

# **Advanced multimodal fusion method for very short-term solar irradiance forecasting using sky images and meteorological data: from single weather array to multi array**

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# Sky Images on Solar Irradiance Forecasting

Ground-based sky imagery: High-frequency data with high spatial resolution.

## **Advances in deep learning solutions:**

- Demonstrated success in sub-hourly forecasting.
- Rapid prediction capabilities, essential for real-time applications.

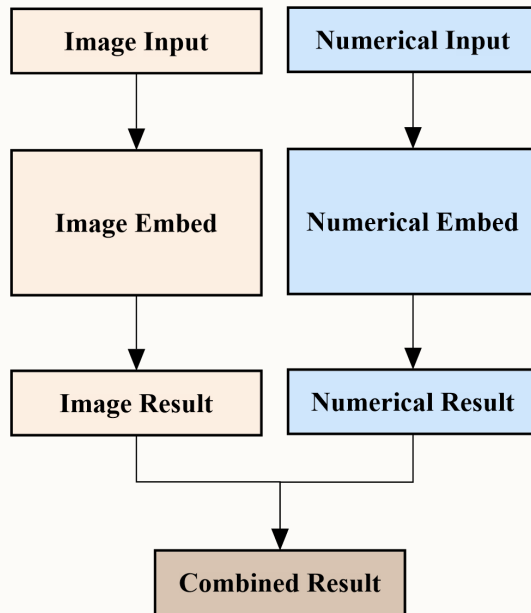
## **Challenges:**

- Deep learning methods with poor interpretability
- Site-specific models due to unique climate and micro-climate conditions.
- Significant investment in time and resources for local data collection



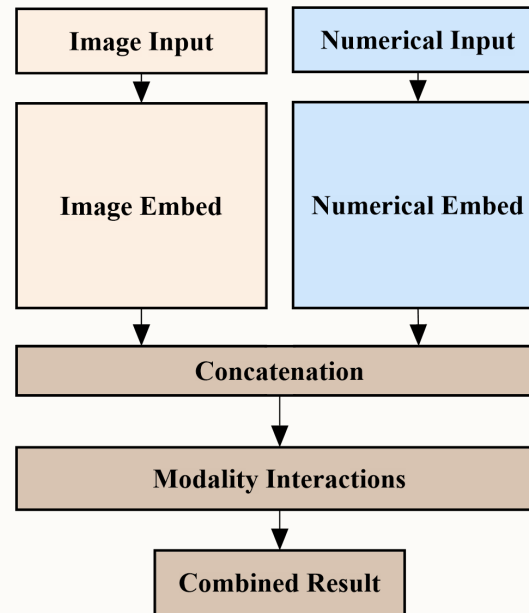


# Current Deep Learning Prediction Methods and Challenges



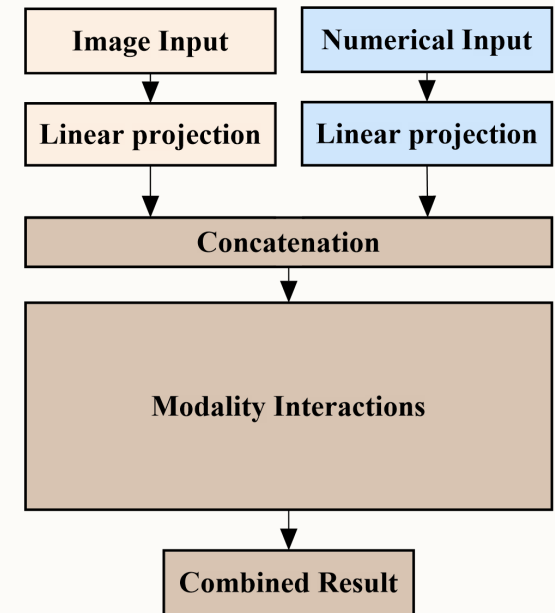
**Traditional Approach**  
(Result level fusion)

- Image and numerical data processed separately
- Combined output generation



**Weak Modular Interaction Model**  
(Late feature-level fusion)

- Image and numerical data processed separately
- Joint feeding into a weak interaction model
- Combined output generation



**Proposed Strong Modular Interaction Model**  
(Early feature-level fusion)

- Linear projection of pictures and values
- Parallel element feeding into a strong interaction model
- Results deduced from inter-element relationships

