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Photovoltaic Vs National Grid Energy in Controlled Environment Agriculture (CEA) for Enhanced WEFE Nexus: A Jordanian Case Study

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Abstract—Jordan is among the most water-scarce nations globally, faces pressing challenges exacerbated by climate change. Controlled Environment Agriculture (CEA) is a great solution for water savings relative to conventional field cultivation, positioning it as a transformative technology for Jordan's Water-Energy-Food-Ecosystem (WEFE) nexus. However, CEA's intensive LED-based lighting demands significant electrical energy, historically supplied by national grids supplied by fossil fuels. This study presents an empirical investigation into whether solar photovoltaic (PV) panels can substitute grid electricity in a CEA unit without compromising plant growth outcomes. Eight plant samples grown in a PV-powered CEA unit were compared against eight grown under national grid (NG) power across a 47–55 day growth cycle. Measured parameters included root length, plant height, leaf count, plant weight, chlorophyll-a content, plant dry matter, and canopy cross-sectional area. Statistical comparison revealed no significant differences between the two energy conditions, with PV plants averaging 99.8 g versus 70.5 g for NG plants, and heights of 35.1 cm (PV) versus 32.5 cm (NG). Further, to determine whether plants grown from PV and NG produce the same yield using machine learning regression models. Additionally, a U-Net convolutional neural network was deployed for image segmentation of green canopy coverage from CCTV footage, achieving a validation accuracy of 86.27%. Results confirm that PV-powered CEA systems are agronomically equivalent to grid-powered systems, supporting their adoption as sustainable, cost-reducing alternatives to advance food security and WEFE resilience.

Keywords—Photovoltaic (PV), National grid (NG), Controlled Environment Agriculture (CEA), WEFE nexus, plant weight, green coverage

I. INTRODUCTION

Global food security is under increasing strain from population growth, land degradation, and the accelerating

consequences of climate change. The Food and Agriculture Organisation of the UN (FAO) estimates that global food production must increase by approximately 50% by 2050 to meet projected demand. However, due to climate change and conflict there is a declining per-capital arable land and freshwater availability. In arid and semi-arid regions like Jordan these pressures are especially acute [1].

Jordan exemplifies the water-agriculture nexus challenge facing arid nations. With a population of approximately 11 million and an annual renewable freshwater availability of roughly 61 m³ per capita compared to the internationally recognised absolute scarcity threshold of 500 m³ per capita per year, Jordan consistently ranks among the most water-stressed countries globally [2]. The agricultural sector, which accounts for approximately 50% of freshwater consumption, faces a projected irrigation deficit exceeding 364 million cubic meters by 2040 and is under mounting pressure to produce more with dramatically less [1],[3]. Historical precipitation records at stations including Amman Airport document a statistically significant declining trend in annual rainfall over recent decades, while temperature projections indicate further increases of 1.5–3.5°C by 2100 under moderate emissions scenarios [4]. These trends collectively threaten the viability of traditional rain-fed and gravity-irrigated farming systems.

Controlled Environment Agriculture (CEA) has emerged as a transformative paradigm for food production that effectively decouples crop growth from external climatic and hydrological constraints [5]. By cultivating plants within enclosed or semi-enclosed structures equipped with precise environmental controls including LED artificial lighting, climate regulation, hydroponic or aeroponic root zone management, and CO₂ enrichment - CEA systems can achieve water savings of up to 90% relative to conventional field agriculture, while delivering

yields per unit area 10–100 times higher depending on crop species and system design [6],[7].

However, CEA systems are energy-intensive [8],[9]. The continuous LED illumination required to substitute for natural sunlight imposes substantial electricity demands, which have historically been met by the national grid primarily powered by fossil fuels. This energy dependency introduces economic vulnerability and an environmental footprint that undermines the sustainability case for CEA. Operating CEA with renewable energy sources could significantly reduce CO₂ emissions [9], [10]. Therefore, the aim of this paper is to employ the Water-Energy-Food-Ecosystem (WEFE) nexus approach, aiming to grow crops that use high water content in a CEA set-up and integrate sustainable energy sources for agricultural crop production leading to better water resource management.

