SAVI)

SAVI was developed to minimize the impact of background soil reflectance on the NDVI, particularly in spots with sparse vegetation cover. It is expressed as:

$$SAVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + L} (1 + L) \quad (13)$$

where  $L$  is a soil adjustment factor that typically ranges from 0 for dense vegetation to 1 for low-density vegetation.

### 3.3.6 Computation Leaf Area Index (LAI)

LAI represents the ratio of the total one-sided area of plant leaves to the ground surface area covered by the canopy. Several empirical relationships have been developed to estimate LAI from vegetation indices. One commonly used approach is expressed as:

$$LAI = \frac{\ln\left(\frac{\frac{0}{69} - SAVI}{\frac{0}{59}}\right)}{0.91} \quad (14)$$

### 3.3.7 Computation of Incoming shortwave solar radiation ( $R_{S\downarrow}$ )

( $R_{S\downarrow}$ ) refers to the direct and diffuse solar radiation reaching the Earth's surface under clear-sky conditions. Its value depends on atmospheric properties, time of day, and geographic location. It can be estimated using empirical relationships given in Equations (15) to (17).

$$R_{S\downarrow} = G_{sc} \times \cos\theta \times d_r \times \tau_{sw} \quad (15)$$

$$d_r = 1 + 0.0033 \times \cos\left(\frac{\text{DOY} \times 2\pi}{365}\right) \quad (16)$$

$$\tau_{sw} = 0.75 + 2 \times 10^{-5} \times Z \quad (17)$$

Table 6: Landsat 8 reflective band calibration coefficients

| Band     | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 | Band 6 | Band 7 | Fixed  |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|
| Landsat8 | 0.356  | 0      | 0.130  | 0.373  | 0.085  | 0.072  | 0.072  | —      |
|          |        |        |        |        |        |        |        | 0.0018 |

Table 7: Infrared and near-infrared bands of the OLI sensor

| Image sensor | Infrared | Near infrared |
|--------------|----------|---------------|
| OLI          | Band 4   | Band 5        |

The solar constant ( $G_{sc}$ ) is approximately  $1367 \text{ W m}^{-2}$ . The solar zenith angle ( $\theta$ ) is calculated as  $\theta = 90^\circ - \beta$ , where  $\beta$  represents the solar altitude angle. The term  $d_r^2$  is the inverse square of the relative distance between the Earth and the Sun, which is derived from the Day of Year (DOY). The atmospheric transmissivity ( $\tau_{sw}$ ) is determined using the mean elevation ( $Z$ ) of the area. To achieve higher precision,  $Z$  is preferably obtained from a Digital Elevation Model (DEM) rather than from simple average elevation values. The value of incoming shortwave radiation ( $R_{S\downarrow}$ ) can vary between  $200$  and  $1000 \text{ W m}^{-2}$ , depending on the time of acquisition and geographical location of the satellite image.

### 3.3.8 Computation of Incoming Longwave Radiation ( $R_{L\downarrow}$ )

The incoming longwave radiation ( $R_{L\downarrow}$ ) represents the thermal energy flux emitted downward from the atmosphere toward the Earth's surface, expressed in  $\text{W m}^{-2}$ . It is calculated using the Stefan–Boltzmann equation as follows:

$$RL \downarrow = \epsilon_a \sigma T_a^4 \quad (18)$$

where  $\epsilon_a$  is the atmospheric emissivity,  $\sigma$  is the Stefan–Boltzmann constant  $5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$ , and  $T_a$  is the near-surface air temperature (K). In this study, the cold pixel temperature is considered as a representative value of the near-surface air temperature. To determine the atmospheric emissivity ( $\epsilon_a$ ), an empirical relationship can be applied.

$$\epsilon_a = 0.85 \times (-\ln \tau_{sw})^{0.09} \quad (19)$$

In relation to Equation (19),  $\tau_{sw}$  denotes the atmospheric transmissivity coefficient. The incoming longwave radiation ( $R_{L\downarrow}$ ) typically varies between 200 and 600  $\text{W m}^{-2}$ , depending on atmospheric conditions such as air temperature, humidity, and cloud cover.

### 3.3.9 Estimation of Outgoing Longwave Radiation ( $RL\uparrow$ )

$RL\uparrow$  was estimated using the Stefan–Boltzmann law as expressed in equation (20):

$$R_L \uparrow = \epsilon_0 \times \sigma T_s^4 \quad (20)$$

In equation (20),  $R_L \uparrow$  denotes the outgoing longwave radiation,  $\epsilon_0$  is the surface emissivity representing thermal radiation behavior within the 6–14  $\mu\text{m}$  wavelength range, and  $T_s$  (in Kelvin) corresponds to the measured surface temperature.

### 3.3.10 Land Surface Temperature ( $T_s$ )

For Landsat 8 imagery, thermal bands 10 or 11 were utilized to derive the  $T_s$ . In this study, the surface temperature was estimated using the following relationship:

$$T_s = \frac{K_2}{\ln\left(\frac{\epsilon_{NB} K_1}{RC} + 1\right)} \quad 21$$

In equation (21),  $RC$  represents the surface-corrected thermal radiance for Landsat 8 bands 10 or 11, while  $K_1$  and  $K_2$  are calibration constants with values of 774.89 and 1321.08, respectively.  $\epsilon_{NB}$  denotes the narrowband emissivity, which was determined from  $\epsilon_0$  using the emissive conversion Table 8 provided below.

### 3.3.11 Surface Emission ( $\epsilon_{NB}$ )

$\epsilon_{NB}$  is defined as the ratio of the thermal energy emitted by the surface to that emitted by an ideal blackbody at an equivalent temperature. The emissivity values corresponding to different land cover types were derived using established empirical relationships and are summarized in Table 8.

### 3.3.12 Selection of Hot and Cold Pixels

The SEBAL algorithm employs two specific indicator pixels to establish fixed boundary conditions for solving the SEB equation. The cold pixel corresponds to a well-irrigated and vegetated surface where the land surface temperature closely matches the ambient air temperature, and evapotranspiration approximates the reference ET. In contrast, the hot pixel represents a dry, bare agricultural field under minimal or no moisture conditions, where evapotranspiration is considered negligible or zero.

### 3.3.13 Calculation of Soil Heat Flux ( $G$ )

( $G$ ) is defined as the amount of heat transferred within the soil and vegetation through molecular conduction. It was calculated using the following relationship:

$$\frac{G}{R_n} = \frac{T_s}{\alpha} \times \left( \frac{0}{0032} \times \alpha + \frac{0}{0062} \times \alpha^2 \right) \times (1 - 0/978 \times NDVI^4) \quad 22$$

In equation (22),  $T_s$  represents the surface temperature,  $\alpha$  is the surface albedo,  $NDVI$  is the vegetation index, and  $R_n$  denotes the net solar radiation. This empirical relationship has demonstrated reliable performance for agricultural lands.

In SEBAL, the ratio of  $\frac{G}{R_n}$  for clear, deep-water bodies and snow-covered surfaces was considered equal to 0.5. This ratio was estimated based on the values of  $nR_n$ ,  $H$ , and  $G$  derived at the time of satellite image acquisition.

$$\Delta_{ins} = \frac{R_n - G - H}{R_n - G} \quad 23$$

Table 8: Surface emissions by land cover type

|               |                                 |                                                      |
|---------------|---------------------------------|------------------------------------------------------|
| NDVI $\geq 0$ | LAI $< 3$                       | $\varepsilon_{NB} = 0.97 + 0.0033 \times \text{LAI}$ |
|               |                                 | $\varepsilon_0 = 0.95 + 0.01 \times \text{LAI}$      |
|               | LAI $\geq 3$                    | $\varepsilon_{NB} = 0.98$                            |
|               |                                 | $\varepsilon_0 = 0.98$                               |
| NDVI $< 0$    | For water ( $\alpha < 0.47$ )   | $\varepsilon_{NB} = 0.99$                            |
|               | For snow ( $\alpha \geq 0.47$ ) | $\varepsilon_0 = 0.985$                              |

### 3.3.14 Calculation of Sensible Heat flux (H)

The final component of the energy balance equation is the ( $H$ ). It represents the amount of heat transferred from the surface to the atmosphere through convection and molecular conduction caused by temperature differences.

$$H = \frac{\rho \times C_p \times dT}{r_{ah}} \quad (24)$$

In equation (24),  $\rho$  represents the air density ( $\text{kg/m}^3$ ),  $C_p$  is the specific heat capacity of air ( $1004 \text{ J kg}^{-1} \text{ K}^{-1}$ ),  $dT$  denotes the temperature difference ( $T_1 - T_2$ ) between heights  $Z_1$  and  $Z_2$  in Kelvin, and  $r_{ah}$  is the aerodynamic resistance to heat transfer ( $\text{ms}^{-1}$ ). The complexity of this computation arises from the presence of two unknown variables,  $r_{ah}$  and  $dT$ , in equation (24).

To incorporate the effect of buoyancy induced by surface heating, the SEBAL algorithm applied the Monin–Obukhov theory through an iterative procedure. Atmospheric stability conditions, particularly under dry surface conditions, were accounted for using the Monin–Obukhov length ( $L$ ). The atmosphere is considered unstable when  $L < 0$ , neutral when  $L = 0$ , and stable when  $L > 0$ . The length was calculated as:

$$L = \frac{\rho C_p U_*^3 T_s}{K_g H} \quad 25$$

In the SEBAL algorithm, the initial values of friction velocity ( $U_*$ ) and aerodynamic resistance ( $r_{ah}$ ) were obtained from the meteorological station under the assumption of neutral atmospheric conditions, as shown below:

$$L = \frac{\ln\left(\frac{Z_2}{Z_1}\right)}{U_* \times K} \quad 27$$

$$L = \frac{KU_x}{\ln\left(\frac{Z_x}{Z_{om}}\right)} \quad 28$$

$$Z_{om} = 0.12 \times h \quad 29$$

$$U_* = U_* \frac{\ln\left(\frac{200}{Z_{om}}\right)}{K} \quad 30$$

In these equations,  $Z_1$  and  $Z_2$  represent the measurement heights above the displacement level, where  $Z_1$  corresponds to the vegetation height and  $Z_2$  is slightly higher. In SEBAL,  $Z_1 = 0.1$  m and  $Z_2 = 2$  m was used.  $K$  is the von Kármán constant (0.41),  $U_*$  represents the friction velocity ( $ms^{-1}$ ),  $Z_{om}$  denotes the momentum roughness length,  $U_x$  is the wind speed at height  $Z_x$ , and  $h$  is the average vegetation height (m).

Initially,  $Z_{om}$  was calculated from the average vegetation height near the meteorological station. Then, the target height and the corresponding average wind speed were used to compute  $U_*$  for the station. Using the derived values of  $U_*$  and  $r_{ah}$ , the wind speed at 200 m ( $U_{200}$ ) for the weather station was calculated, followed by the estimation of  $r_{ah}$  for the entire satellite image.

To determine  $r_{ah}$  across the image,  $Z_{om}$  values for the whole scene were required. When a land use map was available,  $Z_{om}$  values were assigned to each pixel based on land cover categories using Table 9. For agricultural areas without a land use map,  $Z_{om}$  was estimated as a function of the leaf area index (LAI):

$$Z_{om} = 0.018LAI \quad (31)$$

Alternatively,  $Z_{om}$  could be calculated using surface albedo ( $\alpha$ ) and NDVI through the following relationship:

$$Z_{om} = \exp\left[a\left(\frac{NDVI}{\alpha}\right) + b\right] \quad (32)$$

where  $a$  and  $b$  are empirical coefficients estimated through the above calculated wind speed, reference evapotranspiration, wet and cold pixels  $G$ ,  $r_{ah}$ , and  $\varepsilon$  etc. using GetSEBAL plugin in QGIS

Table 9: Roughness length ( $Z_{om}$ ) values for different ground surface types

| Land type | Water | City | forest | Meadow | Desert or vegetation | Snow |
|-----------|-------|------|--------|--------|----------------------|------|
|-----------|-------|------|--------|--------|----------------------|------|

|          |        |     |     |      |     |       |
|----------|--------|-----|-----|------|-----|-------|
| $Z_{om}$ | 0.0005 | 0.2 | 0.5 | 0.02 | 0.1 | 0.005 |
|----------|--------|-----|-----|------|-----|-------|

In the subsequent step, the temperature difference  $dT$  was obtained for image pixels to enable the final computation of sensible heat flux. Hot and cold pixels had already been identified and their primary variables extracted. For the cold pixel, it was assumed that all available energy was consumed by evapotranspiration, whereas for the hot pixel (bare, dry surface) evapotranspiration was assumed to be zero. The selection of these two pixels required expertise because the accuracy of ET estimates depended strongly on their correct identification.

By specifying the hot and cold pixels, the differences between aerodynamic temperature and surface temperature were estimated. A linear regression between the pixel temperature  $T_s$  and the corresponding temperature difference  $dT$  was established of the form

$$T_{air} = T_s - d_T \quad (33)$$

$$dT_{cold} = \frac{H_{cold} \times r_{ah-cold}}{\rho \times C_p} \quad (34)$$

$$dT_{hot} = \frac{H_{hot} \times r_{ah-hot}}{\rho \times C_p} \quad (35)$$

The sensible heat fluxes at the hot and cold pixels were obtained from.

$$H_{hot} = R_n - G \quad (36)$$

$$dT_{cold} = R_n - G - K\lambda ET_{ref} \quad (37)$$

in which  $\lambda ET_{ref}$  denoted the hourly reference evapotranspiration estimated using the FAO PM method. The crop coefficient  $K$  for the cold pixel had a strong influence on SEBAL results and therefore required knowledge of the land-cover at the cold pixel coordinates.

Air temperature for each pixel was then estimated as

$$T_{air} = T_s - d_T \quad (38)$$

so that air density corrections could be applied and an initial  $H$  value per pixel could be computed by substitution into Eq. (24). With this initial sensible heat flux, the Monin–Obukhov length was recalculated and updated values of friction velocity  $U_*$  and aerodynamic resistance  $r_{ah}$  were derived.

Friction velocity at the station was computed (using the 200 m reference) as

$$U_* = \frac{U_{200}K}{\ln\left(\frac{200}{Z_{om}}\right) - \theta_m(200m)} \quad (39)$$

$$r_{ah} = \frac{\ln\left(\frac{Z}{Z_1}\right) - \theta_{hz_2} + \theta_{hz_1}}{KU_*} \quad (40)$$

where  $\psi_m(200\text{ m})$  is the stability correction for momentum at 200 m, and  $\psi_h(Z)$  and  $\psi_h(Z_1)$  are stability corrections for heat transfer at heights  $Z$  and  $Z_1$  (e.g., 2 m and 0.1 m).

Stability correction functions were applied according to the sign of  $L$ . For unstable conditions ( $L < 0$ ) the correction functions were computed as:

If  $L < 0$ :

$$\theta_m(200m) = 2\ln\left(\frac{1 + X_{200m}}{2}\right) + \ln\left(\frac{1 + X^2(200m)}{2}\right) - 2\text{ARCTAN}(X_{200m}) + 0/5\pi \quad (39)$$

$$\theta_h(2m) = 2\ln\left(\frac{1 + X^2(2m)}{2}\right) \quad 40$$

$$\theta_h(0/1m) = 2\ln\left(\frac{1 + X^2(0/1m)}{2}\right) \quad 41$$

If  $L > 0$

$$\theta_m(200m) = -5\frac{2}{L} \quad 42$$

$$\theta_h(2m) = -5\frac{2}{L} \quad 43$$

$$\theta_h(200m) = -5\frac{0/1}{L} \quad 44$$

If  $L = 0$

$$\theta_m, \theta_h = 0 \quad 45$$

The iteration continued by updating  $U_*$ ,  $r_{ah}$ ,  $dT$  and  $H$  across pixels until convergence was achieved, after which the final pixel-wise sensible heat flux  $H$  was reported.

For unstable atmospheric conditions ( $L < 0$ ), the stability correction parameters were computed using the following relationships:

$$X_{200m} = \left(1 - 16 \frac{200}{L}\right)^{0/25} \quad 46$$

$$X(0/1m) = \left(1 - 16 \frac{0/1}{L}\right)^{0/25} \quad 47$$

### 3.3.15 Estimation of evapotranspiration (ET)

Finally,  $ET_a$  in mm/hour was computed using the following relationship:

$$ET_{inst} = 3600 \frac{\lambda ET}{\lambda} \quad 48$$

In this equation,  $\lambda$  represents the latent heat of vaporization, which equals 2450 J/g. To convert the instantaneous ET ( $ET_{inst}$ ) into daily ET, the following relationship was applied:

$$ET_r F = \frac{ET_{inst}}{ET_r} \quad 49$$

Here,  $ET_r$  is the reference evapotranspiration which was estimated using available meteorological data through the FAO-56-PM equation in university of Idaho ET software, and  $ET_{inst}$  is the instantaneous ET calculated in the previous step.

