SPACE-TIME INFECTIOUS DISEASE MODELING, NOWCASTING, COUNTERFACTUALS AND NPIS

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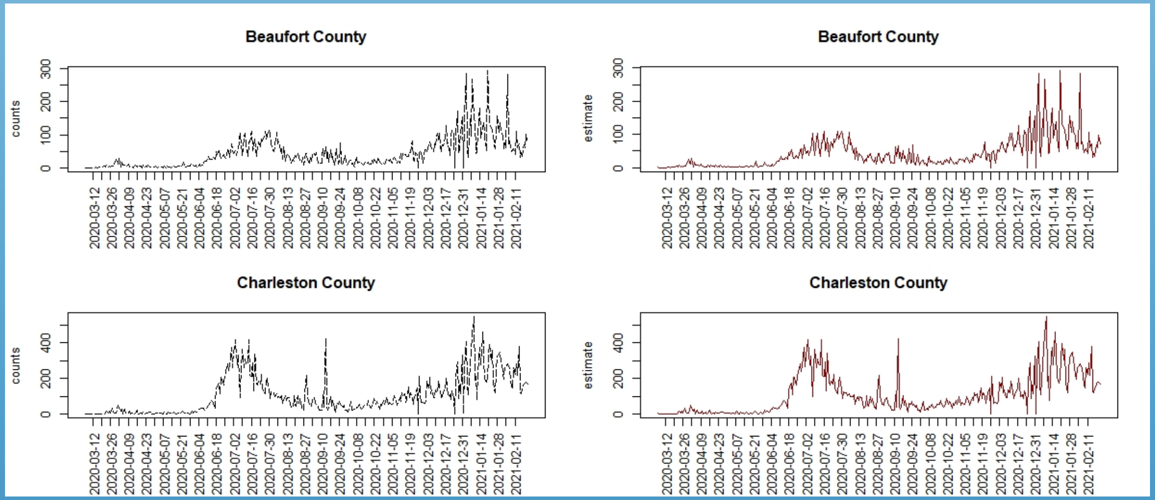
BACKGROUND

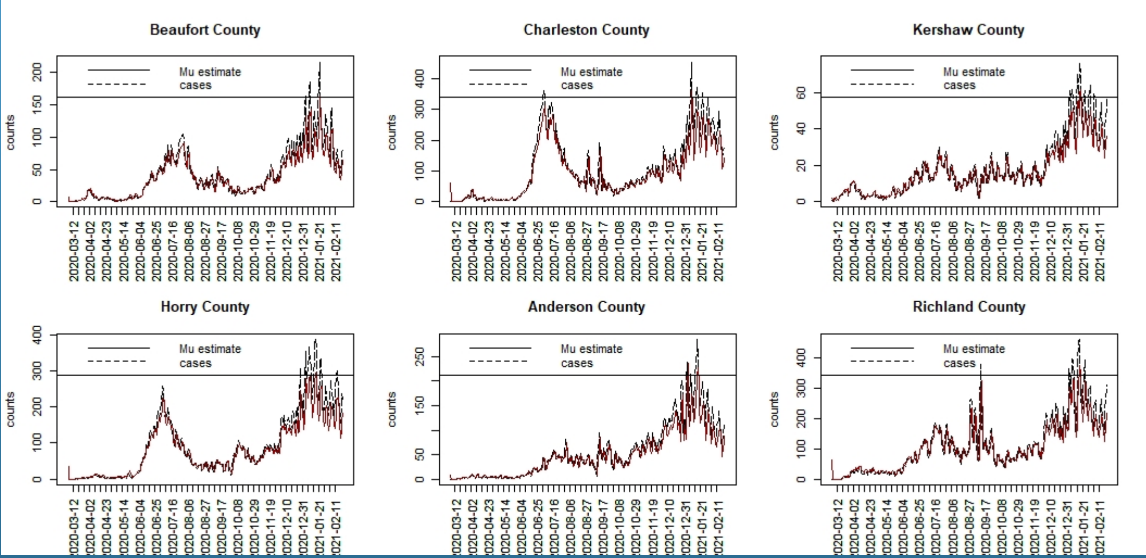
- Infectious disease (ID) modeling in space-time has received growing interest during the Covid-19 pandemic
- Daily data on case numbers and deaths /hospitalisations are available around the globe
- In addition Google mobility data is also available on a daily basis

SPATIO-TEMPORAL ID MODELING

- Descriptive RE models: mimic the behavior of ID by using random effects
  - This can be effective in providing very good fits

- Mechanistic SIR models: include transmission dynamics
- And can include spatial terms either as confounders (ICAR models) or as neighborhood sum terms.

