UNSW AUSTRALIA

Towards a More Accurate Machine Learning Multi-Model Ensemble Method for Direct Solar Irradiance Forecasts

Never Stand Still | Faculty of Engineering | School of Photovoltaic and Renewable Energy Engineering

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AIM

Determine only from radiative scheme ensembles in WRF, what is the Direct Normal Irradiance (DNI) forecast performance without aerosol observational data inputs

MOTIVATION

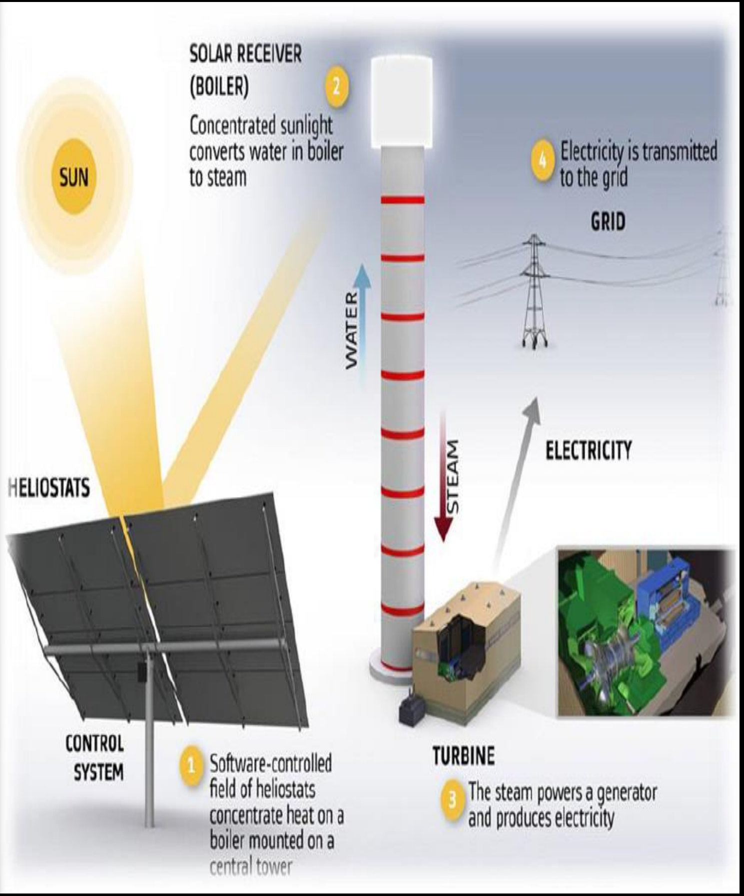
SOLAR FORECAST - importance of accuracy

Short-term irradiance prediction (hrs-days) critical in solar grid integration by anticipating and compensating for power fluctuations. We are investigating:

- ❑ Numerical Weather Prediction (NWP)
  - ❑ Post-processing with Machine Learning
- ❑ Aerosol Transports
- ❑ Cloud Motion Vectors (other UNSW project)

Based on reliability of DNI forecasts CSP plants:

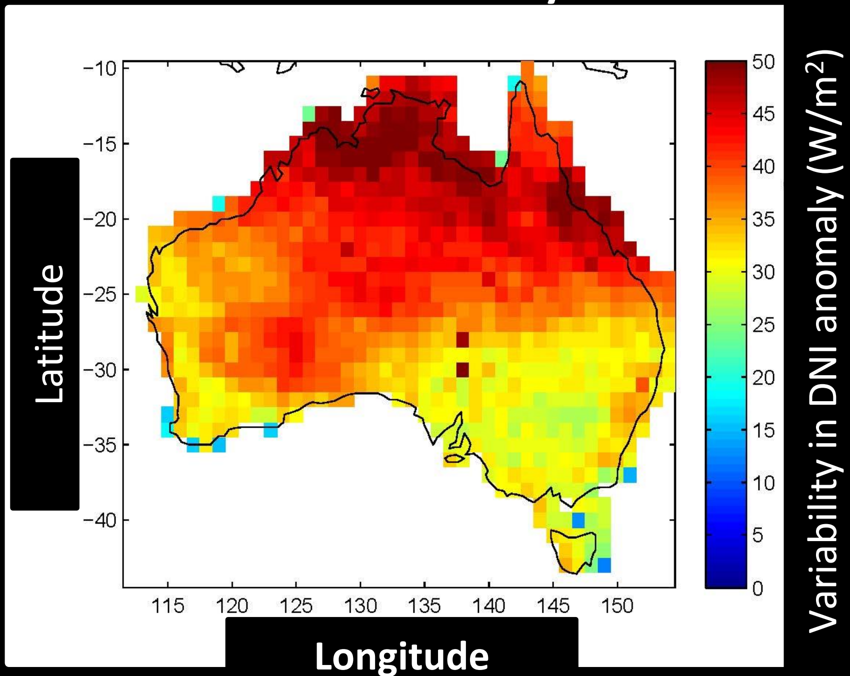
- ✓ dispatch electricity onto grid
- ✓ bid into national electricity market to capture peak prices
- ✓ schedule thermal energy storage



BACKGROUND

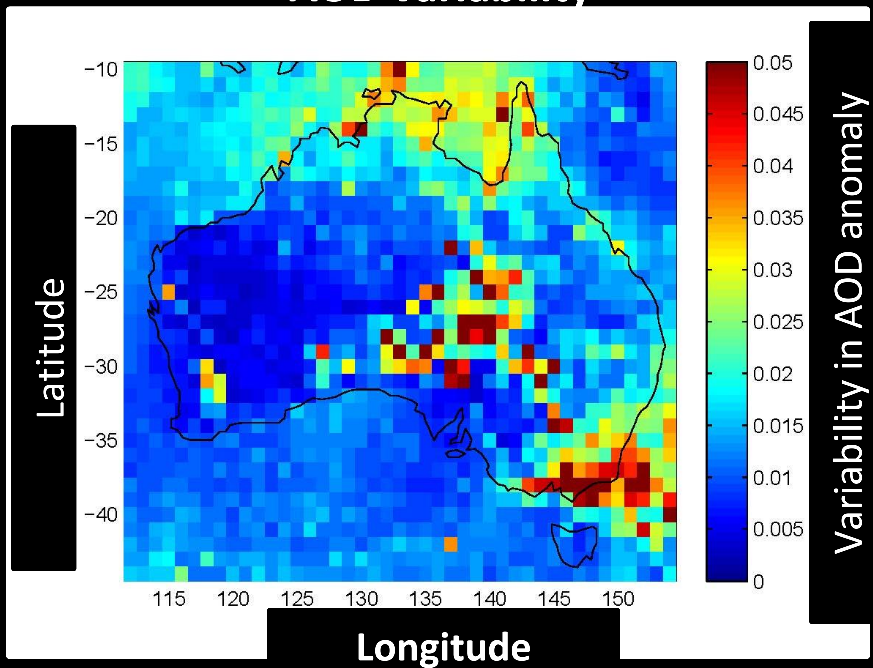
PREVIOUS STUDY[1] - revealed that AEROSOL EVENTS in some REGIONS are particularly IMPORTANT for SOLAR forecasts