The daily actual evapotranspiration ( $ET_{24}$ ) was then obtained as:

$$ET_{24} = ET_r 24 \times ET_r F \quad 50$$

where  $ET_{r24}$  represents the daily reference evapotranspiration. This approach allows the instantaneous satellite-based ET values to be scaled to daily totals using reference ET data.

## 3.4 Implementation of SEBAL Algorithm in Google Earth Engine

The SEBAL algorithm was implemented on the Google Earth Engine (GEE) platform using the JavaScript programming interface (Figure 3). GEE provides access to the complete Landsat archive and ERA5-Land climate datasets, enabling efficient SEBAL processing across large spatial domains with high-performance cloud computing. This approach facilitates ET estimation in areas where ground-based meteorological observations are limited or unavailable. The developed workflow was designed to process single Landsat scenes, perform automated batch computations across multiple acquisition dates, and generate actual evapotranspiration ( $ET_a$ ) outputs for 11 selected

wheat fields. A schematic representation of the stepwise SEBAL processing chain is shown in Figure 4.

### **3.4.1 Data Acquisition and Preprocessing**

Input satellite data included atmospherically corrected surface reflectance and brightness temperature products from Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). Cloud-free images with less than 10% cloud cover were selected to ensure data quality. A total of nine Landsat 8 scenes were acquired covering the wheat growing season from October 2023 to April 2024.

Meteorological inputs required for SEBAL were obtained from the ERA5-Land reanalysis dataset at hourly temporal resolution and matched with the Landsat overpass time. These inputs included near-surface air temperature, dew point temperature, wind speed components, and reference evapotranspiration. Relative humidity was derived from the available variables. Land surface temperature retrieved from the thermal bands was corrected to a common elevation datum using Shuttle Radar Topography Mission (SRTM) elevation data and an average lapse rate of  $6.5\text{ }^{\circ}\text{C km}^{-1}$ . SRTM data were also used to correct slope and elevation effects, while incoming shortwave radiation was estimated and aggregated to daily values.

### **3.4.2 Radiometric Calibration and Surface Parameter Derivation**

Radiometric calibration and atmospheric correction were applied to convert raw Landsat data to surface reflectance and surface albedo. Vegetation indices such as NDVI and SAVI were computed to characterize vegetation cover, and leaf area index (LAI) and surface emissivity were derived to support SEB calculations. Land surface temperature was extracted from the thermal infrared bands, and both incoming and outgoing longwave radiation were calculated using surface emissivity and atmospheric transmissivity. These components were integrated to estimate net radiation at the land surface for each pixel.

### **3.4.3 Soil Heat Flux Estimation**

Soil heat flux was estimated as a fraction of net radiation using surface temperature, albedo, and NDVI. For water or snow-covered areas, a constant ratio was applied. This step allowed partitioning of the available energy between sensible and latent heat fluxes.

#### **3.4.4 Momentum Roughness Length and Hot/Cold Pixel Selection**

Momentum roughness length was derived from CORINE land cover data and adjusted using LAI for agricultural areas. Hot and cold pixels were manually selected within the GEE interface to represent extreme conditions. The cold pixel corresponded to well-watered vegetated surfaces (maximum ET), while the hot pixel represented dry bare soil (minimal ET). These anchor pixels provided boundary conditions for sensible heat flux estimation.

#### **3.4.5 Sensible Heat Flux Calculation**

Sensible heat flux was computed using Monin–Obukhov similarity theory. Friction velocity and aerodynamic resistance were calculated, and an iterative stability correction procedure was applied to account for atmospheric stability. A linear relationship between surface temperature and temperature difference was established based on the anchor pixels, which was then applied to the entire image domain.

#### **3.4.6 Latent Heat Flux and ET Estimation**

Latent heat flux was obtained as the residual of net radiation, soil heat flux, and sensible heat flux. Instantaneous evapotranspiration ( $ET_{inst}$ ) was calculated by converting latent heat flux using the latent heat of vaporization. The evaporative fraction (ETrF) was then computed by normalizing  $ET_{inst}$  with reference ET. Finally, daily ETa was derived by multiplying ETrF with daily reference ET obtained from ERA5-Land meteorological data.

#### **3.4.7 Post-processing and Output Generation**

All intermediate outputs, including albedo, vegetation indices, surface temperature, net radiation, soil heat flux, sensible heat flux, and ETa maps, were exported from GEE to Google Drive and Assets for further analysis. ET statistics were computed at the field level to analyze spatial and temporal variations throughout the growing season. This structured and automated workflow ensured consistent ETa estimation across multiple dates, enabling efficient monitoring of crop water use at the farm scale. The SEBAL model codes developed in Google Earth Engine (GEE) for this study can be accessed at (<https://github.com/Engr-MuradAli/SEBAL-GEE-Wheat-ETa>)

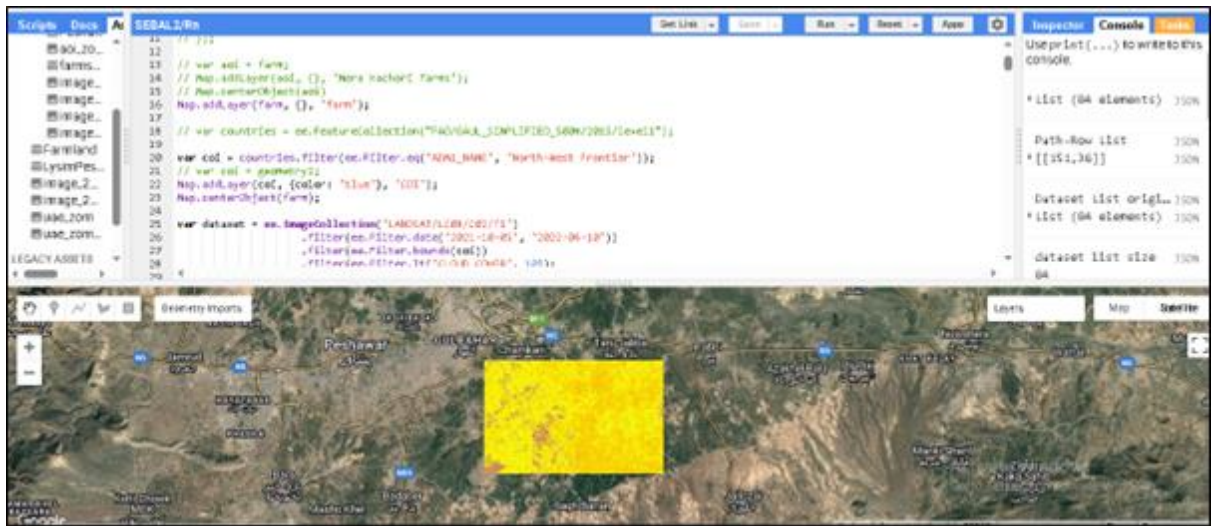


Figure 3: SEBAL model implementation in Google Earth Engine (GEE) using the JavaScript interface.

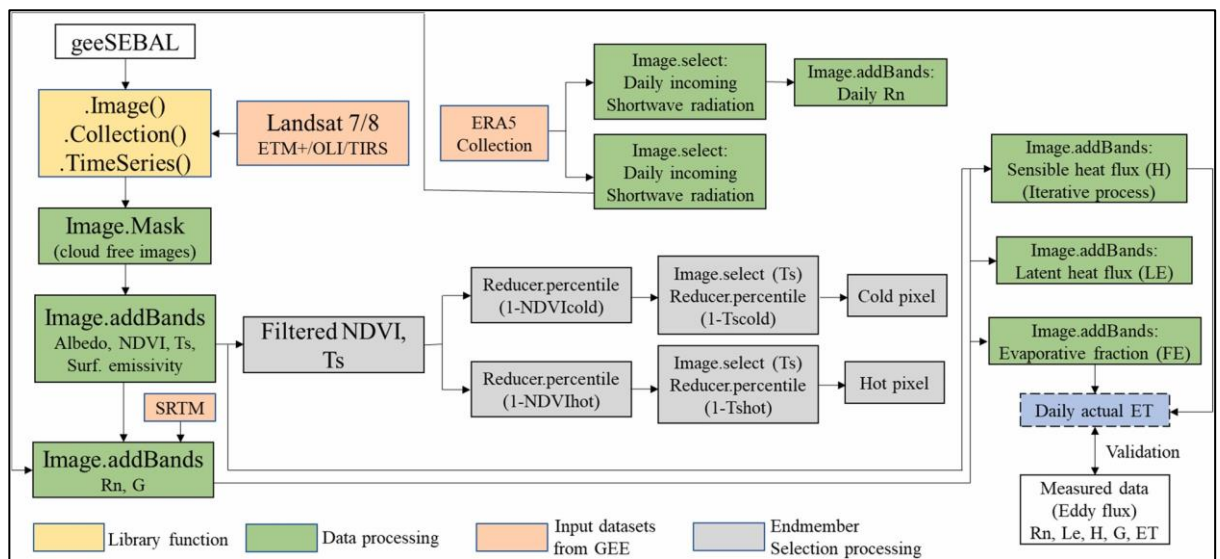


Figure 4: Flow diagram of the geeSEBAL model showing input data (remote sensing and meteorological) and GEE-based processing functions for daily ET estimation

### 3.5 Water–Energy–Food Nexus (WEFN) Assessment

To evaluate the interlinkages between water consumption, energy use, and crop productivity, a Water–Energy–Food Nexus (WEFN) analysis was performed for the eleven wheat fields included in this study. The primary objective was to quantify and compare the resource-use efficiencies of individual fields and to identify trade-offs and synergies among the three sectors under flood irrigation conditions. The analysis followed the conceptual framework of [106] and methodological guidance from FAO and IWMI reports on agricultural water productivity.

In addition to assessing resource interdependencies, the WEFN analysis was also used to evaluate the effectiveness of the SEBAL model in capturing the spatial variations in evapotranspiration ( $ET_a$ ) and its relationship with crop yield and energy use. By linking SEBAL-derived water consumption data with field-measured crop yield and recorded energy inputs, the analysis provides a more comprehensive understanding of how spatial differences in water use influence overall productivity and resource efficiency. This integrated assessment allows for the identification of fields with higher or lower water and energy use efficiencies, thereby supporting the development of targeted management strategies to improve irrigation performance and enhance water–energy–food security.

### **3.5.1 Input Parameters**

The analysis utilized field-level data derived from remote sensing and ground observations, including:

1. Field area (ha)
2. Total seasonal evapotranspiration ( $ET_a$ , mm) obtained using the SEBAL model
3. Total irrigation water applied ( $m^3$ )
4. Wheat yield ( $t\ ha^{-1}$ ) and total production (kg)
5. Water productivity (WP,  $kg\ m^{-3}$ )
6. Total energy consumption (kWh)
7. Energy use efficiency (EUE,  $kg\ kWh^{-1}$ )
8. Groundwater table depth (m)

These parameters were used to quantify the individual components of the WEF nexus at the field scale.

### **3.5.2 Water Consumption**

Quantifying total water consumption is essential for evaluating irrigation performance, estimating crop water productivity, and assessing the water component of the water–energy–food (WEF) nexus. The total water consumption (in cubic meters) for each field was determined by utilizing the SEBAL-based total seasonal actual evapotranspiration ( $ET_a$ ). Specifically, the  $ET_a$  values estimated for each field over the entire wheat growing

season were multiplied by the corresponding field area to calculate the total volume of water consumed through evapotranspiration as shown in equation 51.

$$V = \left( \frac{ET_a}{1000} \right) \times A \quad (51)$$

Where,

$V$  = Total water consumption ( $m^3$ ) per field over entire base period

$ET_a$  = seasonal cumulative actual evapotranspiration (mm) from SEBAL

$A$  = Field Area ( $m^2$ )

### 3.5.3 Crop Yield Data

Accurate crop yield data play a critical role in assessing the Water–Energy–Food Nexus (WEFN), as crop production directly reflects how effectively water and energy resources are being utilized to produce food. Crop yield serves as a key indicator for evaluating agricultural productivity, resource-use efficiency, and food security. By linking yield data with water consumption and energy inputs, it becomes possible to analyze the trade-offs and synergies between different components of the nexus. Higher crop yields with optimal water and energy use indicate better system efficiency, whereas lower yields may signal resource mismanagement or stress conditions affecting crop growth.

For this study, crop yield data were physically recorded from each field at the time of harvest to ensure accuracy and reliability. This field-based measurement provides a realistic estimate of the actual crop production and will be used in subsequent analyses to calculate water productivity ( $kg\ m^{-3}$ ), energy productivity, and to evaluate the overall performance of the irrigation system within the WEFN framework.

### 3.5.4 Estimation of Energy Consumption

Generally, energy usage for groundwater pumping depends on multiple factors such as depth of groundwater table, pump efficiency and specification, and the type of irrigation. However, it is difficult to get most of the information at all locations. Therefore, we have used the average energy consumption per unit amount of groundwater pumping. Previous studies reported that the average energy usage for groundwater pumping (average pumping efficiency is ~50%) is around 0.00051 kWh to lift 1  $m^3$  of groundwater

for 1 meter [107]. Equation (52) has been used to estimate energy consumption for groundwater pumping, which is a function of the volume of groundwater being pumped and the depth of groundwater (or lifting height).

$$E_u = 0.00051 \times Wu_{gv} \times h \quad (52)$$

where,  $E_u$  is energy used for groundwater pumping (kWh),  $Wu_{gv}$  is the volume of groundwater being pumped ( $m^3$ ), and  $h$  is the groundwater lifting height (m).

### 3.5.5 Water Footprint, Energy Intensity, and Water and Energy Productivity

The assessment of water footprints and energy intensity provides valuable insight into the number of natural resources utilized to sustain agricultural production systems. The water footprint (WF) reflects the total volume of water consumed through evapotranspiration and other on-farm processes to produce a specific quantity of crop yield, while the energy quantifies the energy input required for irrigation, pumping, and other field operations but in this study we have considered only the energy required for pumping groundwater for irrigation. These indicators are essential for understanding the resource intensity of crop production and identifying opportunities to optimize resource use. The Water Footprint (WF) and Energy Intensity (EI) were calculated using equation (53) and (54) given by [103].

$$WF = \frac{ET_a (mm) \times Area}{Crop\ yeild\ (ton)} \quad (53)$$

$$EI = \frac{Total\ Energy\ Consumed\ for\ Groundwater\ Pumping(kWh)}{Crop\ yeild\ (ton\ or\ kg)} \quad (54)$$

Water productivity (WP) is a key performance indicator that expresses the relationship between crop yield and the amount of water consumed. It indicates how efficiently water is being converted into agricultural output and helps in identifying fields or practices with higher or lower efficiency levels. Similarly, energy productivity (EP) measures the effectiveness of energy inputs in achieving crop production. High EP values indicate efficient energy utilization, which is vital for reducing production costs and minimizing environmental impacts.

$$WP = \frac{\text{Crop yeild (ton or kg)}}{\text{Total Water Consumed (m3)}} \quad (55)$$

$$EP = \frac{\text{Crop yeild (ton or kg)}}{\text{Total Energy Consumed (kWh)}} \quad (56)$$

In this study, water and energy footprints were calculated based on SEBAL-derived evapotranspiration and energy inputs for groundwater pumping, while crop yield data were obtained through field measurements. These indicators were further used to evaluate the resource-use efficiency of the irrigation system and to understand the interlinkages between water, energy, and food within the Water–Energy–Food Nexus (WEFN) framework. This integrated approach supports the development of more sustainable irrigation and resource management strategies at the field scale.

### 3.5.6 Normalized Water Productivity (NWP)

Normalized Water Productivity represents the relative efficiency of water use among different fields by comparing individual field water productivity (WP) with the maximum value observed across all study sites. This normalization allows for a uniform comparison of irrigation performance and highlights spatial variability in water-use efficiency. Fields with higher NWP values indicate more effective conversion of available water into crop yield, reflecting optimal water management and favourable soil–crop–climate interactions.

The NWP for each field was computed using the following expression:

$$NWP = \left( \frac{WP_i - WP_{min}}{WP_{max} - WP_{min}} \right) \quad (57)$$

where  $WP_i$  is the water productivity of the  $i$ -th field ( $\text{kg m}^{-3}$ ),  $WP_{min}$  is the minimum and  $WP_{max}$  is the maximum water productivity among all fields.

