

DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE FOR WATER DEMAND IN TAIWAN, SHIH-MEN REGION

DÉVELOPPEMENT D'UN SYSTÈME D'INTELLIGENCE ARTIFICIELLE POUR LA DEMANDE EN EAU DANS LA RÉGION DE SHIH-MEN, A TAIWAN

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ABSTRACT

Water constitutes an essential resource for paddy cultivation, with insufficient water supply leading to crop mortality or diminished yields. In Taiwan, precipitation exhibits significant temporal variability, with rainfall during the wet season ranging from 1.5 to 9 times that of the dry season. Geographically, the terrain has steep slopes and short rivers. According to long-term statistics, an average of about 57% of runoff is not effectively utilized and flows directly into the sea. Furthermore, the increasing impact of climate change has rendered water resource availability more unpredictable. Consequently, accurate estimation of crop water demand is vital for both governmental agencies and agricultural practitioners. The extensive scale of irrigation areas complicates direct field investigations. In this regard, remote sensing technologies present significant advantages for large-scale monitoring compared to conventional ground-based surveys. Taiwan's agricultural landscape is characterized by complex cultivation patterns, with fragmented and small field boundaries. The manual analysis rate of aerial imagery is approximately 1,000 hectares per day, depending on conditions, which limits its practical application. The Taiwan Ministry of Agriculture (MOA) operates aircraft equipped with Leica DMCIII large-format cameras, which are capable of generating aerial orthoimages with a spatial resolution of 0.15 meters. These aircraft conduct aerial surveys of Taiwan approximately twice annually, facilitating crop monitoring. Furthermore, the integration of artificial intelligence technologies enables the autonomous identification of crop planting areas. This research introduces a methodology that integrates an Artificial Intelligence (AI) deep learning model to identify paddy field areas with established irrigation formulas to automatically estimate water demand in the Shih-men region of Taiwan. High-resolution orthoimages of paddy fields, which were manually annotated, served as the training data. The AI model was fine-tuned using the Low-Rank Adaptation (LoRA) technique applied to Meta AI's pretrained Segment Anything Model (SAM) with the backbone Visual Transformer Base (ViT-B). SAM, a pixel classification model, directly outputs delineated paddy field areas. When implemented in the Shih-men region, the model attained an F1 score of 0.85.

The MOA has released parcel map data delineating field boundaries, enabling crop identification through object classification models. In this research, a Feature-Classifer model was employed as an alternative approach for paddy field identification. Compared to SAM, the Feature-Classifer demands lower computational resources and processing time. When implemented in the Shih-men region, the model attained an F1 score of 0.84, comparable to that of SAM, although it depends on the availability of parcel map data. Additionally, it was observed that the Feature-Classifer exhibits reduced accuracy in cases where the parcel size is smaller than the feature tile or when the parcel shape is a concave polygon.

Following the delineation of paddy field areas via AI models, irrigation formulas were applied to estimate total water demand. Key factors incorporated into the irrigation calculations included field seepage, effective rainfall within the fields, paddy field evaporation, and canal water conveyance efficiency. Regarding field seepage, this research used the soil management group map as the data, which divided

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soil drainage into three levels. Rainfall and evaporation rates were calculated using weather information released by the Central Weather Administration.

In summary, this study introduces a methodology that integrates artificial intelligence-driven delineation of paddy field areas with the application of irrigation formulas to estimate water demand, thereby offering a potential alternative to manual identification of planting regions. Additionally, the research contributes a labeled dataset comprising high-resolution orthoimages of paddy fields, which is suitable for training AI models. Moreover, the study presents a comparative evaluation of pixel-based and object-based classification approaches for the identification of paddy fields.

Keywords: Artificial intelligence; water supply; water demand; canal water conveyance efficiency; identification of paddy field.