Solar photovoltaic (PV) technology offers an attractive solution as Jordan receives among the highest levels of solar irradiance in the world, averaging over 300 sunny days per year and recording horizontal irradiance levels of approximately 5–6 kWh/m²/day [11]. Therefore, PV can simultaneously address energy cost, grid dependency and environmental sustainability concerns thereby strengthening the WEFE nexus across multiple dimensions.

Existing studies focus mainly on PV integration and renewable mixes affect energy use, emissions and economics [12–15]. And how solar structures and energy constraints modify microclimate, which influences plant growth [13–15],[17]. There is no direct comparison of plant growth in grid vs PV in CEA and hence the motivation of this work.

Further, the CEA unit can be integrated with Internet of Things (IoT) sensor networks and cameras, machine learning (ML), and deep learning (DL) rapidly advancing the capability for real-time, adaptive, and remotely accessible crop management. There has been limited work on applying ML e.g. work presented in [17] developed random forest models to predict crop yield from multispectral imagery and in [18] support vector machines predict lettuce fresh weight from environmental sensors of temperature, humidity and light integral giving an accuracy of 85% trained on 200 samples. Similarly, deep leaning techniques, especially U-Nets [19] developed for biomedical image segmentation has been adopted in agriculture [20]. Precision monitoring of environmental parameters coupled with data-driven predictive models opens new possibilities for optimising resource allocation, predicting yield outcomes, and identifying plant health issues at scales and speeds impossible through conventional agronomic observation alone [21].

Therefore, the contributions of this research are threefold:

- Firstly we present an empirical evaluation of PV-powered performance relative to the national grid (NG) powered of the CEA unit set up with IoT sensors in the Royal Scientific Society in Jordan in terms of the plant growth outcomes.
- Secondly, we determine whether energy sources significantly affect harvest quality by developing machine learning models to predict the plant

yield/weight from agronomic and IoT sensor measurements.

- Finally, we develop a U-Net deep learning segmentation model that integrates NG and PV sensor streams to estimate image-based green-coverage.

The rest of the paper is organised as follows. Section II describes the methodology, whereas, section III presents the results. Discussions are presented in section IV and conclusions in section V.

II. METHODOLOGY

A. CEA Unit Configuration

The CEA unit at the Royal Scientific Society (RSS), Amman, Jordan, consists of a four-shelf hydroponic growing frame fitted with full-spectrum LED lighting arrays. Plants are cultivated in rockwool plugs within nutrient film technique (NFT) channels, with a closed-loop water recirculation system maintaining consistent nutrient solution composition. Environmental parameters of temperature, relative humidity, CO₂ concentration, and light intensity are continuously monitored via IoT sensors and cameras and logged to a centralised data platform, enabling remote monitoring and parameter adjustment as shown in Fig. 1.

The unit was operated under two energy conditions during the experimental period: (1) PV-powered mode, in which a rooftop solar photovoltaic array with battery storage supplied all electrical demand; and (2) national grid mode, in which conventional mains electricity from the Jordanian national grid was used (see Fig. 1). All other growth parameters were held constant across both conditions to ensure that energy source constituted the sole independent variable. A website was developed that displayed sensor data and downloadable as a csv file (Fig. 1).



Fig. 1. CEA unit with IoT sensors (bottom 2 shelves are connected to the grid and top 2 to PV)

TABLE I. Harvest-stage plant growth measurements by energy source

Sample Code	Energy Source	Planting Date	Harvesting Date	Planting Days	Root Length (cm)	Plant Height (cm)	Chlorophyll (a)(mg/g)	Plant Dr matter (%)	Leaf Count (no.)	Plant cross-sec. Area (cm ²)
S1B7	PV	18/03/25	11/05/25	54	20	41	0.64	9.28	73	108
S1D9	PV	18/03/25	04/05/25	47	25	31.5	2.16	9.09	26	107
S2D9	PV	18/03/25	04/05/25	47	31	33	1.94	8.39	30	115
S2D7	PV	18/03/25	11/05/25	54	23	35	0.71	8.9	78	68
S3B9	NG	18/03/25	04/05/25	47	20	30	1.94	8.36	26	108
S3C6	NG	18/03/25	12/05/25	55	20	27	0.75	9.03	44	54
S4A10	NG	18/03/25	04/05/25	47	47	31	2.25	7.99	31	115
S4D7	NG	18/03/25	12/05/25	55	38	42	0.89	8.16	75	128

