# Deep Learning and Satellite Images for Photovoltaic Power Forecasting: A Case Study


Luiz Henrique Buzzi

Lucas Weihmann

Pablo Andretta Jaskowiak

Graduate Program in Electronic Systems Engineering (PPGESE)

Joinville Technological Center (CTJ)

Federal University of Santa Catarina (UFSC)



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# Outline



1. Introduction
2. Datasets: ground and satellite
3. Deep Learning Based Approach
4. Results
5. Final remarks

# Introduction

# Introduction



- Electricity usage is increasing fast: +50% of total energy by 2050
  - High demand for clean (renewable) energy resources
- Solar energy is one of the most promising resources
- Photovoltaic generation
  - Strongly affected by meteorological factors (rain, fog, …)
- Forecasting of photovoltaic power generation allows for a better
  - Integration of energy resources
  - Management of grid infrastructure

# Introduction



Depending on the goal, different problems / possibilities emerge

- Forecasting Horizons
  - Short-term (intra-hour) forecasts: 30min and 60min
- Datasets
  - Satellite data from GOES-16 for forecasts
  - Ground data for actual Global Horizontal Irradiance (GHI)
    - Training and validation
- Deep Learning Approaches taking as input / output
  - Satellite images / Ground GHI observations

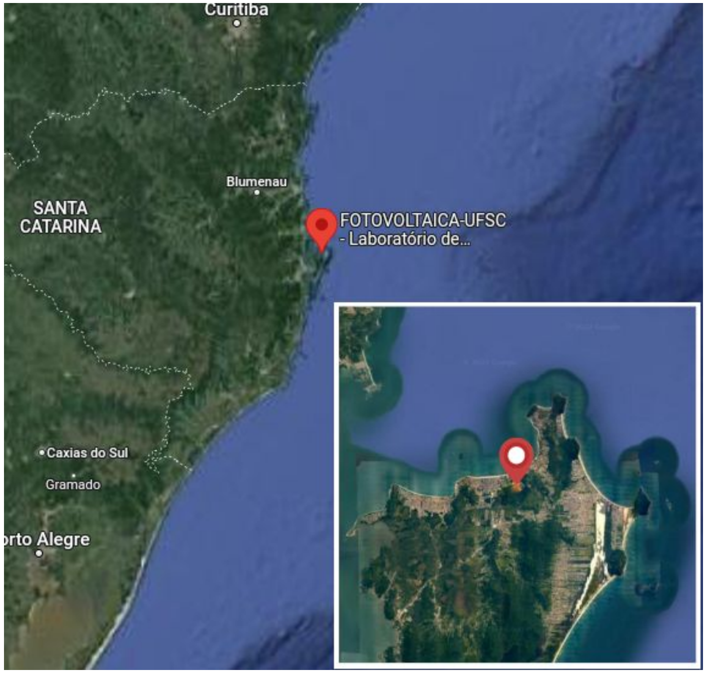
# Datasets

Ground and Satellite

# Dataset



- Ground data from Laboratório Fotovoltaica
  - UFSC - Florianópolis




Location of the solarimetric station

# Dataset



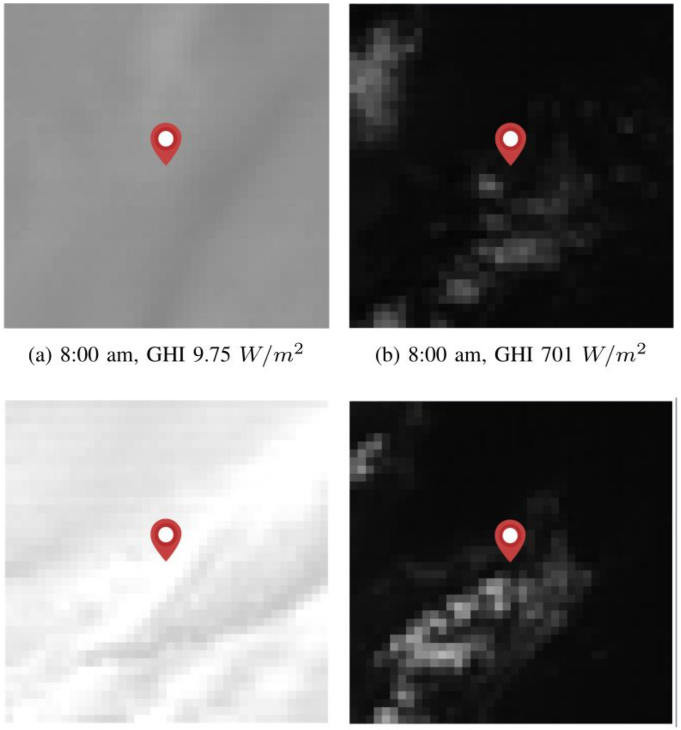
- Ground data from Laboratório Fotovoltaica
  - UFSC - Florianópolis