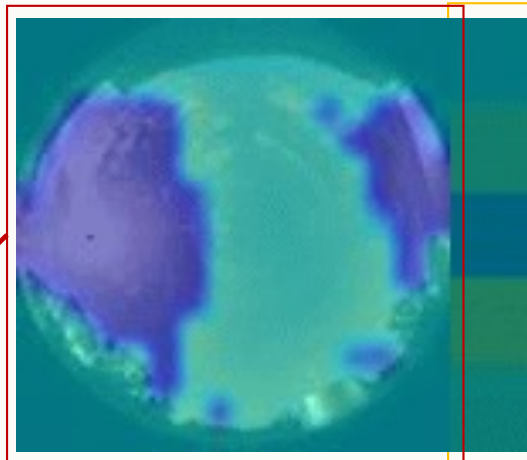


# Deep Learning Innovations in Solar Forecasting

- Utilisation of advanced ViT-E model for deep learning forecasting.
- Patches(Pixel)-meteorological data relationship.
- Noticeably demonstrates the focus on different elements depending on the real-time climate



Original dataset  
from CA, Folsom



Attention on  
Images patches

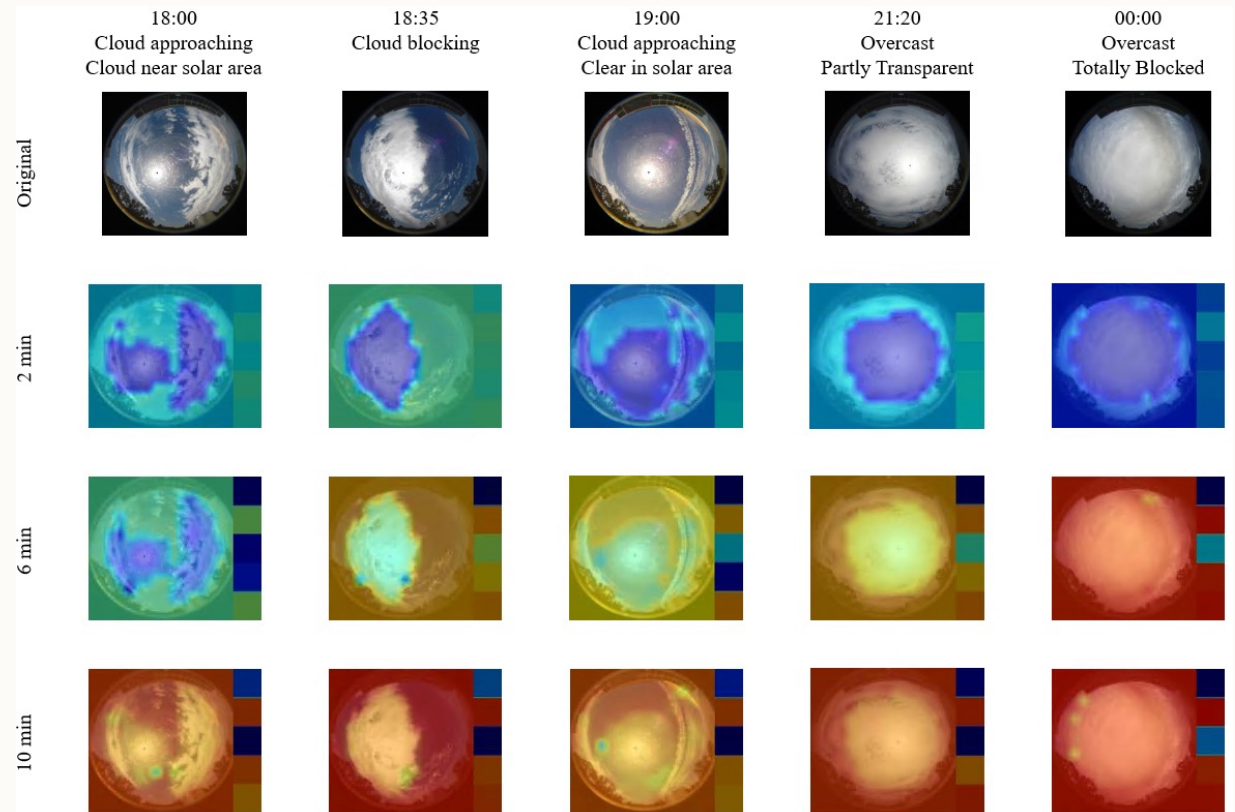
Attention on numerical,  
Top to bottom:

- Irradiance
  - Environmental variables  
(temperature, humidity, pressure)
  - Sky view factor
  - Wind (speed, direction)
  - Solar angles
- Relative attention weight  
heatmap between Image  
& Meteorological data  
In 2-min ahead forecast**



