GeoAI unravels the effects of urban thermal environment on utility-scale floating photovoltaic electricity generation

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ABSTRACT

The dynamic urban thermal environment has an immediate impact on photovoltaic conversion efficiency (PVCE) while unstable weather significantly determines horizontal land surface solar irradiation. This results in an unpredictable uncertainty in electricity generation, posing greatly challenges to the planning of PV installed capacity and the operation of gird load balancing. To tackle this problem, we developed a GeoAI-facilitated geospatial model aimed at accurately estimating monthly electricity generation considering the influence of both thermal environment and whether variability. The model consists of four modules: (i) retrieve photovoltaic surface temperatures (PVSTs) from thermal satellite imagery and collected meteorological data to quantify the varying thermal conditions, (ii) assess the significance of each influential factor in PVST estimation; (iii) develop three comparative machine learning models to build regressions between the identified influential factors and PVSTs; and (iv) calculate the spatiotemporal PVCEs. This leads to a more accurate estimation of monthly electricity generation compared to the conventional method. The empirical investigation in Singapore found that their PVCEs exhibited small variations and monthly electricity generation ranged between 10,000 to 14,000 MWh, benefiting from relatively consistent climate and the water's cooling effect throughout the year in Singapore.

RESEARCH FRAMEWORK

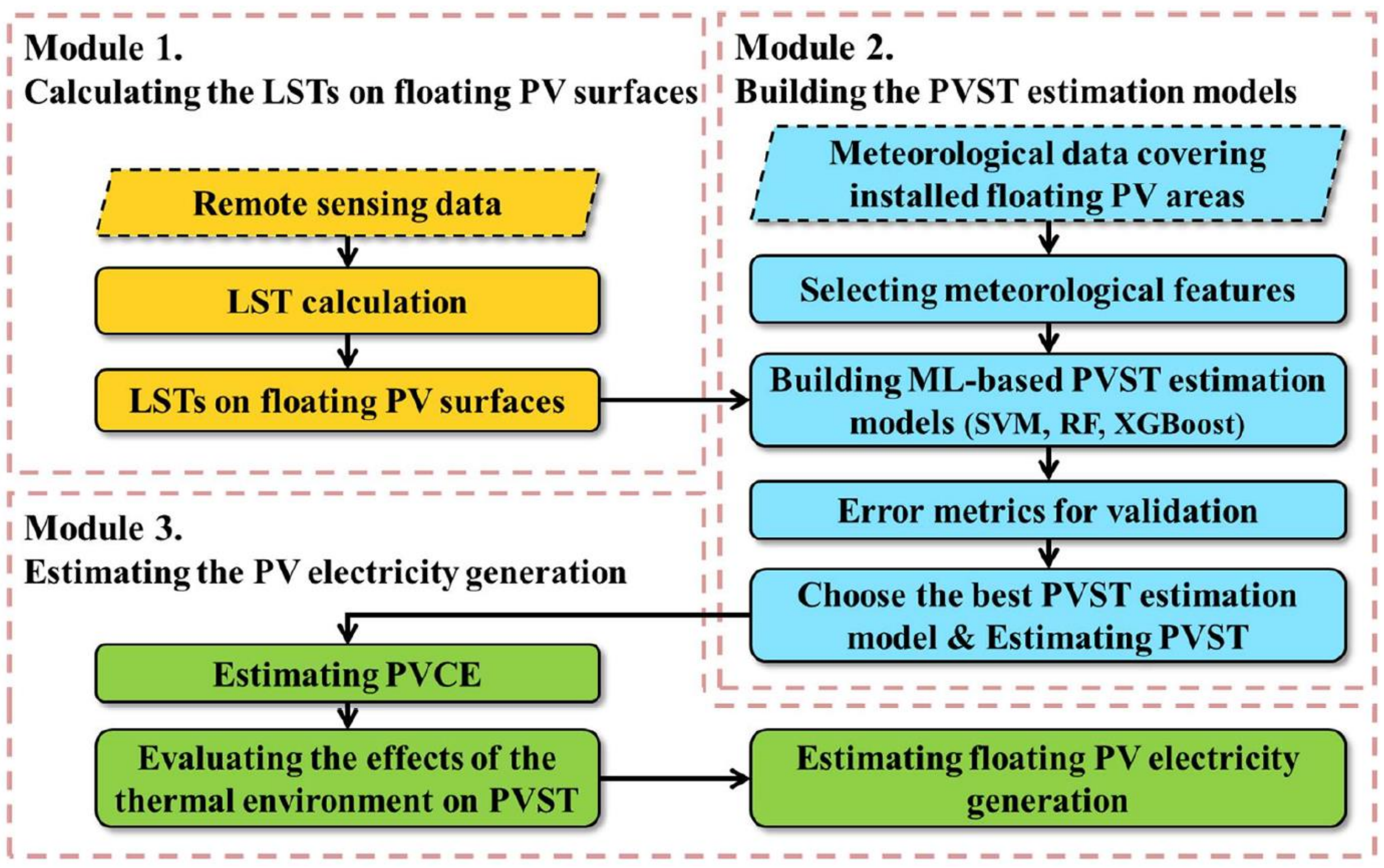
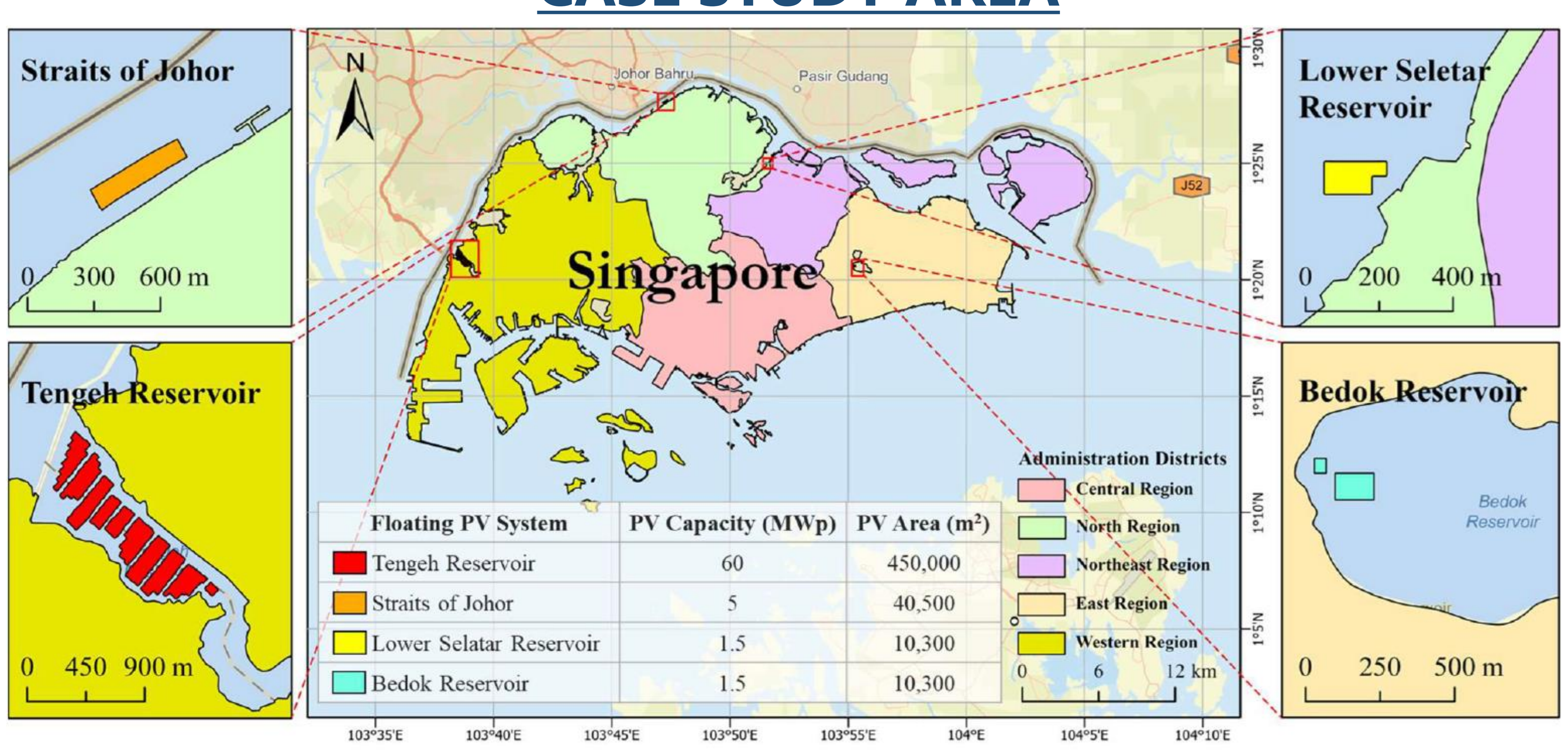