DNI variability



- Gridded hourly solar DNI ground data (2000-2012)
- Spatial resolution of 0.05° (≈5 km)
- Accuracy of ± 20 Wm^{-2}
- **Variability is due to clouds & aerosols**

AOD variability

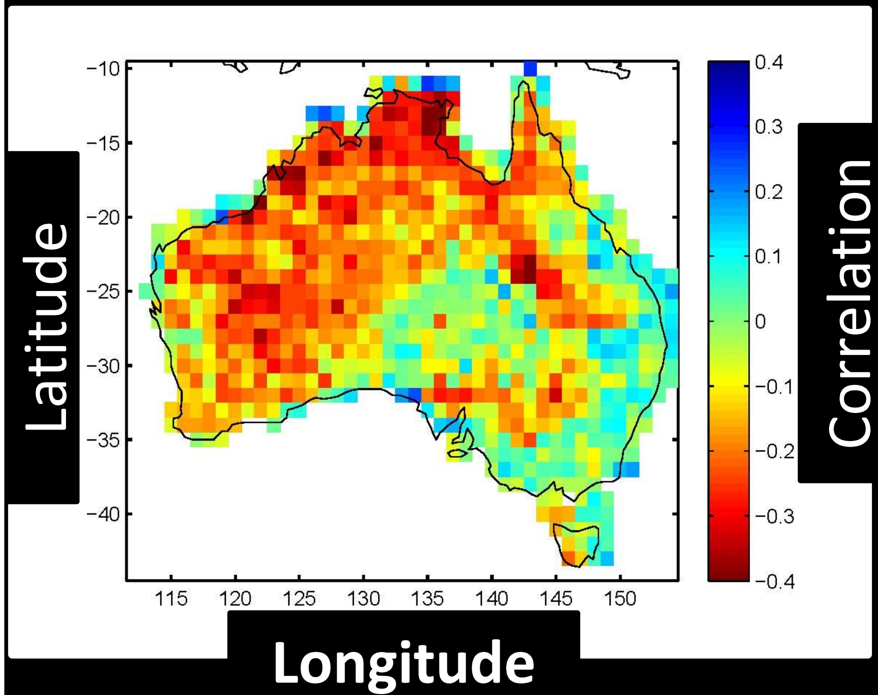


- Gridded monthly AOD data at 550 nm from MODIS Terra (2000-2012)
- Spatial resolution of 1° (≈111 km) Accuracy of ± 15 %

1: Prasad A. et al. (2014), Assessment of DNI-cloud connections using satellite data over Australia, Applied Energy (under review)

BACKGROUND

Correlation of Deseasonalised DNI and AOD anomaly

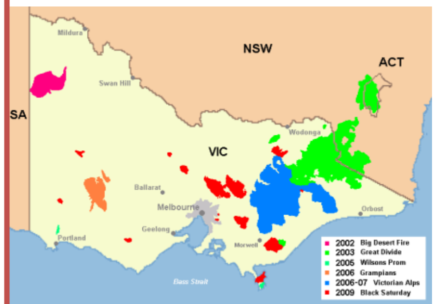


- Strong anti-correlation between DNI and AOD anomaly observed in the north and southeast.
- Strong variability (~0.03-0.05) in the AOD[1].
- Most of these regions active with biomass burning and dust storm activity.

- The total change in AOD and DNI was within ± 0.1 and ± 40 Wm^{-2} respectively over Australia for the period of this study.
- The AOD anomaly significantly decreased over northern Australia which may have led to the increase in DNI over the period.
- These spatio-temporal characteristics of AOD and DNI variability would help in siting future CSP installations in Australia.

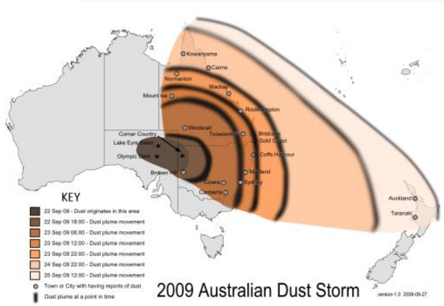
EVENT CASE STUDIES

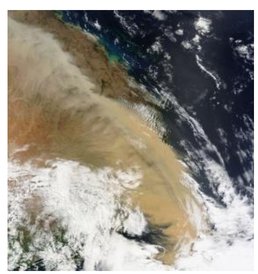
BUSHFIRE



Forecast Horizon: 48 Hours from 2009-02-07-00-00-00 UTC

DUST STORM



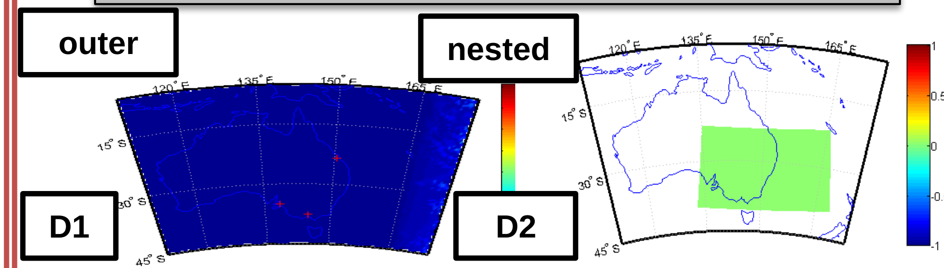


from 2009-09-21-12-00-00 UTC

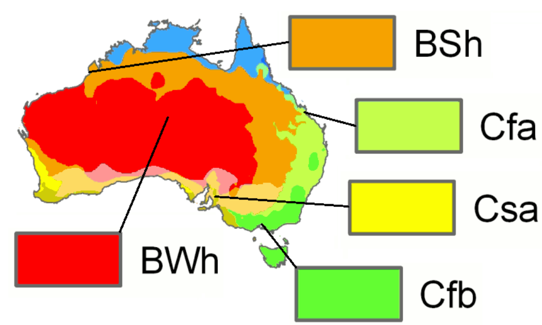
- GFS boundary conditions and NCEP final operational analysis global data at 1 degree grids every six hours. No aerosol input was included.