# Decline in relevance

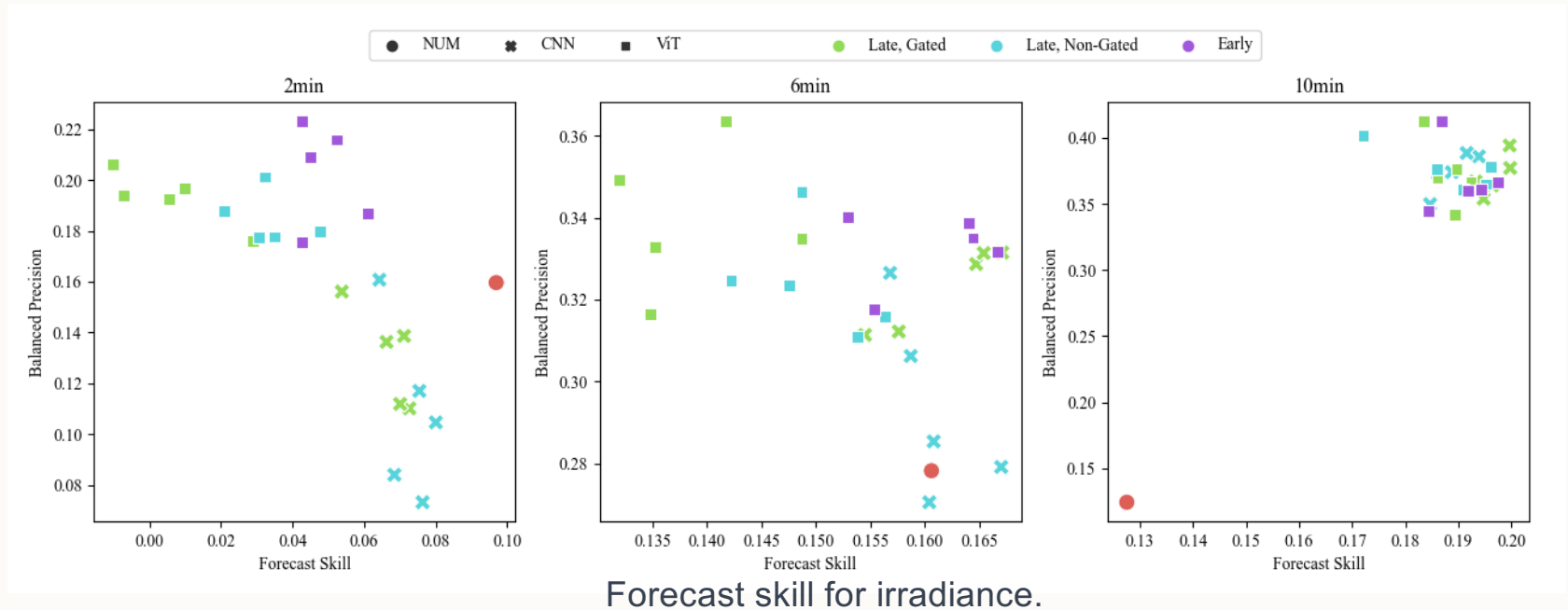
- The correlation between image data and meteorological data is weakening as the prediction scale is extended.
- The model gradually degenerates into a numerical model focusing on meteorological data.





## Comparative Model Performance Over Forecast Horizons

Capability to capture  
ramp events



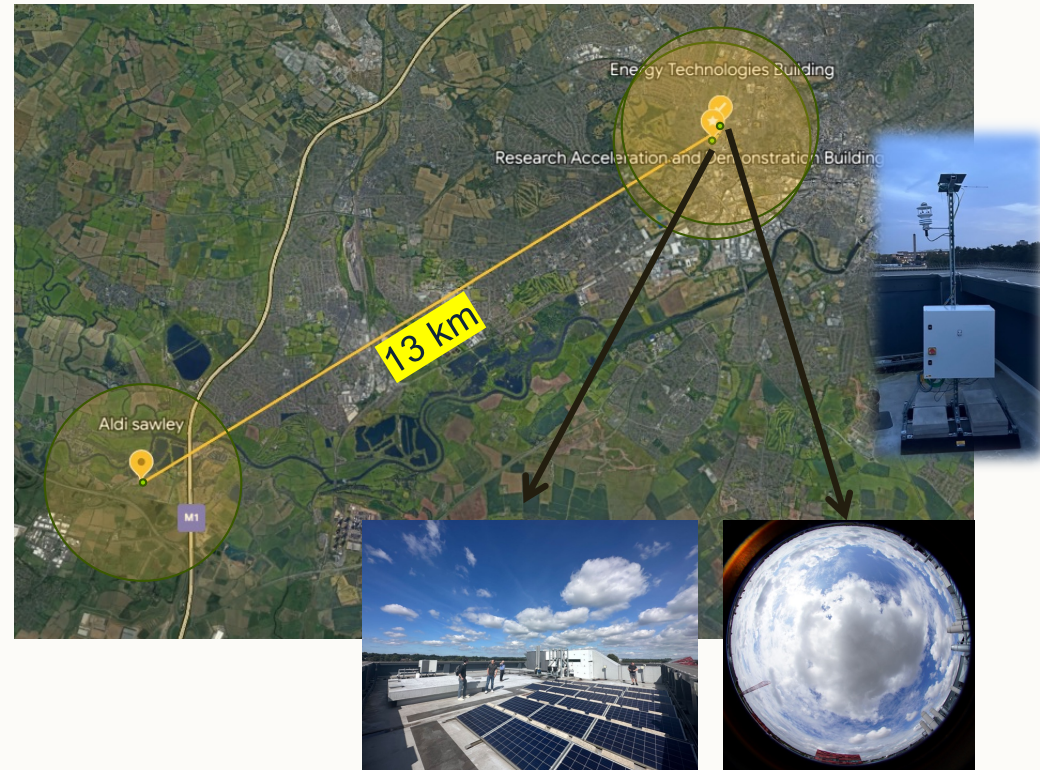
- At the 2-minute forecast interval, distinct performance variations are evident among different models: early fusion exhibits a more pronounced balance.
- As the forecast horizon extends, the differences between models diminish, indicating a convergence (homogenization) in performance.