Fig 1. Research framework built by three interconnected modules.

This study proposes a research framework for the estimation (Fig 1). First, the observed LSTs are used as the training data to estimate the PVST. To achieve this, LSTs on floating PV surfaces are retrieved from remote sensing images. Second, the PVST estimation models are built based on the ML models to estimate PVSTs under a dynamic thermal environment, which are validated by using a set of performance evaluation metrics to identify the best estimation model. Third, the effects of the thermal environment on the PVST are evaluated, and the electricity generation is estimated by adapting to the dynamic PVCE.

CASE STUDY AREA



Floating PV System	PV Capacity (MWp)	PV Area (m²)
Tengeh Reservoir	60	450,000
Straits of Johor	5	40,500
Lower Seletar Reservoir	1.5	10,300
Bedok Reservoir	1.5	10,300

Fig 2. The investigated four floating PV farms in Singapore.

RESULTES

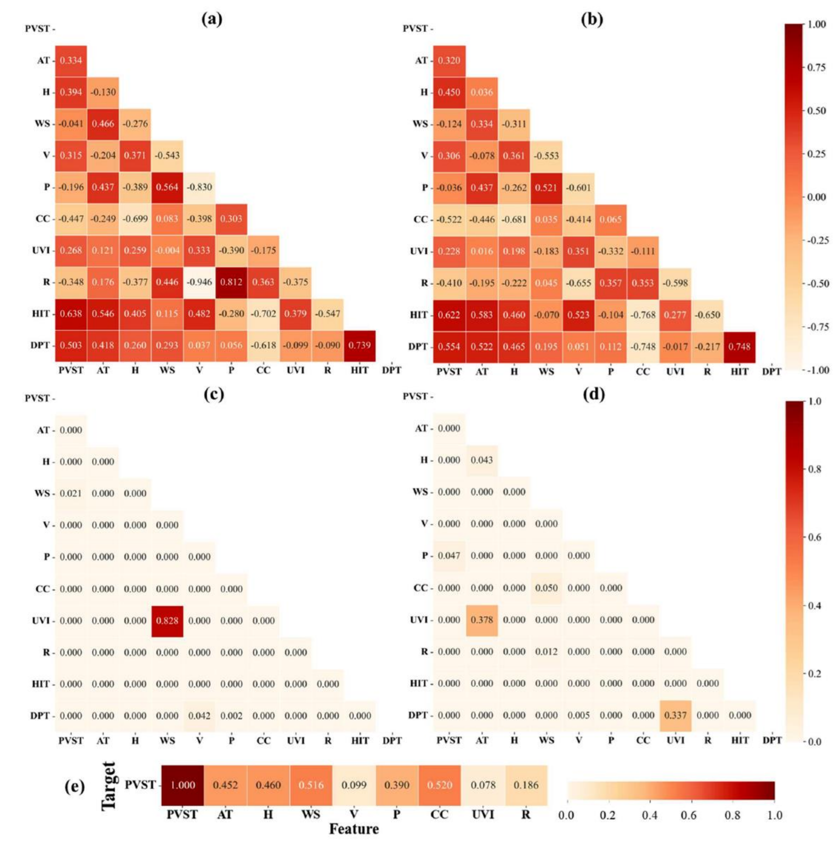


Fig 3. Feature selection heatmaps.
(a) Pearson correlation coefficients.
(b) Spearman's rank correlation coefficients.
(c) P-values for Pearson correlation).
(d) P-values for Spearman's rank correlation.
(e) PPS scores of the remaining eight variables and PVST.

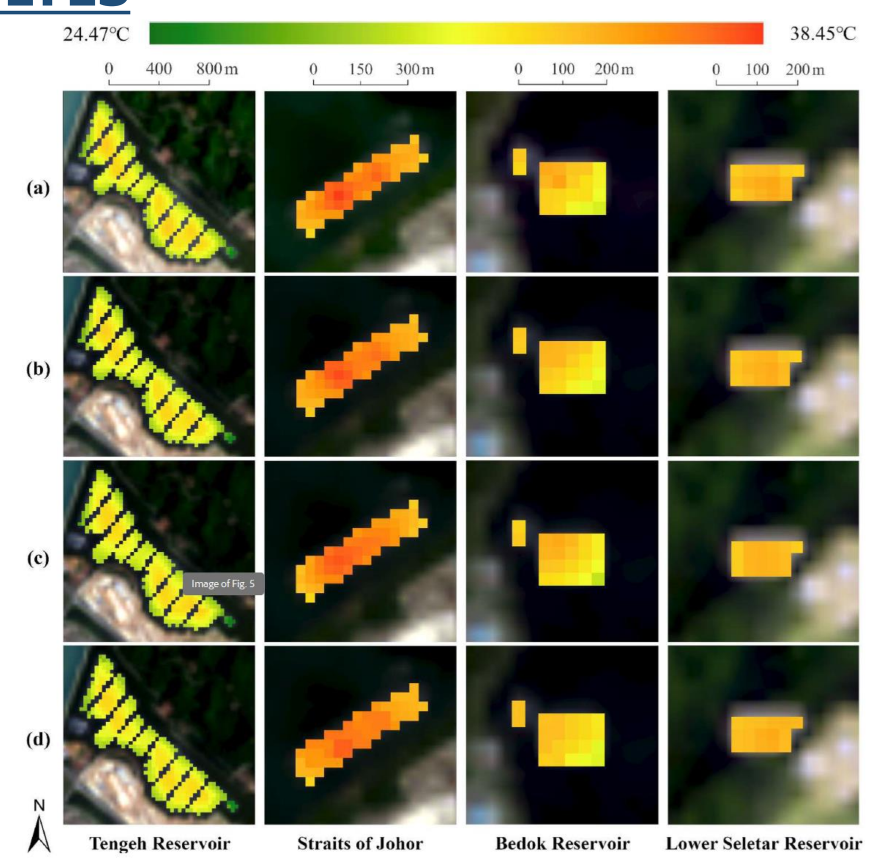


Fig 4. Observed LSTs versus estimated PVSTs from the Landsat imagery.
(a) Observed LSTs.
(b) Estimated PVSTs using RF.
(c) Estimated PVSTs using SVM.
(d) Estimated PVSTs using XGBoost.