WRF MODEL SETUP

DOMAINS – 1 (50 KM) & 2 (10 KM)



REGIONS



Climate zones Koppen classified

- Adelaide (Csa Mediterranean)
- Alice Springs (Bwh Desert)
- Broome (Bsh Semi-Arid)
- Melbourne (Cfb Oceanic)
- Rockhampton (Cfa Humid Subtropical)

Five test sites for solar forecasts & validation with ground datasets

WRF MODEL SETUP – Radiative Schemes

WRF Code	Scheme	Shortwave radiative transfer code technique	Technique
1	Dudhia	Dudhia (1989, JAS)	Fast & simple downward broadband calculation (cloud albedo & absorption)
2	Goddard	Chou and Suarez (1994, NASA Tech Memo)	Spectral Method (clouds)
4	RRTMG	Iacono et al. (2008, JGR)	Spectral method (14 bands, clouds, aerosols)
5	New Goddard	Chou and Suarez (1999, NASA Tech Memo)	Spectral Method (11 bands, clouds)
7	FLG	Gu et al. (2011, JGR), Fu and Liou (1992, JAS)	Correlated k-distribution
99	GFDL	Fels and Schwarzkopf (1981, JGR)	Spectral scheme (cloud s)

Planetary Boundary Layer (YSU Scheme), Microphysics (new Thompson except GFDL uses only Eta Ferrier), Cumulus (Kain Fritsch), Land surface model (Noah)

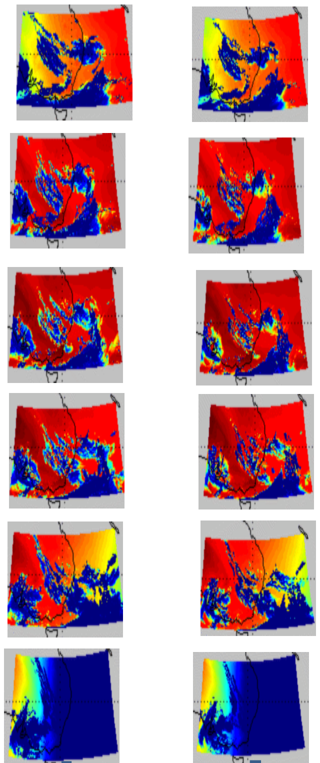
WRF Radiative Transfer Codes for Sensitivity Analysis
(sw: shortwave & lw: longwave)

Domain 1 uses six radiative scheme codes: (1) Dudhia-1sw & RRTM-1lw ; (2) Goddard-2sw & RRTM-1lw; (3) RRTMG-4 sw & lw; (4) New Goddard-5 sw & lw; (5) FLG-7sw & lw; (6) GFDL-99sw & lw

Domain 2 uses four radiative scheme codes:(1) Dudhia-1sw & RRTM-1lw ; (2) Goddard-2sw & RRTM-1lw; (3) FLG-7sw & lw; (4) GFDL-99sw & lw

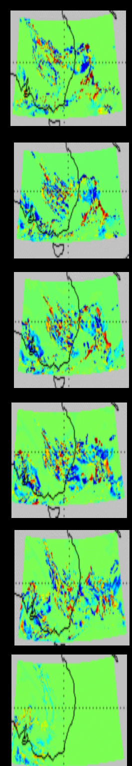
SIMULATIONS – Scheme Intercomparisons

MICROPHYSICS (WSM-3 vs Thompson)



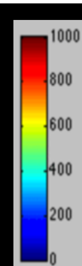
WRF Single Moment-3 Class[2] (Ice, Clouds, Snow)

Thompson Aerosol [3] GOCART Climatology



8 am

22nd Sep (2 hourly shown)

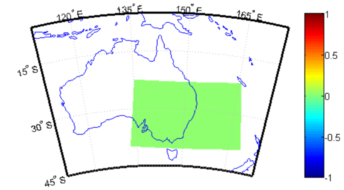


6 pm

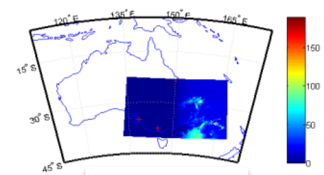
Difference in solar radiation

Dust Storm

SHORTWAVE (Dudhia vs Goddard example)



21st Sep 10 pm – 22nd Sep 6 am



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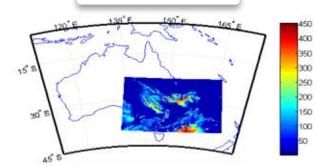
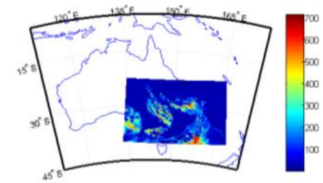
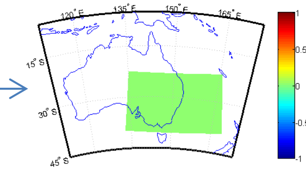


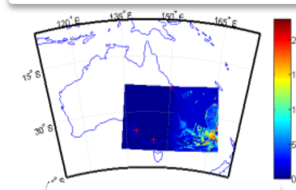
10 am



12 pm



22nd Sep 10 pm – 23rd Sep 6 am



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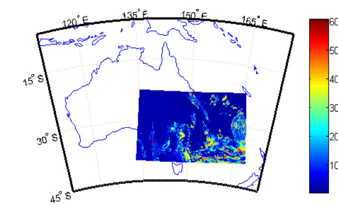

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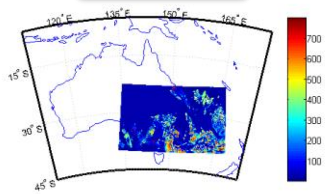