- Only Global Horizontal Irradiance (GHI) is considered
  - Target variable - used only as desired value in training
  - Allows for agnostic forecasts
  - Highly correlated with photovoltaic power output (0.97)

# Dataset



- Satellite Images from GOES-16
- Images from Channel 2 of the Advanced Baseline Imager
- Bright images
  - High reflectance → Low GHI
- Dark images
  - Low reflectance →High GHI

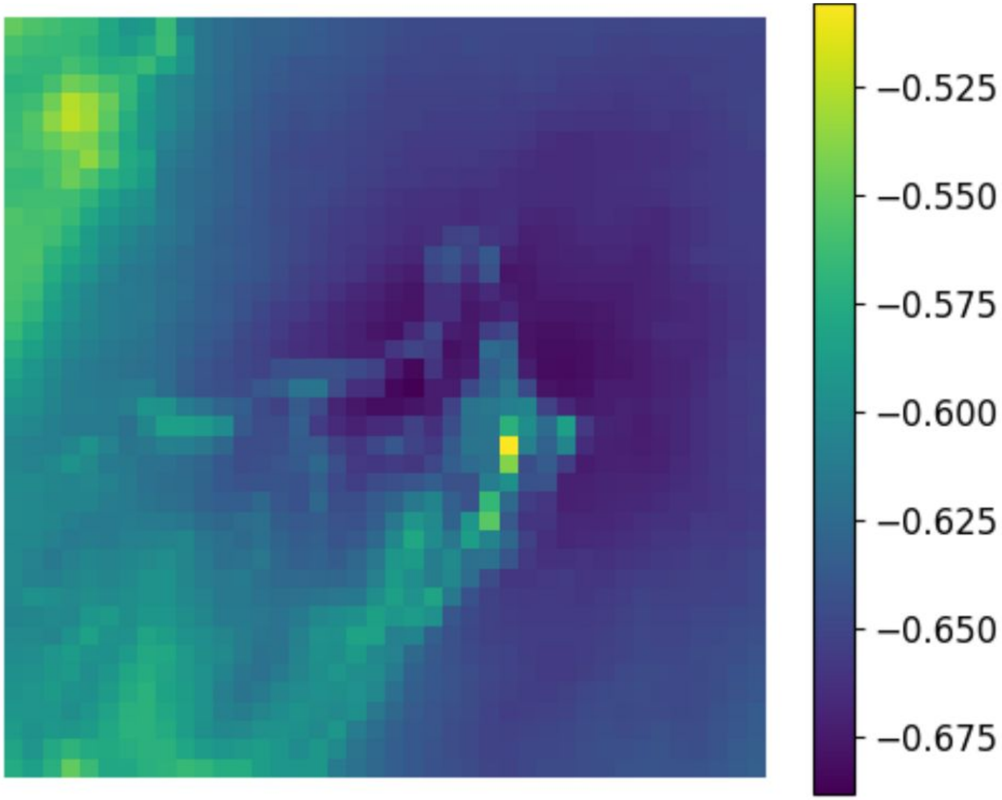


(a) 8:00 am, GHI 9.75 $W/m^2$
(b) 8:00 am, GHI 701 $W/m^2$
(c) 12:30 pm, GHI 31.3 $W/m^2$
(d) 12:30 pm, GHI 1199 $W/m^2$

# Dataset



- Dataset comprehends the years of 2018 and 2019
- Correlation between GHI (ground) and Reflectance (Satellite)