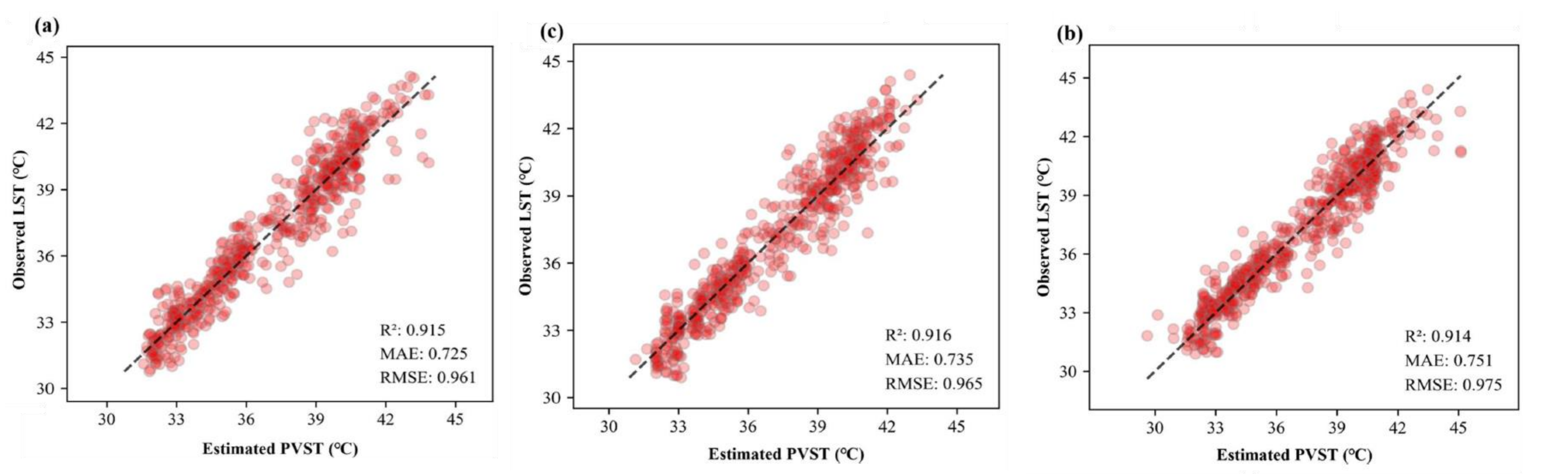


Fig 5. The estimation errors for PVST of three estimation models. (a) RF for the testing dataset. (b) SVM for the testing dataset. (c) XGBoost for the testing dataset.