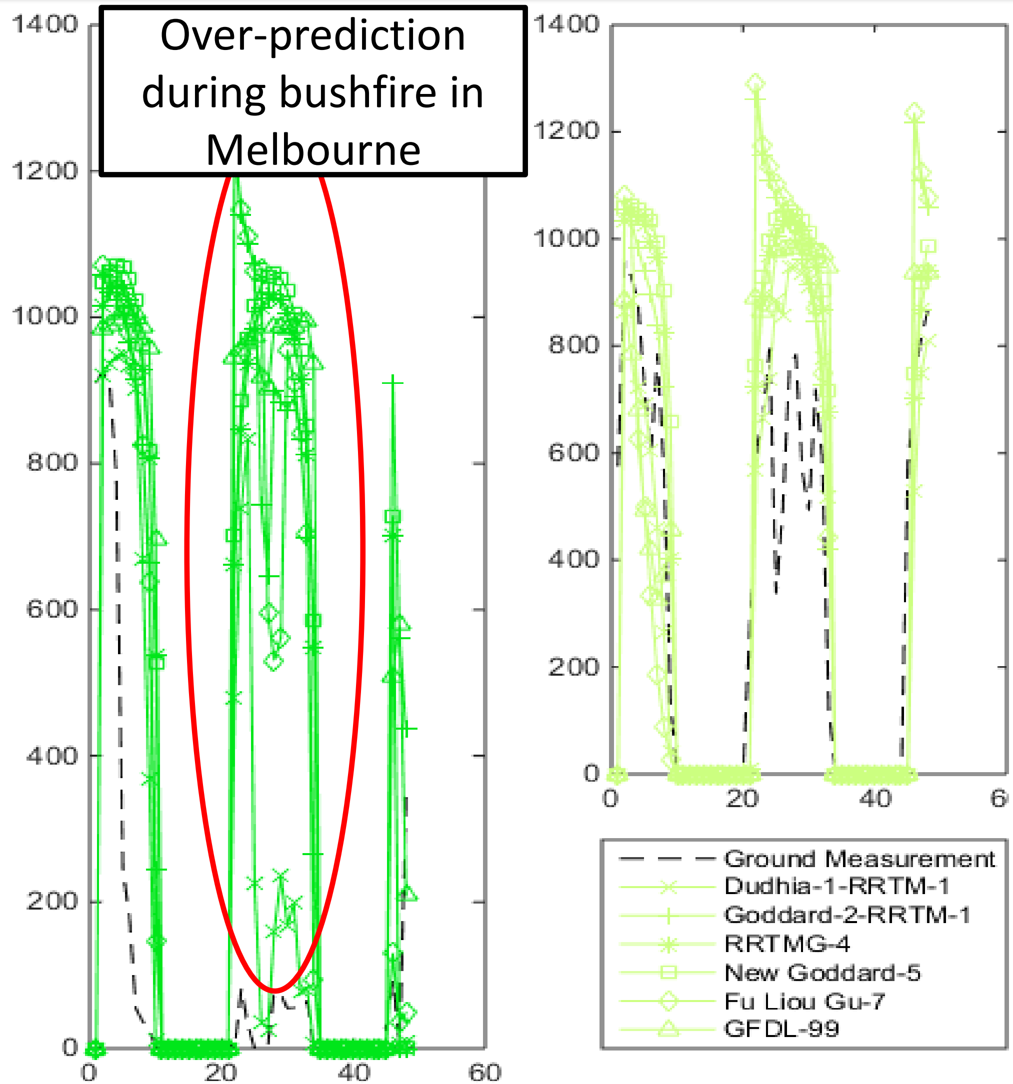
12 pm

2: WSM3, Hong, Dudhia and Chen (2004, MWR) 3: Thompson and Eidhammer (2014, JAS)

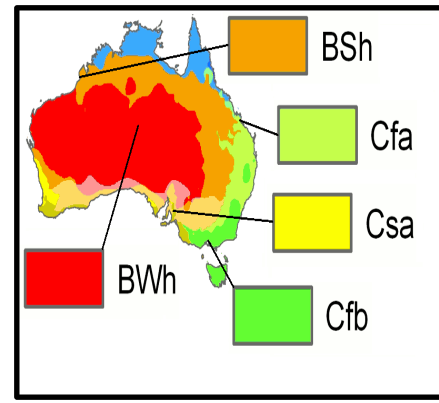
RESULTS – WRF NWP SOLAR FORECASTS

BUSHFIRES - 10KM DNI
(example for 2 locations shown)

Bushfire DNI Forecast Wm^{-2}



Bush D2



48 Hours from 2009-02-07-00-00 UTC
(for each climate zone over two domains)

DNI NWP produced much larger biases than GHI

RESULTS – NWP FORECAST METRICS

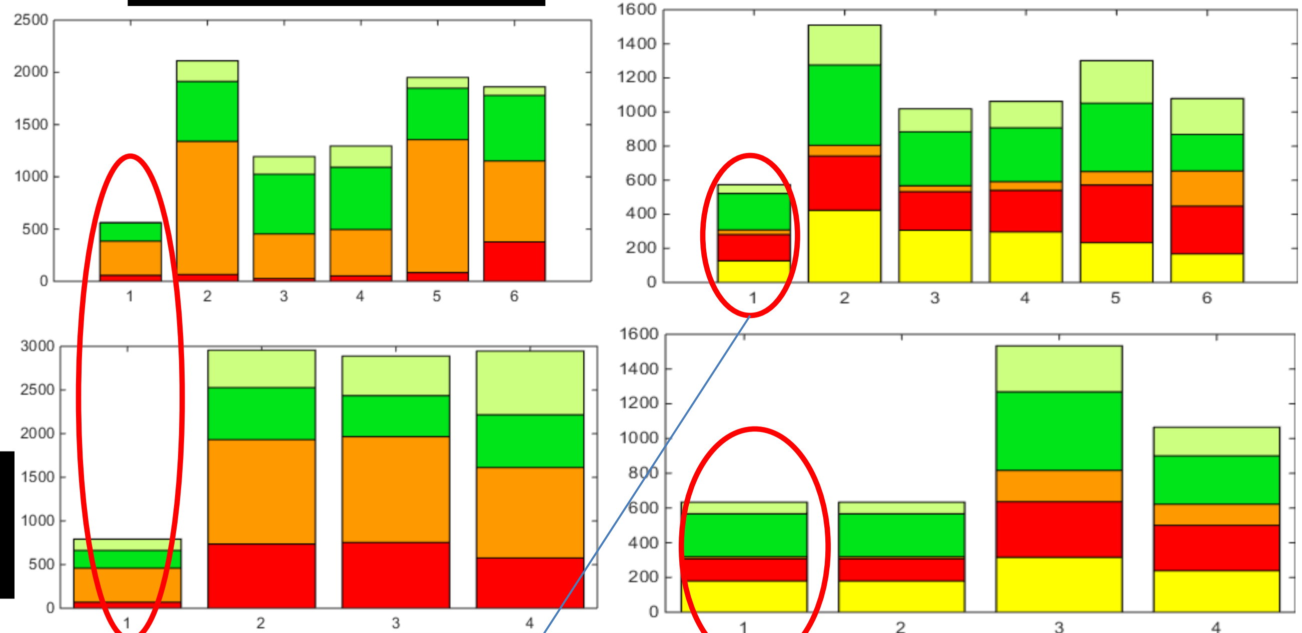
DNI RMSE (avg. stacked contribution from each site)

Bushfire case

Dust storm case

D1 (6 codes)

D2 (4 codes)



Dudhia???