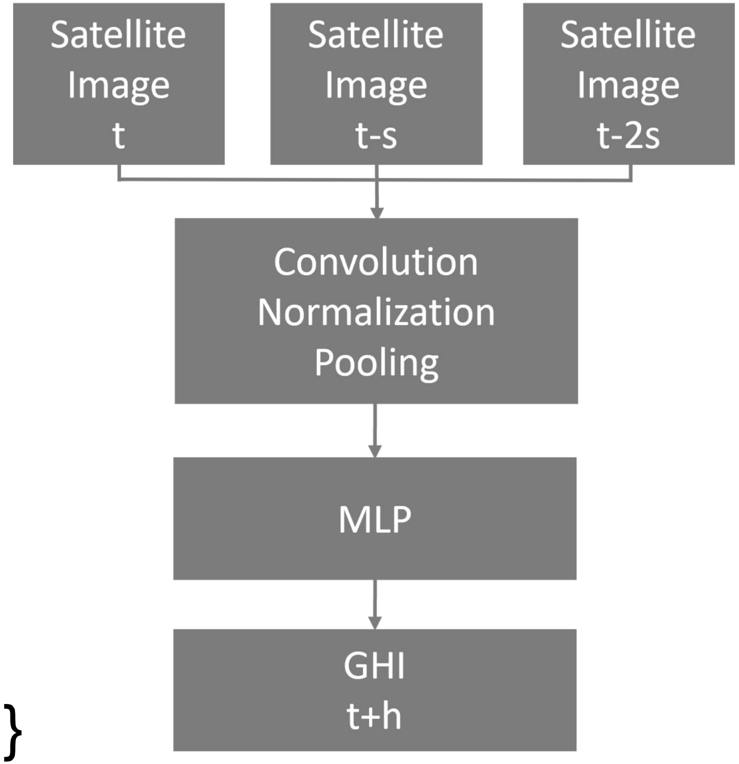
# Deep Learning Based Approach

Architecture and parameters

# Deep Learning Approach



- Models take as input
  - Image at actual time (t)
  - Images at -30min. and -60min.
- Different configurations evaluated
  - Convolutions: {1, 2, 3, 4}
  - Filters: {16, 32}
  - Kernel: {2, 3, 4, 5}
  - Hidden Layers: {1, 2, 3, 4, 5}
  - Dropout: {0.00, 0.15, 0.30, 0.45}
  - Neurons: {64, 128, 256, 512, 1024}



# Results

GHI Forecasting with Satellite data

# Evaluation

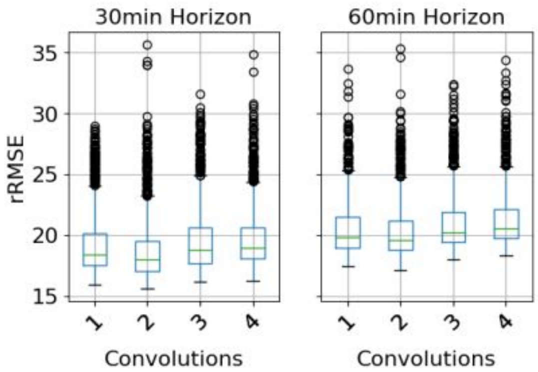


- For evaluation, data was split into three sets (stratified by month)
  - Data from 2018
    - 70% for training set
    - 30% for validation set
  - Data from 2019
    - Not employed before, was used as test set

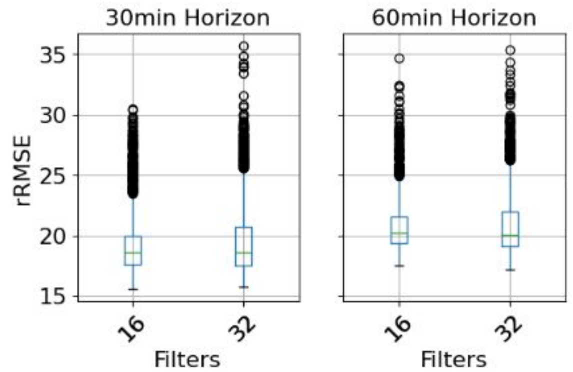
- Evaluation metric
  - relative Root Mean Squared Error (rRMSE)