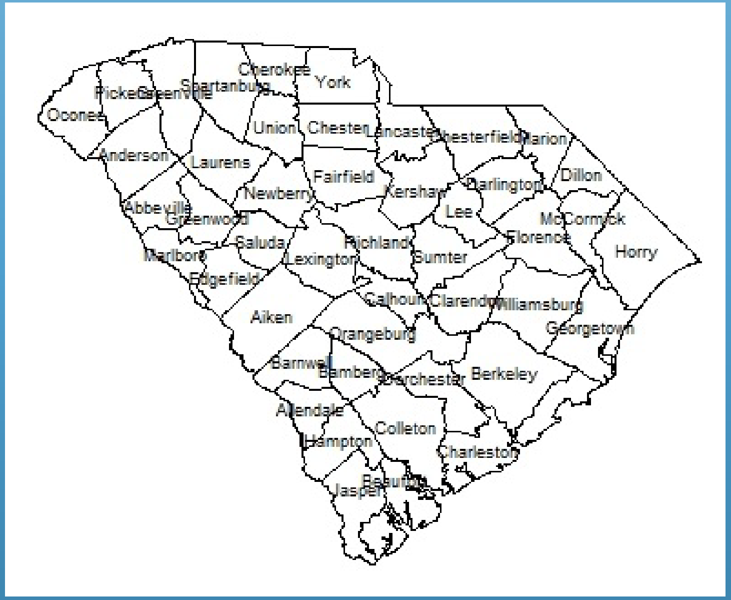


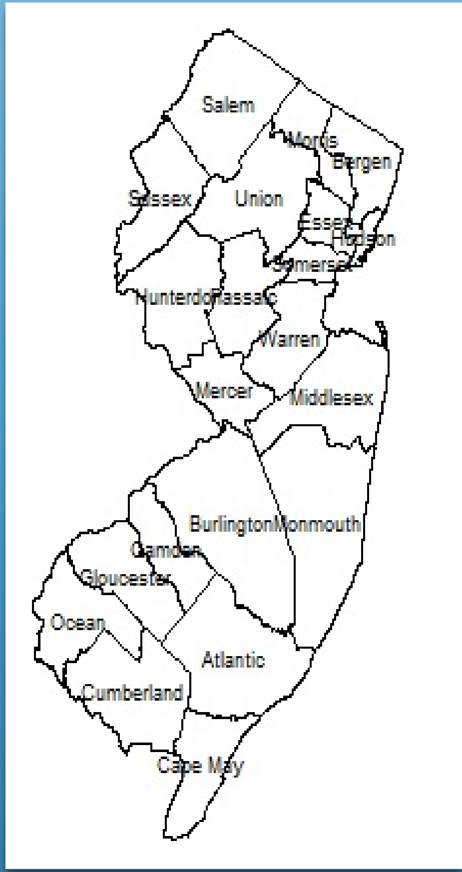


COVID-19 AND NON-PHARMACEUTICAL INTERVENTIONS (NPIs)

- Common NPIs in pandemic involve lockdowns
- Lockdowns both partial or complete
- Release from lockdown

- Some issues in determining effects of lockdowns
- Comparison of different public health policy areas
  - South Carolina and New Jersey





PREDICTION, GOODNESS OF FIT AND PROSPECTIVE/RETROSPECTIVE MODELING

- Prediction is of great importance in time series modeling.
    - Questions like "How well can I predict the next time" etc
    - Predictive capability is not the same as goodness –of-fit (GOF)
        - A model with good predictive capability may not be the best model in terms of GOF
- Prospective modeling (real time) may not provide as good explanation as retrospective descriptive model

MODEL FORMULATION

- Data model including a spatial setting (daily case counts)

$$y_{ij} \sim f(\mu_{ij})$$

$$E(y_{ij}) = \mu_{ij}$$

$$f(\mu_{ij}) : \text{Poisson}(\mu_{ij})$$

MODELLING CONSTRUCTS

- Transmission model
  - Observed new infectives at *i* th location and time *j* : y_{ij}
  - True infective count at *i* th location and time *j*: I_{ij}
  - Susceptible pool at *i* th location and time *j* : S_{ij}
  - Removal at *i* th location and time *j* : R_{ij}
- Accounting equation
  - Idealised

$$S_{ij} = S_{i,j-1} - I_{i,j-1} - R_{i,j-1}$$

SIR MODEL INGREDIENTS

- Mean model

$$\mu_{ij} = S_{ij}\, exp(\, p^{r}_{i,j-1}\,)$$
$$p^{r}_{i,j-1} = propagator$$

- Propagator is a function of the previous counts locally and from neighborhoods as well as other factors (such as predictors or random effects)
- A simple lag model could be: $p^{r}_{i,j-1} = \alpha_0 + \alpha_1 log(\, y_{i,j-1}\,) + v_i$