RESUME

L'eau constitue une ressource essentielle pour la riziculture, avec un approvisionnement en eau insuffisant donnant lieu à une perte des cultures ou à une diminution des rendements. À Taiwan, les précipitations présentent une forte variabilité temporelle, avec des précipitations pendant la saison des pluies allant de 1,5 à 9 fois celles de la saison sèche. Sur le plan géographique, le terrain possède des pentes raides et des rivières courtes. Selon les statistiques à long terme, une moyenne d'environ 57% du ruissellement n'est pas utilisée efficacement et se déverse directement dans la mer. En outre, l'impact croissant du changement climatique a rendu la disponibilité des ressources en eau plus imprévisible. Par conséquent, une estimation précise des besoins en eau des cultures est essentielle à la fois pour les agences gouvernementales et les praticiens agricoles. L'étendue des zones d'irrigation rend toutefois les enquêtes de terrain complexes. À cet égard, les technologies de télédétection présentent des avantages significatifs pour la surveillance à grande échelle par rapport aux enquêtes terrestres conventionnelles. Le paysage agricole de Taïwan se caractérise par des modes de culture complexes, avec des parcelles fragmentées et petites. Le taux d'analyse manuelle de l'imagerie aérienne est d'environ 1 000 hectares par jour, selon les conditions, ce qui limite son application pratique. Le ministère de l'agriculture de Taiwan (MOA) exploite des avions équipés de caméras Leica DMCIII à grand format, qui sont capables de produire des ortho-images aériennes avec une résolution spatiale de 0,15 mètre. Ces avions effectuent des relevés aériens de Taiwan environ deux fois par an, ce qui facilite le suivi des cultures. De plus, l'intégration des technologies d'intelligence artificielle permet une identification autonome des zones de culture.

Cette recherche présente une méthodologie qui intègre un modèle d'apprentissage profond d'intelligence artificielle (IA) pour identifier les rizières avec des formules d'irrigation établies afin d'estimer automatiquement la demande en eau dans la région de Shih-men à Taiwan. Les ortho-images à haute résolution des rizières, qui ont été annotées manuellement, ont servi de données d'entraînement. Le modèle d'IA a été affiné à l'aide de la technique LoRA (Low-Rank Adaptation) appliquée au modèle pré-entraîné SAM (Segment Anything Model) de Meta AI, avec la base du transformateur visuel (ViT-B). SAM, un modèle de classification en pixels, sort directement les zones de rizières délimitées. Lorsqu'il est mis en œuvre dans la région de Shih-men, le modèle a atteint un score F1 de 0,85.

Le ministère de l'Agriculture (MOA) a publié des données cartographiques de parcelles représentant les limites des parcelles, permettant l'identification des cultures grâce à des modèles de classification d'objets. Dans cette recherche, un modèle de classification par caractéristiques a été utilisé comme approche alternative pour l'identification des rizières. Par rapport à SAM, le classificateur de caractéristiques exige des ressources de calcul et un temps de traitement réduit. Lorsqu'il a été mis en œuvre dans la région de Shih-men, le modèle a atteint un score F1 de 0,84, par rapport à celui de SAM, bien qu'il dépende de la disponibilité des données cartographiques des parcelles. De plus, il a été observé que le classificateur de caractéristiques présente une précision réduite dans les cas où la taille de la parcelle est inférieure à celle de la tuile caractéristique ou lorsque la forme de la parcelle est un polygone concave.

Suite à la présentation des rizières via des modèles d'IA, des formules d'irrigation ont été appliquées pour estimer la demande totale en eau. Les facteurs clés intégrés dans les calculs d'irrigation comprenaient l'infiltration sur le terrain, les précipitations efficaces sur les parcelles, l'évaporation des rizières et l'efficacité du transport de l'eau par canal. En ce qui concerne les infiltrations sur le terrain, cette recherche a utilisé la carte du groupe de gestion des sols comme données, qui divisaient le drainage du sol en trois niveaux. Les taux de précipitations et d'évaporation ont été calculés à partir des informations météorologiques publiées par l'Administration météorologique centrale (CWA).