48 Hours Lead Time

D1	Scheme	D2
1	Dudhia	1
2	Goddard	2
3	RRTMG	
4	New Goddard	
5	FLG	3
6	GFDL	4

- Significant difference in forecast error based on choice of scheme and location

- **DNI & GHI –** NRMSE, MAE & MBE (Wm^{-2} average stacked contribution from other sites) also analysed → similar trends

MUST post-process to reduce bias and evaluate the best multi-model ensemble radiative schemes for each site

→ **Machine Learning**

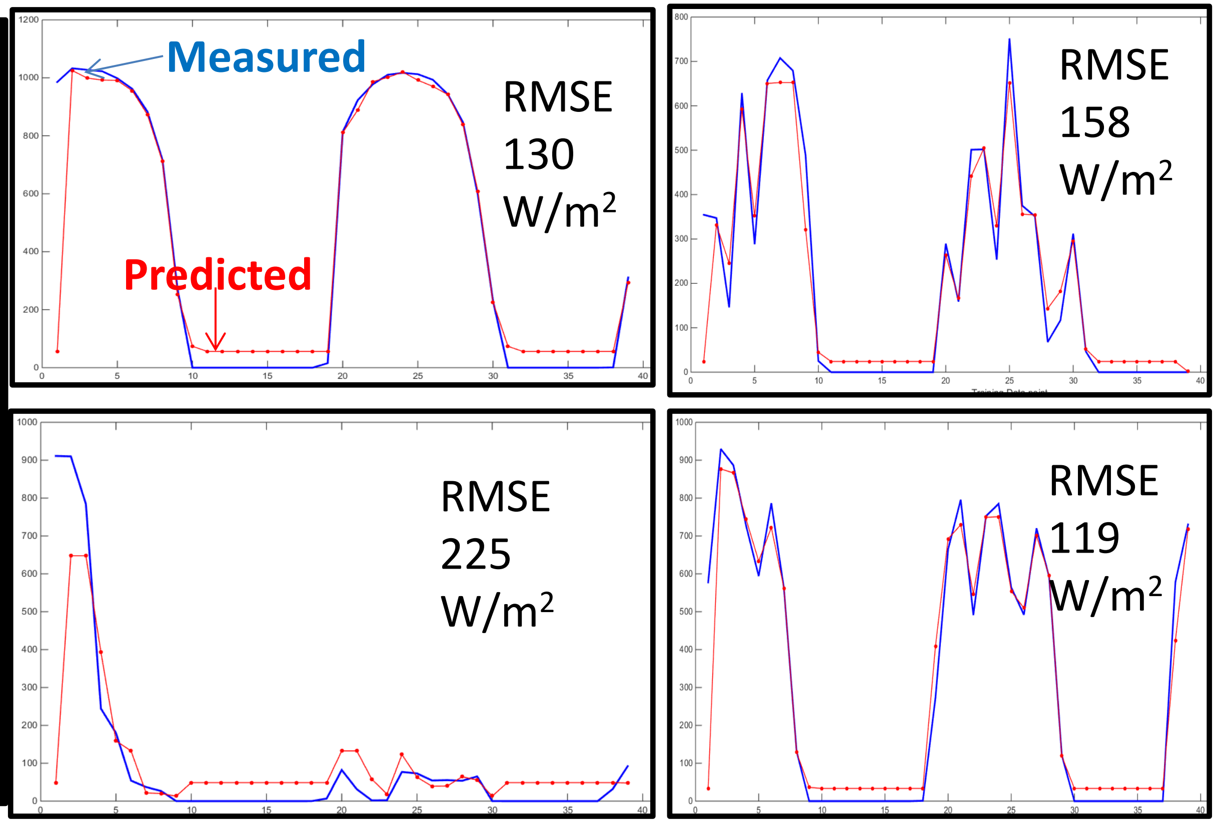
Machine Learning with Boosted Decision Tree Regression[3] – BUSHFIRE CASE (48 Hours from 2009-02-07 00:00:00 UTC)

Alice Springs (Bwh Desert)

Broome (Bsh Semi-Arid)

DNI Forecast Wm-2

Y



Melbourne (Cfb Oceanic)

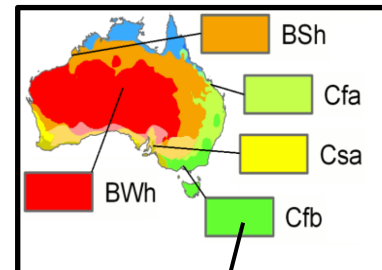
Rockhampton (Cfa Humid Subtropical)

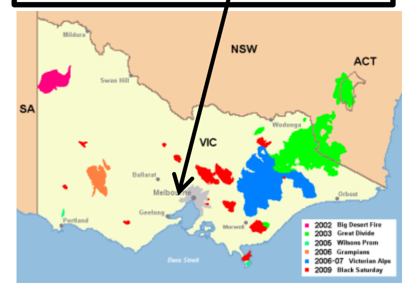
Training Data Point (Hour)