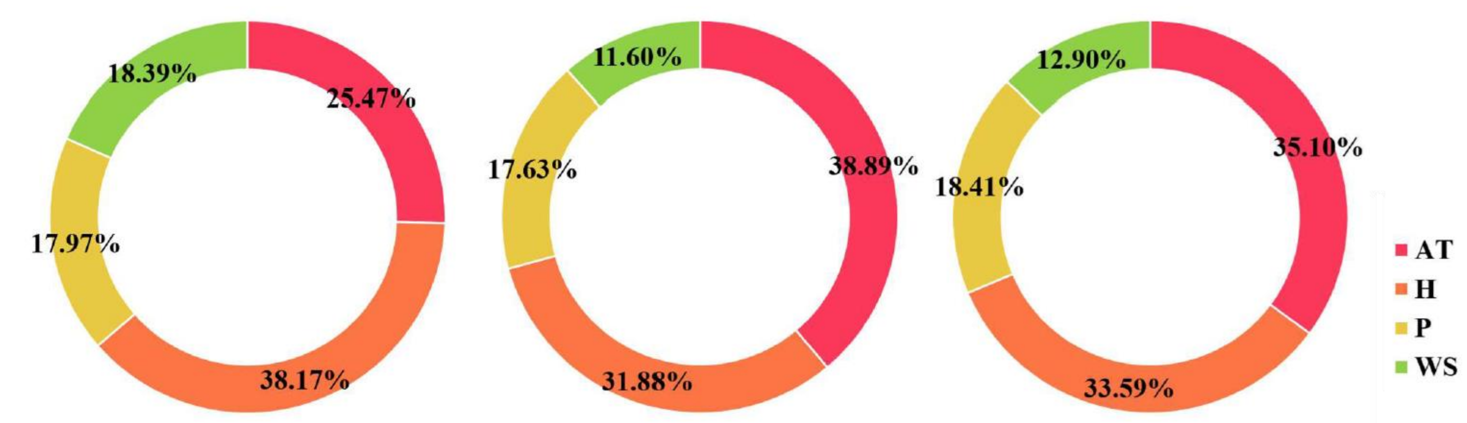


Fig 6. Feature importance on PVST estimation in RF. (a) MDI. (b) PI. (c) SHAP.

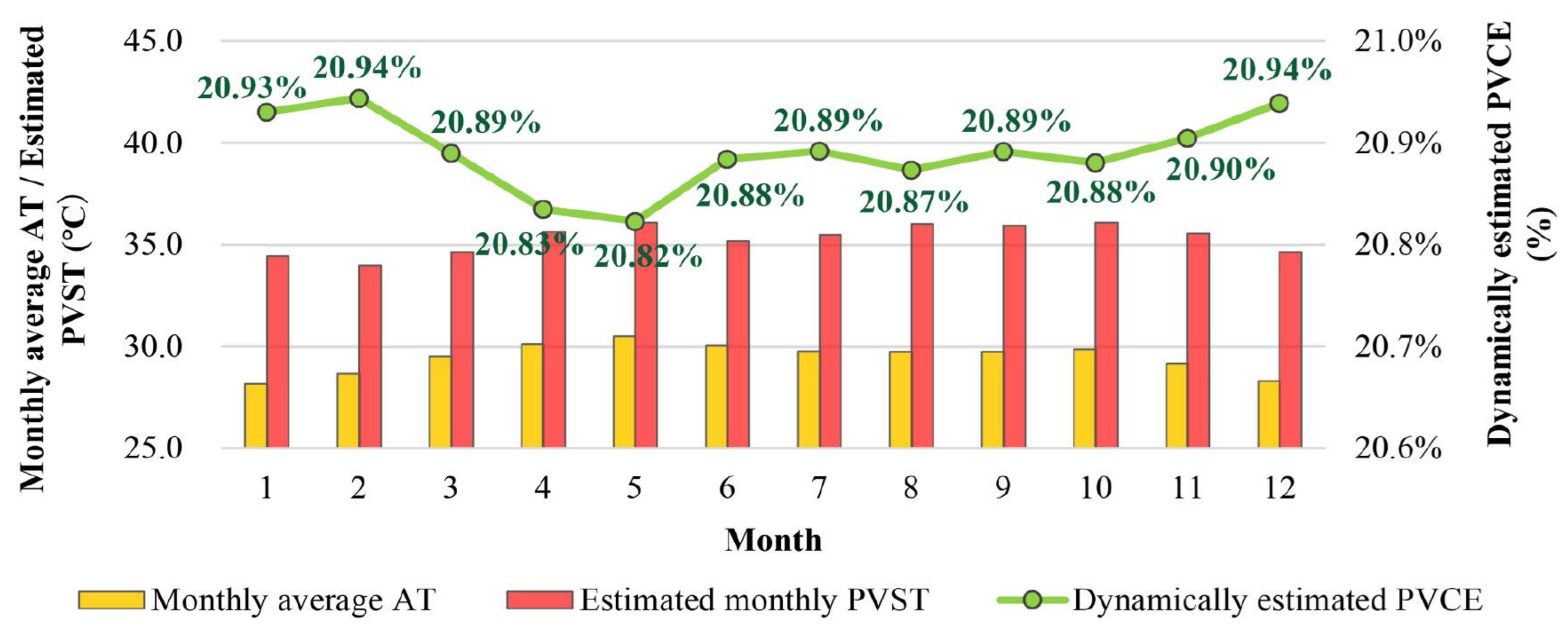


Fig 7. Estimated monthly PVCE based on the estimated PVST.

