Model Averaging for Probabilistic Time Series Forecasts

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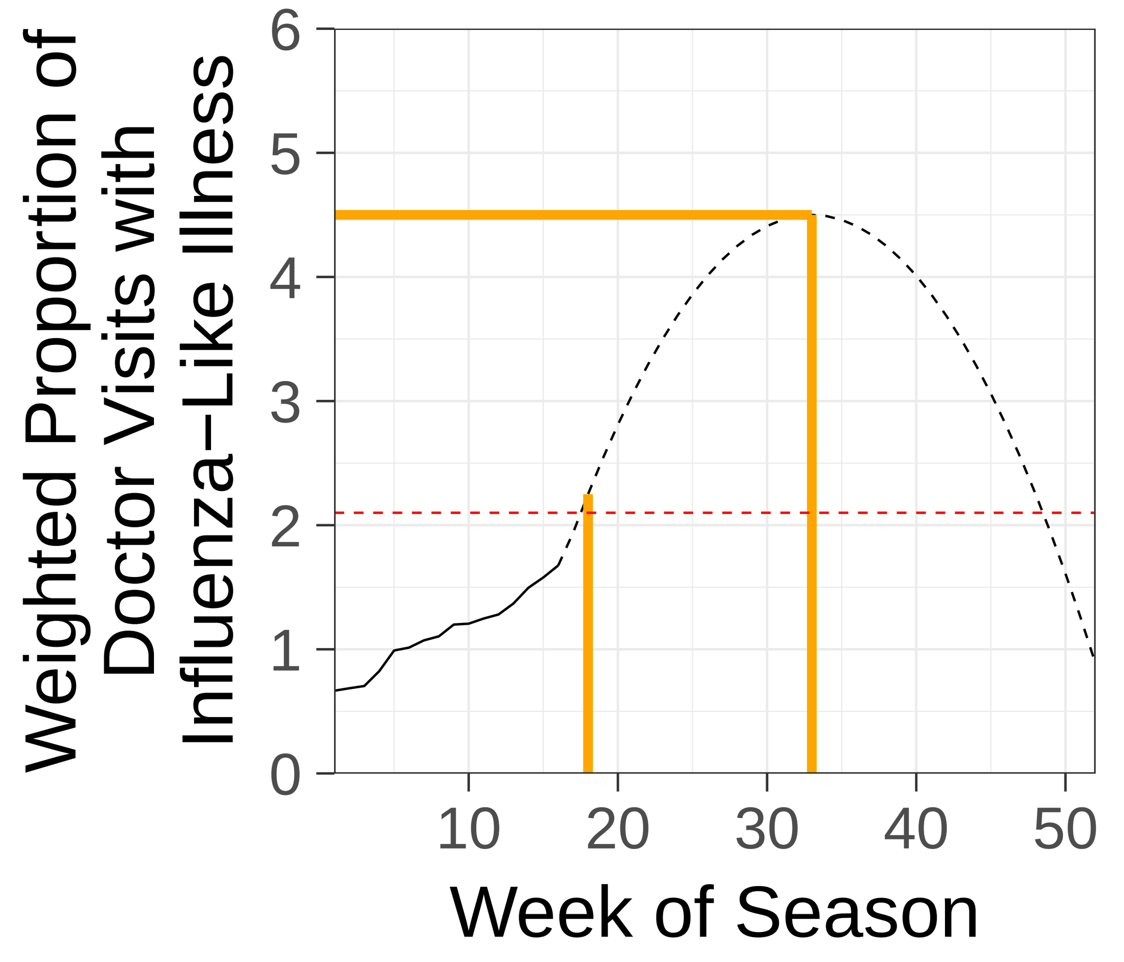
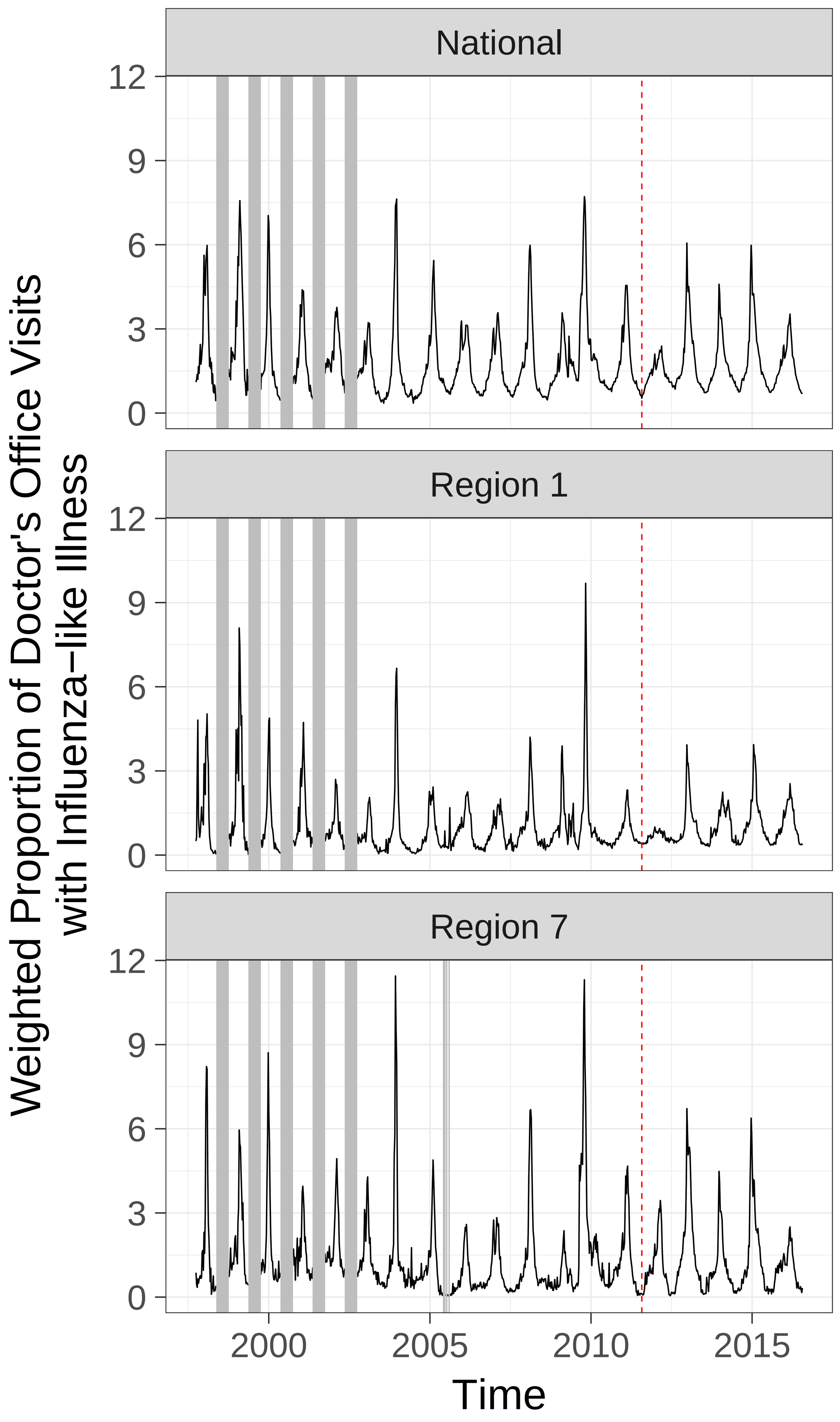
Introduction