High NWP values demonstrate improved irrigation efficiency and effective crop water utilization, whereas lower values indicate potential water losses or stress conditions reducing water-use efficiency.

### 3.5.7 Normalized Energy Productivity (NEP)

Normalized Energy Productivity expresses the comparative efficiency of energy use in crop production by normalizing each field's energy productivity (EP) across the observed range. It reveals how effectively the energy inputs, particularly for groundwater pumping, are converted into crop yield. The NEP was determined as:

$$NEP = \frac{EP_i - EP_{min}}{EP_{max} - EP_{min}} \quad (58)$$

where  $EP_i$  is the energy productivity of the  $i$ -th field ( $\text{kg kWh}^{-1}$ ),  $EP_{max}$  and  $EP_{min}$  represent the maximum and minimum EP values, respectively. Higher NEP values signify more efficient energy utilization, often linked with lower pumping depths or efficient irrigation management, while lower values point toward higher energy intensity or system inefficiencies.

### 4 Normalized Yield Index (NYI)

The Normalized Yield Index represents the relative yield performance of each field by scaling yield values between their minimum and maximum across the study area. It allows direct comparison of productivity levels under varying field conditions, management practices, and soil characteristics.

The NYI was calculated as:

$$NYI = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \quad (59)$$

where  $Y_i$  is the yield of the  $i$ -th field ( $\text{ton ha}^{-1}$ ), while  $Y_{max}$  and  $Y_{min}$  denote the highest and lowest yields recorded among all fields. High NYI values indicate better productivity and resource-use efficiency, whereas lower values suggest yield limitations due to water, soil, or management constraints.

### 5 Water–Energy–Food Nexus Index (WEFNI)

The Water–Energy–Food Nexus Index (WEFNI) provides an integrated assessment of the interconnections among water, energy, and food production. It combines the normalized indicators (NWP, NEP, and NYI) to reflect the overall resource-use performance and sustainability of each field within the WEF nexus framework.

It was computed as the arithmetic mean of the three normalized parameters:

$$WEFNI = \frac{NWP + NEP + NYI}{3} \quad (59)$$

The index ranges from 0 to 1, where higher values indicate stronger synergy and efficiency among water, energy, and food components. Fields with higher WEFNI values represent balanced and sustainable resource use, while those with lower values indicate potential inefficiencies in one or more components of the nexus.

## 6 Results and Discussion

### 6.1 Weather Pattern

During the growing wheat season (October 2023 to April 2024), the maximum and minimum air temperatures were recorded as 36 °C in April and 3 °C in January, respectively. At the beginning of the season, temperatures were relatively high but gradually decreased until January, after which a steady increase was observed toward the end of the season. Similarly, light rainfall events occurred in October and November, while December and January received very little precipitation. From February onward, rainfall increased significantly, contributing to favorable moisture conditions during the later growth stages of wheat, as shown in Figure 5. The maximum wind speed reached 7 m/s, while the minimum was 0.11 m/s. The average wind speed ranged between 1 and 2 m/s throughout the growing season. Similarly, relative humidity varied between a maximum of 87% and a minimum of 33%, with an average ranging from 50% to 60%, as shown in Figure 6.

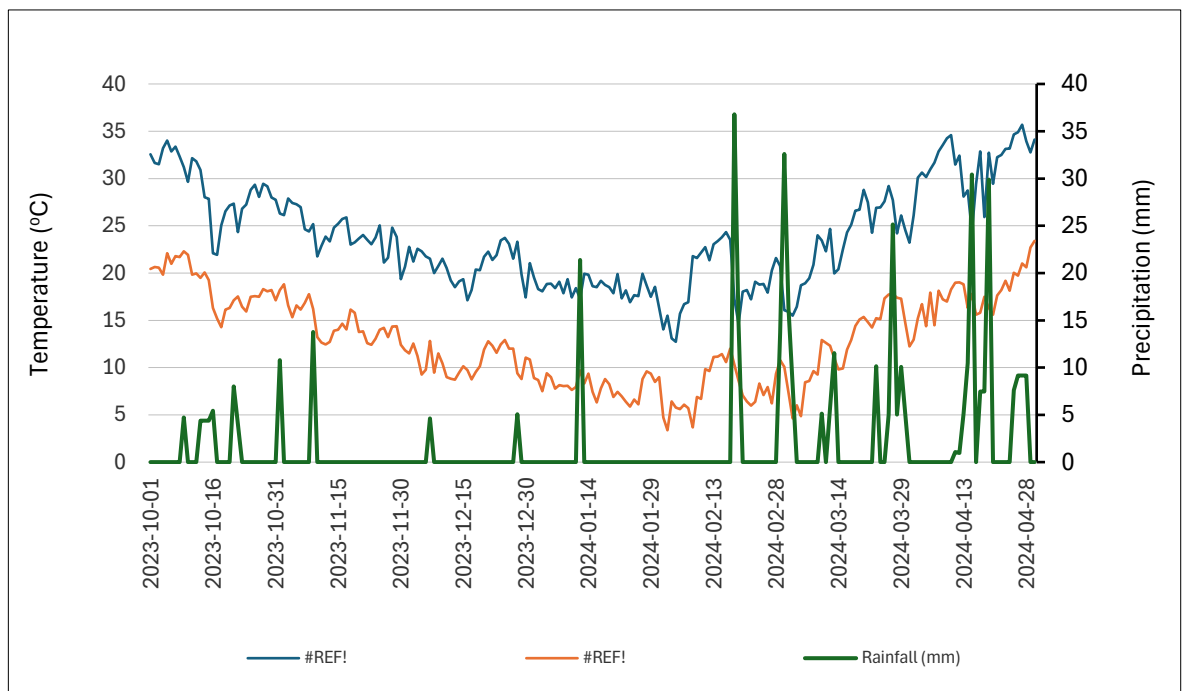


Figure 5: Daily rainfall and maximum and minimum temperature for the wheat growing season

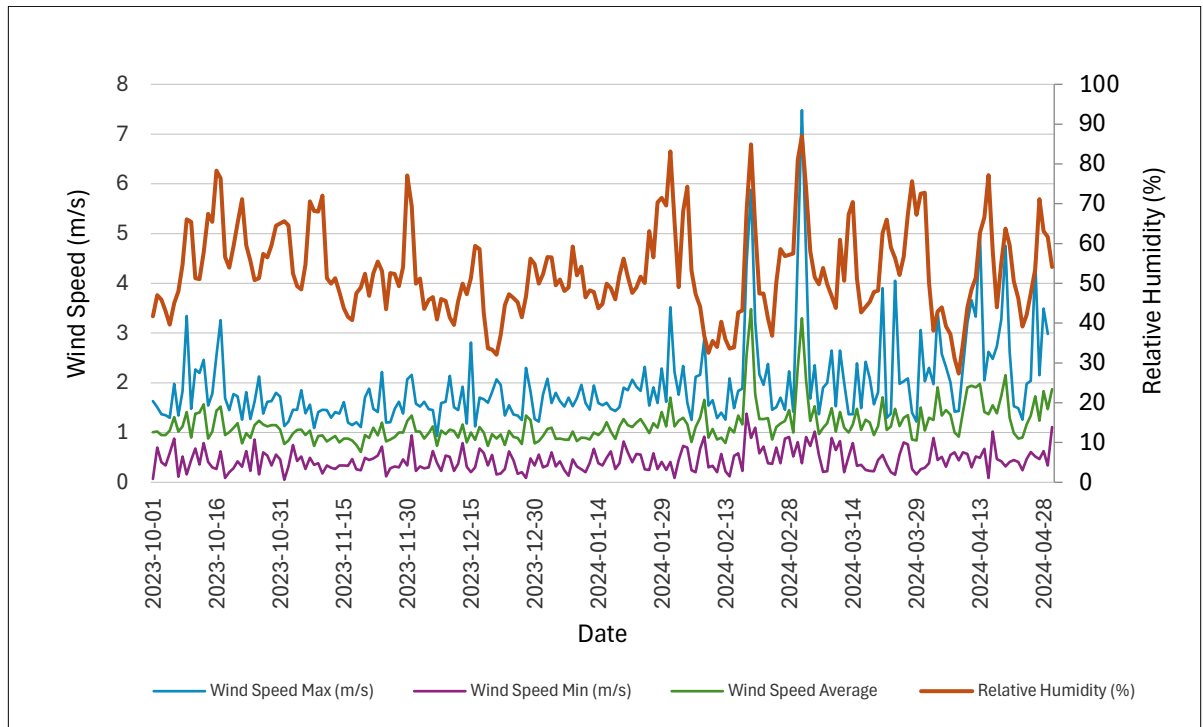


Figure 6: Daily relative humidity and maximum, minimum, and average wind speed recorded throughout the wheat growing season.

## 6.2 Vegetation Indices (NDVI, SAVI) and Surface Albedo Dynamics

The Normalized Difference Vegetation Index (NDVI) for the selected fields was low during the initial growth stage of the wheat crop and reached its peak by the end of March and early April 2024, as shown in Figure 7. From the beginning of the season, NDVI increased gradually; however, after February, the increase became more rapid, reaching its maximum in early April, followed by a decline, as illustrated in Figure 8. Figure 9 presents the typical NDVI trend across different wheat growth stages, showing minimum values during the emergence stage and peak values during the flowering and grain-filling stages.

The analysis of vegetation indices across the selected fields showed clear spatial variation in crop vigor during the wheat growing season. The maximum NDVI values ranged from 0.253 to 0.668, with the lowest value recorded in Field-4 (0.253) and the highest in Field-7 (0.668). Other fields exhibited moderate to high NDVI values, indicating healthy crop growth in most areas.

Similarly, the maximum SAVI values ranged from 0.155 to 0.448, with the minimum observed in Field-4 (0.155) and the maximum in Field-7 (0.448). The SAVI pattern closely followed the NDVI trend, confirming consistent vegetation dynamics across the fields.

These findings indicate that fields with higher NDVI and SAVI values experienced better canopy development and vegetation cover, reflecting favourable crop conditions, while fields with lower values may have faced stress conditions or sparse crop cover.

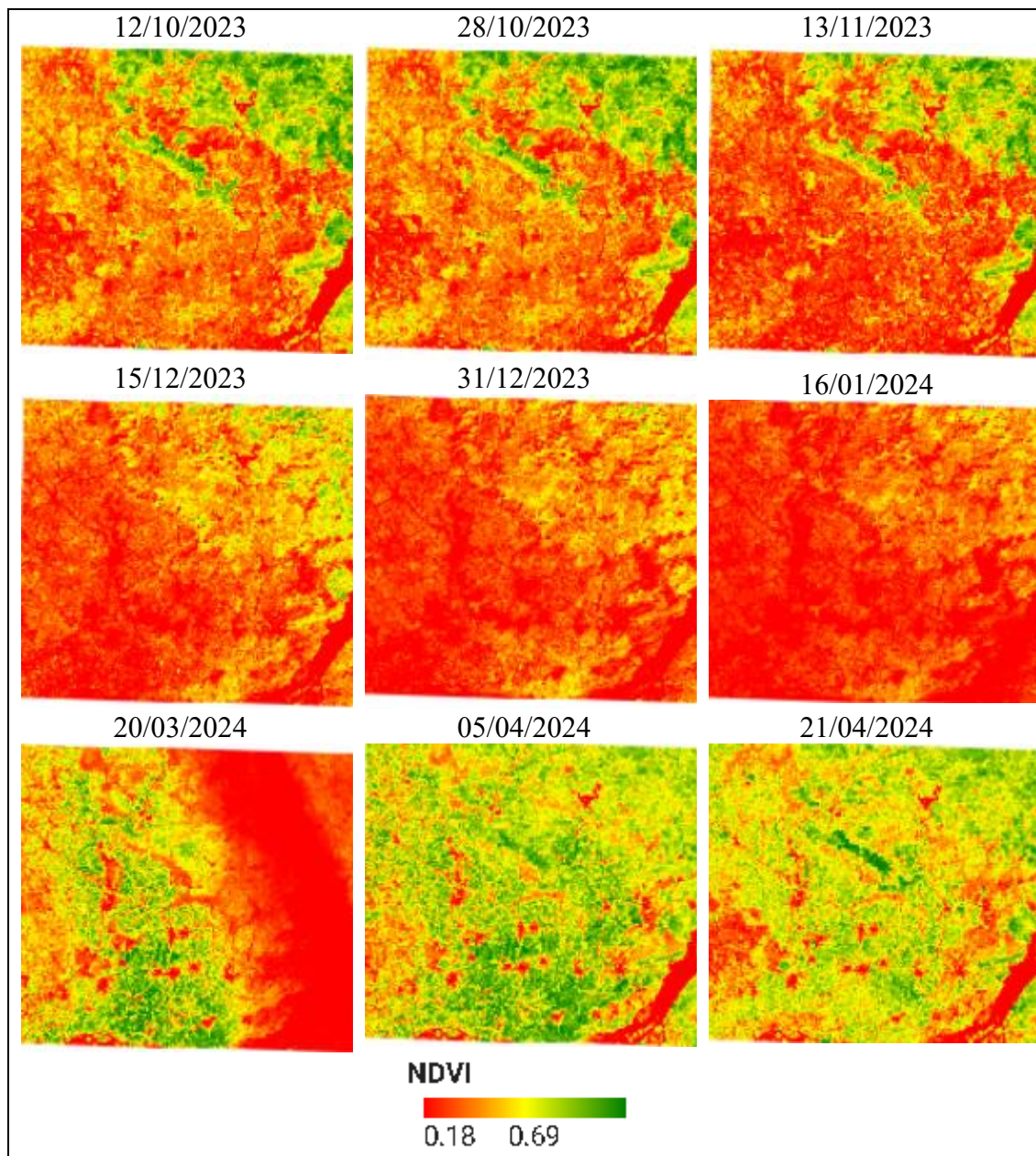


*Figure 7: Normalized Difference Vegetation Index (NDVI) dynamics over the wheat growth period, indicating crop development stages.*

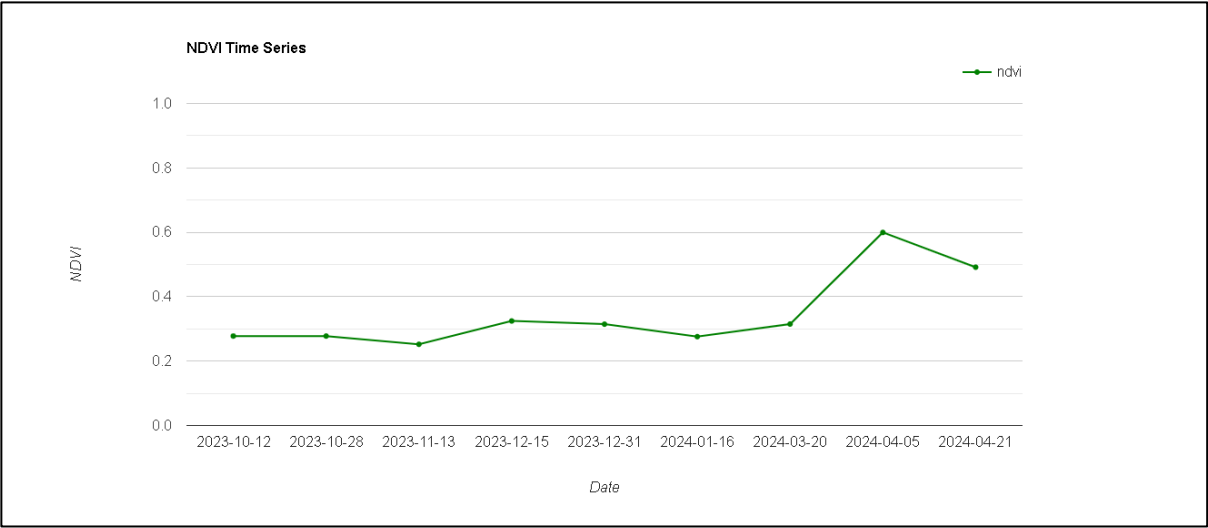


Figure 8: NDVI time series line chart illustrating vegetation dynamics during the wheat growing season

