AMI DATA FOR ENERGY EFFICIENCY AND CONSERVATION

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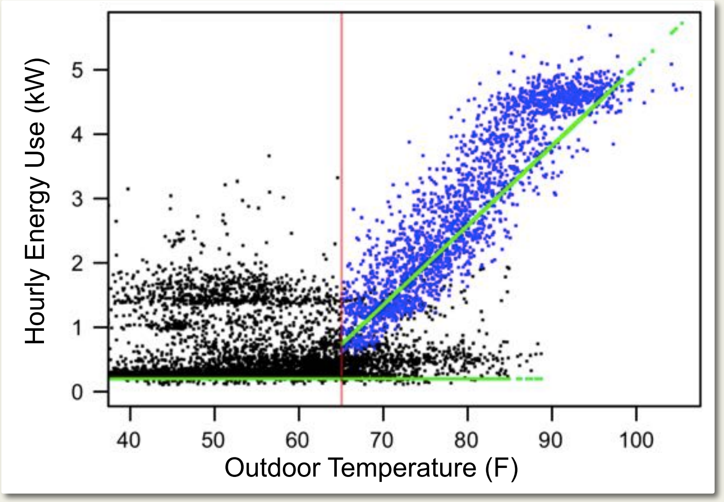
Billing data is often used for efficiency and conservations studies

Empirical assessments of efficiency / conservation programs

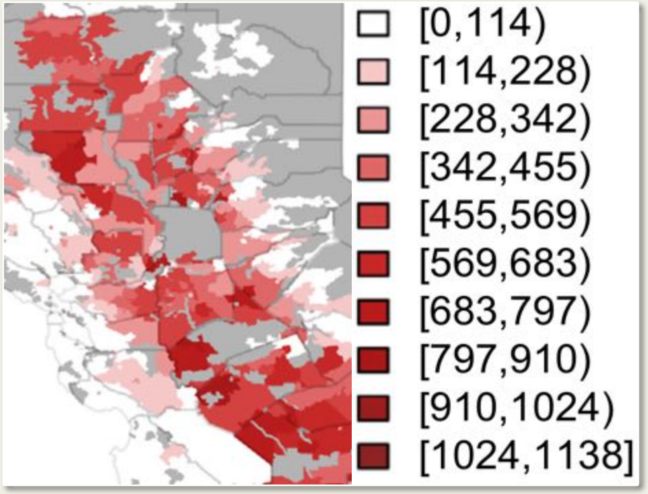
- Must control for outdoor temperature effects which vary among groups
- There are standard models for accounting for temperature effects:

  PRInceton Scorekeeping Method (PRISM) , Change point models (Fels 1988, Kissock 2002)

Baselines of current Infrastructure/behavior, enabled by AMI



Classification of cooling hours, and estimation of temperature response.



Estimated # of hours of AC use per house per year, (Dyson et al. 2014)

AMI data create potential for even more insights

What do thermal models tell us about a residence?

Thermal efficiency of infrastructure

- Effective thermal resistance

Efficiency / Behavior

- Non-HVAC Energy Use
- HVAC Energy Use

Behavior

- HVAC Schedule

What could we ask about energy efficiency or conservation?

- Baseline current infrastructure efficiency and behavioral practices.
- Test hypotheses of
  - Landlord/tenant effects on efficiency versus behavior
  - Geographic indicators of efficiency versus behavior
- Cluster consumers to target efficiency programs.
- Explain differing energy use within similar populations.

Bias in thermal models from smart meters

No measurement of indoor temperature or internal heat gains
Implicitly assume that they are **independent** of outdoor temperature

No estimate of thermal mass of the home, which may dampen the effect of a periodic outdoor temperature signal.

Classification bias,

Parameters are sensitive to classifications

Classifications are sensitive to large deviations.

Models are more likely to misclassify ambiguous readings, which can lead to systemic bias.

This work

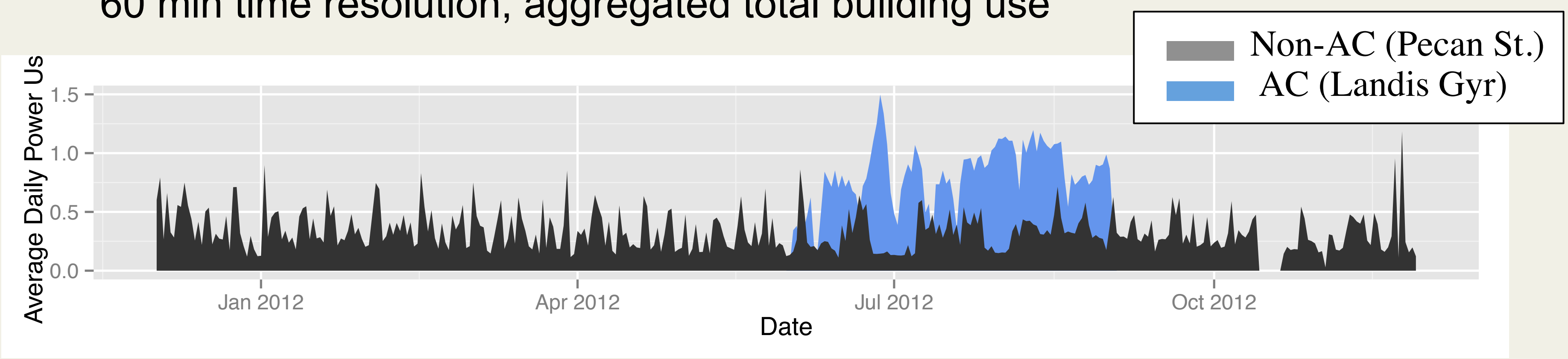
Evaluates a set of models (existing and novel) for their ability to identify thermal and behavioral properties from smart meter data, focus on **bias** in estimates