En résumé, cette étude introduit une méthodologie qui intègre la présentation des rizières basée sur l'intelligence artificielle avec l'application de formules d'irrigation pour estimer la demande en eau, offrant ainsi une alternative potentielle à l'identification manuelle des régions de culture. De plus, la recherche contribue à un ensemble de données marquées comprenant des ortho-images de haute résolution des rizières, adapté à l'entraînement de modèles d'IA. En outre, l'étude présente une évaluation comparative des approches de classification basée sur les pixels et basée sur les objets pour l'identification des rizières.**

Mots-clés : Intelligence artificielle; Approvisionnement en eau; Demande en eau; Efficacité du transport de l'eau par canal; Identification des rizières.

INTRODUCTION

Taiwan receives abundant annual precipitation; however, its capacity for effective water retention remains severely limited. The island's rugged topography, characterized by steep slopes and short, rapid river systems, inherently accelerates hydrological runoff. According to statistics from the Water Resources Agency, Taiwan's average annual precipitation is approximately 95.07×10^9 tons, of which an estimated 54.7×10^9 tons discharges directly into the sea (Water Resources Agency, 2024). Furthermore, Taiwan exhibits pronounced temporal variability in rainfall distribution; precipitation during the wet season accounts for 78.8% of the annual total, whereas the dry season contributes a mere 21.2% (Water Resources Agency, 2024). Consequently, optimal allocation of available water resources is critical.

In recent decades, global climate change has significantly intensified the vulnerability of agricultural water management systems worldwide. Rising global temperatures and shifting meteorological patterns have altered the frequency, intensity, and temporal distribution of precipitation, leading to a higher incidence of severe droughts and flash floods. For subtropical regions like Taiwan, these climatic disruptions directly compromise regional hydrological stability (Hsu Huang-Hsiung, Ming-Hsu Li, 2024). Elevated ambient temperatures accelerate crop evapotranspiration rates, thereby driving up baseline agricultural water demand during critical growth stages. Concurrently, the amplification of extreme weather events prolongs dry spells and makes seasonal rainfall less predictable, rendering traditional, static irrigation scheduling obsolete. Consequently, integrating dynamic, high-precision forecasting methodologies is no longer just an operational preference, but a critical necessity to mitigate climate-induced water scarcity and ensure sustainable agricultural resilience.

Paddy cultivation represents a cornerstone of Taiwanese agriculture, spanning an area exceeding 2.5×10^9 m² (Yang Jialing, Zheng Jiaqi, Wang Borong, Wu Yijian, 2016). Accurately predicting agricultural water demand is highly complex due to the dynamic nature of paddy field environments. Irrigation requirements fluctuate significantly across distinct phenological growth phases, each demanding specific ponding water depths (WL), which subsequently alter soil infiltration rates (PERC). Beyond standard crop transpiration, paddy field evapotranspiration (ET_{rice}) dynamics are highly sensitive to whether the field maintains a ponding depth.

In conventional water demand forecasting models, the total cultivated area serves as a critical baseline parameter. Currently, crop area mapping relies heavily on seasonal, manual field surveys. However, the vast extent of these agricultural zones is highly disproportionate to the limited number of field investigators, leading to temporal lags and reliance on empirical equations that introduce a certain degree of imprecision. Artificial Intelligence (AI) offers a powerful alternative to mitigate these labor-

intensive constraints. Deep learning models can automatically segment and identify active cultivation footprints from high-resolution orthophotos, providing a scientific, objective, and scalable methodology for agricultural land surveys.

By integrating these highly accurate, spatially explicit AI-derived planting areas with conventional irrigation formulas, soil classification maps, meteorological data, and channel conveyance efficiency metrics, regional water resource authorities can achieve significantly more precise and granular estimations of agricultural water demands.

METHODOLOGY

Workflow Overview

The proposed methodology consists of two primary operational phases. First, historical orthophotos are utilized to fine-tune a deep learning model, which is subsequently deployed to perform inference on concurrent orthophotos of the Shih-men region to extract paddy field boundaries and calculate exact surface areas. Second, these precise spatial metrics are integrated into conventional empirical irrigation formulas to estimate total regional water requirements. Finally, the model's estimations are validated against historical actual water consumption data to assess predictive accuracy.