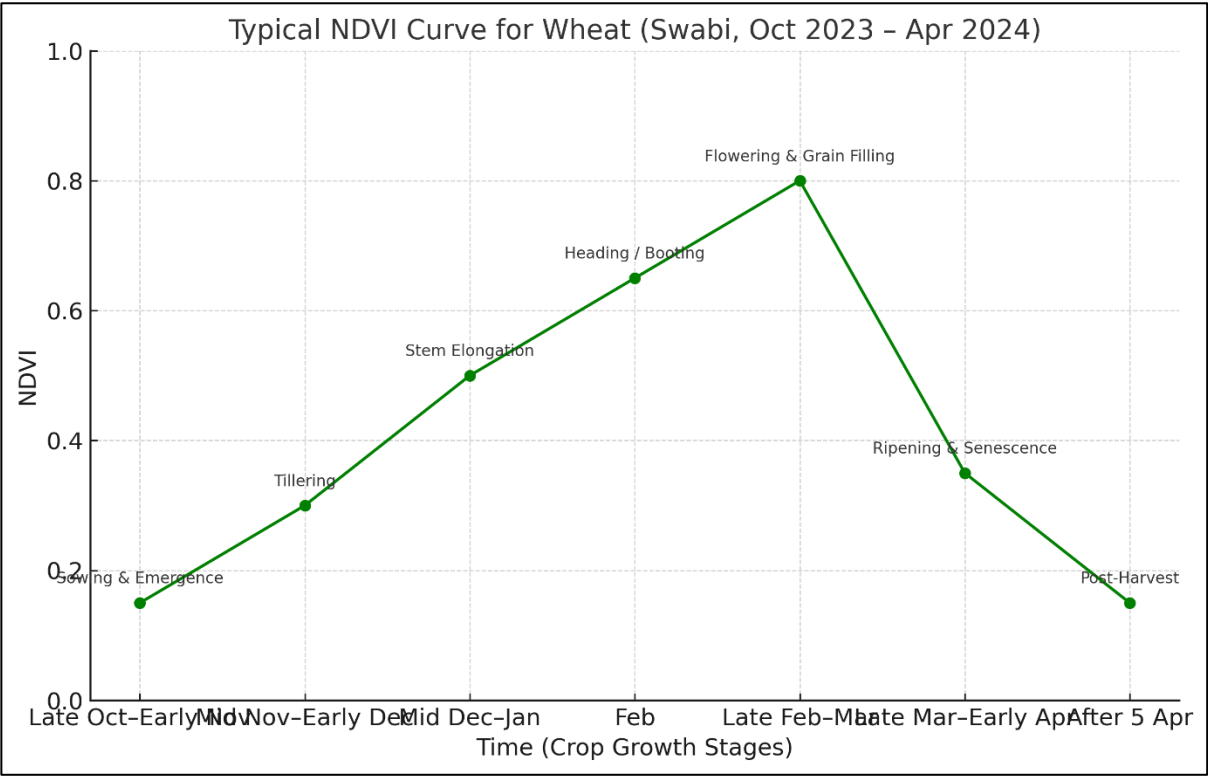
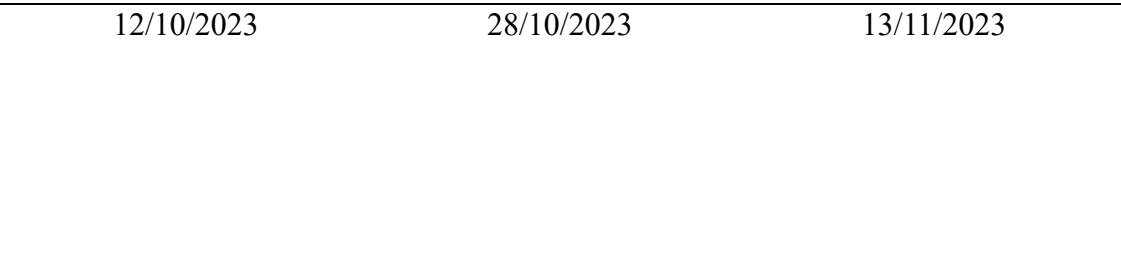


Figure 9: Typical NDVI curve for different wheat growth stages



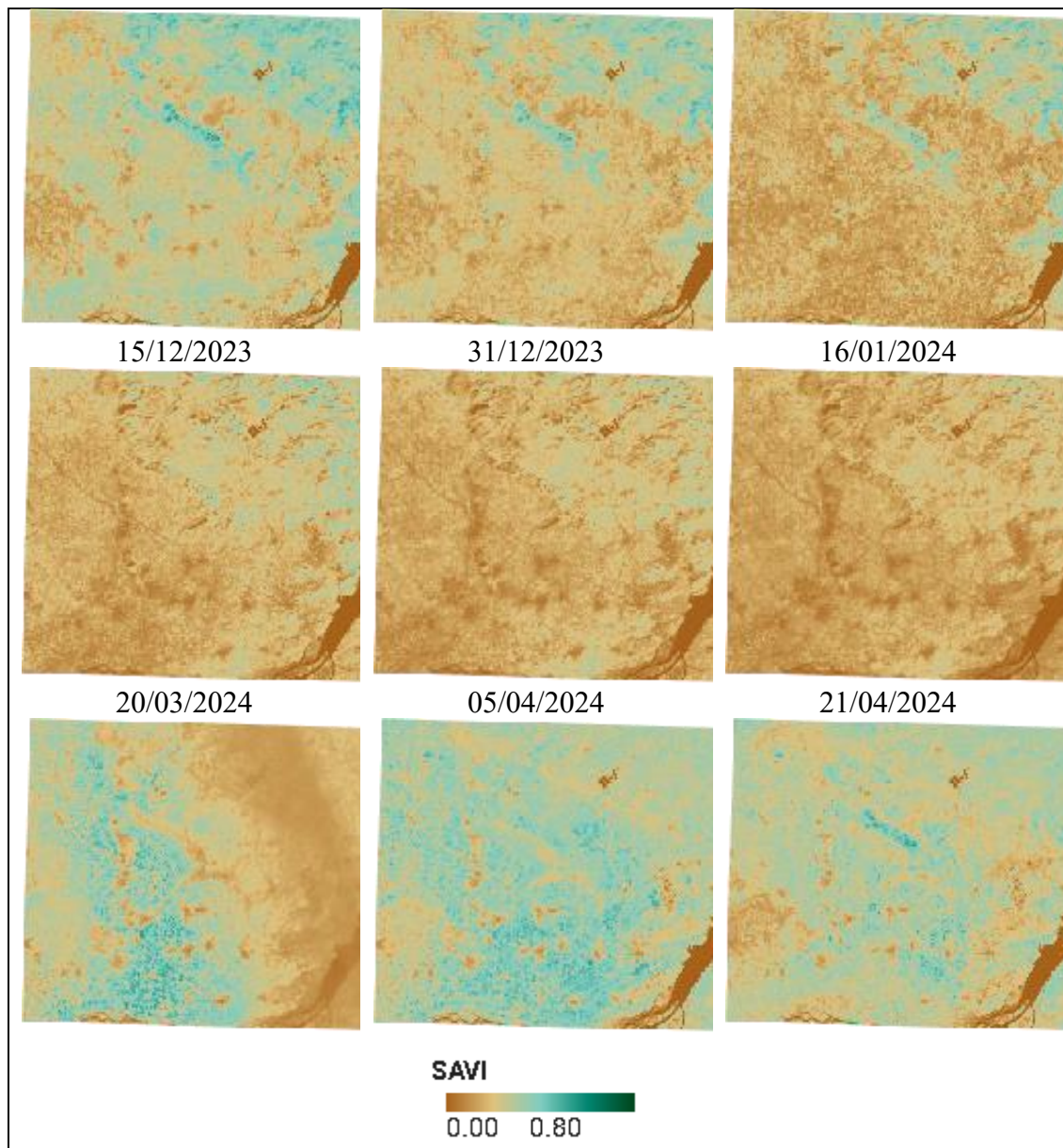


Figure 10: SAVI maps illustrating the spatial variation in vegetation cover across the selected fields during the wheat growing season.

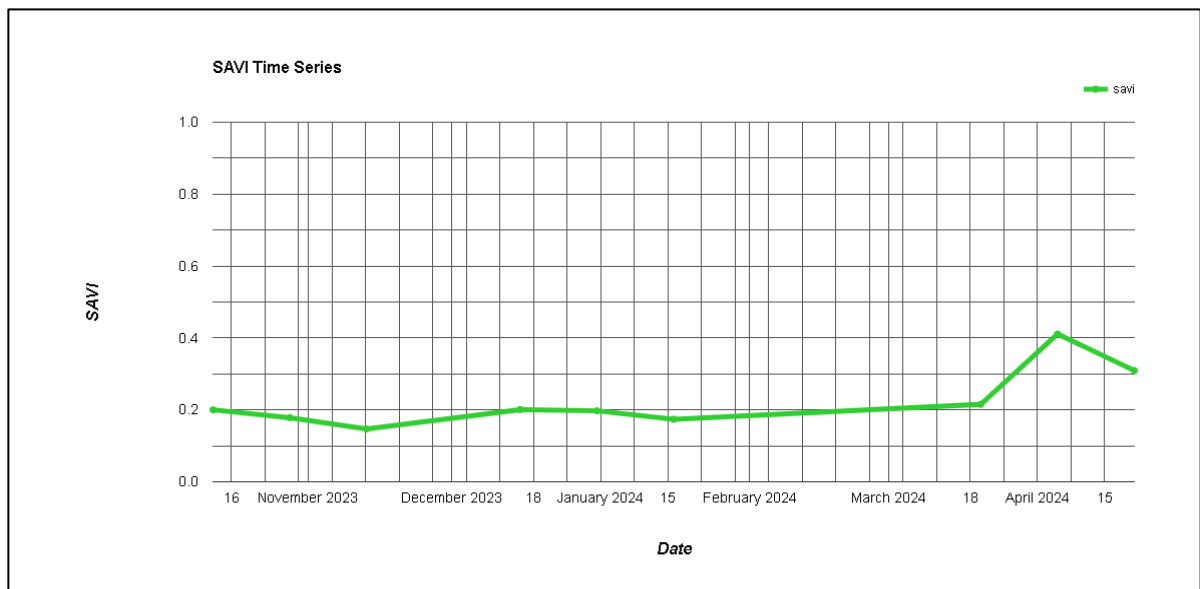


Figure 11: SAVI time series showing temporal variation in vegetation cover over the wheat growing season.

The temporal variation of surface albedo for all selected fields (Field-1 to Field-11) exhibited a clear seasonal pattern throughout the wheat growing season. During the initial growth stage (October–December 2023), the surface albedo values were relatively high, ranging from approximately 0.20 to 0.28, reflecting the predominance of bare soil and sparse vegetation cover. As the crop entered the vegetative and reproductive stages (January–March 2024), a steady decline in albedo was observed across all fields. The minimum albedo values, ranging from 0.12 to 0.18, were recorded between March and early April, corresponding to peak canopy development and maximum vegetation density, as also supported by the NDVI and SAVI results.

Toward the end of the growing season, particularly in mid to late April, surface albedo values increased again to 0.20–0.26, which can be attributed to crop senescence, reduced leaf area, and increased soil exposure following harvesting activities. Although the temporal trend was consistent across all fields, slight variations in the magnitude of albedo values were observed from field to field. These differences are likely due to variations in crop management, soil moisture, and surface characteristics. Overall, the observed albedo dynamics are consistent with expected vegetation development patterns in wheat fields and highlight the role of albedo as a key parameter in SEB models, including SEBAL.

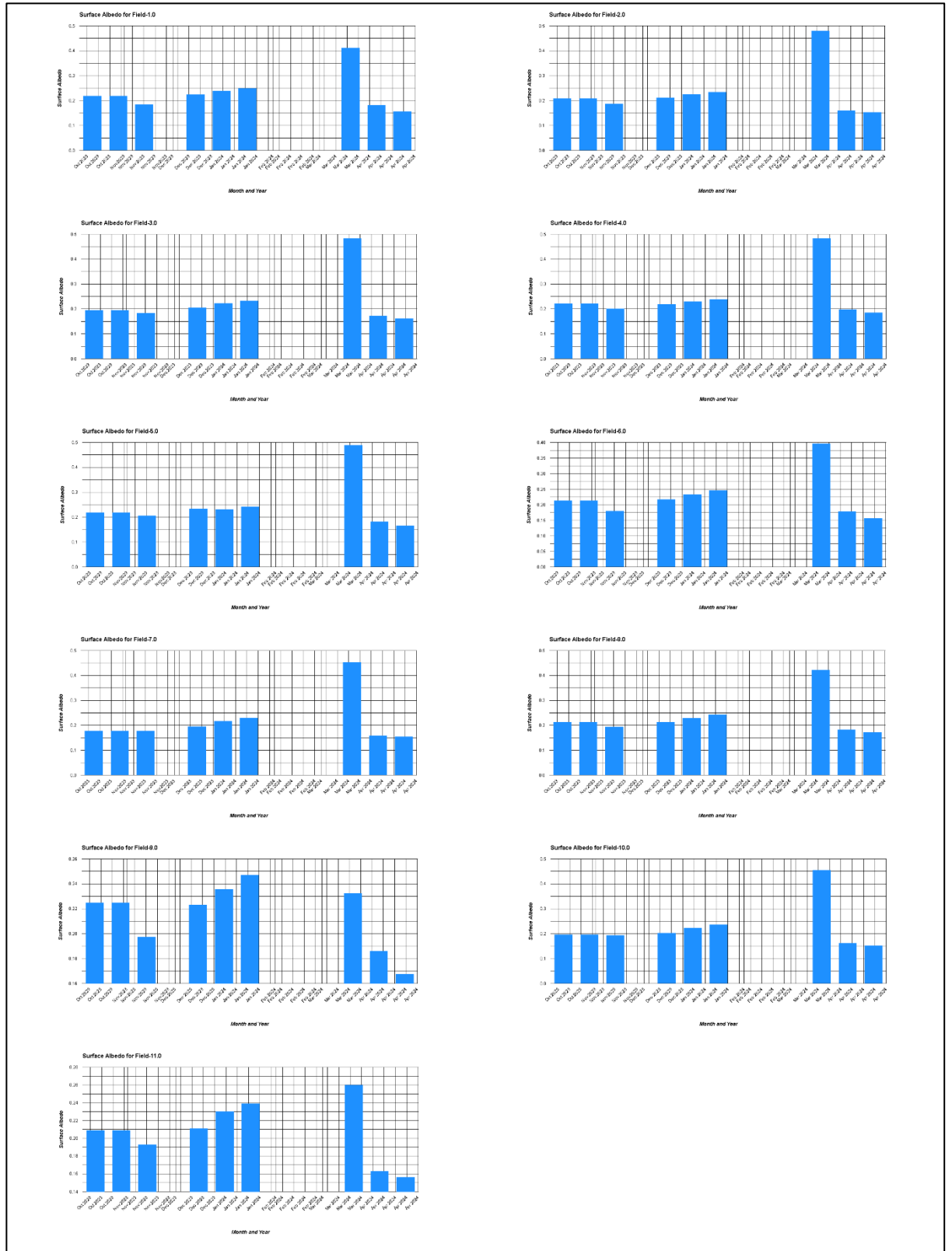


Figure 12: Fieldwise surface albedo for the whole growing season (oct 2023-Apr 2024)

### 6.3 Daily Actual Evapotranspiration (ET<sub>24</sub>) Dynamics

The temporal dynamics of daily actual evapotranspiration (ET<sub>a</sub>) represented as ET<sub>24</sub> in the graphs was estimated using the SEBAL model revealed a clear seasonal pattern that

closely aligns with the phenological stages of the wheat crop.  $ET_a$  values varied both temporally (across the growing season) and spatially (among the 11 selected fields).

At the beginning of the season (October–December 2023),  $ET_a$  values ranged between 2.5- and 5.0-mm  $day^{-1}$ . This moderate level of evapotranspiration corresponds to the early crop establishment stage when canopy cover is low, and the primary source of  $ET_a$  is soil evaporation. During this period, NDVI and SAVI values were relatively low, indicating sparse vegetation cover, while surface albedo values were relatively high due to the exposed soil surface.

As the crop advanced into the vegetative and reproductive stages (January–March 2024),  $ET_a$  showed a declining trend initially (2.0–3.5 mm  $day^{-1}$ ), reflecting cooler temperatures and slower crop growth in January. However, a sharp increase in  $ET_a$  was observed toward the peak growth period (March–April 2024), with daily  $ET_a$  reaching 6.5 to 7.5 mm  $day^{-1}$  in several fields as shown in Figure 14. This increase corresponds to maximum canopy development, as supported by the highest NDVI (0.7–0.8) and SAVI (0.35–0.45) values recorded during this time. Simultaneously, surface albedo reached its lowest values (0.12–0.18), indicating strong absorption of net radiation, which directly enhances latent heat flux and  $ET_a$ .