Detailed data

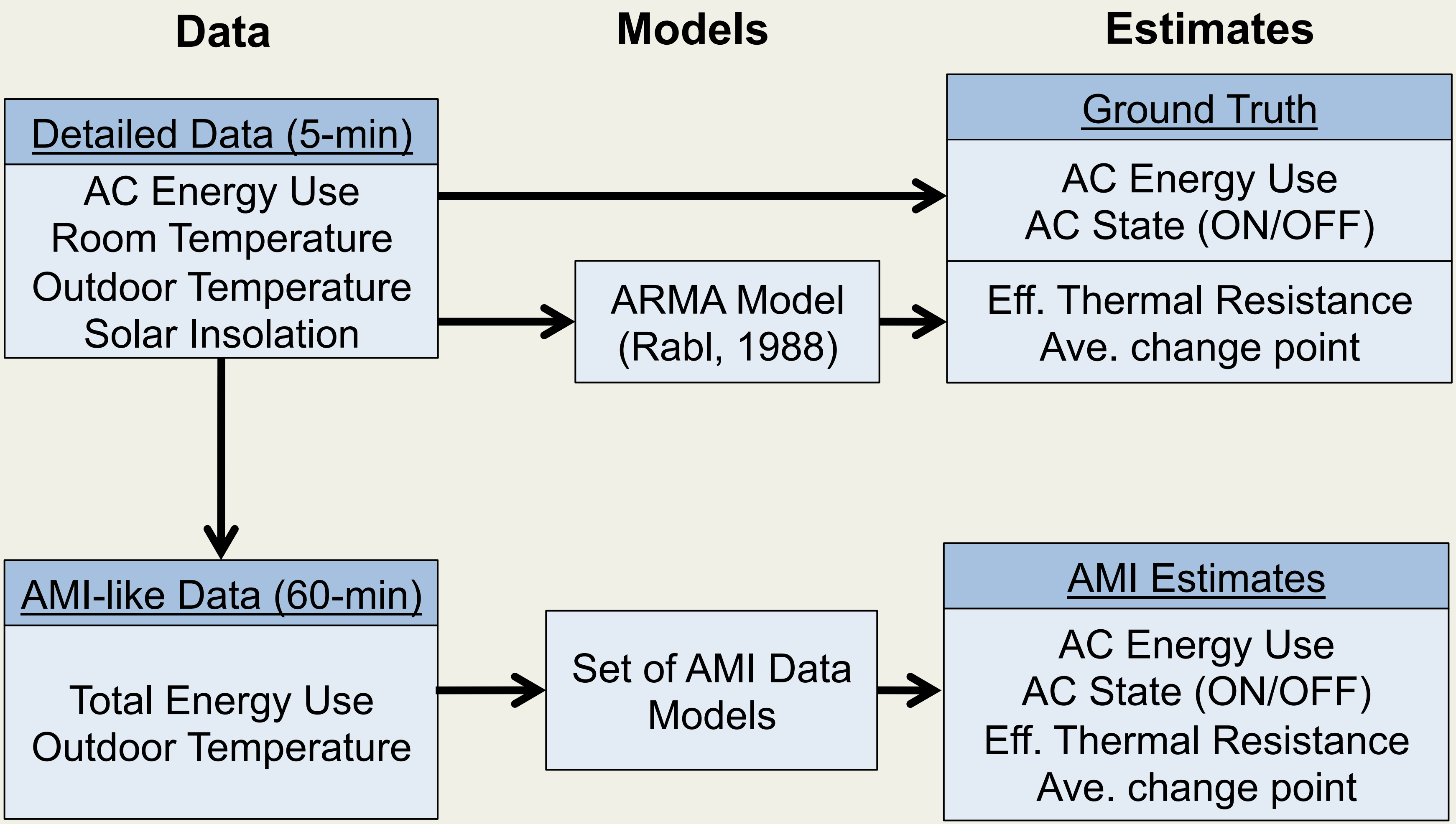
Thermostat Data	~ 4000 Residences 5-min resolution 3 summer months	**Thermostat:** Room temp, Set point **Power Meter:** AC electricity use
Pecan St.	25 Residences 5-min resolution 12 months	**Power Meter:** AC electricity use **Power Meter:** All other electricity use
Forecast.io	Zip-code 1h resolution	Outdoor Temperature Clearness Index