BEST SC WAIC MODEL (5A)

$$p^{r}_{i,j-1} = \alpha_0 + \alpha_1 log(y_{i,j-1}) + \alpha_2 log(\sum_{k \in \delta_i} y_{k,j-1}) + v_i$$

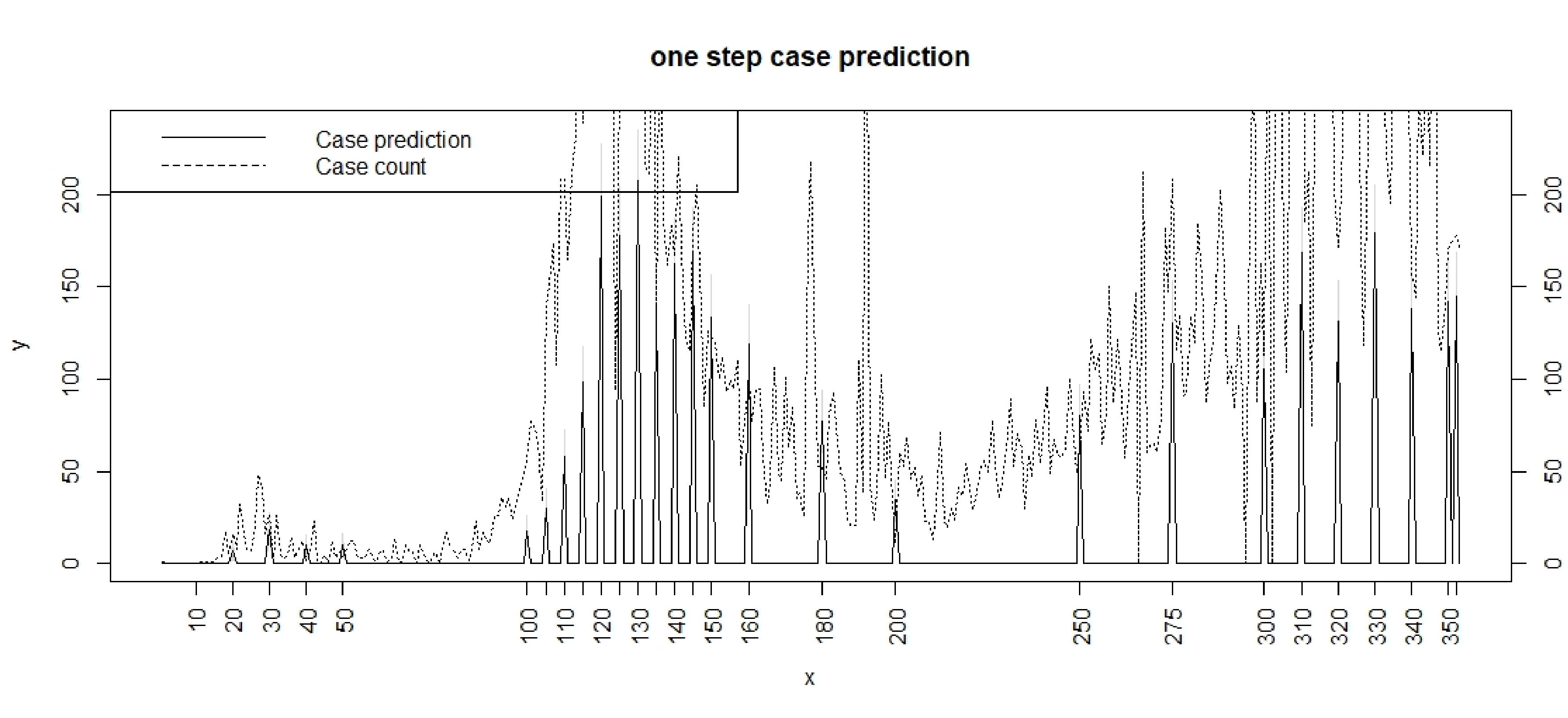
- Assumes 20% asymptomatic rate
- Includes previous case count
- Neighborhood previous total case count
- Unstructured random effect
- **Lawson, A. B.** and Kim, J. (2022) Bayesian Space-time SIR modeling of Covid-19 in two US states during the 2020/2021 pandemic. PlosOne 17(12): e0278515. https://doi.org/10.1371/journal.pone.0278515