Toward the end of the growing season (late April), a slight decline in  $ET_a$  was observed in some fields, consistent with crop senescence and increasing albedo due to reduced canopy cover and partial soil exposure. The temporal pattern of  $ET_a$  clearly reflects crop growth dynamics, climatic influences (temperature, wind, relative humidity), and surface characteristics. Spatially, differences in  $ET_a$  magnitude were observed across fields. For example, Field-7, Field-9, and Field-11 consistently exhibited higher  $ET_a$  values, likely due to denser crop cover, better soil moisture availability, or favorable management practices. Conversely, Field-4 consistently showed lower  $ET_a$  values, which may indicate sparser vegetation, delayed planting, or limited water availability. Complete dynamics of wheat daily actual evapotranspiration are shown in Figure 13, Figure 14, and Figure 15.

Overall, these results demonstrate the robust performance of the SEBAL model in capturing field-scale  $ET_a$  variability through the integration of remote sensing indices (NDVI, SAVI, surface albedo) and meteorological data. The observed seasonal trends

are consistent with wheat crop water use patterns in semi-arid agro-ecosystems of Pakistan.

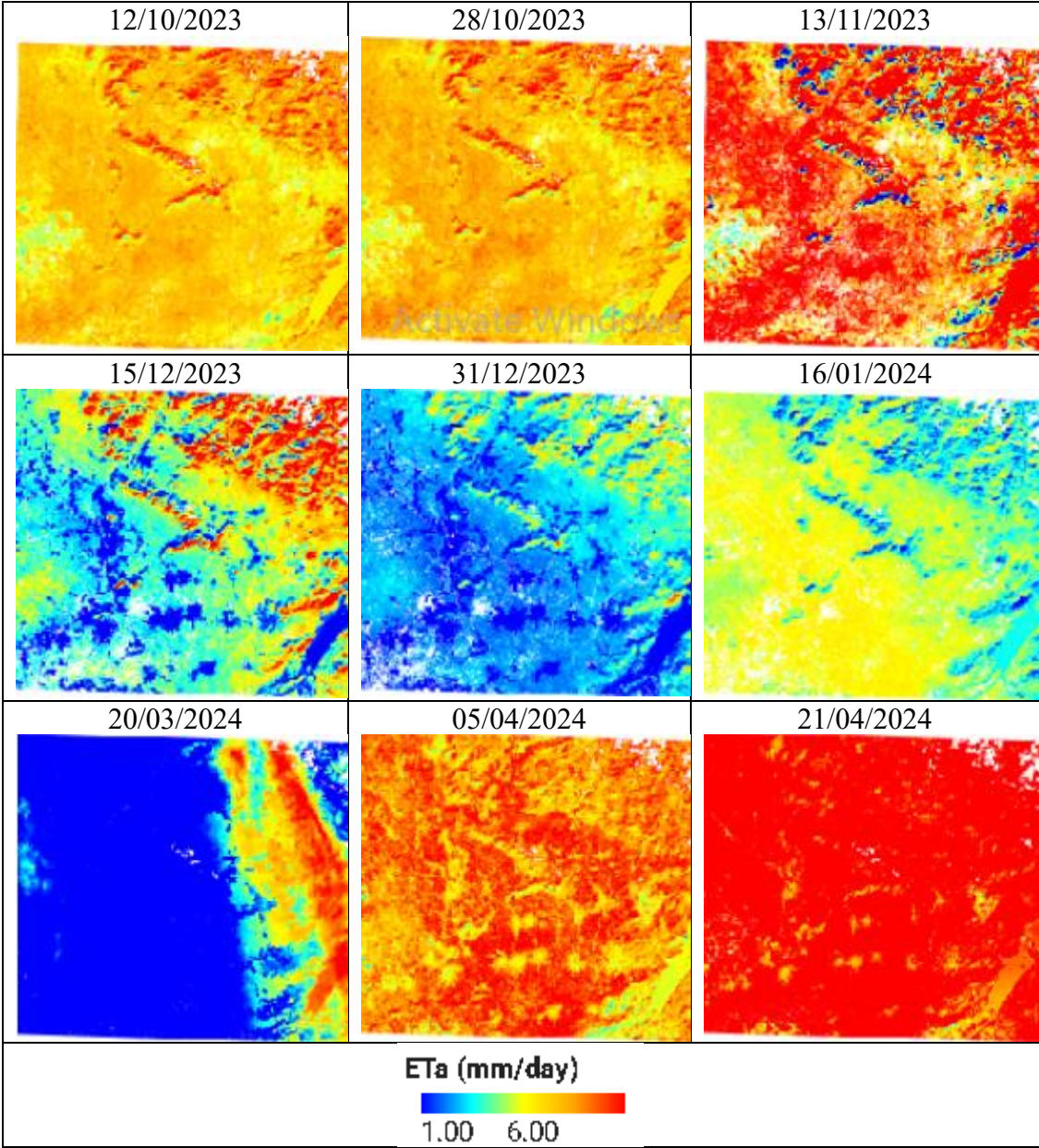


Figure 13: Spatial distribution maps of daily actual evapotranspiration (ETa) estimated using the SEBAL model for all selected dates during the wheat growing season (October 2023–April 2024).

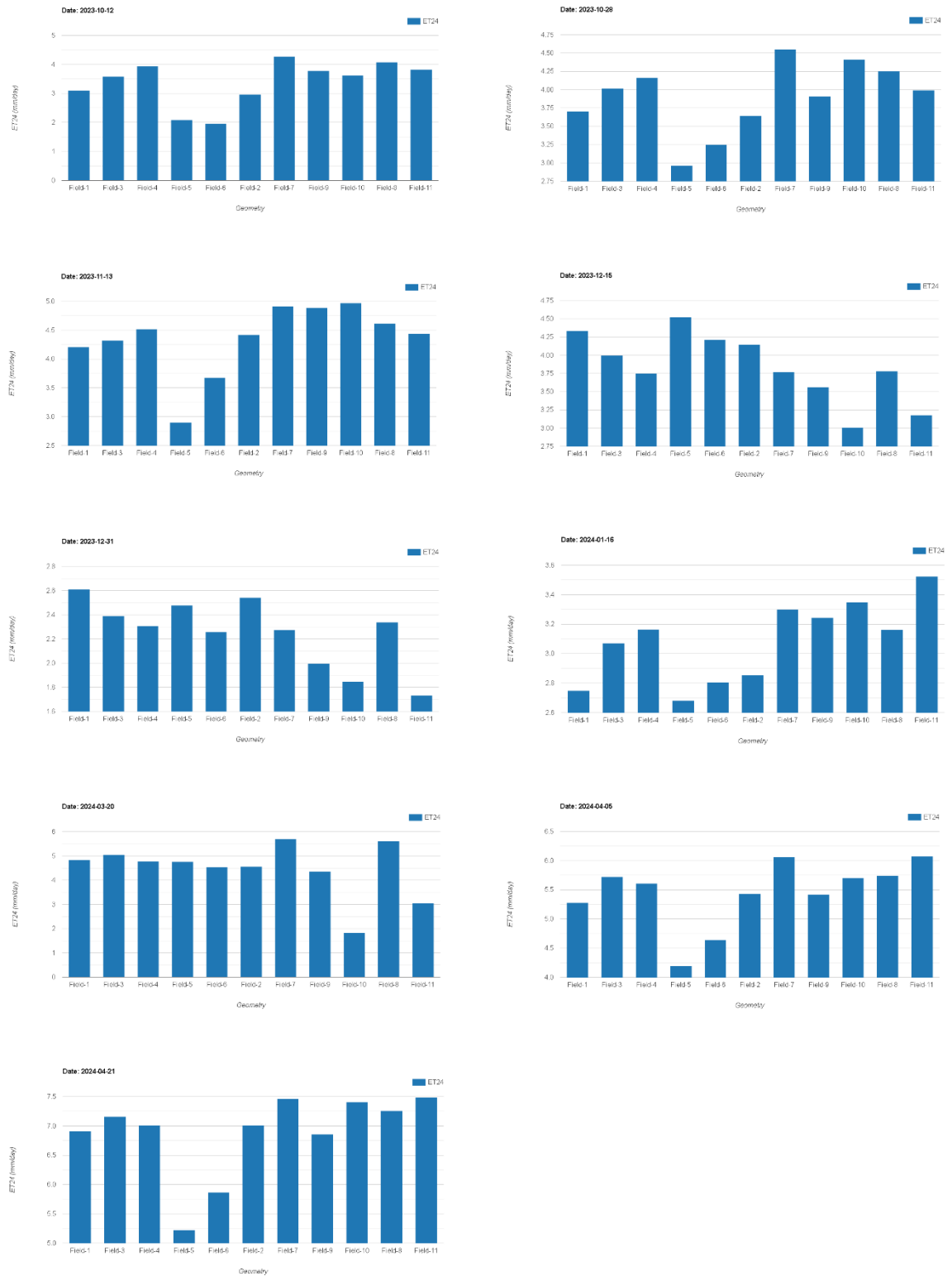


Figure 14: Field-wise daily  $ET_a$  estimated using the SEBAL model for the wheat growing season.

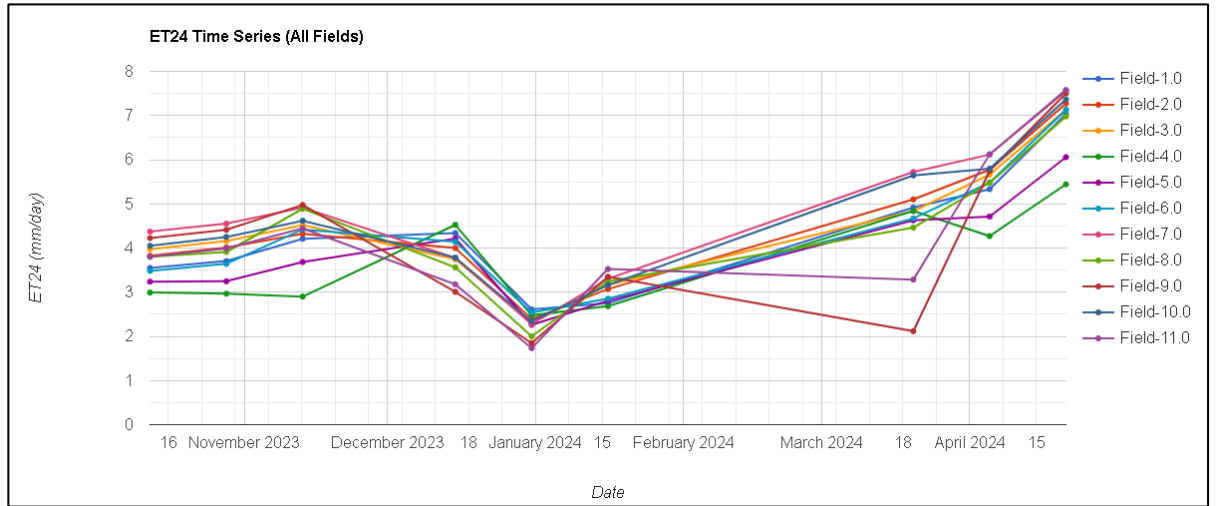


Figure 15: Time series line charts of daily actual evapotranspiration (ET<sub>a</sub>) for all selected fields (Field-1 to Field-11) throughout the wheat growing season (October 2023–April 2024).

## 6.4 Hourly Actual Evapotranspiration (ET<sub>inst</sub>) Dynamics

The temporal distribution of hourly actual evapotranspiration (ET<sub>inst</sub>) across the selected wheat fields showed distinct diurnal and seasonal variations consistent with crop phenology and prevailing meteorological conditions. As shown in Figure 16, ET<sub>inst</sub> values fluctuated throughout the season, reflecting the dynamic balance between net radiation, temperature, humidity, and wind speed.

During the early growing period (October–December 2023), ET<sub>inst</sub> values were relatively low, generally ranging between 0.2- and 0.9-mm h<sup>-1</sup> across most fields. This lower evapotranspiration rate is primarily attributed to sparse vegetation cover, moderate air temperatures, and the dominance of soil evaporation over plant transpiration. At this stage, the crop was still in its establishment phase, as confirmed by low NDVI and SAVI values, while surface albedo remained high due to exposed soil surfaces.

From January to February 2024, a gradual increase in ET<sub>inst</sub> was observed, corresponding to the vegetative growth phase. Hourly ET<sub>a</sub> values during this period typically ranged from 0.8 to 1.5 mm h<sup>-1</sup>, with higher peaks recorded during mid-day hours (10:00–14:00). The increase reflects enhanced canopy development, higher net radiation, and rising air temperatures following the winter period.

The maximum ET<sub>inst</sub> values were recorded during March and early April 2024, coinciding with the peak growth and reproductive stages of the wheat crop. During this period, hourly ET<sub>a</sub> ranged from 1.5 to 3.5 mm h<sup>-1</sup>, with some fields such as Field-7,

Field-9, and Field-11 showing consistently higher rates. These high  $ET_a$  values align with maximum NDVI (0.7–0.8) and SAVI (0.35–0.45) values and minimum albedo (0.12–0.18), indicating dense canopy cover and active transpiration. The diurnal  $ET_{inst}$  pattern during this phase exhibited a clear peak around noon, consistent with the maximum incoming solar radiation and vapor pressure deficit.

Toward the end of the growing season (late April 2024),  $ET_{inst}$  values showed a declining trend across all fields, ranging from 0.5 to 1.5 mm h<sup>-1</sup>, corresponding to crop senescence and reduced green biomass. Increased surface albedo and partial soil exposure further contributed to this decline, as shown in Figure 16-Figure 17. Spatially, variations in hourly  $ET_a$  were evident among the fields. Field-7, Field-9, and Field-11 exhibited higher hourly  $ET_a$  values throughout most of the season, likely due to favorable soil moisture and denser crop stands, whereas Field-4 consistently showed lower  $ET_a$  values, indicating potential water stress or lower vegetation density.

Overall, the hourly  $ET_{inst}$  dynamics effectively captured short-term fluctuations in surface energy exchange and crop water use. When combined with the daily  $ET_a$  analysis (Figure 15), these results illustrate how the SEBAL model successfully characterizes both diurnal and seasonal evapotranspiration patterns in wheat fields under semi-arid climatic conditions of Pakistan.