- Predictions of infectious disease are helpful to public health decision makers.
- We focus on three quantities:
  1. timing of season onset
  2. timing of season peak week
  3. incidence in season peak week



- Predictions updated weekly.
- Relative performance of different models varies.
- Can we combine predictions from these models to improve performance?

Data



Component Models

- Our ensembles combine predictions from three component models:
  1. Kernel Density Estimation (KDE)
     - separate distribution estimates for each target based on observed values in training-phase seasons
     - predictions do not change over the season
  2. Kernel Conditional Density Estimation (KCDE) with Copulas
     - KCDE: separate predictive distributions for flu incidence in each future week of the season given recent observations of wILI and the current week of the season.
     - Copula: model dependence among incidence in different weeks
     - Get predictive distributions for onset timing, peak timing, and peak incidence as integrals of joint distribution for incidence in all remaining weeks
  3. Seasonal Auto-Regressive Integrated Moving Average (SARIMA)
     - Log-transform wILI, first-order seasonal differencing
     - Integrate to obtain predictive distributions for onset timing, peak timing, and peak incidence as with KCDE

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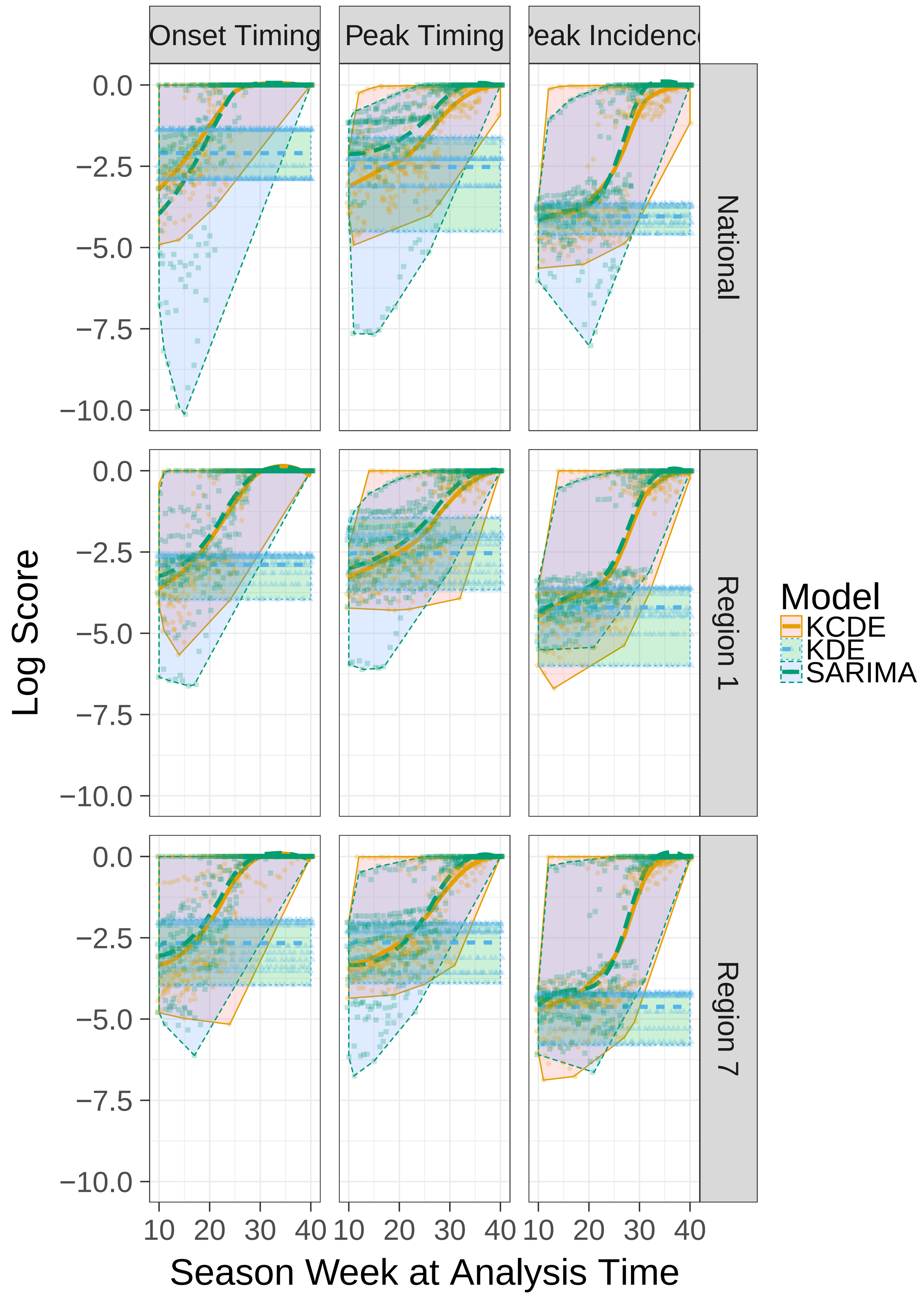
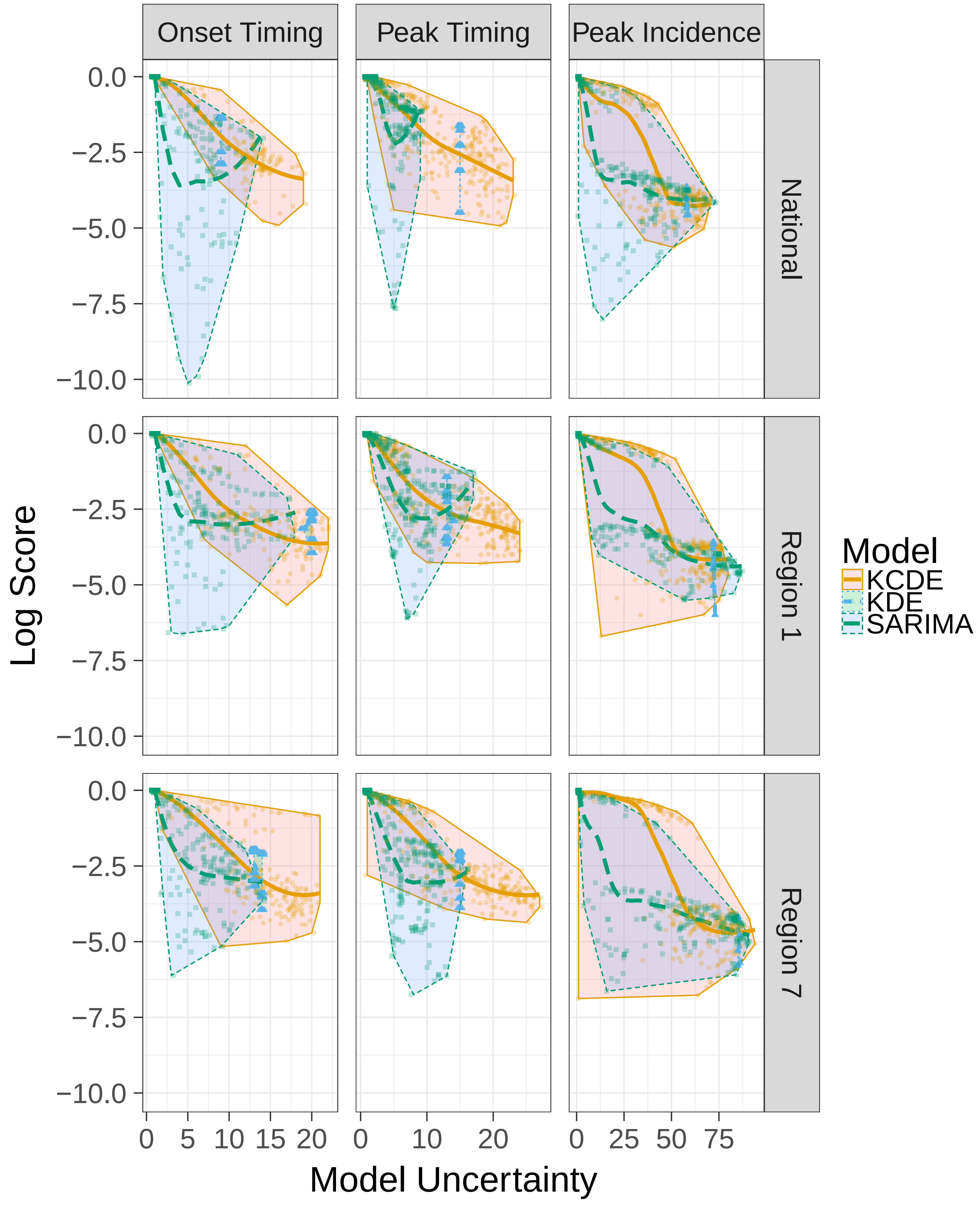
Performance Varies with Week