ONE STEP PREDICTION

- Assume that we have retrospective counts and can fit any model at a given time
- We know the best model overall for a given study area
- However we don't know this at previous times
- What we can do is make predictions at different time horizons in the past and see if the model holds well
- Unfortunately the best model for prediction varies over time!
- In SC the time horizons we looked at were (in days)

10,20,30,40,50,100,105,110,115,120,125,130,135,140,145,150,160,180,200,250,275,300,310,320,330,340,350,352

CASE COUNT ONE STEP PREDICTION



DEATH MODELS

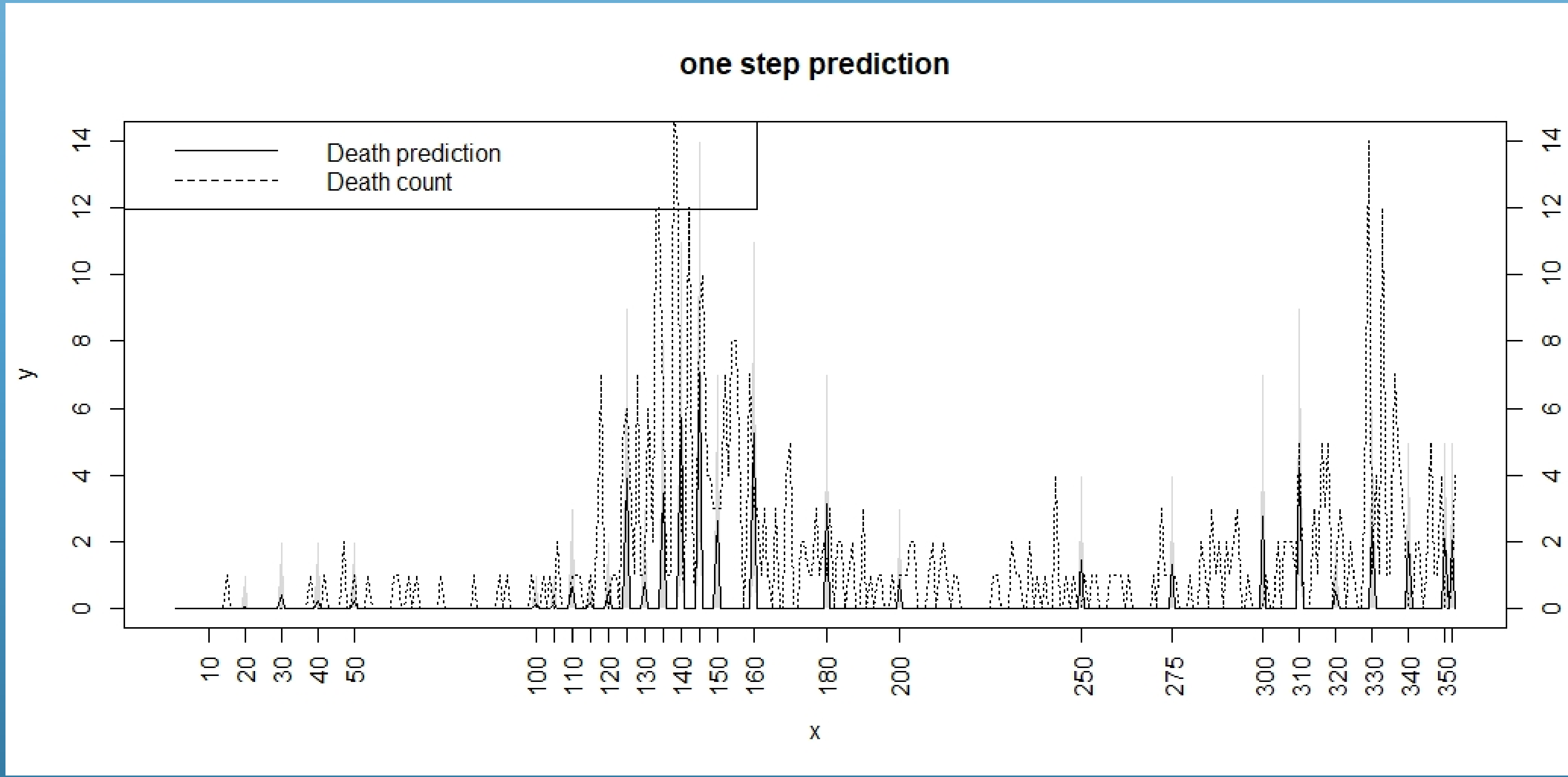
Death models are assumed to be dependent on case counts and cumulative cases