….Reduced to AMI data

60 min time resolution, aggregated total building use



Comparison Method



AMI data Models

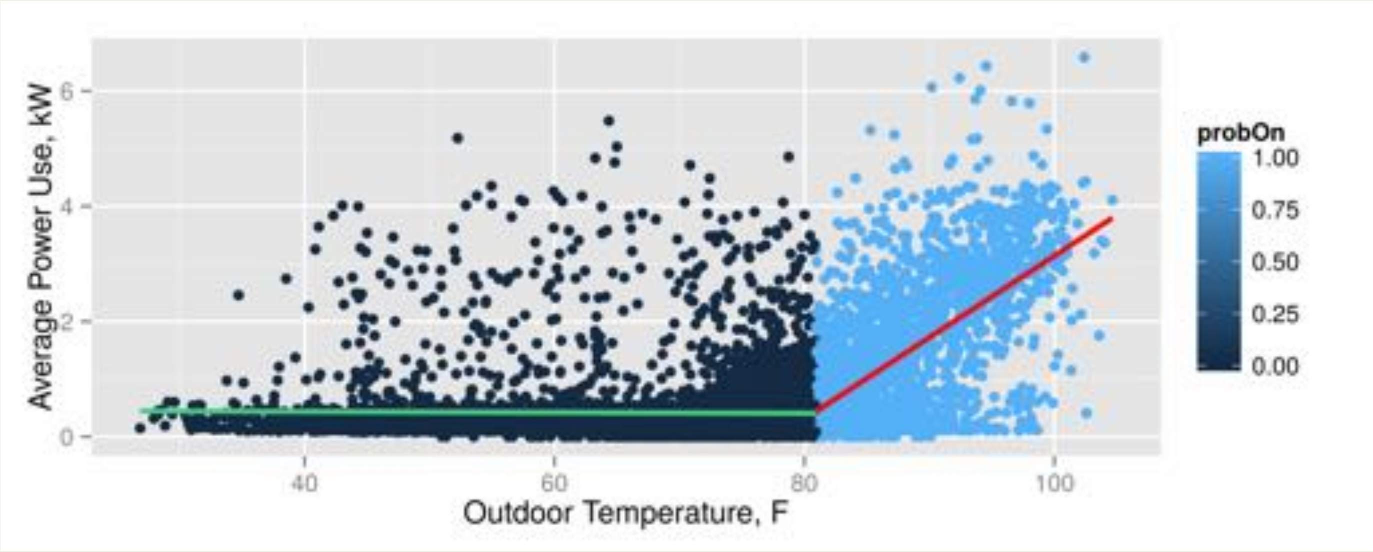
Change point only models

Similar to models used for energy efficiency evaluation (Fels, 1988, Kissock 2002)

Change point can be used as a breakpoint or a a point to define HDH/CDH

Change point is estimated by maximum likelihood (or minimal RMSE)

Change Point Only	Intersecting	Hourly Data	Gaussian Errors
Classification	Cooling Intercept	Daily Data	Kernel Errors



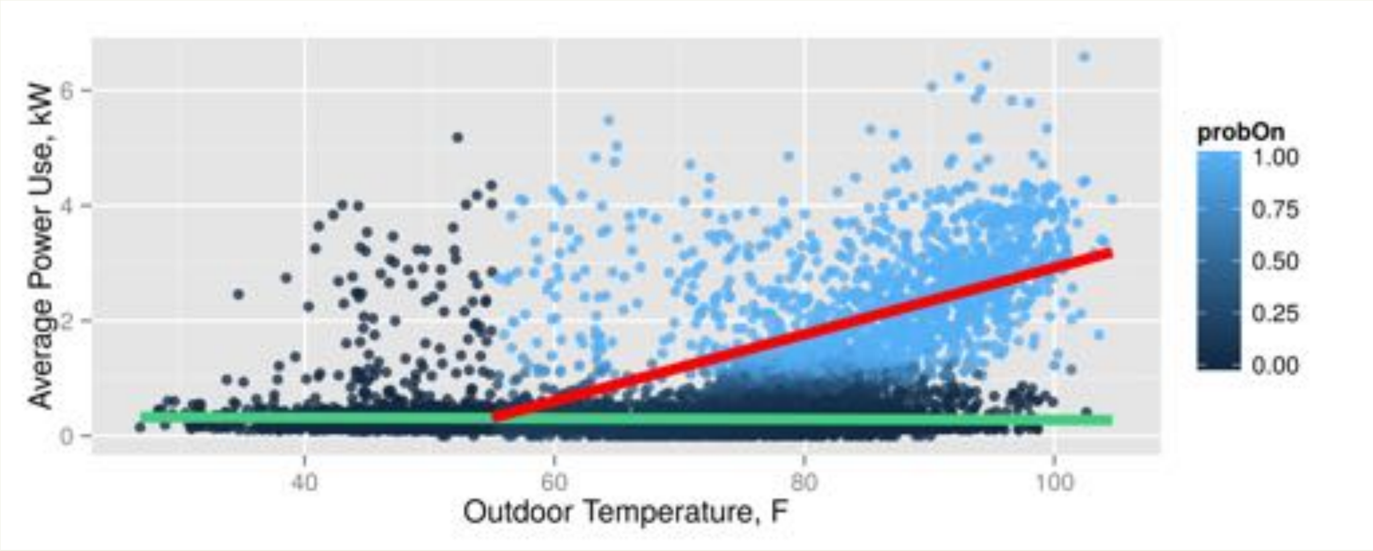
AMI data Models

Change point + classification models

Similar to models used in (Dyson et al. 2014; Albert and Rajagopal, 2014)

Observations above the change point may or may not be in a cooling state.

Change Point Only	Intersecting	Hourly Data	Gaussian Errors
Classification	Cooling Intercept	Daily Data	Kernel Errors