Log Scores vs.
Season Week at Analysis Time



Performance Varies with Uncertainty

Log Scores vs. Model Uncertainty



Ensemble Models

- The ensemble models we consider are *weighted averages* of the component models:

$$f(y|\mathbf{x}) = \Sigma_{m=1}^{M} \pi_m(\mathbf{x}) f_m(y|\mathbf{x}), \text{ where}$$

  - y is a possible value for one of the prediction targets
  - $\mathbf{x}$ is a vector of covariates such as recent incidence, time of year at which we are making the predictions, ...
  - $f_m(\cdot)$ are predictive distributions from $M = 3$ component models
  - $\pi_m(\mathbf{x})$ are model weights with $\Sigma_{m=1}^{M} \pi_m(\mathbf{x}) = 1 \, \forall \mathbf{x}$
- We consider six variations:

	Component Model Weights Vary with...					
Model	Region	Prediction Target	Week of Season	SARIMA Uncertainty	KCDE Uncertainty	Current wILI
EW						
CW	X	X				
FW	X	X	X	X	X	
FW-reg-w	X	X	X			
FW-reg-wu	X	X	X	X	X	
FW-reg-wui	X	X	X	X	X	X

- Weighting functions estimated via gradient tree boosting

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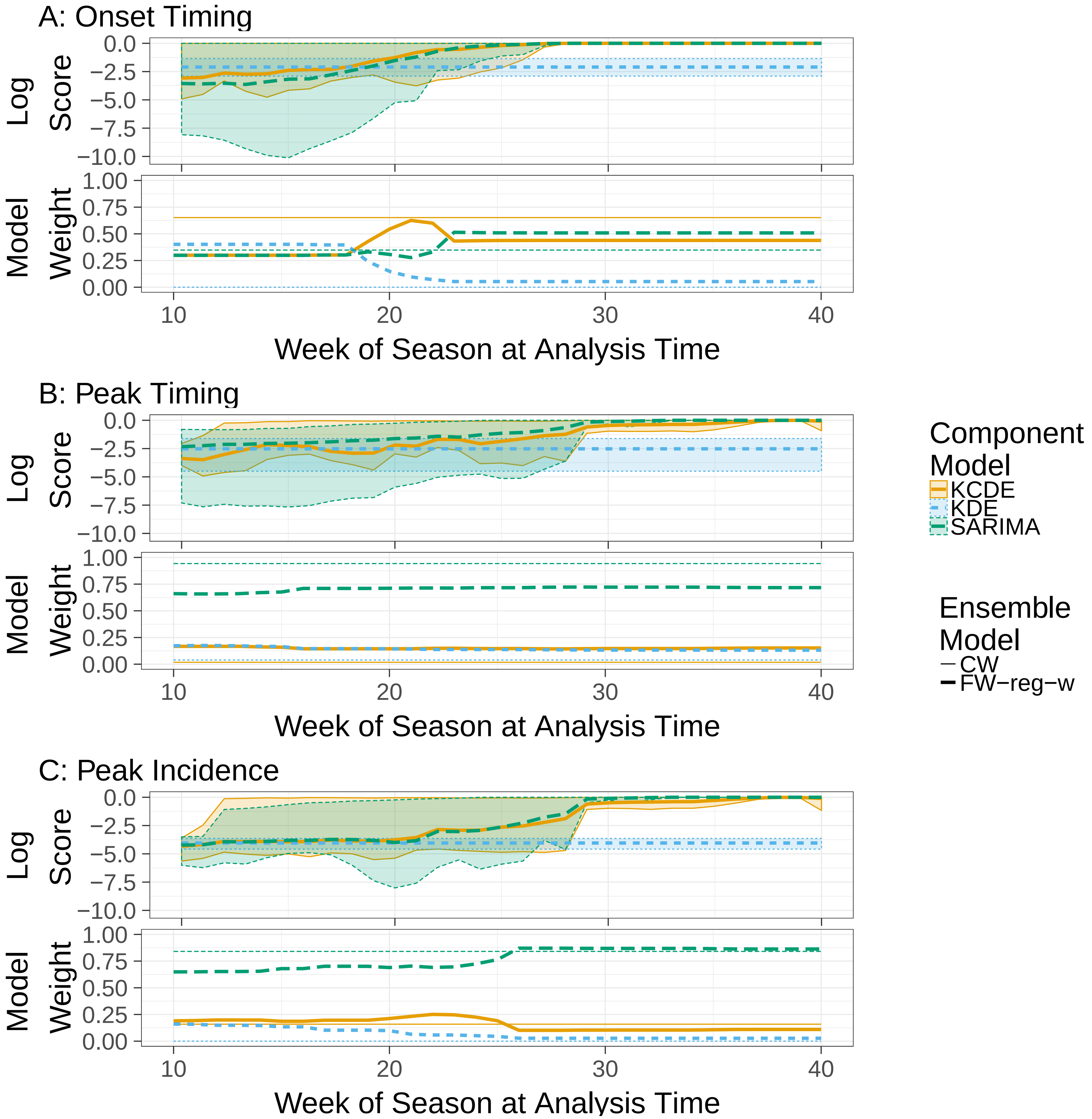
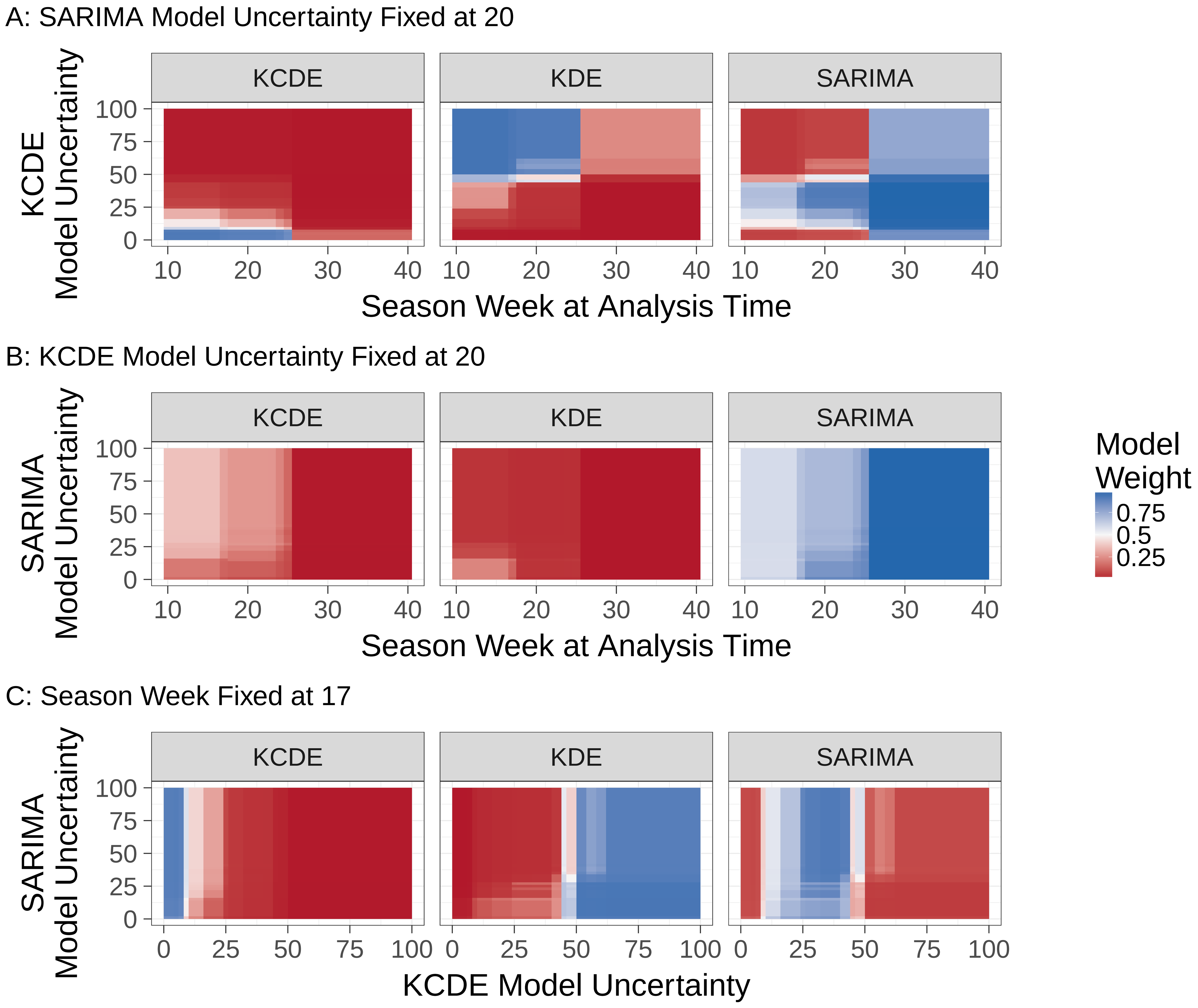
Weights as a Function of Week