X

LSBoost function MATLAB: Avg. Execution time 8.04s

When 80% data for training set aside – gave lowest RMSE

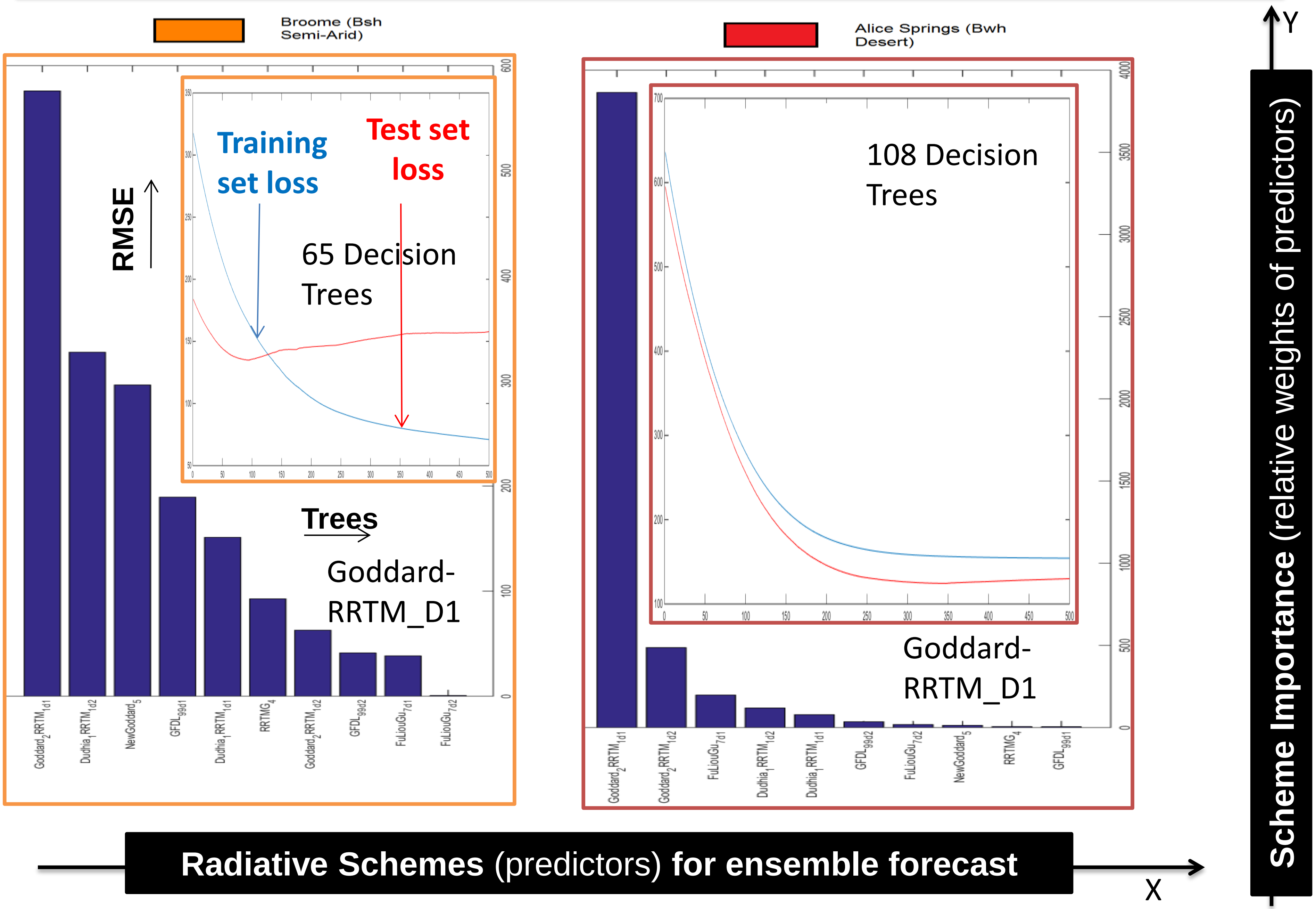


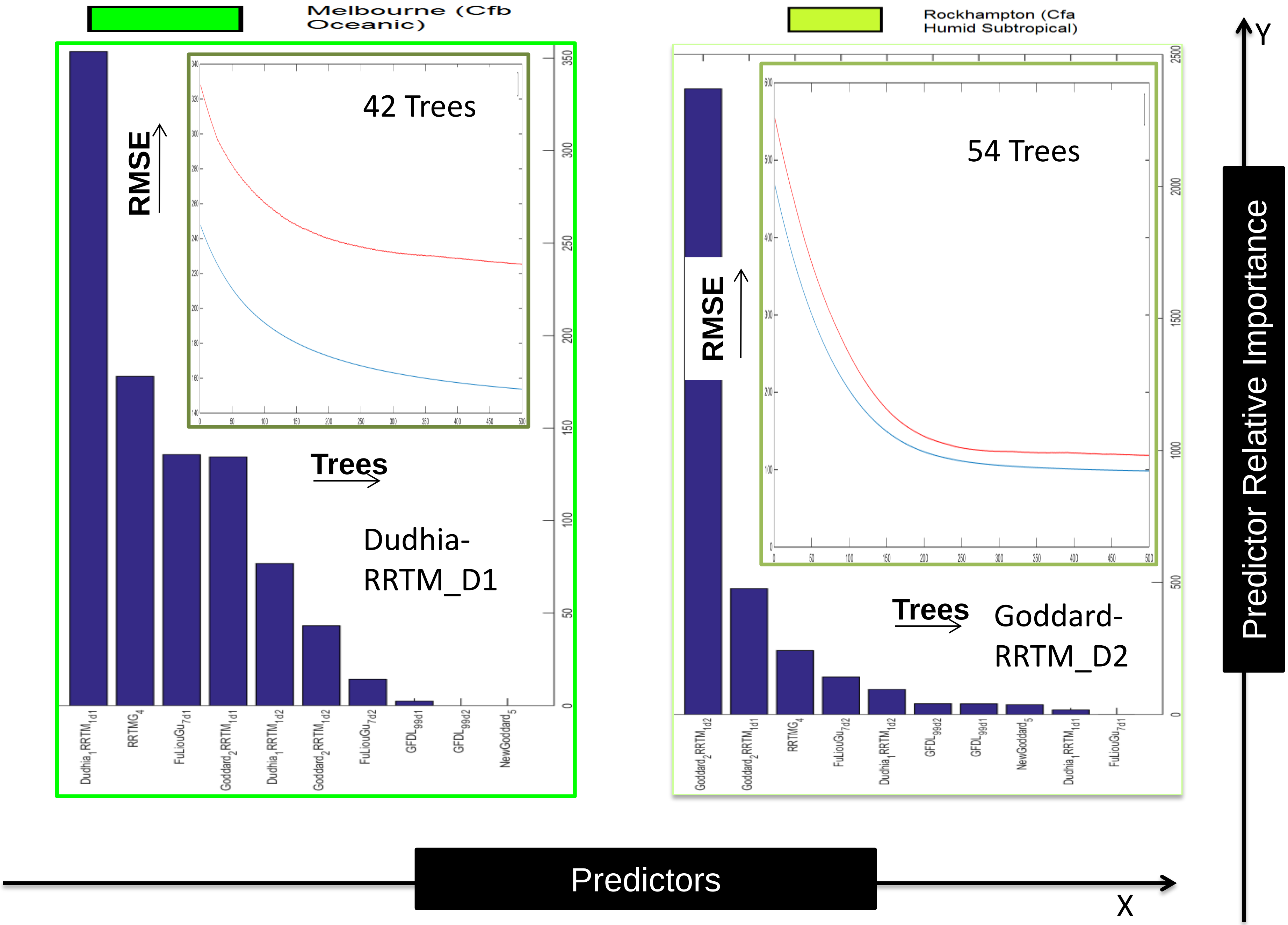


LSBoost uses Least-squares loss function

3: Friedman, J. Greedy function approximation : A gradient boosting machine. Annals of Statistics, 2001

Radiative Scheme Ensemble Learner – BUSHFIRE CASE





Melbourne (Cfb Oceanic)
42 Trees
RMSE
Trees
Dudhia-RRTM_D1
Rockhampton (Cfa Humid Subtropical)
54 Trees
RMSE
Trees
Goddard-RRTM_D2
Predictors
X
Y
Predictor Relative Importance