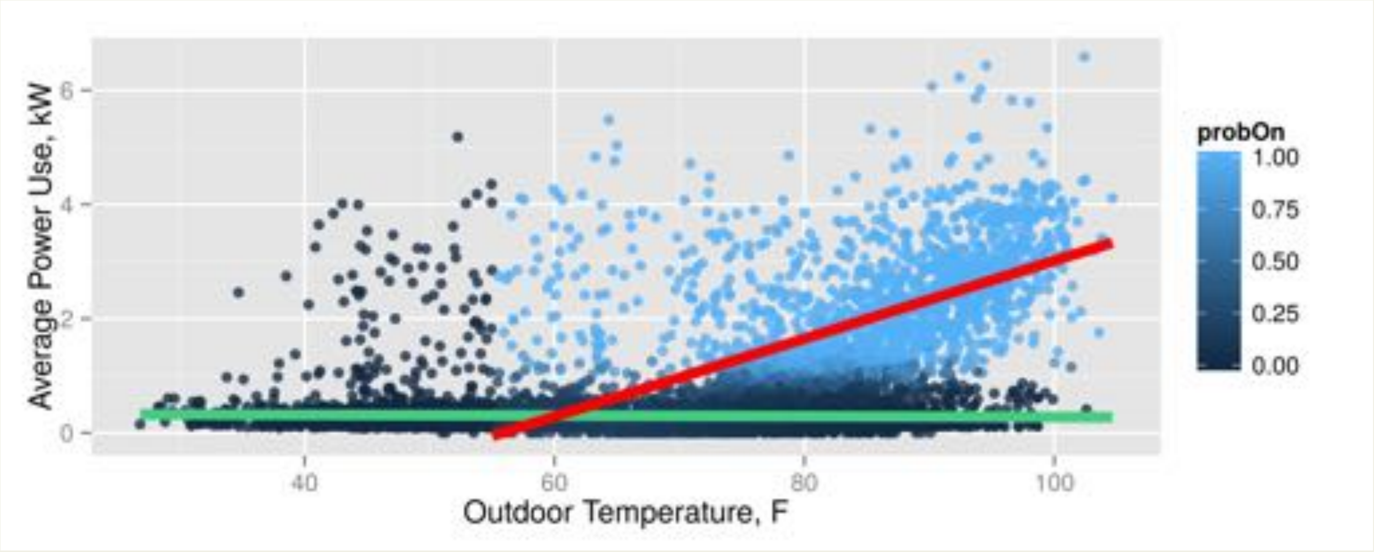
AMI data Models

Intercept for cooling times

Allows the cooling energy to be non-zero at the change point.

Difficult to assign physical significance value when it is negative

Change Point Only	Intersecting	Hourly Data	Gaussian Errors
Classification	Cooling Intercept	Daily Data	Kernel Errors



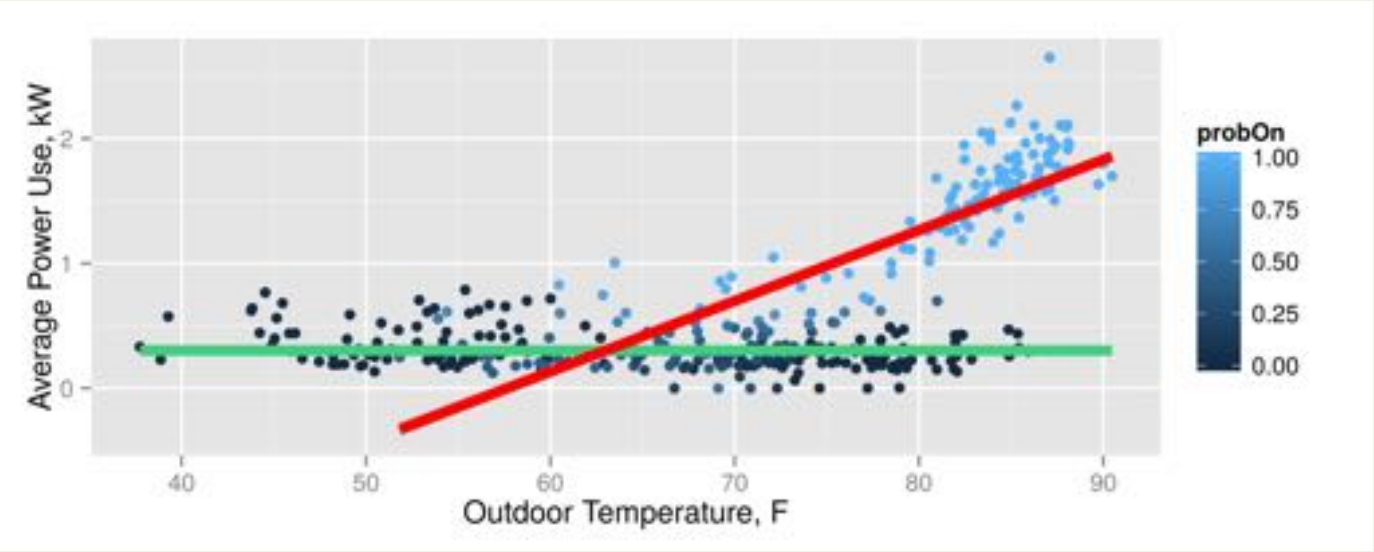
AMI data Models

Daily data

Regress onto cooling degree hours instead temperature above change point

May average out specious correlations due to diurnal effects

Change Point Only	Intersecting	Hourly Data	Gaussian Errors
Classification	Cooling Intercept	Daily Data	Kernel Errors