# Future work

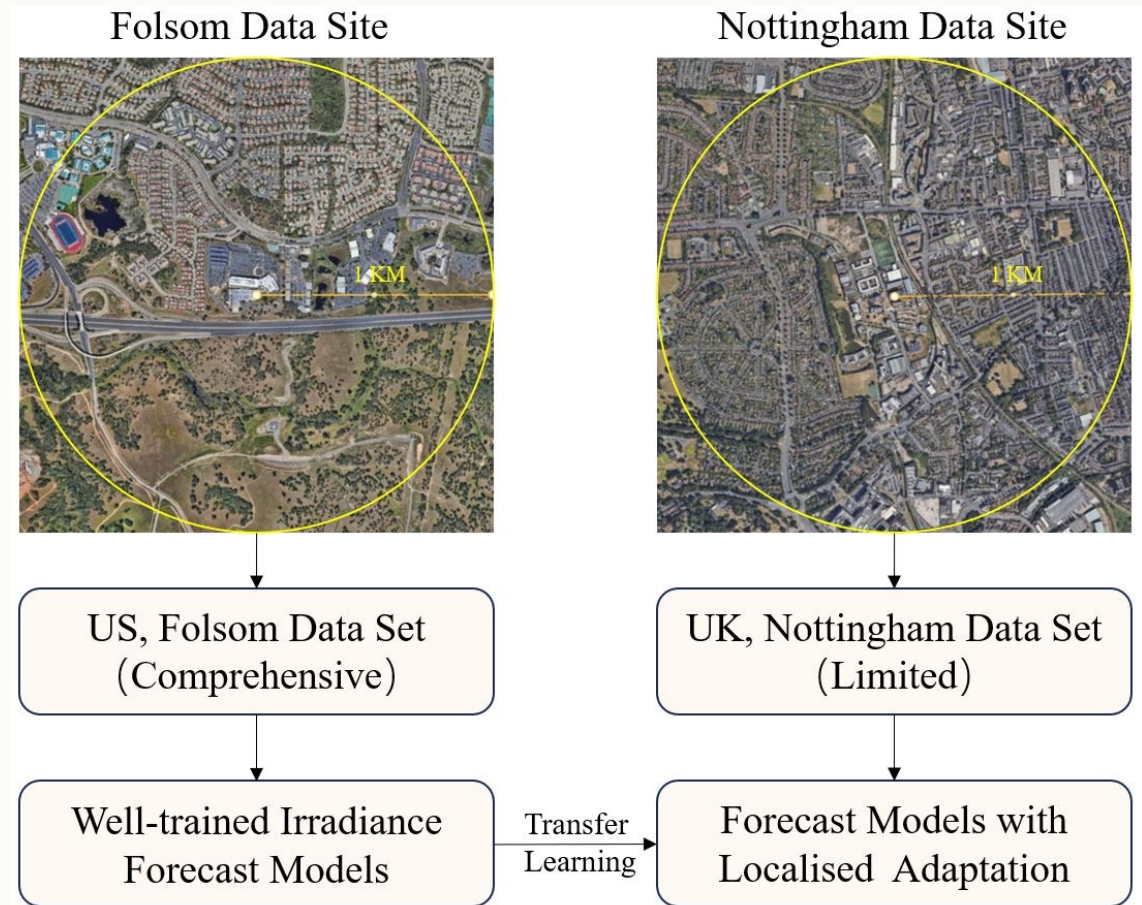
- Future Explorations:
  - Transferability under different climate types
  - Transferability under similar microclimate types
  - Climate type transferability in urban/non-urban settings
  - Interconnectivity between multiple sites





# Transportability of priori knowledge

- A priori model knowledge is transferable, despite differences in meteorological and geographic data.
- Initial result:
  - Model training time reduced by 90% using migration methods.
  - Migrated model achieves fit with only 2 weeks of data, compared to 12-18 weeks for non-migrated models.







# Acknowledgement

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