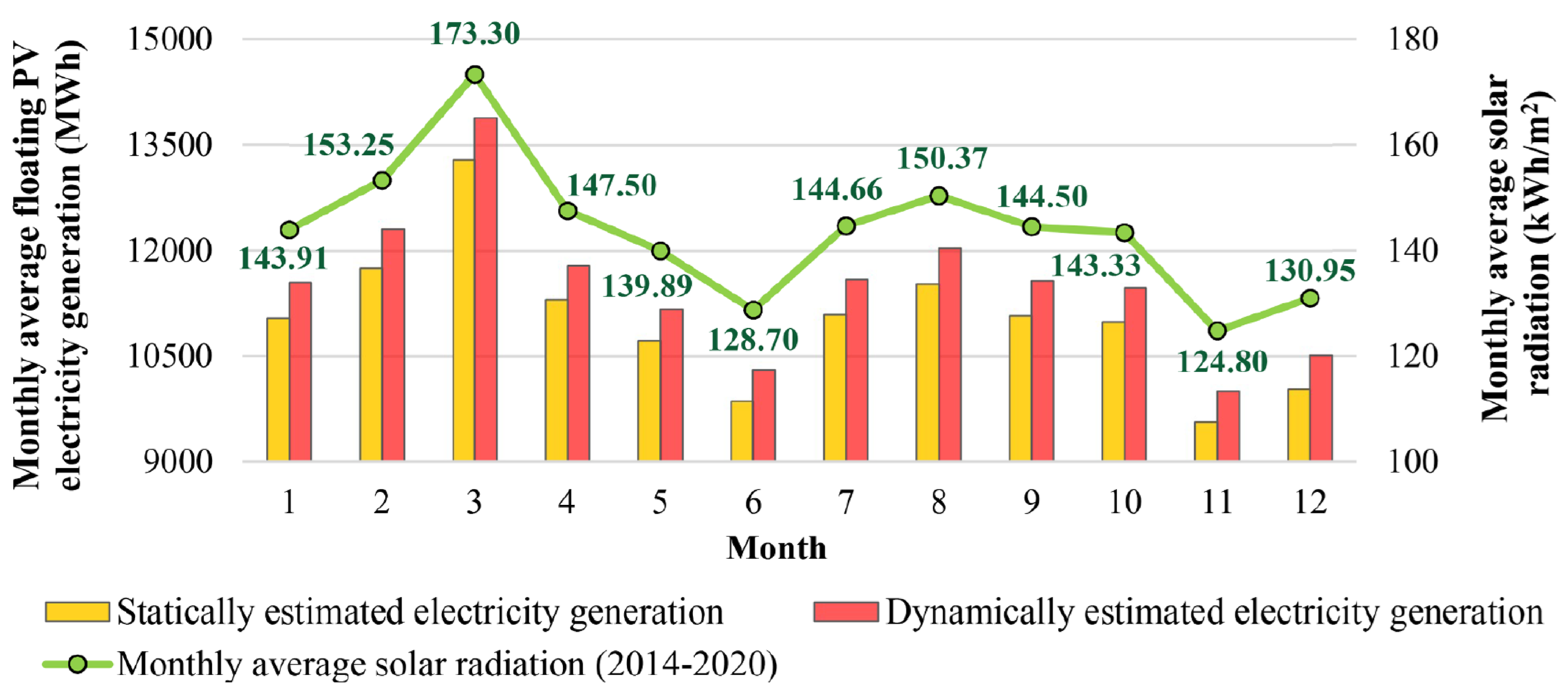


Fig 8. The electricity generation estimation of four floating PV farms (static vs dynamic).

DISCUSSION

The proposed methodology is generalizable for different PV farms. Future study can quantify carbon mitigation capacity of floating PVs, influenced by dynamic thermal environment and water-cooling effects.