Weights as a Function of Week & Uncertainty



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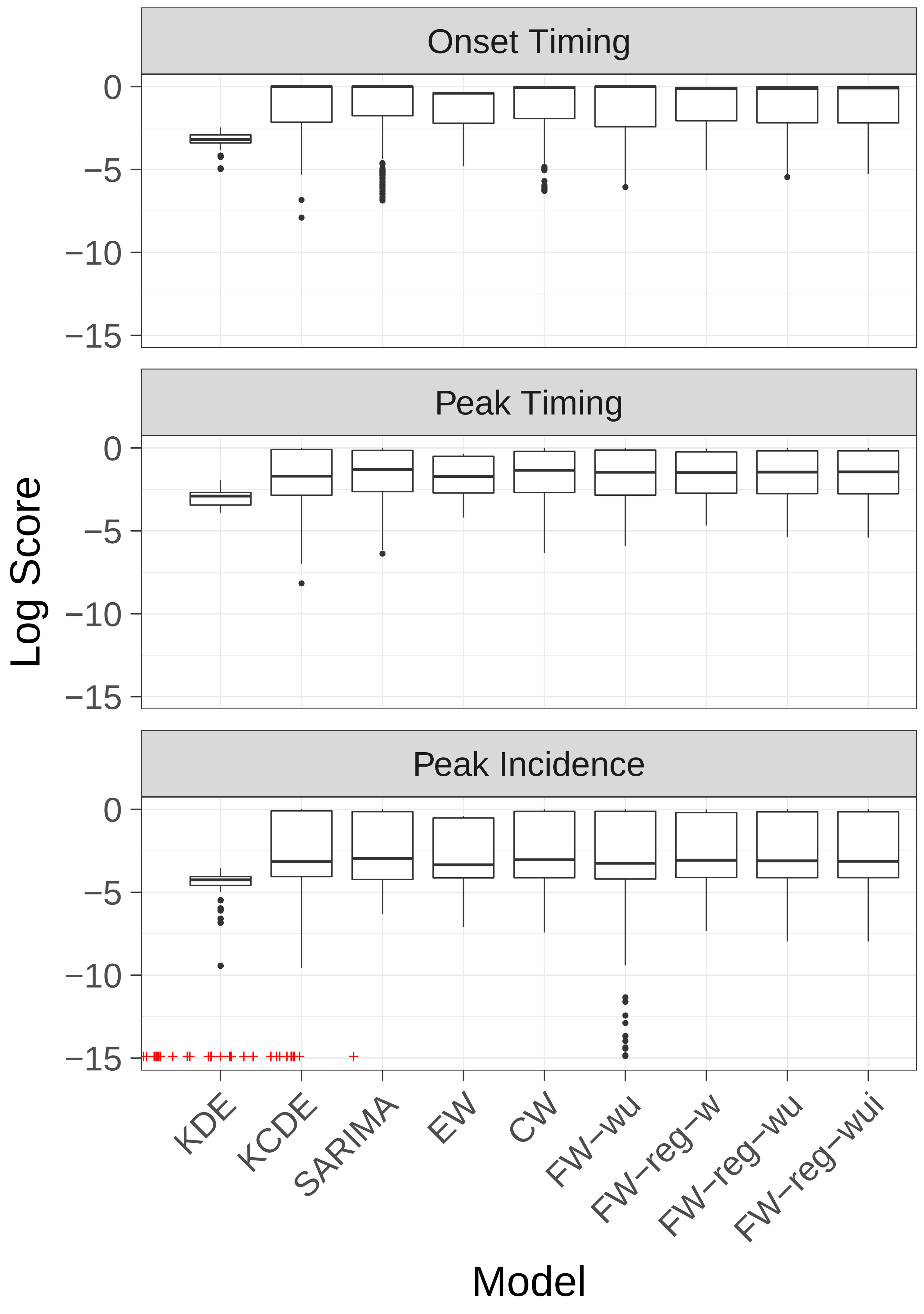
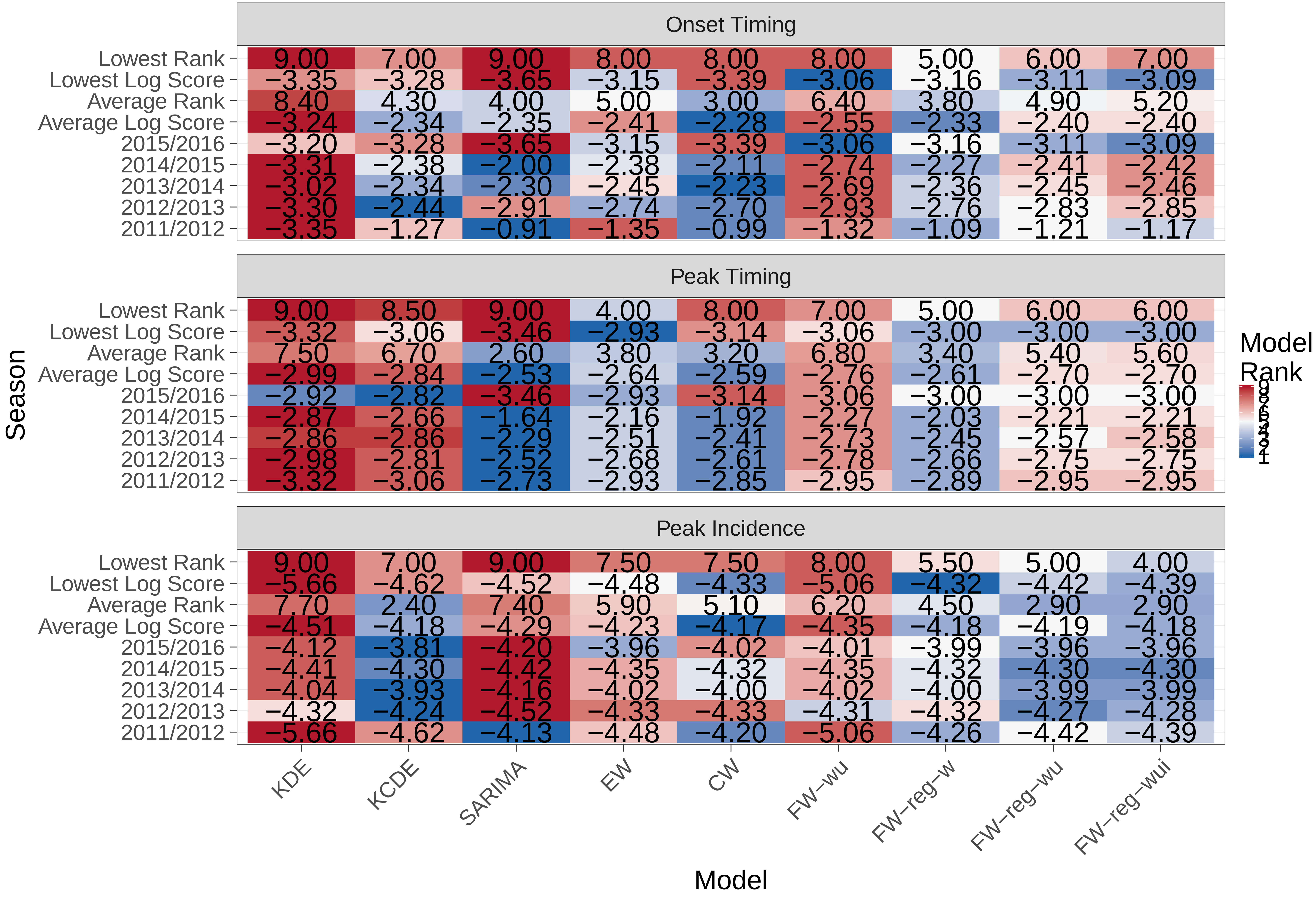
Aggregated Results – All Regions and Test Phase Seasons