A total of 60 kale plants were grown simultaneously from 18 March to 11 May 2025, with half assigned to PV-powered shelves and half to NG-powered shelves. Plants were sown on the same date and harvested when they reached maturity, with harvesting dates ranging from 47 to 55 days after planting. At harvest, the following parameters were recorded for each plant: root length (cm), plant height (cm), plant fresh weight (g), plant dry matter (%), leaf count, canopy cross-sectional area (cm²), and chlorophyll-a content (mg/g), the latter measured using a SPAD portable chlorophyll meter. The CEA unit set-up is shown in Fig 1.

B. Machine Learning Modelling

Four supervised learning regression models were implemented in Python (scikit-learn v1.3) to predict plant fresh weight at harvest from measured growth and environmental covariates. The models evaluated were: Linear Regression, K-Nearest Neighbours (KNN, k=3), Decision Trees, and Random Forest (n_estimators=30). Decision Trees were trained on unscaled data, whereas Linear Regression and KNN were trained on standardized predictors with weight (g) as target. The complete 60-plant dataset was split into training and test sets. Feature inputs included root length, plant height, leaf count, canopy cross-sectional area, chlorophyll-a, dry matter percentage, total light hours accumulated, energy source, and planting duration. Model performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R²).

C. Deep Learning Image Segmentation

A U-Net convolutional neural network was trained to perform binary semantic segmentation of plant canopy versus background in CCTV images from the CEA unit to detect percentage of green coverage to identify potential patterns or dependency i.e PV results in better growth rate of the plant. A total of 581 images were captured from the four-shelf CCTV feed over the growth cycle. From these, 110 images were manually annotated using the VGG Image Annotator (VIA), with polygon masks drawn around visible plant canopy regions. The annotated dataset was partitioned into training (n=65), validation (n=22), and test (n=23) sets. All images were resized to 256×256 pixels prior to model input. An example of the training image is shown in Fig. 2 alongside their defined masks with annotated borders. The green hue did not form part of the U-net training data.

The U-Net architecture comprised a contracting path (encoder) with four levels of max-pooling and an expansive path (decoder) with transposed convolutions and skip connections and was implemented in TensorFlow/Keras. The model was trained using binary cross-entropy loss with the Adam optimiser for 15 epochs. Model performance was evaluated using pixel-wise accuracy, Dice coefficient, and visual comparison of predicted versus ground-truth segmentation masks.



Fig. 2. Example image obtained from CCTV images

III. RESULTS

This section presents the results. Sub-section A shows the plant growth rate parameter comparison, whereas, sub-section B and C show the results from machine and deep learning models.

A. Plant Growth Rate Parameter Comparison

Table I presents the full harvest-stage measurements for the eight representative plant samples, four grown under PV power (S1B7, S1D9, S2D9, S2D7) and four under national grid power (S3B9, S3C6, S4A10, S4D7).

Comparative analysis of group means revealed the following outcomes across key parameters shown in Fig. 2. Average plant fresh weight was 99.8 g for PV-grown plants and 70.5 g for NG-grown plants. Average plant height was 35.1 cm (PV) versus 32.5 cm (NG). Average root length was 24.8 cm under PV power compared to 31.3 cm under NG power. Average canopy cross-sectional area was 99.6 cm² (PV) versus 101.1 cm² (NG). Average chlorophyll-a content was 1.40 mg/g (PV) versus 1.50 mg/g (NG). While PV-grown plants showed marginally higher weight and height, and NG-grown plants showed marginally longer roots and slightly higher chlorophyll-a, none of these differences reached statistical significance given the sample sizes involved, with effect sizes

consistently small. These results are consistent with no material difference in plant growth outcomes attributable to energy source.