$$d_{i,j} \sim Pois(\mu_{ij}^{d})$$

$$log(\mu_{ij}^{d}) = \alpha_0^d + \alpha_{1j}^d \, log(y_{i,j}) + \alpha_{2j}^d \, log(T_{i,j-1}) + v_i^d$$

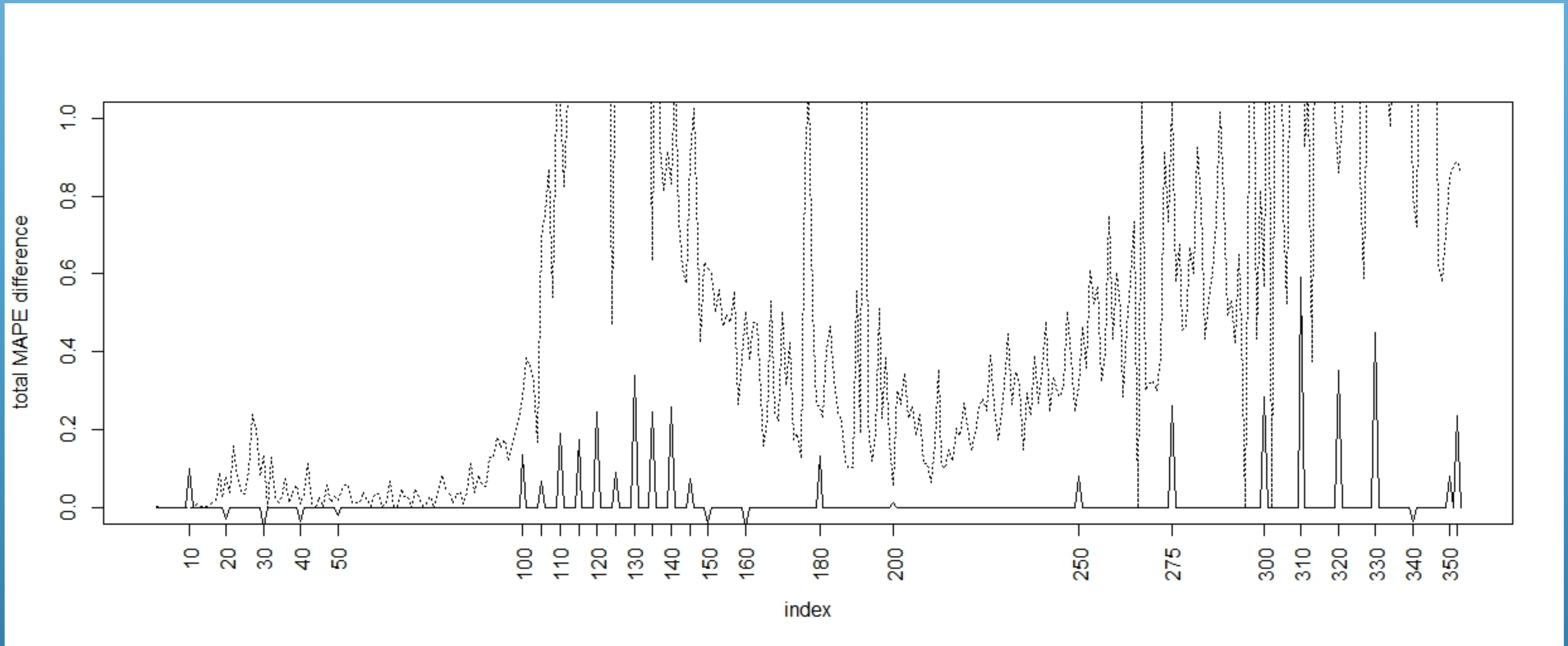
$$where \;\; T_{ij} = \sum_{k=1:j} y_{i,k}$$