# Results

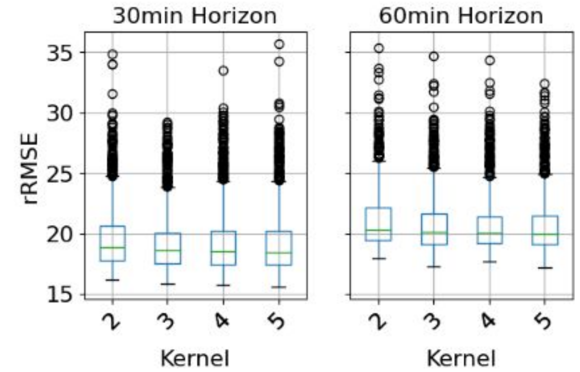




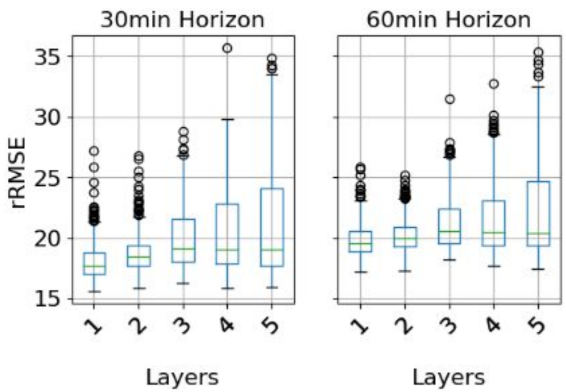

(a)



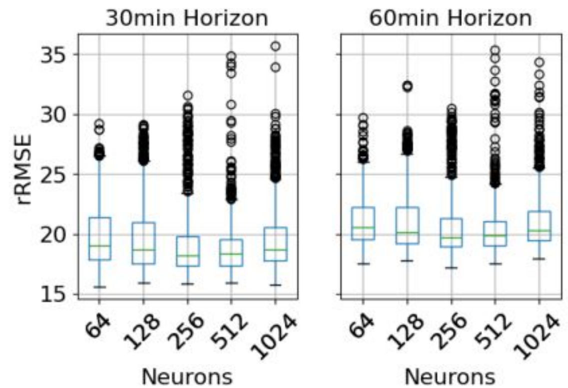

(b)



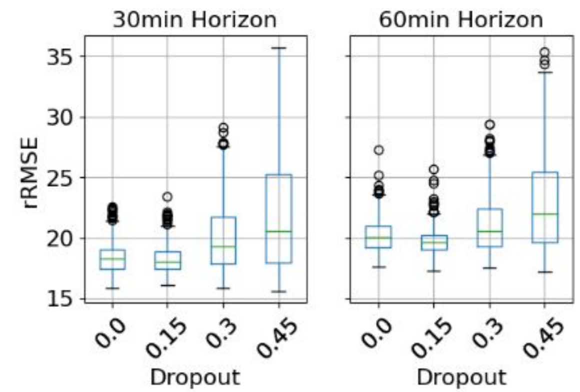

(c)




(d)