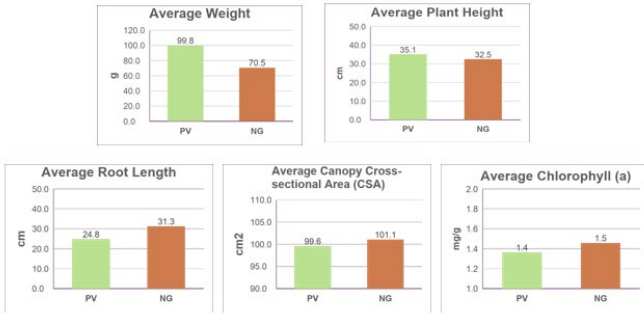


Fig. 3. Comparative analysis of plant growth parameters using national grid vs PV

Further, we added the total number of light hours per plant from planting to harvest date and plotted it against the final weight of the plant to determine trends as shown in Fig. 4.

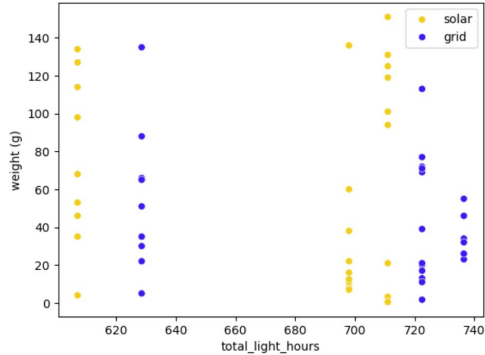


Fig. 4. Plant weight distributon by total light hours and energy source

In Fig.4, yellow dots reprsent plants grown undr LED light from PV and blue dots from NG. In both harvests plants grown under PV LED light have higher distribution of weight values compared to plants grown under light powered by NG.

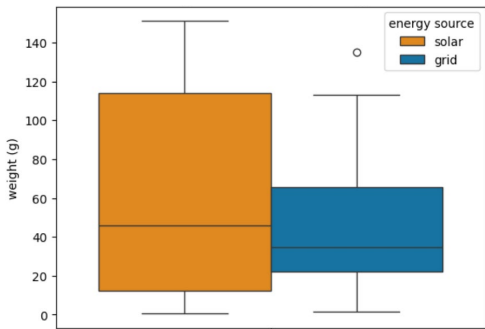


Fig. 5. Plant distribution by energy source

The box plot shown in Fig. 5 shows that the plants from the PV have higher median weight and maximum weight compared to those powered by NG.

In Fig. 5, assuming that other controllable factors such as pH, temperature and humidity are the same, the receiving PV light had an imapct on the plant’s weight distribution as plants

powered by PV received less light hours in total with median number of hours being more than 20 hours less than the NG. Similarly, as expected flowering plants tend to have more weight compared to non flowering plants. As flowering ca be spotted early on during the plants’ growth cycle, hence potentially can be a good indicator of better yield.

B. Machine Learning Model Performance

As the dataset was small (60 in total), we decided to train simple models to predict the target variable of weight. Table II summarises the performance metrics for the four regression models used to predict plant fresh weight from environmental and morphological covariates.

Table II. ML performance metrics

Model	Mean Squared Error (MSE)	Root MSE (RMSE)	R ²
Linear Regression	1625.6	40.3	0.4140
KNN n_neighbours =3)	2241.7	47.3	0.1919
Decision Trees	2261.9	47.5	0.1846
Random Forest (n_estimators = 30)	2298.0	47.9	0.1715

Linear Regression achieved the best predictive performance with an R² of 0.414, MSE of 1625.6, and RMSE of 40.3 g. The ensemble and non-parametric models (KNN, Decision Trees, Random Forest) performed substantially worse, with R² values below 0.20. The pattern of true versus predicted values from the best-performing Linear Regression model showed systematic underestimation of high-weight plants and overestimation of low-weight plants, consistent with the model capturing a meaningful linear signal in the data while being limited by the variance attributable to unmeasured factors as shown in Fig. 6.