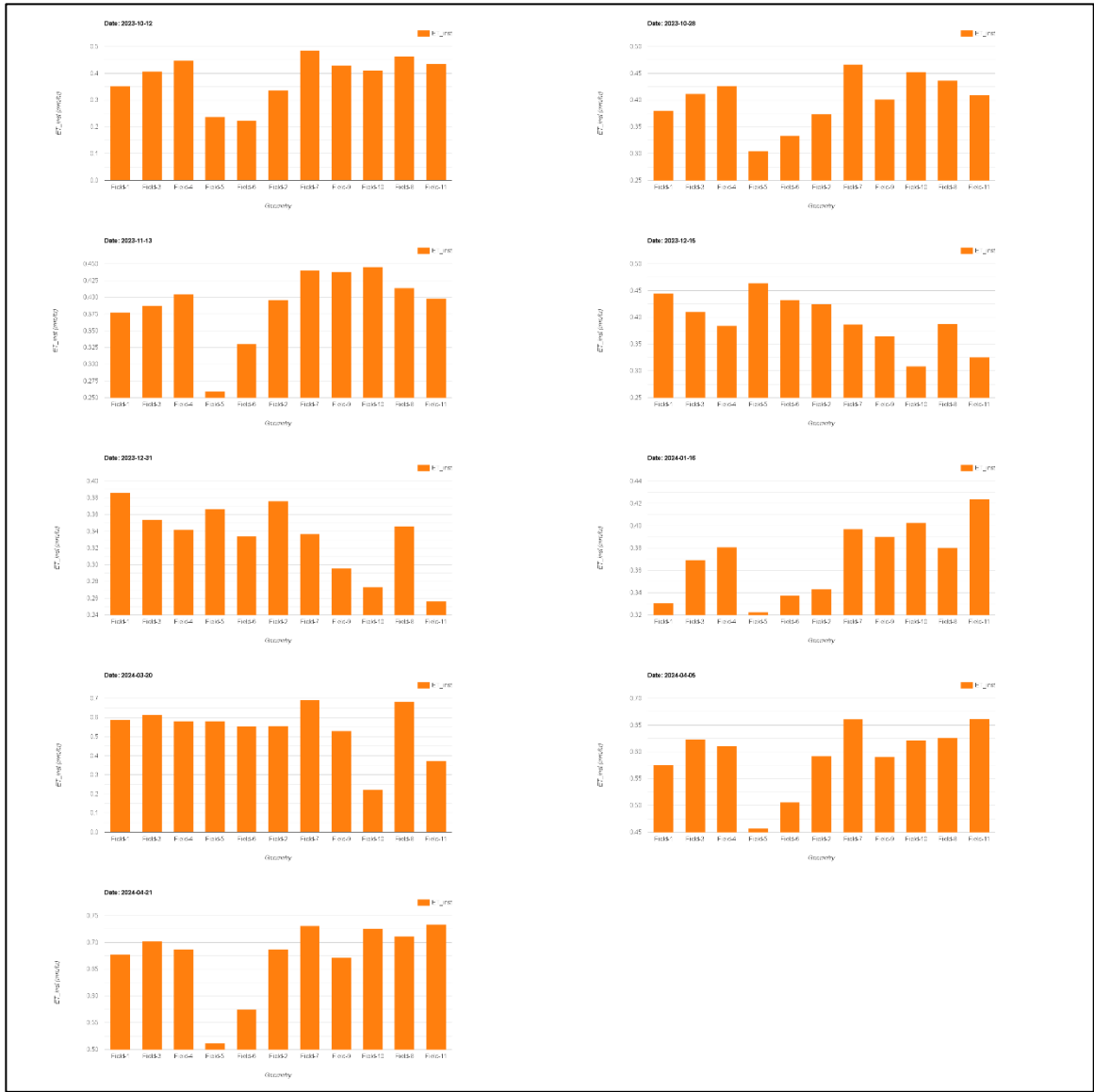


Figure 16: Field-wise hourly  $ET_a$  estimated using the SEBAL model for the wheat growing season

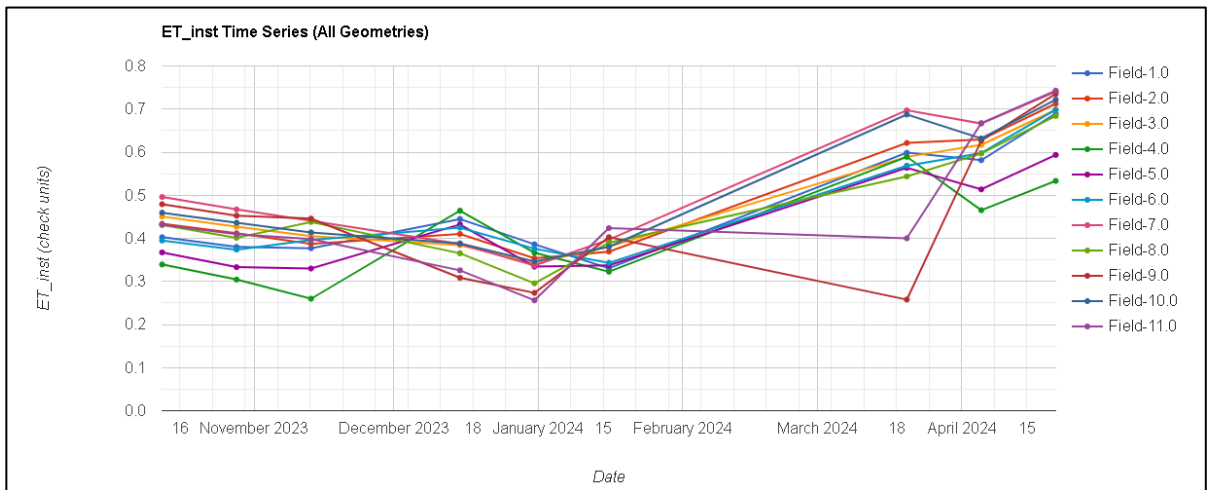


Figure 17: Time series line charts of daily  $ET_a$  for all selected fields (Field-1 to Field-11) throughout the wheat growing season (October 2023–April 2024).

## 6.5 Seasonal Actual Evapotranspiration (ET<sub>a</sub>)

The seasonal ET<sub>a</sub> estimated using the SEBAL model and adjusted with the respective ETrf values for each field exhibited notable spatial variability across the wheat-growing area. The total seasonal ET<sub>a</sub> values ranged from 456 mm to 668 mm during the 2023–2024 growing season (October to April). Among all the fields, Field-7 recorded the highest seasonal ET<sub>a</sub> (668 mm), while Field-5 showed the lowest (456 mm), indicating significant differences in water consumption likely associated with variations in vegetation vigor, soil moisture availability, and crop management practices.

Fields 7, 9, and 11 consistently exhibited higher ET<sub>a</sub> totals (668 mm, 577 mm, and 548 mm, respectively), which aligns with their higher NDVI (0.65–0.70) and SAVI (0.40–0.45) values observed during the peak growth stages. These fields demonstrated strong canopy development and sustained transpiration throughout the season, reflecting better crop conditions and sufficient water supply, either through effective irrigation or favorable soil water retention. Conversely, Fields 4 and 5, which showed lower ET<sub>a</sub> values (489 mm and 456 mm), correspond to areas where NDVI and SAVI were relatively low and surface albedo remained higher, indicating sparse crop cover, delayed growth, or possible water stress conditions.

Overall, the spatial distribution of seasonal ET<sub>a</sub> clearly reflects the combined influence of biophysical and meteorological factors captured by SEBAL. The higher evapotranspiration rates during March and April contributed substantially to the total seasonal ET<sub>a</sub>, coinciding with the reproductive and grain-filling stages of wheat when water demand peaks. The observed range (456–668 mm) aligns with previously reported seasonal ET<sub>a</sub> values for irrigated wheat under semi-arid conditions, confirming the reliability of the SEBAL-derived estimates. These results highlight the spatial heterogeneity of crop water use and emphasize the significance of integrating remote sensing-based ET<sub>a</sub> estimation for field-scale water management and yield optimization in wheat production systems of Pakistan.

The spatial differences in seasonal actual evapotranspiration (ET<sub>a</sub>) observed across the wheat fields gives important insights into crop performance and water use efficiency during the 2023–2024 growing season. Fields with higher ET<sub>a</sub> values, particularly Field-7, Field-9, and Field-11, are indicative of more vigorous crop growth and efficient

utilization of available water resources. These fields likely experienced optimal irrigation scheduling and favorable soil moisture conditions, which supported sustained transpiration and biomass accumulation, ultimately contributing to higher yield potential. In contrast, fields exhibiting lower  $ET_a$  values, such as Field-4 and Field-5, may have been subjected to moisture stress, uneven irrigation, or suboptimal soil conditions, leading to reduced transpiration and limited canopy development.

The relationship between seasonal  $ET_a$  and vegetation indices (NDVI and SAVI) further reinforces the strong coupling between crop water use and vegetation vigor. The fields with higher NDVI and SAVI values not only demonstrated greater seasonal  $ET_a$  but also corresponded to areas of enhanced photosynthetic activity and canopy density, suggesting efficient energy partitioning toward latent heat flux. Conversely, lower  $ET_a$  fields exhibited higher surface albedo, reflecting reduced energy absorption and weaker evaporative cooling due to sparse vegetation cover.

From a water management perspective, the observed  $ET_a$  range (456–668 mm) indicates moderate to high water consumption consistent with the typical requirements of irrigated wheat in semi-arid environments. The results emphasize the potential of remote sensing–based  $ET_a$  estimation to identify spatial disparities in crop water use, enabling more precise irrigation management. By integrating SEBAL-derived  $ET_a$  with ground-based irrigation data, future studies can assess irrigation efficiency and quantify yield response factors, thereby contributing to improved water productivity and sustainable wheat production in water-limited regions of Pakistan.



Figure 18: Seasonal actual evapotranspiration ( $ET_a$ ) for all selected wheat fields during the 2023–2024 growing season.

## 6.6 Calibration of SEBAL-Derived Actual Evapotranspiration

To assess the accuracy and reliability of the SEBAL-estimated actual evapotranspiration ( $ET_a$ ), the results were compared with  $ET_a$  values computed using the FAO-56 PM equation implemented in CROPWAT 8.0. The FAO-56 based daily reference evapotranspiration ( $ET_o$ ) was converted to wheat actual daily evapotranspiration ( $ET_c$ ) using the FAO dual crop coefficient approach, which accounts for crop characteristics, irrigation practices, and soil properties, thus providing a robust reference for field-scale evapotranspiration [108]. Daily SEBAL  $ET_a$  values for each field were compared with corresponding FAO-56  $ET_c$ , and statistical indicators including the coefficient of determination ( $R^2$ ), root mean square error (RMSE), and mean bias were calculated, as shown in Figure 19.

The comparison revealed a generally strong correlation between SEBAL and FAO-56  $ET_c$  across most fields, demonstrating the capability of the SEBAL model to accurately estimate crop water use at field scale. The  $R^2$  values ranged from 0.54 to 0.93, indicating moderate to high agreement between the two methods. The highest correlations were observed in Field-11 ( $R^2 = 0.93$ ), Field-8 ( $R^2 = 0.85$ ), and Field-7 ( $R^2 = 0.84$ ), suggesting strong consistency between SEBAL and the FAO-56  $ET_c$  estimates. Conversely, Field-5 exhibited the lowest correlation ( $R^2 = 0.54$ ), reflecting higher variability possibly due to uneven irrigation or soil heterogeneity.

The regression slopes between SEBAL and FAO-56  $ET_c$  ranged from 0.63 to 1.14, indicating some degree of field-specific bias. Fields such as Field-1, Field-2, and Field-5 showed slopes below 1.0, suggesting that SEBAL slightly underestimated at higher FAO-56  $ET_c$  values. In contrast, Field-10 and Field-11 had slopes above 1.0, implying a tendency to overestimate  $ET_a$  during peak evaporation conditions. The cumulative regression across all fields yielded an overall relationship of  $SEBAL = 0.698 \times ET_c + 1.22$  ( $R^2 = 0.63$ ,  $RMSE = 0.87 \text{ mm day}^{-1}$ ), indicating that, while SEBAL captures the general evapotranspiration dynamics effectively, localized calibration improves its accuracy.

The RMSE values ranged between 0.44- and  $0.87\text{-mm day}^{-1}$ , demonstrating acceptable error levels for field-scale ET estimation under semi-arid conditions. The bias values were relatively small for most fields, ranging between  $-0.07$  and  $+0.45 \text{ mm day}^{-1}$ , confirming that SEBAL neither consistently overestimates nor underestimates  $ET_a$  across all fields but shows minor site-specific deviations.

Overall, the calibration results confirm that SEBAL-derived  $ET_a$  estimates are physically consistent and reliable, with field-level variability largely influenced by differences in irrigation scheduling, soil moisture status, and canopy structure. Fields with denser vegetation and better irrigation management (e.g., Field-7, Field-9, and Field-11) showed higher agreement with FAO estimates, whereas sparsely vegetated or moisture-stressed fields (e.g., Field-4 and Field-5) exhibited larger deviations.

These findings validate the SEBAL model's suitability for estimating actual evapotranspiration in semi-arid agro-ecosystems of Pakistan. Applying field-specific regression corrections derived from the calibration results can further enhance SEBAL's predictive performance for operational water management and irrigation planning.

*Table 10: Calibration statistics between SEBAL and FAO-56 (PM) actual evapotranspiration.*

| Parameter                     | Field-1 | Field-2 | Field-3 | Field-4 | Field-5 | Field-6 | Field-7 | Field-8 | Field-9 | Field-10 | Field-11 | Cumulative |
|-------------------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|----------|------------|
| Intercept (a)                 | 0.625   | 0.705   | 0.807   | 0.807   | 0.722   | 0.778   | 0.998   | 0.871   | 0.868   | 1.072    | 1.142    | 0.698      |
| Intercept (b)                 | 1.560   | 1.240   | 1.000   | 0.980   | 1.160   | 0.940   | 0.450   | 0.760   | 0.550   | -0.360   | -0.550   | 1.220      |
| $R^2$                         | 0.630   | 0.720   | 0.780   | 0.840   | 0.540   | 0.640   | 0.880   | 0.830   | 0.800   | 0.830    | 0.930    | 0.630      |
| RMSE ( $\text{mm day}^{-1}$ ) | 0.790   | 0.690   | 0.650   | 0.550   | 0.660   | 0.570   | 0.660   | 0.640   | 0.560   | 0.620    | 0.440    | 0.870      |
| Bias ( $\text{mm day}^{-1}$ ) | 0.018   | 0.028   | 0.211   | 0.185   | 0.253   | 0.138   | 0.446   | 0.2182  | -0.001  | -0.069   | -0.032   | -0.044     |

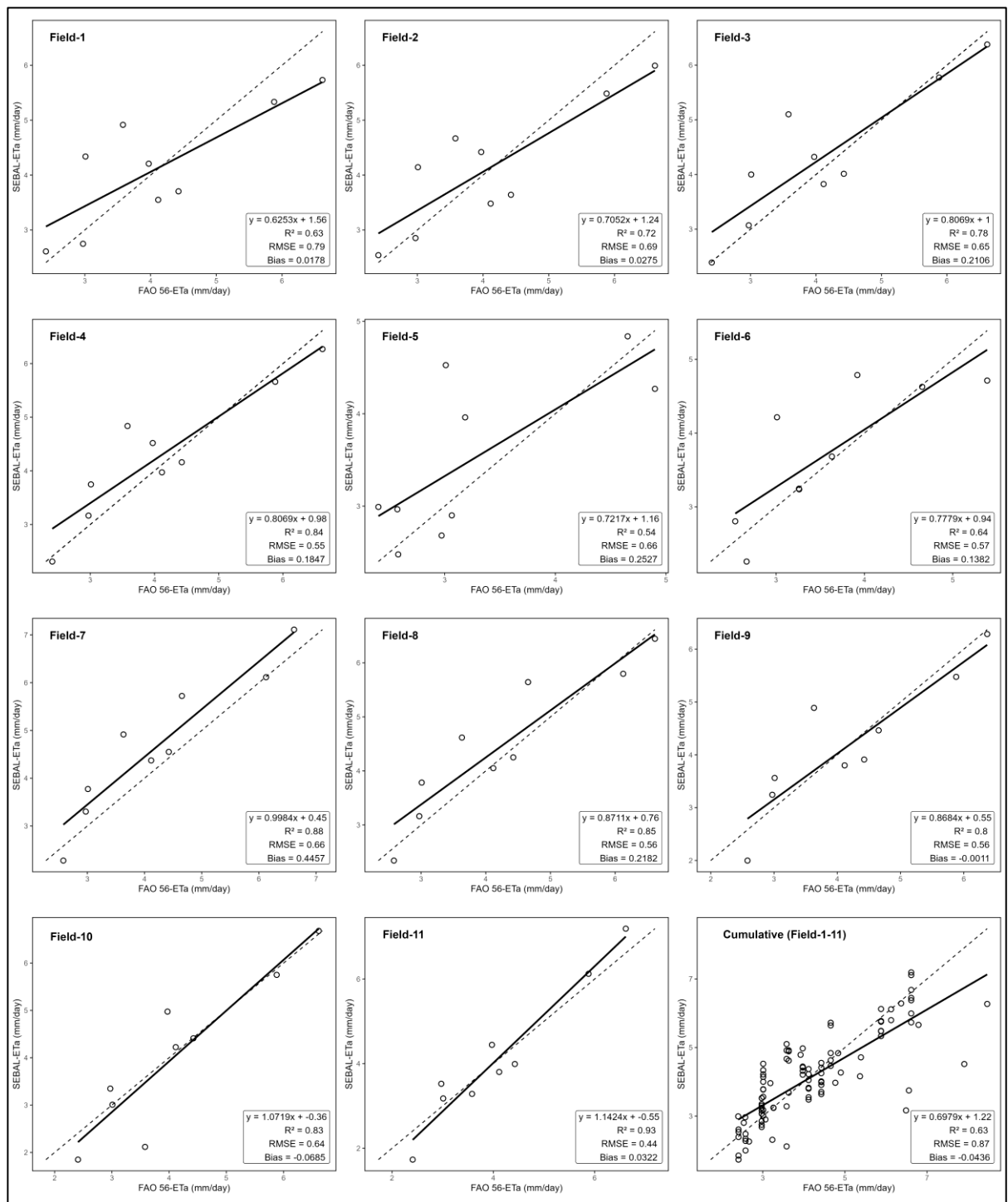


Figure 19: Comparison between SEBAL-estimated and FAO-56 (PM) Wheat actual evapotranspiration ( $ET_a$ ) for all wheat fields during the 2023–2024 growing season. The solid line represents the regression fit between SEBAL and FAO  $ET_a$ , while the dashed line indicates the 1:1 relationship.