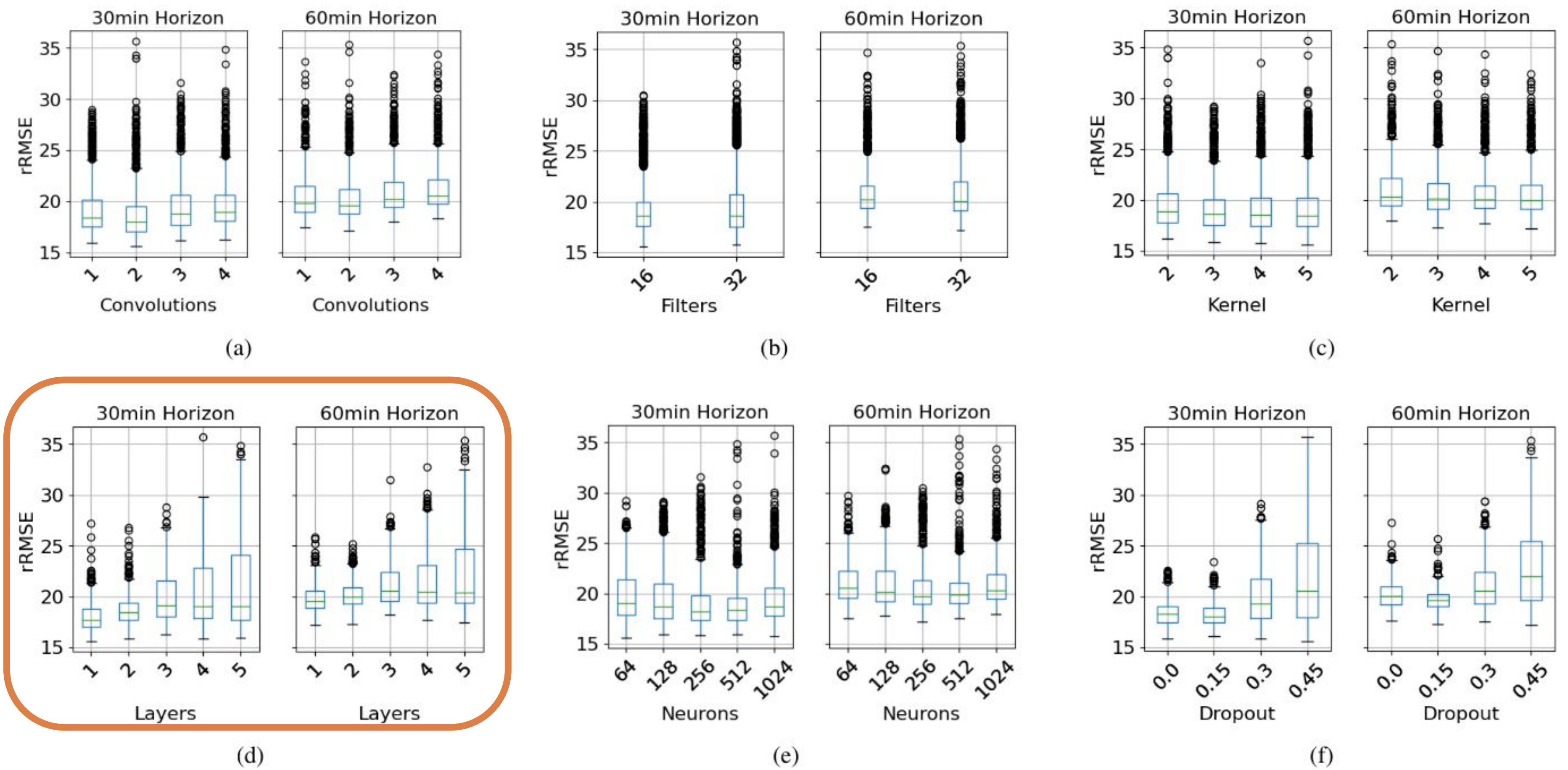

(e)




(f)