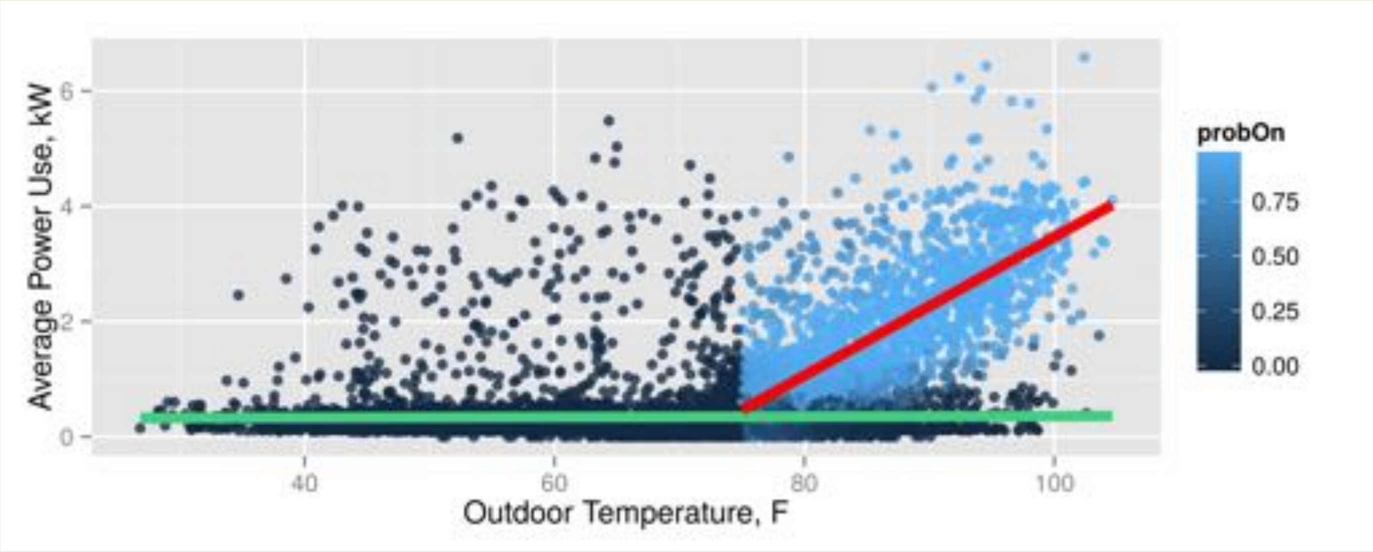
AMI data Models

Kernel density errors

Assess probability of residuals using a kernel density estimator.

Reduces the effect of outliers on the classification of ON/OFF.

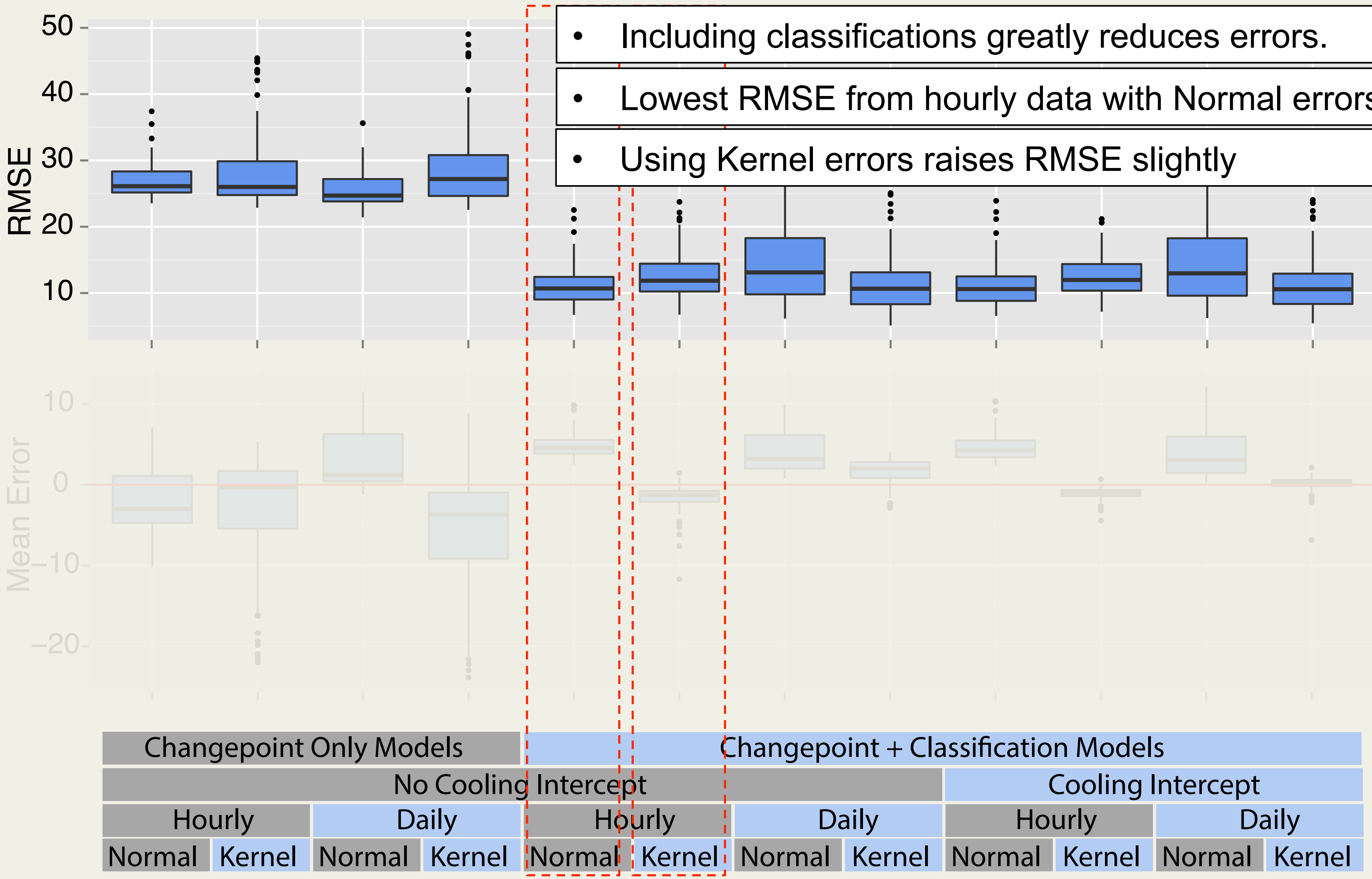
Change Point Only	Intersecting	Hourly Data	Gaussian Errors
Classification	Cooling Intercept	Daily Data	Kernel Errors