DEATH COUNT ONE STEP PREDICTION



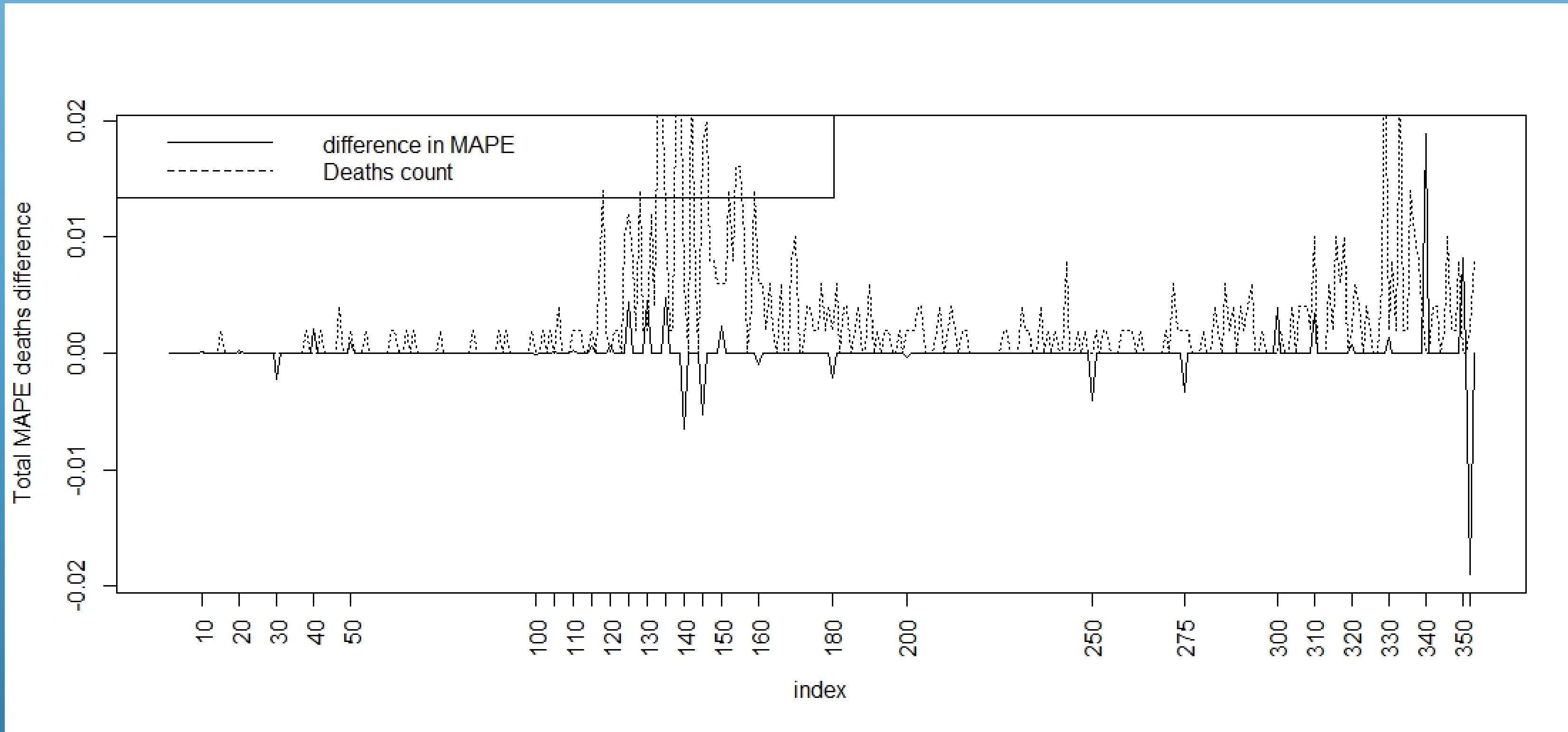
MAPE CASE COUNT DIFFERENCE

- One step difference between simple lag model and best fit neighborhood model



MAPE DEATH COUNT DIFFERENCE

- Death model differences



NOWCASTING AND COUNTERFACTUALS

- Nowcasting is often used to predict incident counts of disease when reporting delays occur.
- Nowcasting has been proposed for NPIs during the pandemic (eg unemployment prediction: Nicholas and Middleton (2021) *Chance*
- However this has not been applied to spatio-temporal ID modeling

NOWCASTING

- Consider historical data on cases, a good model*, and fix a time (T) when prediction is to take place. Then allow unsupervised prediction for K time units
- Essentially use McMC sampling from the converged posterior up to time T
- A large parameter sample is then taken and the SIR model is allowed to evolve to time T+K
- Hence a counterfactual is produced in each region.