## 6.7 Water–Energy–Food Nexus (WEFN) Assessment

WEFN analysis was conducted to evaluate the mutuality among water use, energy consumption, and crop yield across the selected eleven wheat fields during the 2023–24 growing season. The analysis utilized SEBAL-derived evapotranspiration ( $ET_a$ ) in combination with field-level measurements of yield, groundwater depth, and energy use

to assess resource-use efficiency and identify performance variations under flood irrigation conditions.

### **6.7.1 Field-Level Water and Energy Use**

Field-level seasonal water consumption was derived by multiplying the total SEBAL-based seasonal  $ET_a$  with the respective field areas. Seasonal  $ET_a$  values ranged from 456 mm to 668 mm, corresponding to total water use between 1,903 m<sup>3</sup> (Field-6) and 742,420 m<sup>3</sup> (Field-10). This variation reflects differences in field size, crop vigor, and irrigation management. Groundwater depth measurements ranged from 11.6 m to 33.5 m, significantly influencing the energy required for pumping. The total energy use varied widely from 21.6 kWh in small fields to over 5,194 kWh in large fields demonstrating how field scale and hydrogeological conditions strongly affect energy footprints (Table 11).

### **6.7.2 Water and Energy Productivity Indicators**

The performance indicators derived revealed substantial spatial variability. Water productivity (WP) ranged from 0.45 to 0.73 kg/m<sup>3</sup>, with an average of 0.58 kg/m<sup>3</sup>. Fields with higher yields (particularly Fields 7, 8, 10, and 11) exhibited higher WP values, indicating more effective water use. Energy productivity (EP) showed even greater variability, ranging from 30.87 to 106.55 kg/kWh, with energy intensity (EI the inverse of EP) ranging from 0.009 to 0.032 kWh/kg. As shown in Figure 21 field with high EP have low EI values and vice versa. This variation indicates that fields with deeper groundwater levels and lower yield (e.g., Fields 1 and 2) consumed more energy per unit of yield compared to fields with shallower water tables (e.g., Fields 7 and 11). To make the results uniform the efficiency was considered 50 % for all fields (Table 12).

### **6.7.3 Relationships Between Water, Energy, and Yield**

The interrelationships between water use, energy consumption, and crop yield were examined through pairwise regression analysis (Figure 22) to understand how different resource-use parameters influence one another. The analysis revealed several statistically significant trends that highlight the underlying resource dynamics in irrigated wheat production systems.

A strong positive linear correlation was observed between yield and water productivity (WP), indicating that fields producing higher yields also tend to use water more effectively. This is particularly evident in Fields 7, 8, 10, and 11, where higher yields

coincided with elevated WP values. Similarly, energy productivity (EP) showed a positive association with yield, suggesting that fields with better crop performance also tend to be more energy efficient. This reflects the benefits of adequate irrigation scheduling, higher canopy cover, and better soil-water availability.

A negative relationship between EP and groundwater depth was also evident, confirming that deeper water tables increase energy requirements for pumping, thus reducing energy productivity. This aligns with the measured depth-to-water values, which were lowest in the best-performing fields and highest in those with poor EP.

Importantly, energy intensity (kWh/kg) i.e. the quantity of energy required to produce a unit mass of wheat—showed inverse trends compared to WP and EP. Fields with higher yield and resource-use efficiency exhibited lower energy intensity values, while low-yield, poorly performing fields had much higher energy intensities. Specifically:

- i. Energy intensity vs. yield showed a negative correlation, meaning that as crop yield increased, the energy required per kilogram of wheat decreased.
- ii. Energy intensity vs. WP also exhibited a clear inverse relationship, as fields that used water efficiently typically required less energy per unit of production.
- iii. Energy intensity vs.  $ET_a$  demonstrated that fields with higher seasonal evapotranspiration, supported by good crop vigor and proper irrigation, achieved lower energy intensity. This reflects more productive use of both water and energy resources.
- iv. Conversely, fields with shallow canopy development lower yield and lower  $ET_a$  showed higher energy intensity, indicating inefficient resource use and potentially poor irrigation management.

These relationships collectively indicate that energy intensity serves as a sensitive indicator of overall resource-use efficiency. Fields with high yield, high WP, and high EP simultaneously demonstrate low energy intensity, pointing to synergistic effects between water and energy use efficiencies.

As summarized in table Table 12 this integrated relationship analysis highlights that optimizing water use through improved irrigation practices not only improves yield but also indirectly enhances energy efficiency, which is critical in areas relying on groundwater pumping. Energy intensity, therefore, can serve as a key performance

indicator (KPI) for identifying fields or management zones with inefficient resource use and for targeting interventions aimed at reducing production costs and environmental impacts.

#### **6.7.4 WEF Nexus Index (WEFNI), Normalized Performance Indicators, and Field Ranking**

To evaluate and compare the performance of wheat fields in terms of water, energy, and crop productivity, WEFNI was computed using normalized performance indicators: Normalized Water Productivity (NWP), Normalized Energy Productivity (NEP), and Normalized Yield Indicator (NYI). Normalization scales all indicators to a 0–1 range, enabling fair comparison among fields of varying size, groundwater depth, and management conditions. A value of 1 represents the best-performing field for a given indicator, while 0 represents the lowest performance.

As summarized in Table 12, the NWP values ranged from 0 to 1. Fields 7 and 8 achieved the highest values (0.91–1.00), indicating superior water use efficiency, whereas Field 5 recorded the lowest NWP, reflecting inefficient irrigation and lower yield. A similar trend was observed for NEP, with Field 11 showing the highest energy productivity (1.00), followed by Fields 7 and 10. Lower NEP values were recorded in Fields 1 and 2, primarily due to their greater groundwater depths and, consequently, higher energy consumption.

NYI values mirrored the patterns of NWP and NEP. Fields 7 and 8 showed the highest NYI, supported by higher yield and strong canopy development throughout the season, while Fields 5 and 6 had the lowest NYI. This consistency across indicators reflects the interconnected nature of yield, water use, and energy consumption.

The resulting WEFNI values ranged from 0.04 (Field 5) to 0.90 (Field 7), with an overall mean of 0.41. Fields 7, 8, and 11 scored highest on the WEFNI scale ( $\geq 0.70$ ), indicating balanced performance across all three dimensions of the nexus. Medium-performing fields (1, 2, 3, 4, and 9) exhibited moderate values in one or two indicators but lagged in the third, suggesting targeted opportunities for efficiency improvement. Fields 5 and 6 recorded the lowest index values, largely due to their poor water and energy productivity and low yields.

Based on the integrated WEFNI scores, each field was ranked from 1 (highest) to 11 (lowest).

- i. Field 7 ranked 1st, followed by Fields 8 and 11 (2nd and 3rd), demonstrating high performance in NWP, NEP, and NYI simultaneously.
- ii. Fields 1, 2, 3, and 4 occupied mid-level rankings due to moderate performance.
- iii. Fields 5 and 6 ranked at the bottom, reflecting overall low resource-use efficiency.

This ranking is visually presented in Figure 23 Figure 24 which provides a clear comparative overview of field performance. Fields with high WEFNI values consistently exhibited low energy intensity, further confirming the synergistic relationships among yield, water, and energy efficiency.

This ranking-based interpretation is valuable for practical decision-making, as it helps identify priority fields for targeted interventions such as improving irrigation scheduling, optimizing energy use, or enhancing crop management practices. By combining normalized indicators and WEFNI-based ranking, this framework allows both quantitative comparison and strategic resource allocation for improved water–energy–food security in irrigated wheat systems.

*Table 11: Field-level area, total crop yield, actual evapotranspiration, total water used, groundwater depth, and energy consumption for selected wheat fields*

| <b>Field</b> | <b>Area<br/>(ha)</b> | <b>Total<br/>Yield<br/>(ton)</b> | <b>ET<sub>a</sub><br/>(mm)</b> | <b>V<br/>(m<sup>3</sup>)</b> | <b>DTW<br/>(m)</b> | <b>Total<br/>Energy Used<br/>(kWh)</b> |
|--------------|----------------------|----------------------------------|--------------------------------|------------------------------|--------------------|----------------------------------------|
| 1            | 7.53                 | 21.09                            | 530                            | 39939                        | 33.54              | 683.10                                 |
| 2            | 4.40                 | 12.76                            | 537                            | 23617                        | 33.54              | 403.94                                 |
| 3            | 0.63                 | 1.88                             | 557                            | 3482                         | 27.44              | 48.73                                  |
| 4            | 0.69                 | 2.18                             | 559                            | 3876                         | 27.44              | 54.24                                  |
| 5            | 1.30                 | 2.66                             | 456                            | 5906                         | 22.26              | 67.04                                  |
| 6            | 0.39                 | 1.05                             | 489                            | 1903                         | 22.26              | 21.60                                  |
| 7            | 14.02                | 68.00                            | 668                            | 93698                        | 17.07              | 815.86                                 |
| 8            | 3.34                 | 13.52                            | 577                            | 19280                        | 17.07              | 167.88                                 |
| 9            | 5.16                 | 16.51                            | 557                            | 28720                        | 25.61              | 375.11                                 |
| 10           | 137.93               | 434.48                           | 538                            | 742420                       | 13.72              | 5194.67                                |
| 11           | 30.35                | 104.72                           | 548                            | 166340                       | 11.59              | 982.83                                 |
| Avg          | 61.71                |                                  | 547.00                         | 102653                       | 22.87              | 801.37                                 |

Note:  $ET_a$  = actual evapotranspiration.  $V$  = Total water used derived from SEBAL-based  $ET_a$  estimates.  $DTW$  = Depth to Groundwater Table represents field-level measurements.

Table 12: Derived performance indicators including water productivity, energy productivity, energy intensity, normalized values, and WEF Nexus Index (WEFNI) for selected wheat fields.

| Field | Y/A<br>(ton/ha) | WP<br>(kg/m <sup>3</sup> ) | EP<br>(kg/kWh) | EI<br>(kWh/kg) | NWP  | NEP  | NYI  | WEFNI | Rank |
|-------|-----------------|----------------------------|----------------|----------------|------|------|------|-------|------|
| 1     | 2.80            | 0.53                       | 30.87          | 0.032          | 0.28 | 0.00 | 0.27 | 0.18  | 10   |
| 2     | 2.90            | 0.54                       | 31.58          | 0.032          | 0.33 | 0.01 | 0.30 | 0.21  | 9    |
| 3     | 3.00            | 0.54                       | 38.48          | 0.026          | 0.32 | 0.10 | 0.34 | 0.25  | 8    |
| 4     | 3.15            | 0.56                       | 40.24          | 0.025          | 0.41 | 0.12 | 0.39 | 0.31  | 6    |
| 5     | 2.05            | 0.45                       | 39.61          | 0.025          | 0.00 | 0.12 | 0.00 | 0.04  | 11   |
| 6     | 2.70            | 0.55                       | 48.68          | 0.021          | 0.37 | 0.24 | 0.23 | 0.28  | 7    |
| 7     | 4.85            | 0.73                       | 83.35          | 0.012          | 1.00 | 0.69 | 1.00 | 0.90  | 1    |
| 8     | 4.05            | 0.70                       | 80.56          | 0.012          | 0.91 | 0.66 | 0.71 | 0.76  | 2    |
| 9     | 3.20            | 0.57                       | 44.02          | 0.023          | 0.45 | 0.17 | 0.41 | 0.35  | 5    |
| 10    | 3.15            | 0.59                       | 83.64          | 0.012          | 0.49 | 0.70 | 0.39 | 0.53  | 4    |
| 11    | 3.45            | 0.63                       | 106.55         | 0.009          | 0.65 | 1.00 | 0.50 | 0.72  | 3    |
| Avg   | 3.21            | 0.58                       | 57.05          | 0.02           | 0.48 | 0.35 | 0.41 | 0.41  | -    |

Note: WP = water productivity, EP = energy productivity, WEFNI = Water–Energy–Food Nexus Index. EI = Energy Intensity = energy used per unit of crop yield (kWh/kg). Normalized values were used for composite index calculation. NWP = Normalize water productivity, NEP = Normalized energy productivity, NYI = Normalized yield index

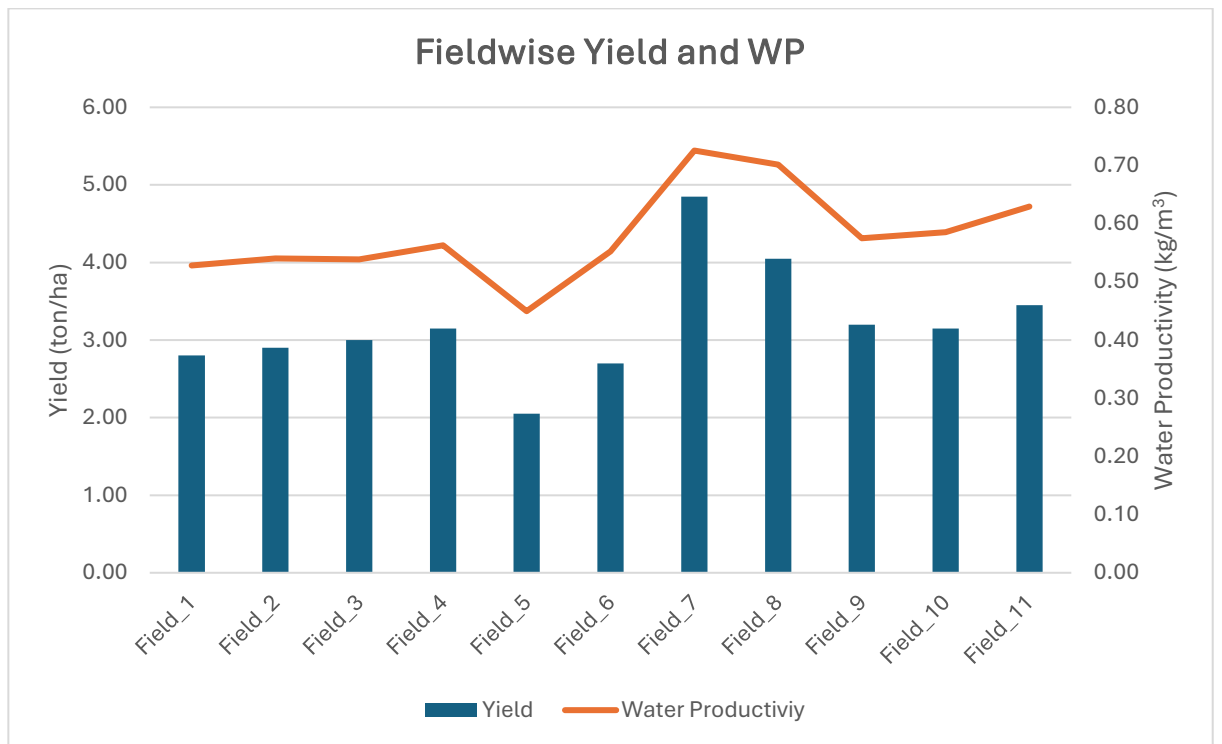


Figure 20: Spatial comparison of wheat yield and water productivity across the study fields.

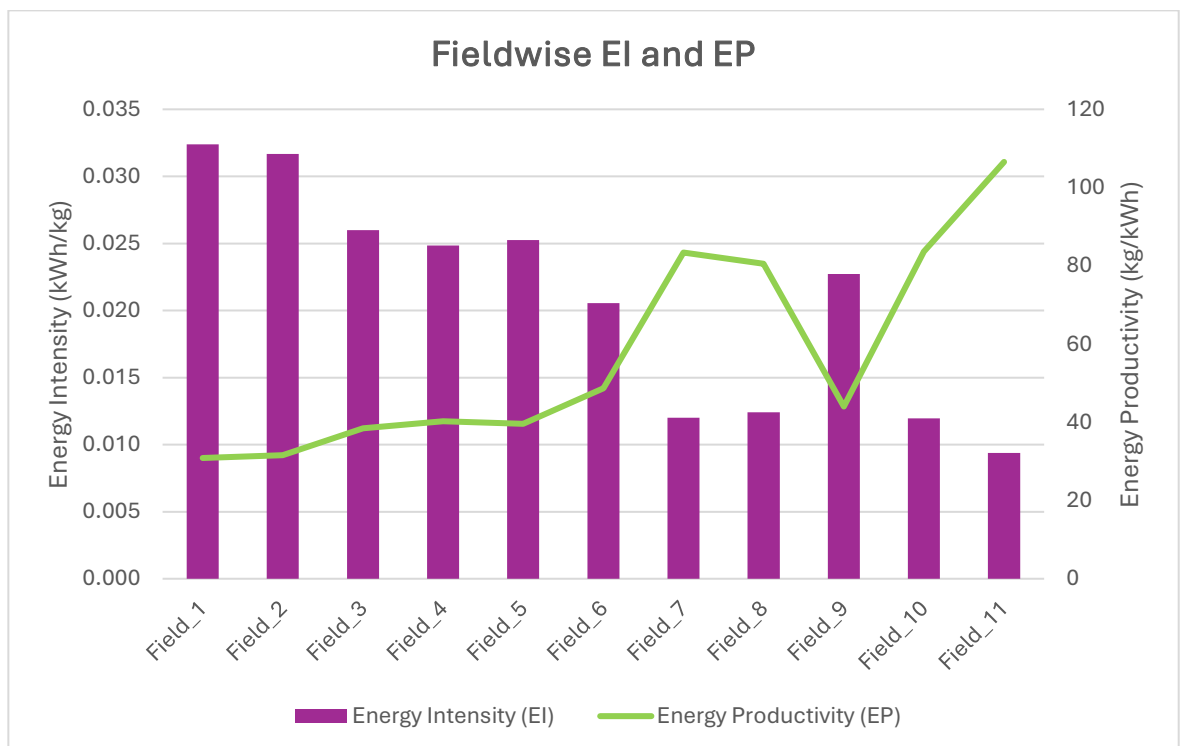


Figure 21: Field-wise variation in energy intensity and energy productivity.