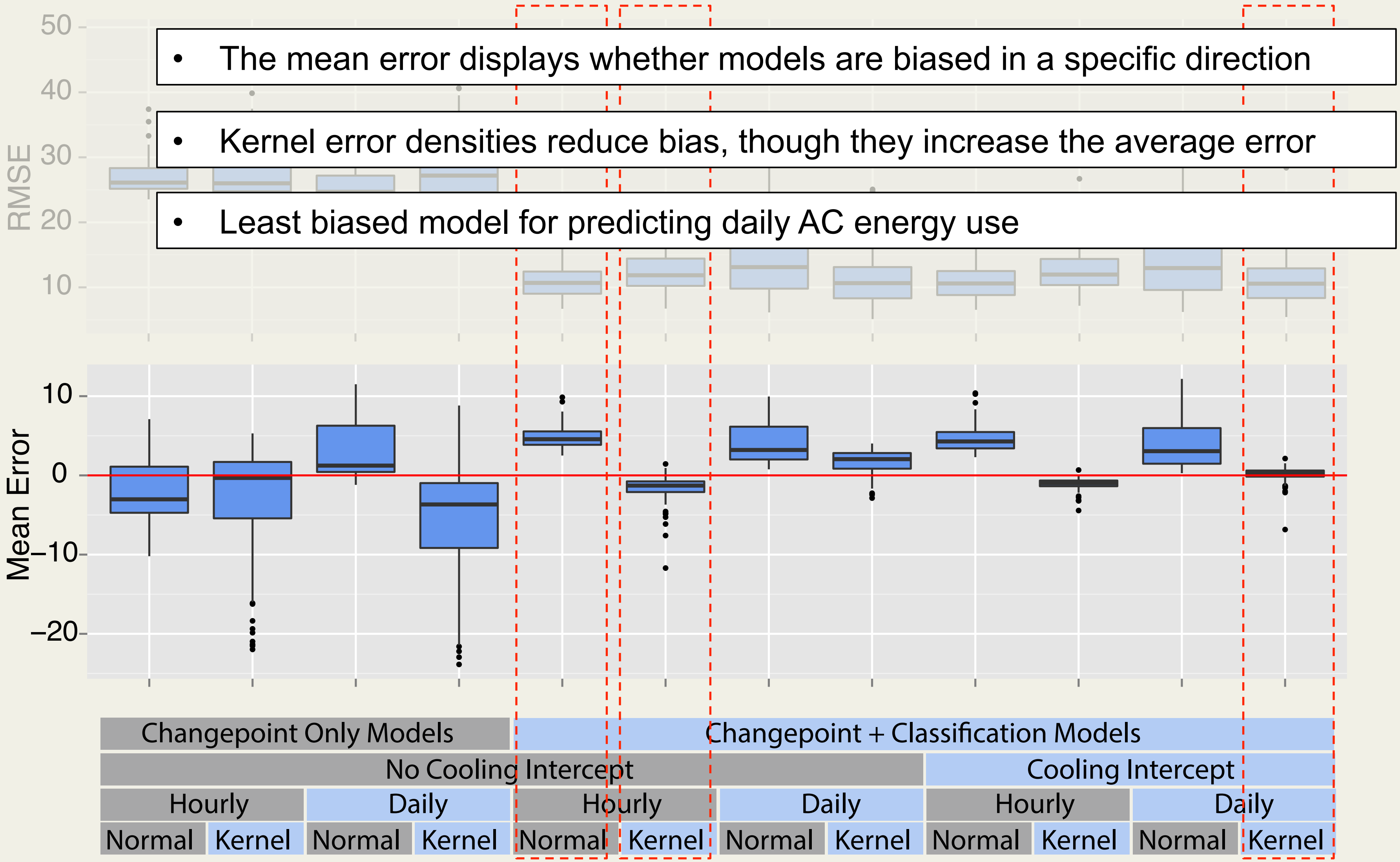
RESULTS

Prediction of Daily AC Energy Use

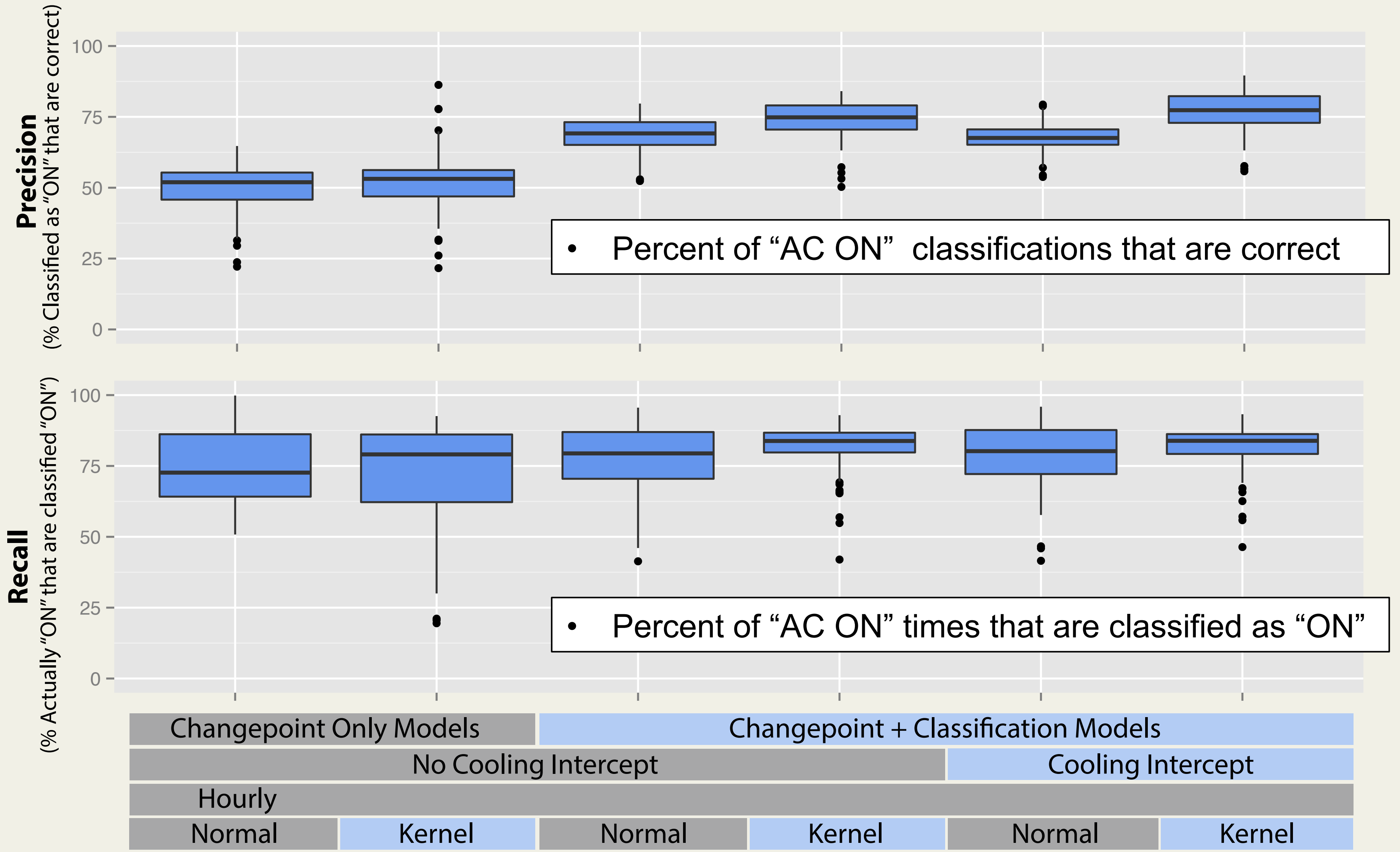
- Including classifications greatly reduces errors.
- Lowest RMSE from hourly data with Normal errors
- Using Kernel errors raises RMSE slightly