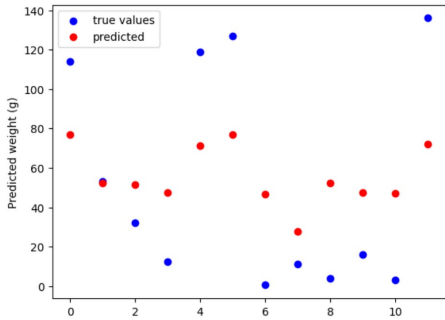


Fig. 6. True and predicted plant weight values

The superior performance of Linear Regression over more complex models is consistent with the relationship between sensor inputs and plant growth being approximately linear under the tightly controlled CEA environment, and with the overfitting tendency of ensemble methods when trained on small datasets.

C. U-Net Deep Learning Segmentation Results

The U-Net model trained for 15 epochs achieved a final validation accuracy of 86.27%, a Dice coefficient of 0.1619, and a validation loss of 0.3994. Training accuracy stabilised at approximately 78% after the first two epochs, while validation accuracy remained consistently higher at 86.27%, reflecting the class imbalance between background (dominant) and plant pixels. The low Dice coefficient - a metric that more sensitively

penalises spatial misalignment between predicted and ground-truth masks than pixel-wise accuracy indicates that while the model correctly classified background pixels at high rates, its localisation of plant canopy was imprecise.

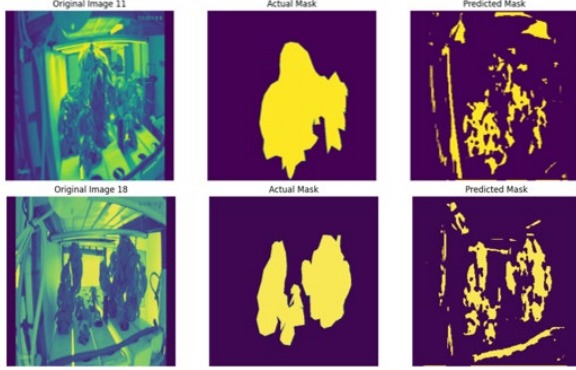


Fig. 7. U-Net results showing the original image, in grayscale, actual and predicted mask

Visual inspection of predicted segmentation masks confirmed this pattern: the model identified the approximate region and scale of plant canopy but produced fragmented and scattered pixel classifications rather than the contiguous mask shapes present in the ground truth annotations. This performance reflects the combination of limited training data (65 annotated images), challenging image conditions from wide-angle CCTV optics with LED spectral distortion, and the high visual complexity of overlapping multi-plant canopy structures. No ExG vegetation index applied at this point, the images were simply read in grayscale and hence when displayed were with green hue. Fig. 7 shows due to the LED lighting and the colour similarity with the surrounding background colour, identifying plant edges proved challenging.

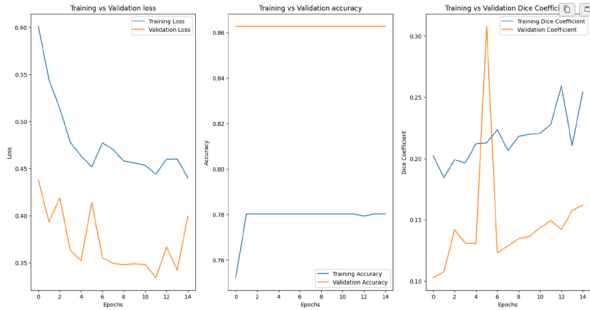


Fig. 8. Training vs validation loss (left); training vs validation accuracy (middle) and training versus dice coefficient (right)

Fig. 8 shows that the final training epoch validation accuracy was 86.27%, dice coefficient 16.19% and loss was 39.94%.

IV. DISCUSSION

The finding that PV-powered and grid-powered CEA units produced statistically equivalent plant growth outcomes is of considerable practical and policy significance. The marginal numeric differences observed in PV plants slightly heavier and taller on average, grid plants with slightly longer roots are most plausibly attributable to within-group variation in individual plant genetics, shelf positioning effects, or minor

inconsistencies in nutrient solution rather than to the energy source itself. This is consistent with the theoretical expectation that, given adequate battery storage to buffer PV intermittency, the LED lighting experienced by plants under PV power is functionally indistinguishable from grid-supplied LED lighting in terms of photosynthetic flux. This is also supported by [23] that energy typically constitutes 20-30% of CEA operating costs making PV substitution economically beneficial.