# Results



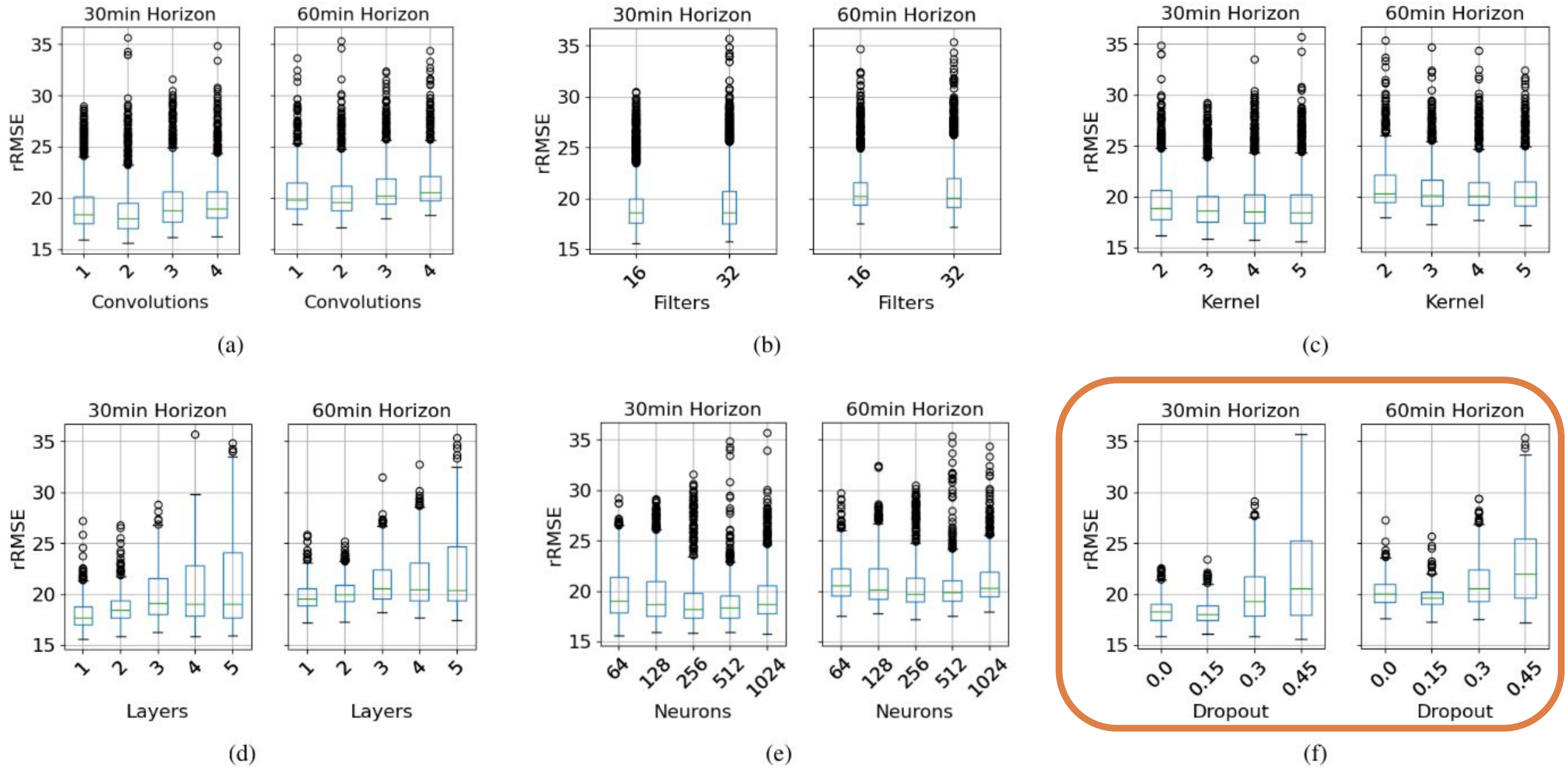



(a) (b) (c)

(d) (e) (f)

# Results






(a) (b) (c)

(d) (e) (f)