- * Lawson, A. B. and Kim, J. (2022) Bayesian Space-time SIR modeling of Covid-19 in two US states during the 2020/2021 pandemic. PlosOne

COUNTERFACTUAL GENERATION

- Case counts

$$\{y_{i,k}^{p}\} \sim Pois(\{\mu_{i,k}\})$$

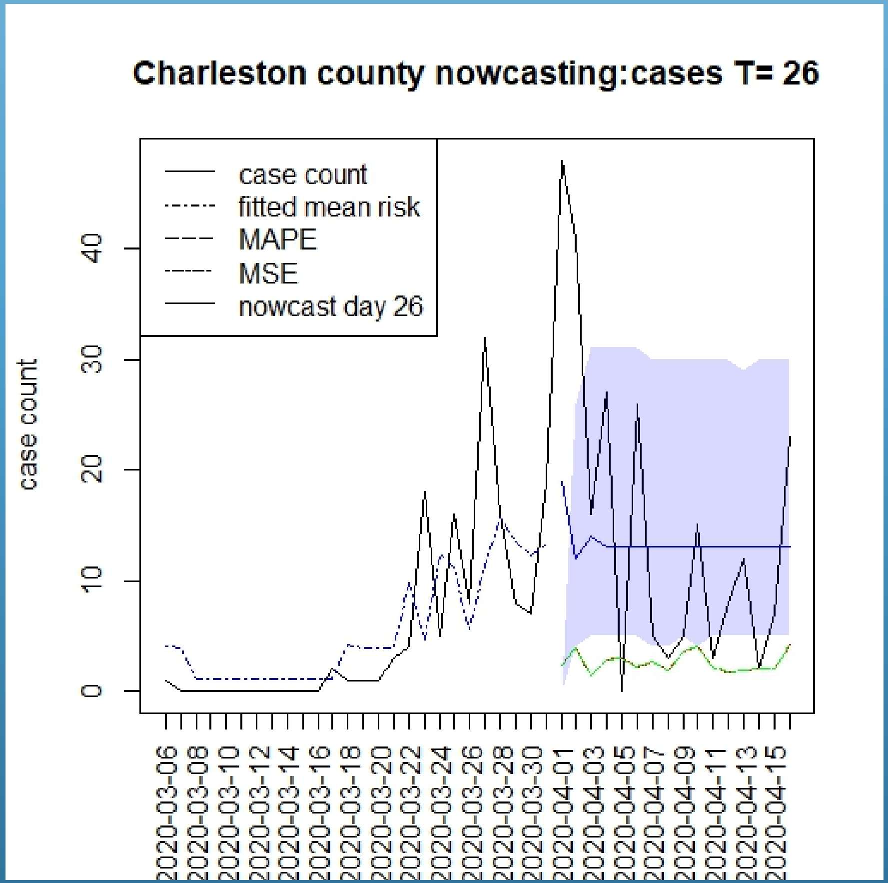
$$\{\mu_{i,k}\} = \{\alpha_0\} + \{\alpha_1\} log(y_{i,k-1}^{p}) + \{\alpha_2\} log(\sum_{l \in \delta_i} y_{l,k-1}^{p}) + \{v_i\}$$