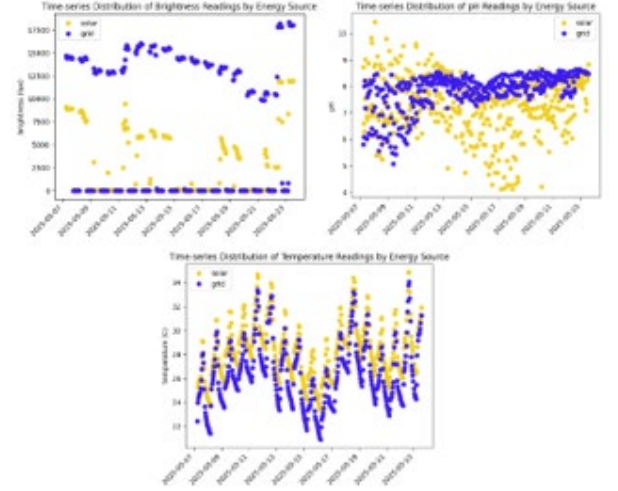


Fig. 9. Time series distribution of brightness (top left), pH (top right) and temperature (bottom) by energy source

Further, from the sensor readings that were taken every 30 mins throughout the growth period from May 7th to May 23rd 2025 we observe that PV source has significantly lower sensor-measured brightness levels, as well as lower pH values overall but higher temperature. The brightness readings do not take into account plant positioning relative to the door to a room where they were grown, which could also be a source of additional light. The temperature distribution in particular follows a visibly similar pattern with a difference of up to 2°C (see Fig. 9).

The ML results while representing a meaningful predictive signal, falls well short of the performance levels reported in CEA machine learning studies with larger datasets. This limitation is acknowledged and attributed primarily to sample size. The 60-plant dataset, divided into training and test sets, provides insufficient statistical power to resolve the multi-dimensional relationships between environmental inputs and plant growth outcomes. The superiority of Linear Regression over ensemble methods in this context is instructive: tree-based models such as Random Forest overfit to small training sets, memorising noise rather than learning generalisable relationships.

Similarly, the U-Net model's validation accuracy of 86.27%, while superficially promising, is inflated by the class imbalance inherent in CEA imagery, backgrounds occupy the majority of pixels, so a model that predicted all pixels as background would achieve high accuracy without any useful segmentation. Furthermore, the CCTV images, variable LED spectral composition, and multi-plant frames represent a more complex segmentation task, justifying the lower Dice

coefficient observed (0.1619) and pointing to areas for methodological improvement and a more honest assessment of performance.

These results carry direct implications for the WEFE nexus in Jordan. The dual water and energy benefits of PV-powered CEA, a 90% reduction in water use relative to field irrigation, combined with independence from the fossil-fuel-dependent national grid can now be pursued simultaneously without agronomic trade-offs. Given that irrigation accounts for over 50% of Jordan's national water budget and the projected 2040 irrigation deficit of 364 MCM represents a structural threat to food security, the uptake of PV-CEA systems could materially contribute to closing this gap while reducing operational costs for farmers. Further, the combination of improved image segmentation with the IoT sensor data already collected in the CEA unit creates a pathway toward continuous, automated monitoring of plant growth rates enabling real-time resource optimization.

V. CONCLUSIONS

This study has demonstrated that PV panels can supply the energy demands of a CEA unit without materially compromising plant growth outcomes relative to national grid. Within the WEFE nexus framework, PV-powered CEA simultaneously addresses the water dimension by up to 90% reduction in irrigation water use and the energy dimension through displacement of fossil-fuel grid electricity.

ML model performance was constrained by dataset size, and improvement to R^2 values above 0.80 is anticipated as the plant-level dataset expands beyond the current 60-sample baseline. The U-Net deep learning model for canopy segmentation achieved a validation accuracy of 86.27% but a Dice coefficient of only 0.1619, reflecting the challenges of limited annotated training data and complex imaging conditions.

Collectively, these results advance the case for integrated, AI-assisted, PV-powered CEA systems as a viable contribution to food security, water conservation, and energy transition in Jordan and comparable arid-region economies.

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