Deep Learning Architecture and Model Training

This study adopts the Segment Anything Model (SAM) developed by Meta's Fundamental AI Research (FAIR) team (Kirillov, Alexander and Mintun, Eric and Ravi, Nikhila and Mao, Hanzi and Rolland, Chloe and Gustafson, Laura and Xiao, Tete and Whitehead, Spencer and Berg, Alexander C. and Lo, Wan-Yen and Dollár, Piotr and Girshick, Ross, 2023) as the architectural head, integrated with a Vision Transformer Base (ViT-B) backbone. To optimize training efficiency and accommodate domain-specific agricultural features, the Low-Rank Adaptation (LoRA) method (Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, 2022) was applied for parameter-efficient fine-tuning. The training dataset comprised manually annotated orthophotos spanning the Hualien, Taoyuan, and Taichung regions, encompassing 6,250 field parcels with a collective area of $16.29 \times 10^6 \text{ m}^2$. The resulting fine-tuned model was then deployed for inference in the Shih-men administrative area.

The core architecture, SAM, is a pixel-based deep learning. Its workflow is segregated into three functional modules:

- **Image Encoder:** Employs a ViT structure as a feature extractor to capture rich, high-dimensional visual representations from input imagery.
- **Prompt Encoder:** Transforms guiding signals (e.g., text, points, or bounding boxes) into sparse or dense feature vectors aligned with the image encoder's embedding space.
- **Mask Decoder:** Merges embeddings from both the image and prompt encoders to execute pixel-level classification and output precise segmentation masks.

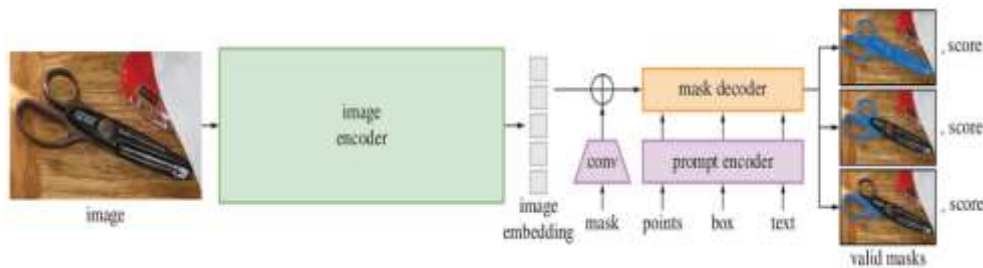


Figure 1. SAM model architecture (Segment Anything, 2023)

Aerial Remote Sensing Data

High-resolution aerial imagery was provided by the Aerial Survey and Remote Sensing Branch of the Forestry and Nature Conservation Agency, MOA, which conducts cyclical aerial campaigns aligned with seasonal cropping schedules. Imagery was captured using a Digital Mapping Camera III (DMCIII) along systematic flight paths. Raw data underwent geometric and radiometric calibration to generate orthorectified imagery containing four spectral bands (Red, Green, Blue, and Near-Infrared) at a ground sampling distance (GSD) of 0.15 m. Example shown in



Figure 2.



Figure 2. Aerial imagery of Hualien, 2024

To ensure seasonal robustness, the training datasets captured diverse phenological stages:

- **Hualien (Spring 2024):** Captured during vigorous vegetative growth, serving as the baseline representative for the reproductive phase. Because Hualien parcels are predominantly paddies, negative control samples (non-paddy features) were sourced from other regions.

- **Taoyuan (Spring 2025):** Provided rich negative class data, including alternative crops, woodlands, and artificial structures.
- **Taichung (Summer 2025):** Captured paddy fields primarily in the ripening phase.
- Dataset Preparation and Preprocessing

The training dataset was constructed through meticulous parcel-level manual annotation. Each individual agricultural parcel within the survey zones was visually inspected and assigned a binary semantic label designating it as either a paddy field or a non-paddy field. The high-resolution aerial imagery was subsequently paired with these corresponding vector annotations to generate synchronized image-mask datasets.