Boosted Decision Tree Regression – DUST STORM CASE

(48 hrs from 2009-09-21 12:00:00 UTC)

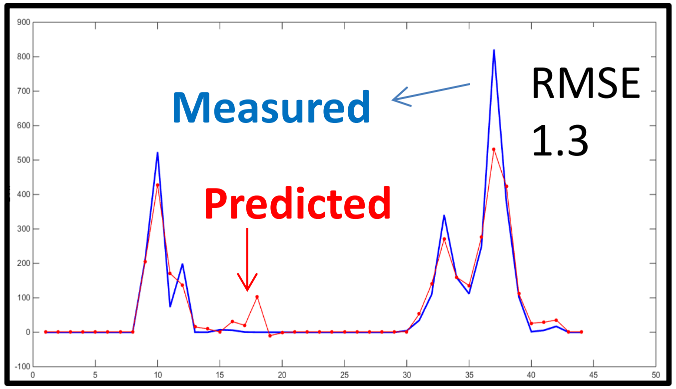
Y

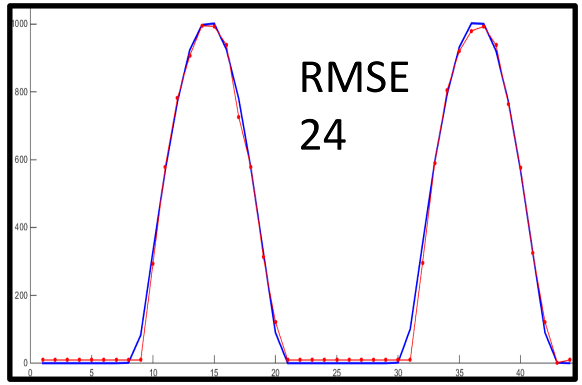
DNI Forecast Wm^{-2}

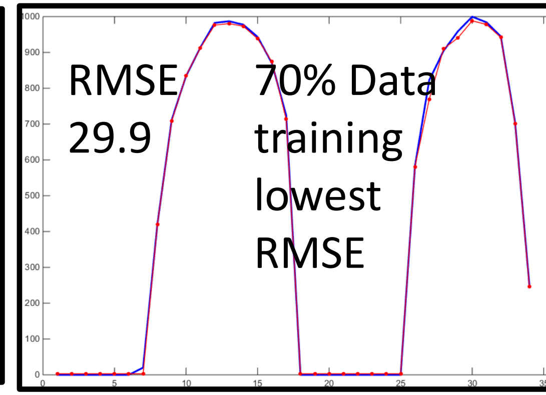
Adelaide (Csa Mediterranean)

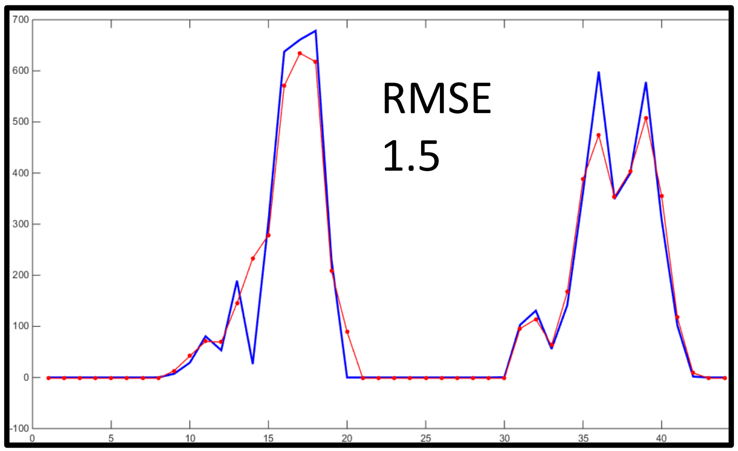
Alice Springs (Bwh Desert)

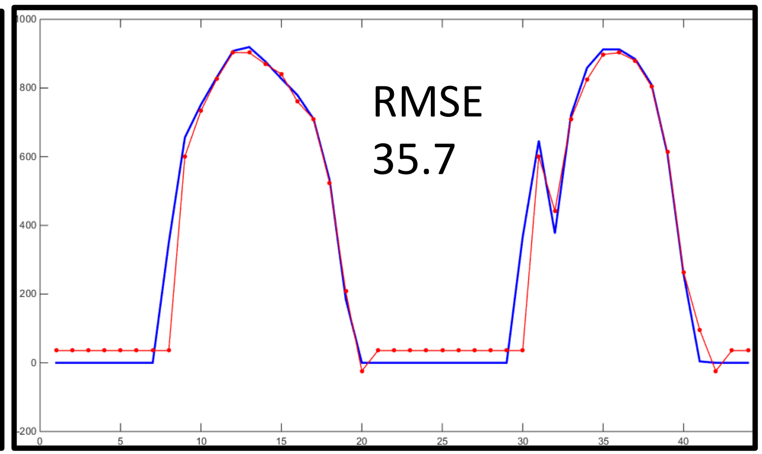
Broome (Bsh Semi-Arid)

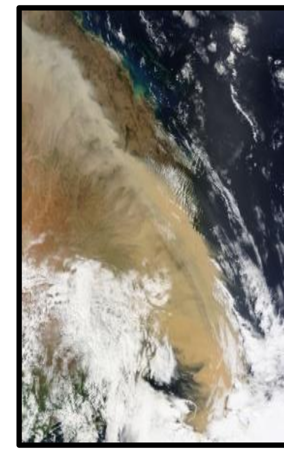






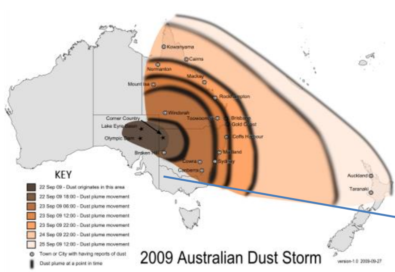






Melbourne (Cfb Oceanic)

Rockhampton (Cfa Humid Subtropical)