Prediction of Daily AC Energy Use

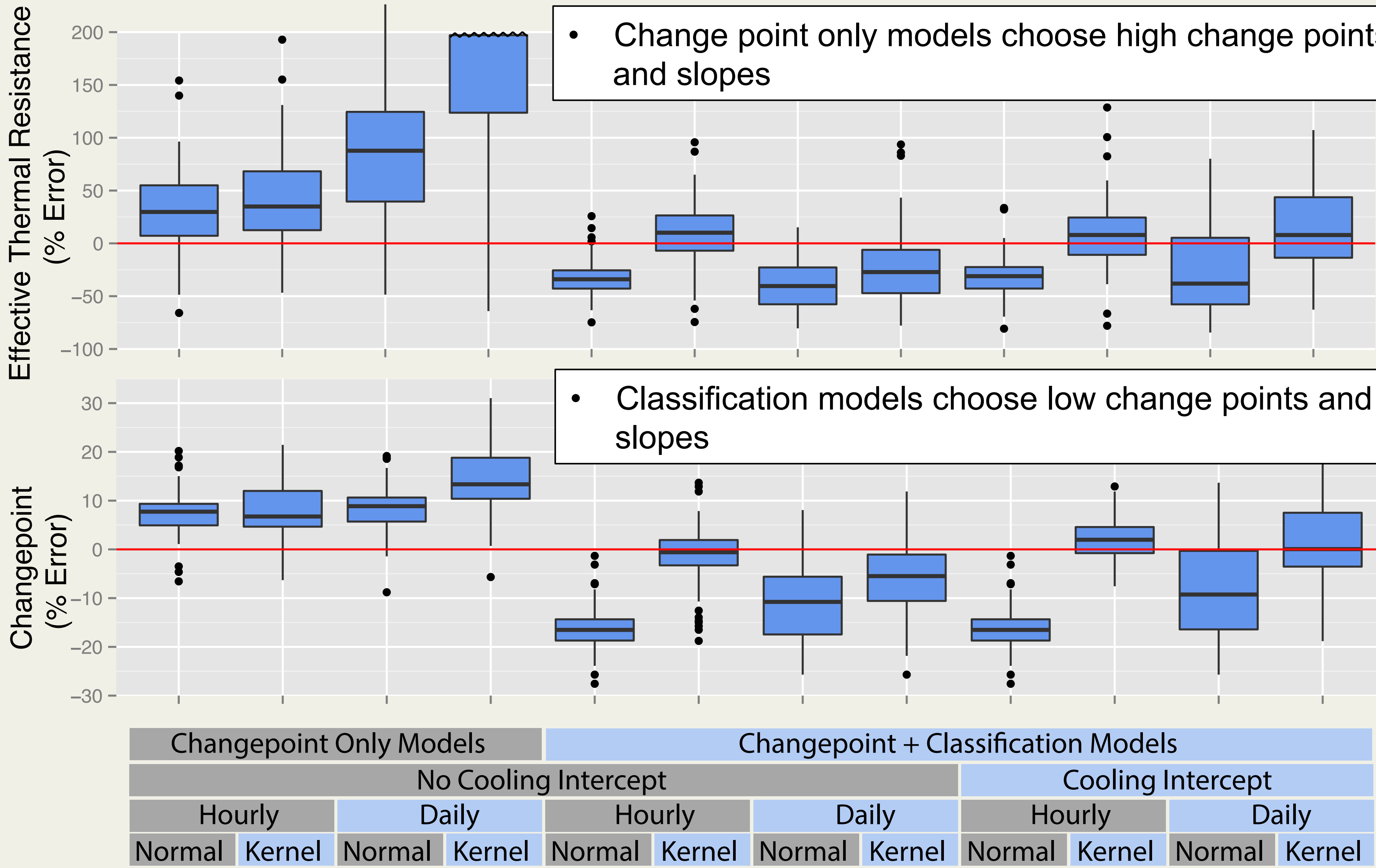


AC ON/OFF, Hourly



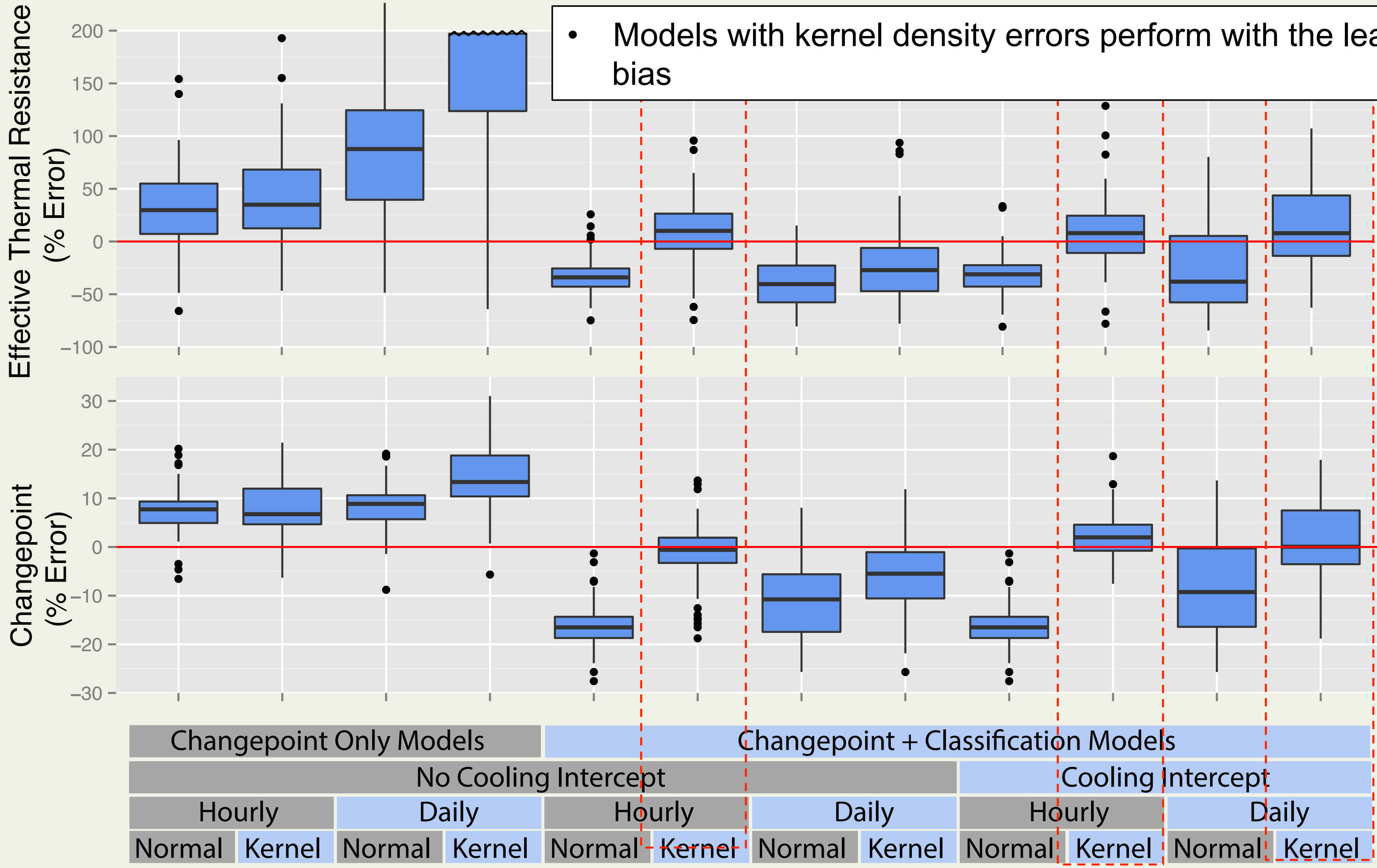
Thermal Resistance and Change points

- Change point only models choose high change points and slopes
- Classification models choose low change points and slopes



Thermal Resistance and Change points

- Models with kernel density errors perform with the least bias



Concluding Remarks

Minimizing square or absolute errors may not give the best models

Additional detail is not always helpful.

Best arrangement we've found so far…

Endogenously classify readings by cooling mode, and to use a kernel density to estimate error distribution shapes.

Enabling new future research

Thank You

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