To facilitate efficient deep learning training and accommodate network input dimensions, both the orthophotos and annotation masks were partitioned into standardized, non-overlapping tiles of 256×256 pixels, as illustrated in

Figure 3 and

Figure 4. Furthermore, a background suppression technique was implemented to enhance target feature salience and prevent contextual confounding. In this preprocessing step, peripheral features surrounding the target labeled parcels were masked out (blackened). This strategy effectively eliminated extraneous background noise, thereby ensuring the model optimizes its weight parameters strictly on relevant agronomic spectral and spatial characteristics without overfitting to irrelevant surroundings.

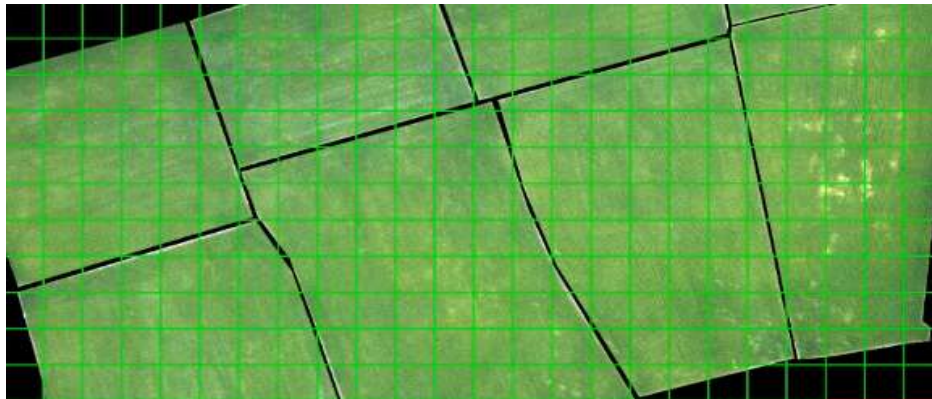


Figure 3. Image data cut in Classify Tiles

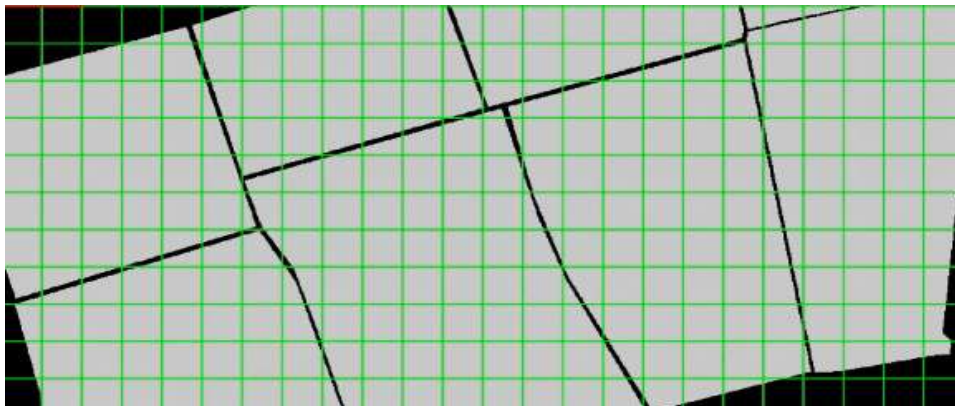


Figure 4. Labeling data cut in Classify Tiles

While initial model iterations trained purely on Hualien and Taoyuan data exhibited performance deficits during the ripening stage, the incorporation of the Taichung multi-temporal dataset established a balanced model capable of robust detection across both reproductive and ripening phases.