# Results

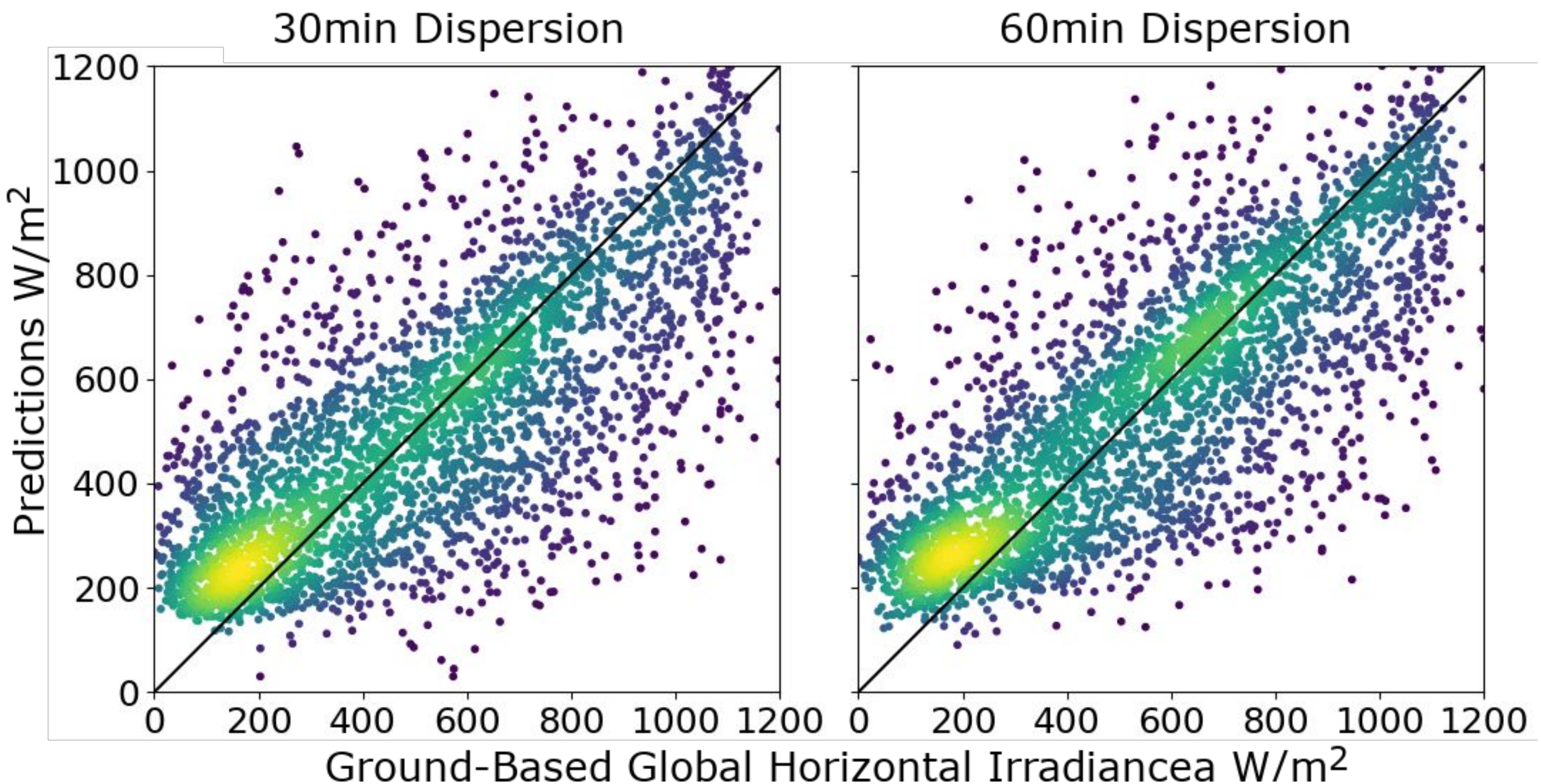


| Horizon (min) | # Convolutions | # Filters | Kernel Size | # Layers | Dropout | # Neurons | rRMSE (%) | Model # |
|---|---|---|---|---|---|---|---|---|
| **30** | 2 | 16 | 5 | 1 | 0.45 | 64 | 15.6 | M01 |
| | 2 | 32 | 4 | 1 | 0.45 | 1024 | 15.8 | M02 |
| | 2 | 32 | 5 | 1 | 0.30 | 64 | 15.8 | M03 |
| | 2 | 16 | 3 | 2 | 0.45 | 64 | 15.8 | M04 |
| | 2 | 16 | 3 | 2 | 0.30 | 64 | 15.8 | M05 |
| **60** | 2 | 32 | 5 | 1 | 0.45 | 256 | 17.2 | M06 |
| | 2 | 32 | 3 | 2 | 0.15 | 256 | 17.2 | M07 |
| | 1 | 32 | 3 | 5 | 0.15 | 256 | 17.5 | M08 |
| | 1 | 16 | 5 | 1 | 0.30 | 64 | 17.5 | M09 |
| | 1 | 32 | 5 | 1 | 0.45 | 512 | 17.5 | M10 |

# Results



- Results for top models, considering both horizons



# Final Remarks

Future work directions

# Final Remarks



- Importance of photovoltaic power generation forecasting
  - Allows for widespread adoption and better grid integration
- Short term forecasting of Global Horizontal Irradiance (GHI)
  - 30 and 60 minutes
- Satellite images provide reasonable short forecasts
  - Slightly worse results than ground data (Pelisson et al. 2020)
- We consider only images
  - No cloud segmentation or integration with ground data
  - No calendar, hour information, etc

# Final Remarks: Future Work



- Consider different architectures as candidates
  - Implement competitors (no source codes available)
- Incorporate different data sources into the models
  - Ground data
  - Hour information
  - Season
- Add solar zenith angle correction and verify its influence

# Questions?



Thank you for your attention. Glad to answer any questions.

pablo.andretta@ufsc.br

With thanks to:

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