Results By Test Phase Season



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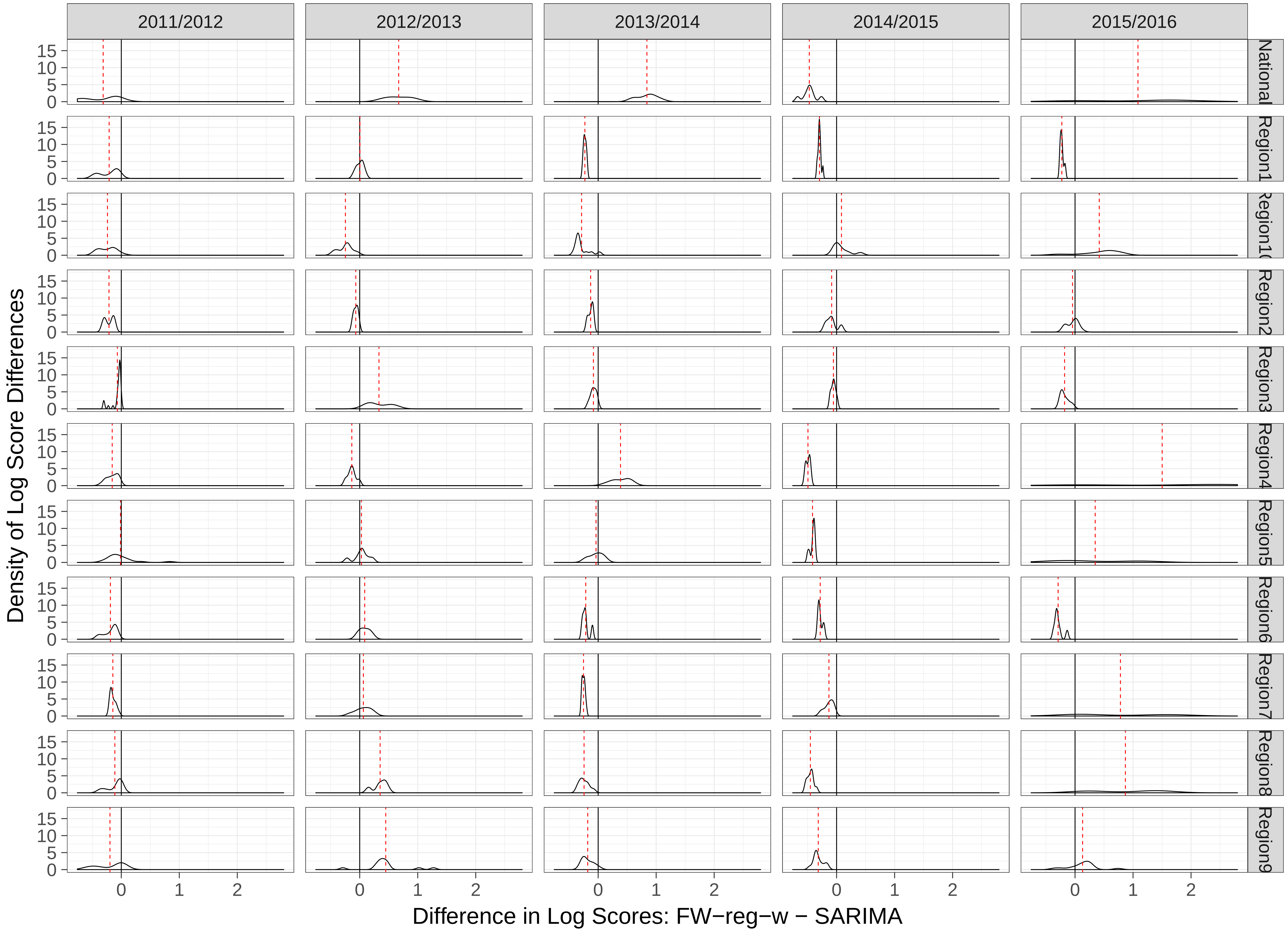
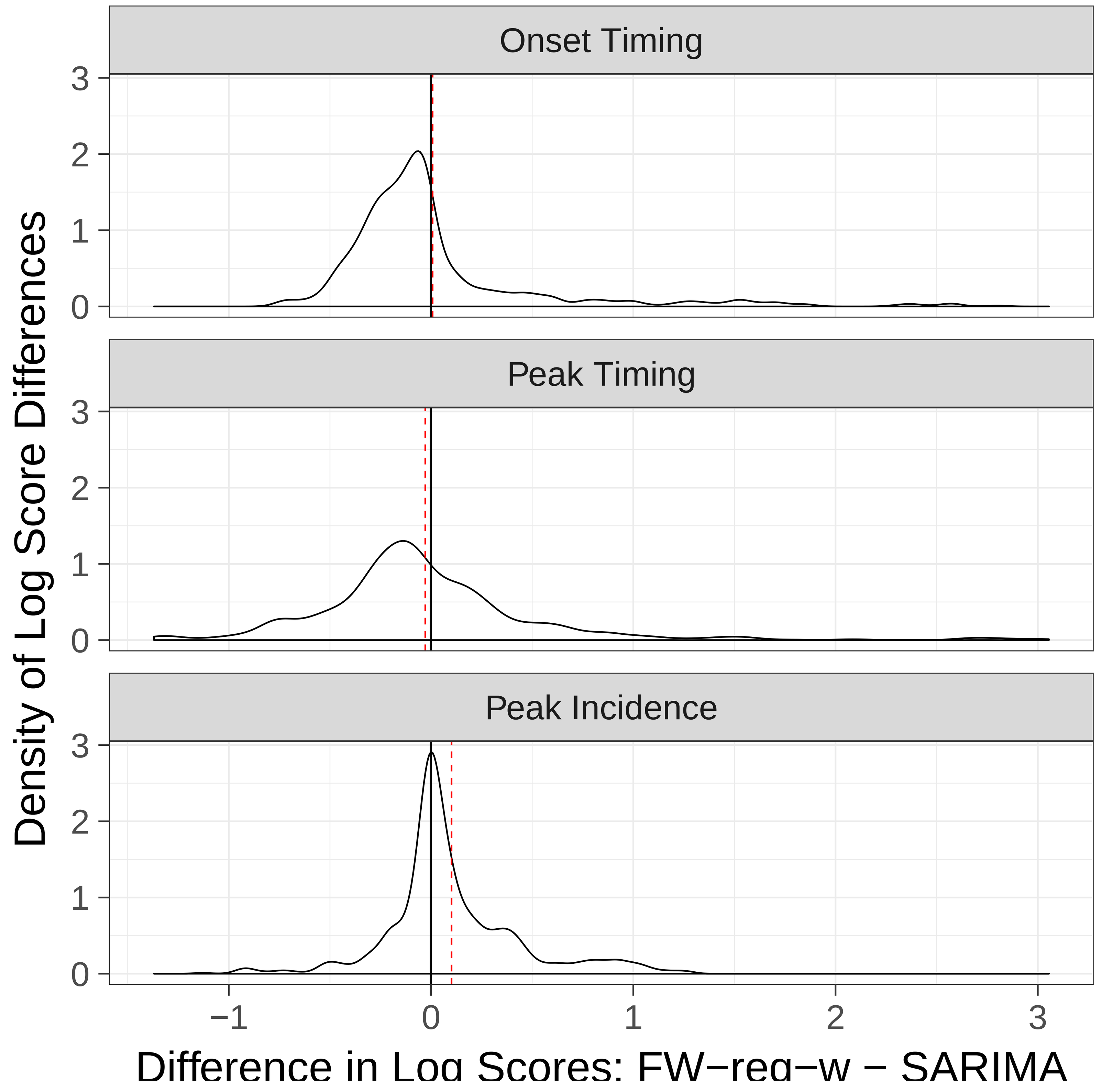
Log Score Differences for Onset Timing via SARIMA and FW-reg-w



Log Score Differences for SARIMA and FW-reg-w



Conclusions

- Ensemble methods had similar performance as the best of the component models in aggregate
- Ensemble methods had more stable performance across region-seasons than the component models
- In future work, would benefit from using a more diverse set of component models.