Irrigation Water Demand Estimation

The Shih-men Management Office estimates net paddy field irrigation requirements $IN_{net, rice}$ utilizing standard operational formulas (Irrigation Management, 2020):

$$IN_{net, rice} = ET_{rice} + SAT + PERC + WL - P_e$$

Formula 1. Water estimation formula

Where:

- ET_{rice} represents crop evapotranspiration.
- SAT is the initial soil saturation requirement needed to facilitate land puddling and root establishment during the early vegetative phase, empirically established at 200 mm.
- $PERC$ denotes soil infiltration loss, varying as a function of localized soil taxonomy.
- WL signifies the ponding water depth tailored to specific phenological growth stages.
- P_e represents effective precipitation.

To execute this formula spatially, this study coupled AI-derived crop layers with the official MOA soil taxonomy map, real-time meteorological feeds from the Central Weather Administration (CWA), and localized hydraulic conveyance coefficients.

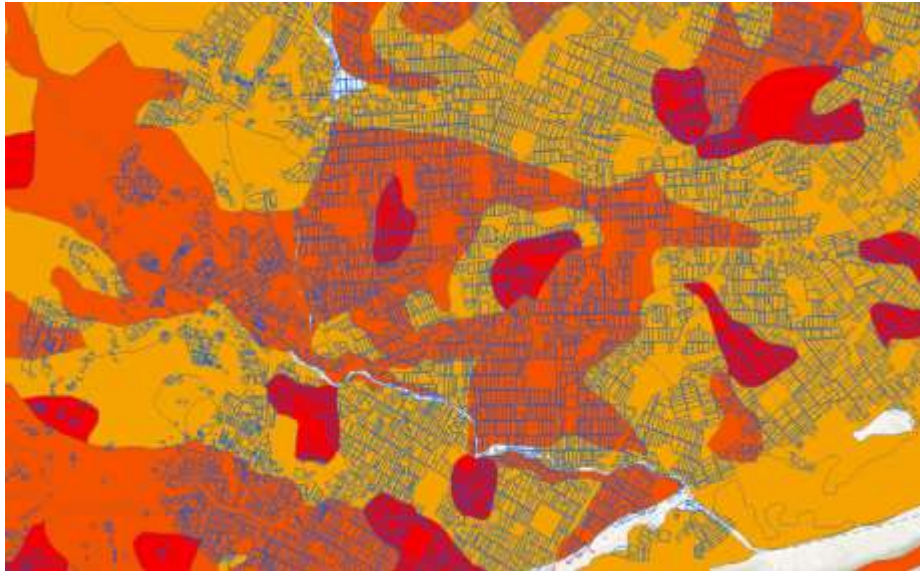


Figure 5. Soil type map overlaying with parcel map

Evapotranspiration Modeling

Crop evapotranspiration is driven by complex thermodynamic interactions. This study implemented the standard FAO-56 Penman-Monteith equation (Richard G. Allen, Luis S. Pereira, Dirk Raes, Martin Smith, 1998) to estimate reference evapotranspiration (ET_0), capturing atmospheric evaporative demand under standard conditions:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{(T + 273)} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

Formula 2. FAO-56 Penman-Monteith equation

Where key driving variables include net radiation (R_n), soil heat flux (G), mean air temperature (T at 2 m height), and wind speed (u_2). Vapor capacities are defined by saturation vapor pressure (e_s), actual vapor pressure (e_a), and the vapor pressure deficit ($e_s - e_a$). Thermodynamic properties are governed by the slope of the saturation vapor pressure curve (Δ) and the psychrometric constant (γ).

Continuous meteorological data were extracted from four proximal CWA automated weather stations: Bade Fruit and Vegetable Cooperative, Tea Research and Extension Station, Agricultural Engineering Research Center, and the Taoyuan District Agricultural Research and Extension Station (DARES). Spatial approximation was achieved using a nearest-neighbor approach relative to each parcel centroid.

RESULTS AND DISCUSSION

The validation test set comprised manually annotated parcels within the Shih-men region collected during the Spring 2025 season, encompassing 163,468 m² of active paddy fields and 1,667,605 m² of non-paddy land cover. Direct evaluation of the deep learning model yielded an initial F1-score of 0.86. Example shown in

Figure 6. To eliminate false positives occurring outside legitimate agricultural boundaries, the segmentation outputs were intersected with the official MOA land-use parcel maps. This post-processing topological constraint significantly improved classification accuracy, yielding a final F1-score of 0.99.