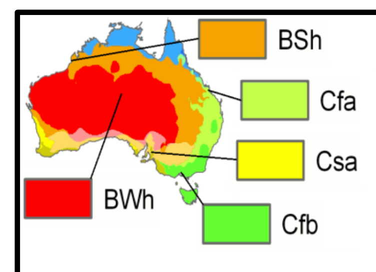


Adel & Melb.
no storm

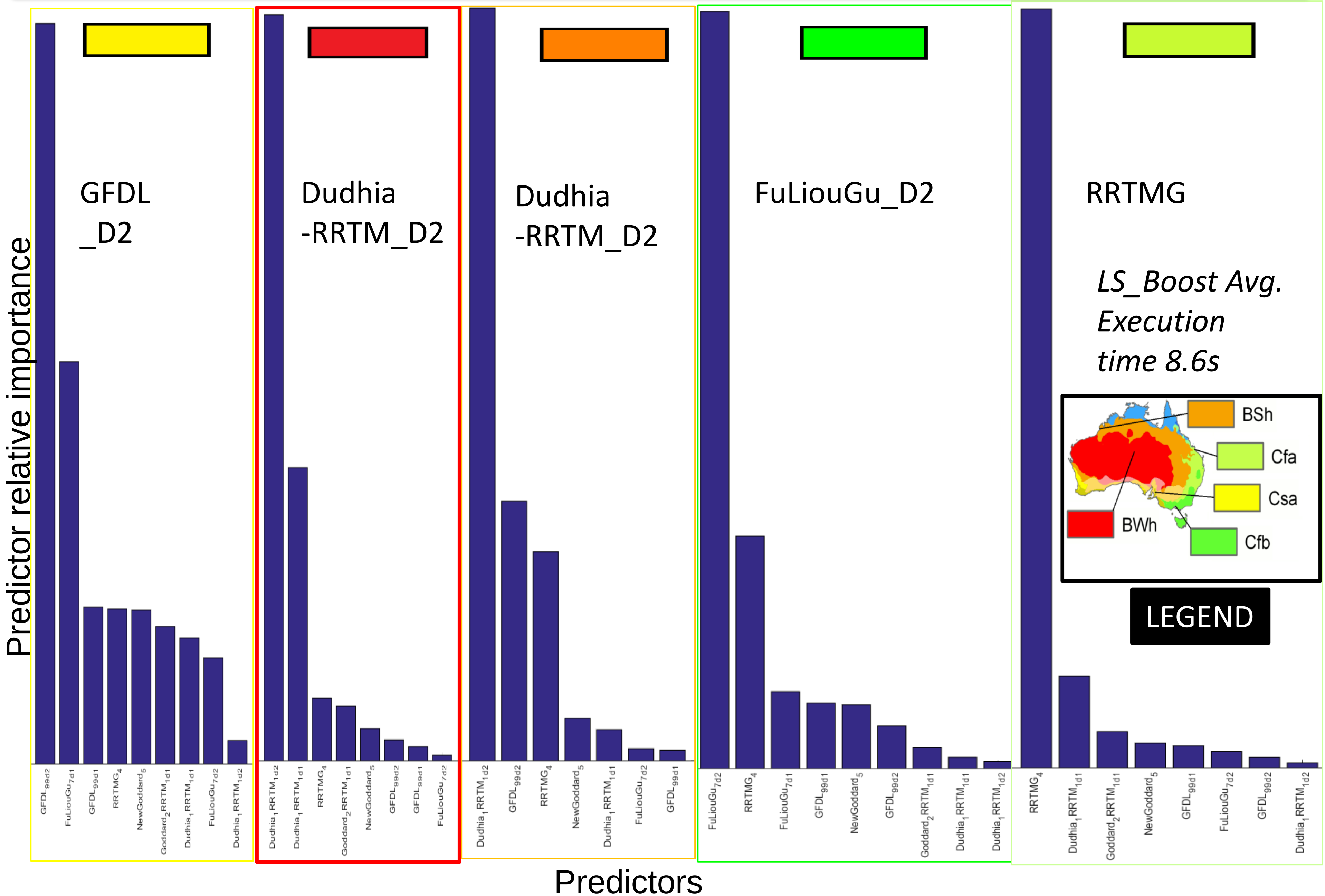
Training Data Point (Hour)

X

90% data set aside for
training gave lowest RMSE



Radiative Scheme Ensemble Learner – DUST STORM CASE



SUMMARY – Predictors from machine learning and NWP forecasts

DNI

Koppen Classification	Mediterranean	Desert	Semi-Arid	Oceanic	Humid Subtropical
Location	Adelaide	**Alice Springs**	Broome	**Melbourne**	**Rockhampton**
Dust storm Case RMSE (W/m^2) **- Sep '09**	**1.34**	**23.83**	**29.93**	**1.54**	**35.70**
Most important radiative scheme predictor	GFDL_D2	**Dudhia-RRTM_D2**	**Dudhia-RRTM_D2**	FuLiouGu_D2	**RRTMG**
No. of Decision Trees	44	150	89	67	119
Bushfire Case RMSE (W/m^2) **- Feb '09**	No ground data	**129.97**	**157.82**	**225.32**	**118.51**
Most important radiative scheme predictor	N/A	**Goddard-RRTM_D1**	**Goddard-RRTM_D1**	**Dudhia-RRTM_D1**	**Goddard-RRTM_D2**
No. of Decision Trees	N/A	108	65	42	54

GHI

Dust storm Case RMSE (W/m^2) **- Sep '09**	2.6	**40.4**	2.3	1.8	1.3
Most important radiative scheme predictor	GFDL_D2	**Dudhia-RRTM_D1**	**Dudhia-RRTM_D2**	**Dudhia_RRTM_D1**	**Dudhia_RTM_D1**
Bushfire Case RMSE (W/m^2) **- Feb '09**	No ground data	100.8	84.3	**157**	84.3
Most important radiative scheme predictor	N/A	**Goddard-RRTM_D1**	**Dudhia-RRTM_D2**	**Goddard-RRTM_D1**	**Goddard-RRTM_D2**

CONCLUSIONS

- ❑ Overall, Dudhia-RRTM for dust and fire seem to be the most consistent predictor for DNI in Australia from this study (without aerosol input)
- ❑ Results in Feb gave higher RMSE than in Sep.
- ❑ Goddard-RRTM seems to produce better results in February than September at non-major aerosol event sites
- ❑ GFDL gave better prediction for [Mediterranean zone] Adelaide (no ground data in Feb)
- ❑ RRTMG must be tested with aerosol input, without YSU/KF scheme and run at higher resolutions alongside (10KM) CAM scheme
- ❑ Further shortwave ensemble performance evaluation with other PBL and cumulus schemes using Thompson required

Other WRF ensemble test **literature supporting conclusions**: Evans, 2011, Climate Dynamics, Evaluation of a WRF Physics Ensemble over South-East Australia

- In Evans et al. 36 member ensemble test, YSU-KF-RRTMG also ranked below YSU-KF-Dudhia
- MYG-KF-WDM5-Dudhia ranked highest followed by
- However, RRTMG with other PBL & Cu schemes ranked higher than with YSU-KF used in this study

THANK YOU!

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