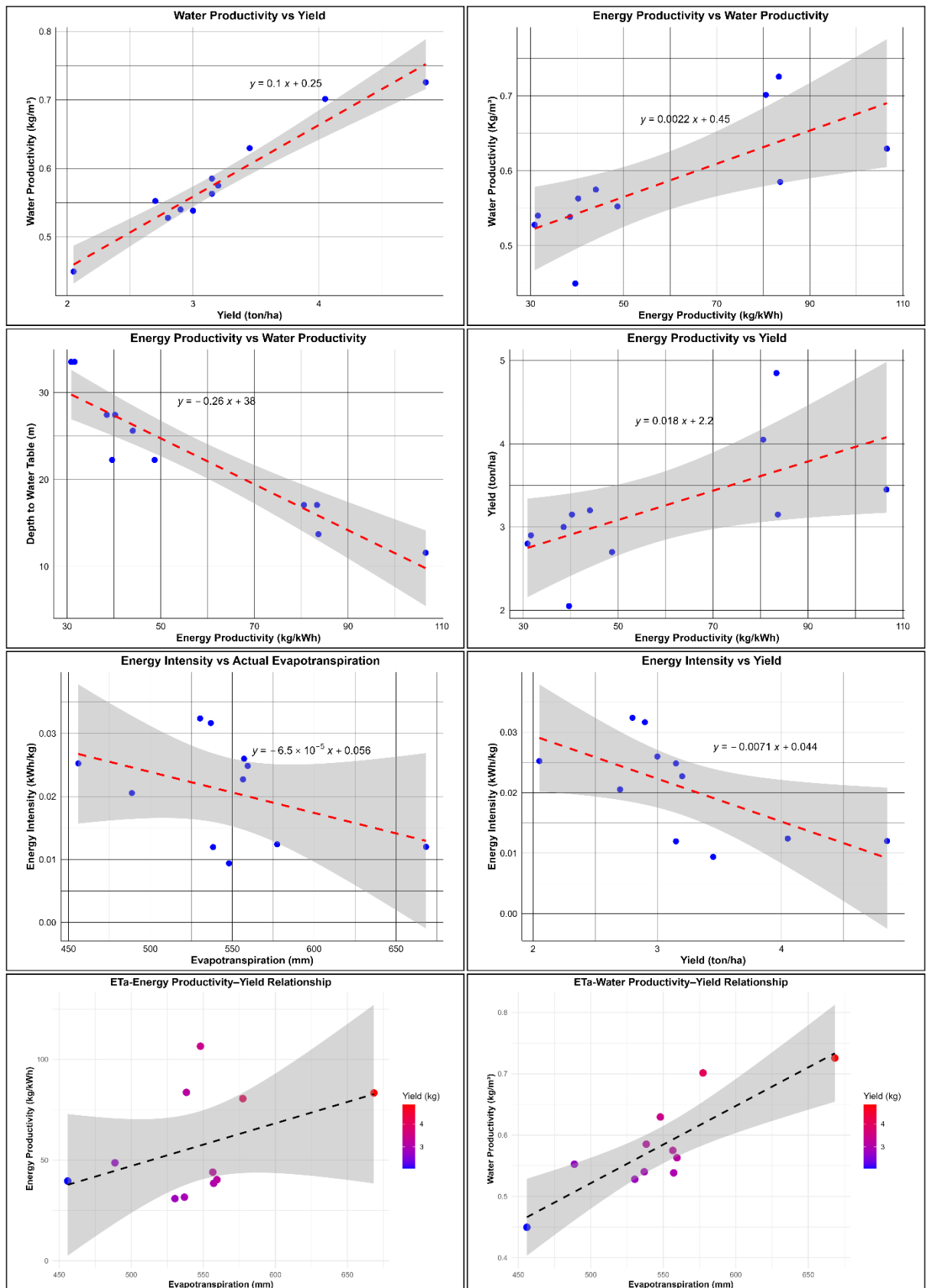


Figure 22: Relationships among water productivity, energy productivity, energy intensity, and crop yield.

## Normalized Water-Energy-Food Nexus Indicators per Field

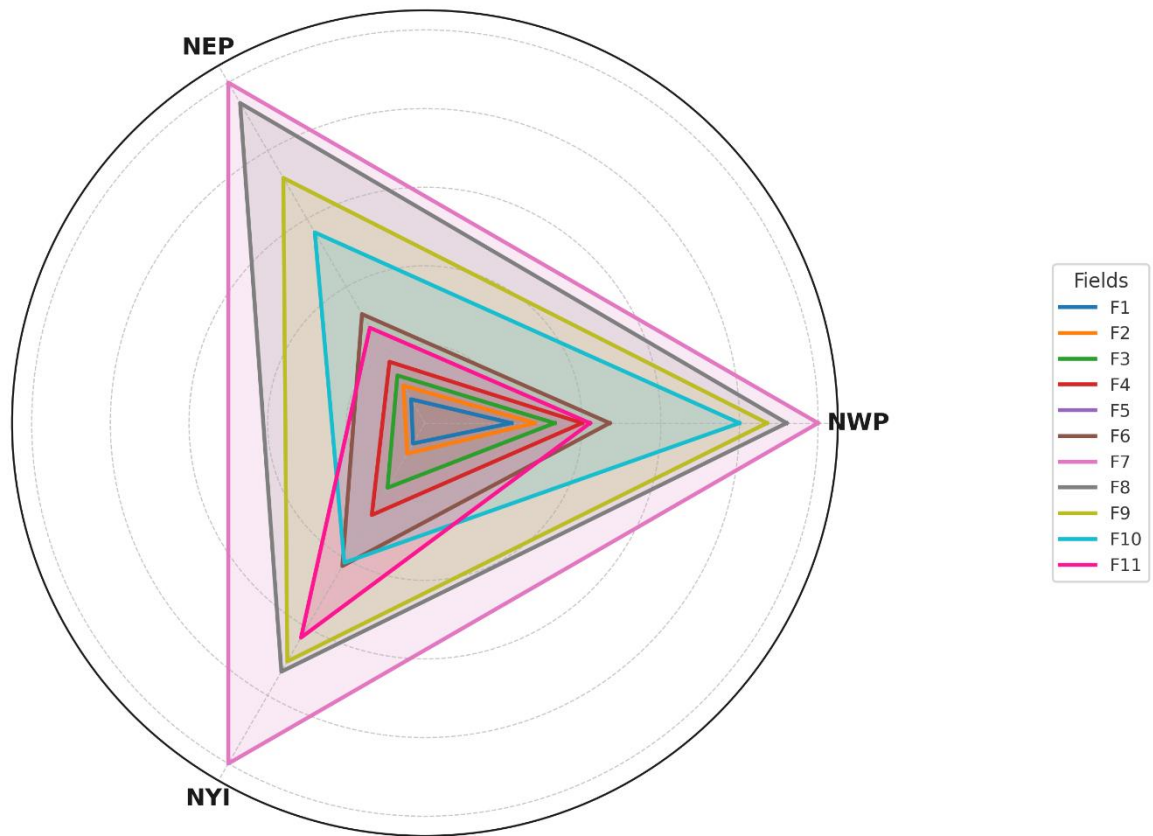


Figure 23: Normalized Water-Energy-Food Nexus Indicators per Field (NWP, NEP, NYI).

*Note: Each polygon represents an individual flood-irrigated wheat field. The distinct color palette improves differentiation among fields, while the three axes (Normalized Water Productivity – NWP, Normalized Energy Productivity – NEP, and Normalized Yield Index – NYI) illustrate the relative balance of water, energy, and food performance`*

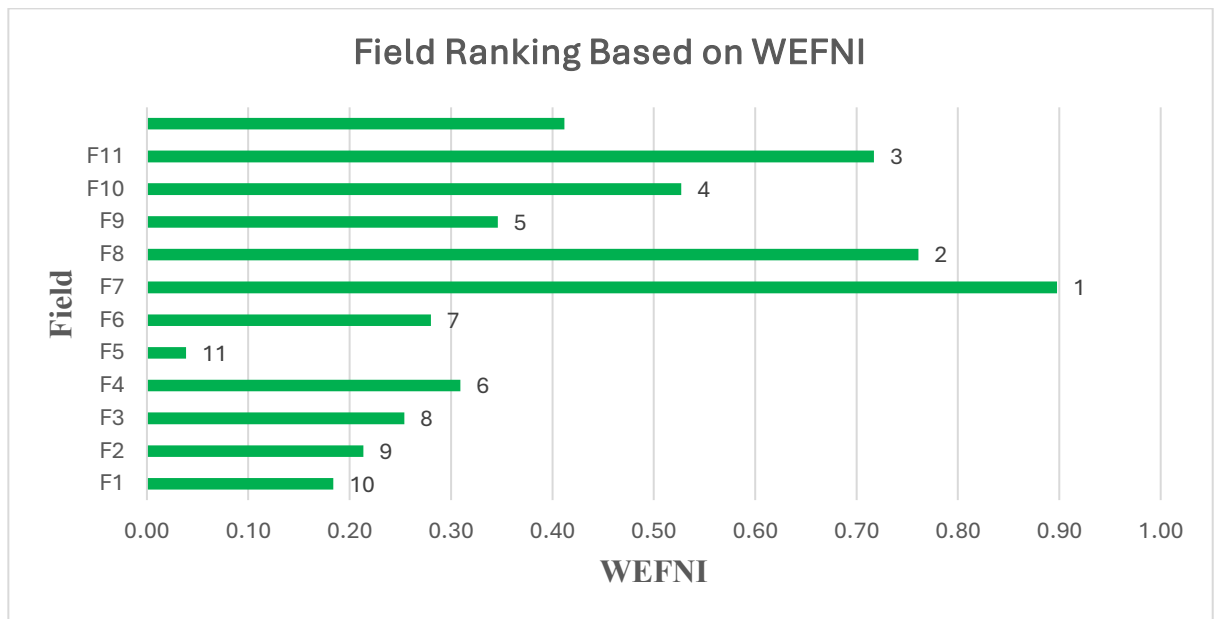


Figure 24: Field ranking based on WEF Nexus Index (WEFNI).

*Note: Fields are sorted in descending order of WEFNI values. Rank 1 corresponds to the highest performing field and Rank 11 to the lowest.*

## 7 Conclusion and Recommendations

### 7.1 Conclusion

This study successfully estimated and analyzed  $ET_a$  of wheat fields in Swabi District, Pakistan, during the 2023–2024 growing season using the SEBAL model implemented in GEE. The model was calibrated against the FAO-56-PM approach to enhance its reliability under local semi-arid conditions. The integration of remote sensing, meteorological data, and field measurements allowed for accurate quantification of water consumption and its linkages with crop yield and energy use within the WEFN framework.

The results demonstrated that SEBAL effectively captured the spatiotemporal variability of evapotranspiration across different field conditions. The SEBAL-derived  $ET_a$  values showed strong correlation with the FAO-56  $ET_c$ , with  $R^2$  values ranging from 0.54 to 0.93, RMSE between 0.44–0.87 mm day<sup>-1</sup>, and minimal bias across fields. These results confirm that SEBAL effectively captures the spatiotemporal dynamics of evapotranspiration across diverse soil and management conditions. Fields with dense vegetation cover and optimized irrigation schedules (e.g., Fields 7, 8, and 11) exhibited the highest agreement with  $ET_c$ , while moisture-stressed or poorly managed fields (e.g., Fields 4 and 5) showed greater deviations. This demonstrates that local calibration enhances SEBAL's accuracy and adaptability for field-scale water management.

The WEF Nexus analysis provided a holistic understanding of the relationships between water consumption, energy use, and crop yield. Normalized indicators such as Normalized Water Productivity (NWP), Normalized Energy Productivity (NEP), and Normalized Yield Index (NYI) together formed the Water–Energy–Food Nexus Index (WEFNI). The results revealed significant spatial variability among the eleven fields, with WEFNI values ranging from 0.04 to 0.90. High-performing fields (7, 8, and 11) achieved balanced efficiency across all three dimensions, whereas low-performing fields (5 and 6) displayed low resource-use efficiency due to poor water management and excessive energy consumption.

Overall, the study confirms that:

- i. The SEBAL model, when properly calibrated, is a robust and scalable approach for field-level  $ET_a$  estimation in Pakistan's semi-arid agroecosystems.
- ii. The integration of SEBAL-based  $ET_a$  with WEFN assessment enables comprehensive evaluation of irrigation performance and sustainability.
- iii. Spatial variability in WEFNI highlights the need for site-specific management strategies and policy interventions to enhance overall resource-use efficiency.

The findings demonstrate the potential of remote sensing-based models like SEBAL for supporting data-driven decision-making in irrigation management, water allocation, and sustainable agricultural planning in water-scarce regions.

## **7.2 Recommendations**

This research demonstrates that integrating remote sensing-based evapotranspiration estimation with WEF Nexus indicators can significantly improve field-level water and energy management. However, to maximize its practical value and ensure the wider adoption of this approach, further actions are required at the research, farm, and policy levels. The following recommendations outline a pathway for refining the SEBAL model, improving irrigation management, enhancing energy efficiency, and supporting data-driven agricultural decision-making in semi-arid regions.

### **7.2.1 Model Improvement and Calibration**

1. Multi-season and multi-crop calibration: Extend SEBAL calibration to additional crops (e.g., maize, rice, sugarcane, cotton etc) and growing seasons to test model robustness and generalizability under varying agro-climatic conditions.
2. Enhanced validation: Incorporate ground-based flux tower or lysimeter data for direct energy balance verification, where available.
3. Uncertainty quantification: Include uncertainty analysis (e.g., confidence intervals or error propagation) for  $ET_a$  and WEFN indicators to better inform decision-making.

### **7.2.2 Irrigation and Water Management**

4. Field-specific irrigation scheduling: Use SEBAL-derived  $ET_a$  maps to guide irrigation timing and depth, replacing conventional calendar-based irrigation with water demand-based scheduling.

5. Targeted interventions for low-performing fields: Prioritize management improvements in fields with low WEFNI values (e.g., Fields 5 and 6) through soil moisture monitoring and irrigation optimization.
6. Adoption of precision and deficit irrigation: Encourage adoption of drip or sprinkler systems where feasible to improve water use efficiency (WUE) and reduce non-beneficial water losses.

### **7.2.3 Energy Efficiency and Policy Implications**

7. Energy–water co-optimization: Develop policies promoting energy-efficient irrigation systems, such as variable-speed pumps and solar-powered pumping units, to reduce operational costs and emissions.
8. Monitoring and benchmarking: Incorporate WEFN indicators (NWP, NEP, NYI, and WEFNI) into provincial agricultural and irrigation monitoring programs for assessing farm performance and sustainability.
9. Incentive programs: Encourage government and extension agencies to establish incentive mechanisms for farmers who adopt energy-efficient and water-saving technologies.

### **7.2.4 Future Research Directions**

10. Decision-support tools: Integrate calibrated SEBAL outputs with GIS-based dashboards or mobile applications to provide farmers and irrigation managers with near–real-time  $ET_a$  and WEFN information.
11. Cross-scale studies: Expand the analysis to basin or regional scales to link field-level  $ET_a$  and WEFN performance with large-scale water allocation and policy decisions.
12. Climate change assessment: Examine how climate variability and long-term warming trends affect  $ET_a$  dynamics and WEFN efficiency to guide adaptation strategies.

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