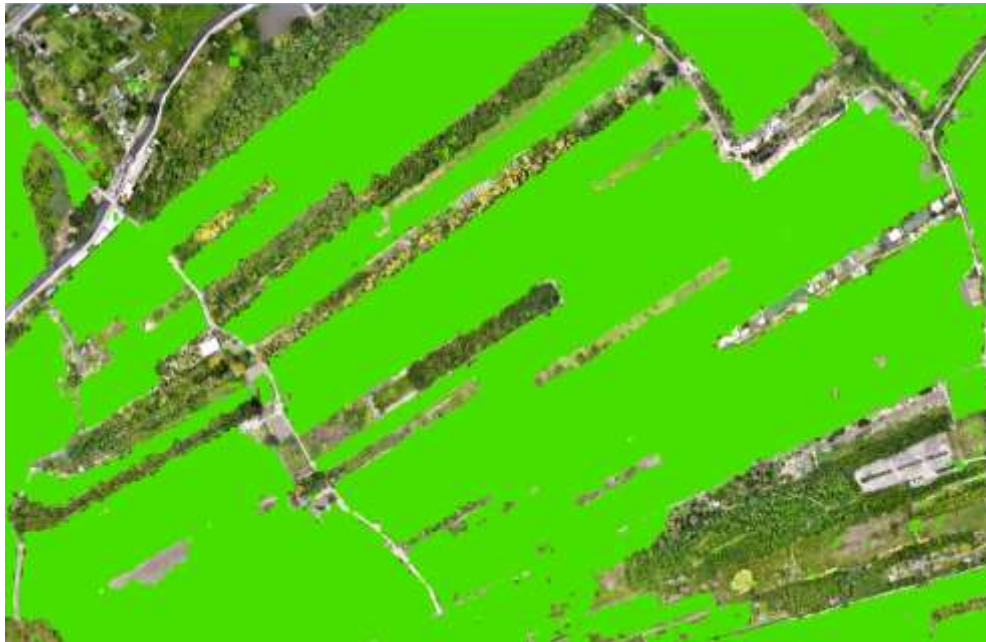


Figure 6. Influence results of model on Shih-men region.

Following validation, regional-scale inference was executed across the entire Shih-men management jurisdiction. The model successfully delineated 25,861 distinct paddy parcels, accumulating a total active cultivation area of 42,998,600 m² (approximately 4,300 ha).

By inserting these high-fidelity spatial dimensions into the irrigation framework, daily water demands were computed at the individual parcel level. Example shown in

Figure 7. Aggregating these temporal simulations from January 10, 2025, to June 28, 2025 (corresponding to the first annual cropping season), the cumulative agricultural water requirement for the region's paddy fields reached 32,130,240 tons (approximately $32.13 \times 10^6 \text{ m}^3$). Compared against the Shih-men region's historical average annual water allocation budget of approximately 2.0×10^9 tons, this specific crop season's paddy irrigation accounts for approximately 16% of total regional water resources.



Figure 7. Data of water demands of each parcel.

CONCLUSIONS

This study demonstrates that integrating AI computer vision models with high-resolution aerial remote sensing can successfully automate labor-intensive agricultural field surveys. By deploying a fine-tuned SAM architecture, accurate, large-scale mapping of paddy field footprints was achieved efficiently. Embedding these highly granular spatial datasets into conventional irrigation equations permits a far more precise, data-driven estimation of regional water allocation needs.

Future iterations of this framework can be enhanced by incorporating larger, more geographically diverse training sets and implementing incremental learning strategies to ensure long-term model robustness. Furthermore, expanding the deep learning objectives from binary classification to multi-class phenological stage recognition would allow the framework to dynamically adjust irrigation depths data in real-time. Overall, this methodology establishes a scalable and objective paradigm shift for modern, climate-resilient water resource management.

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