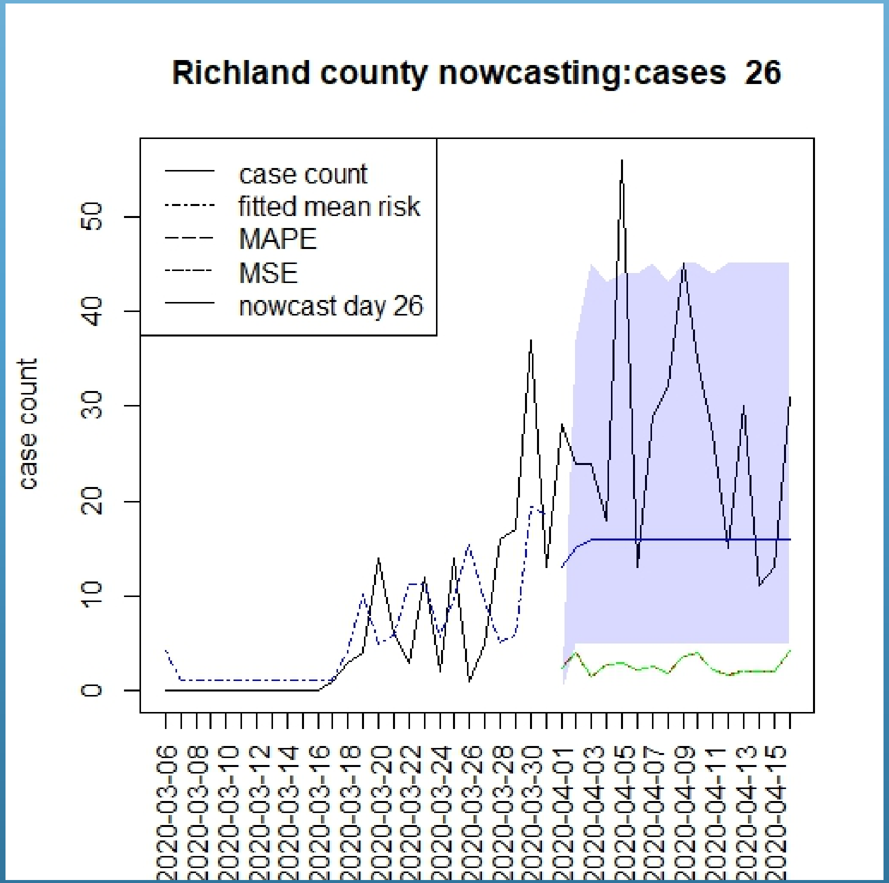
$\{\}$ denoes the sampled parameter set

δ_i is the neighborhood set of the i th region

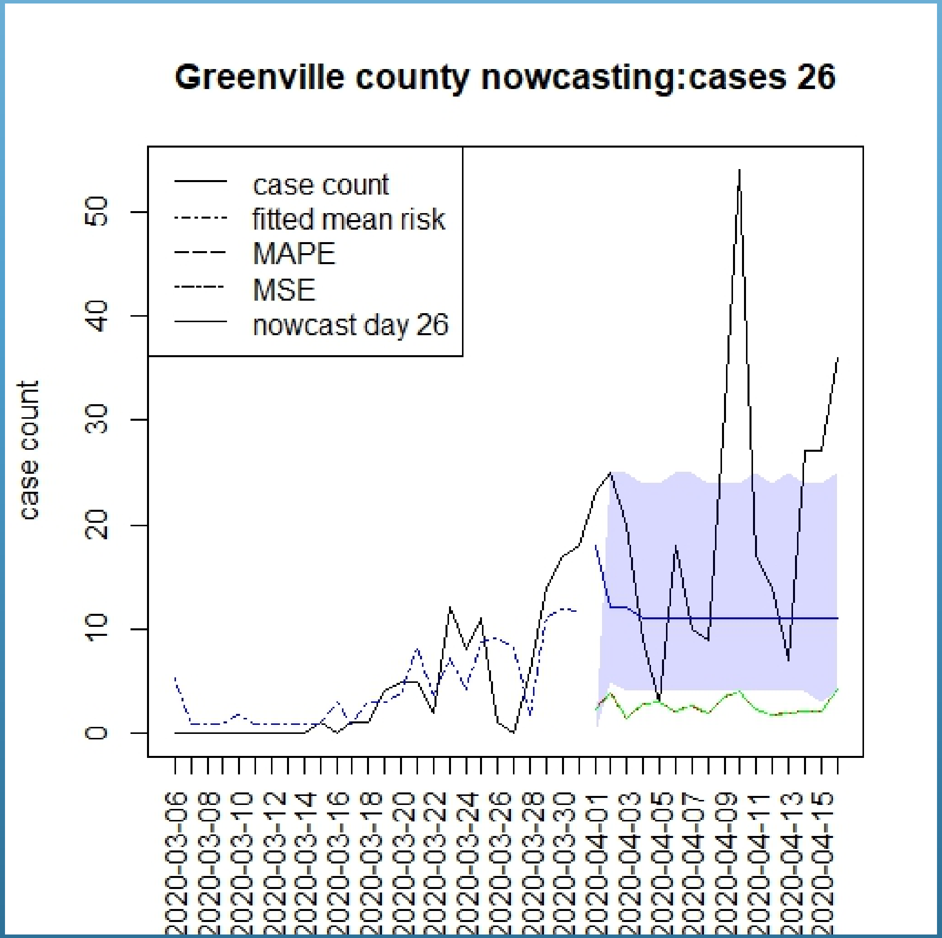
- Similar generation for deaths

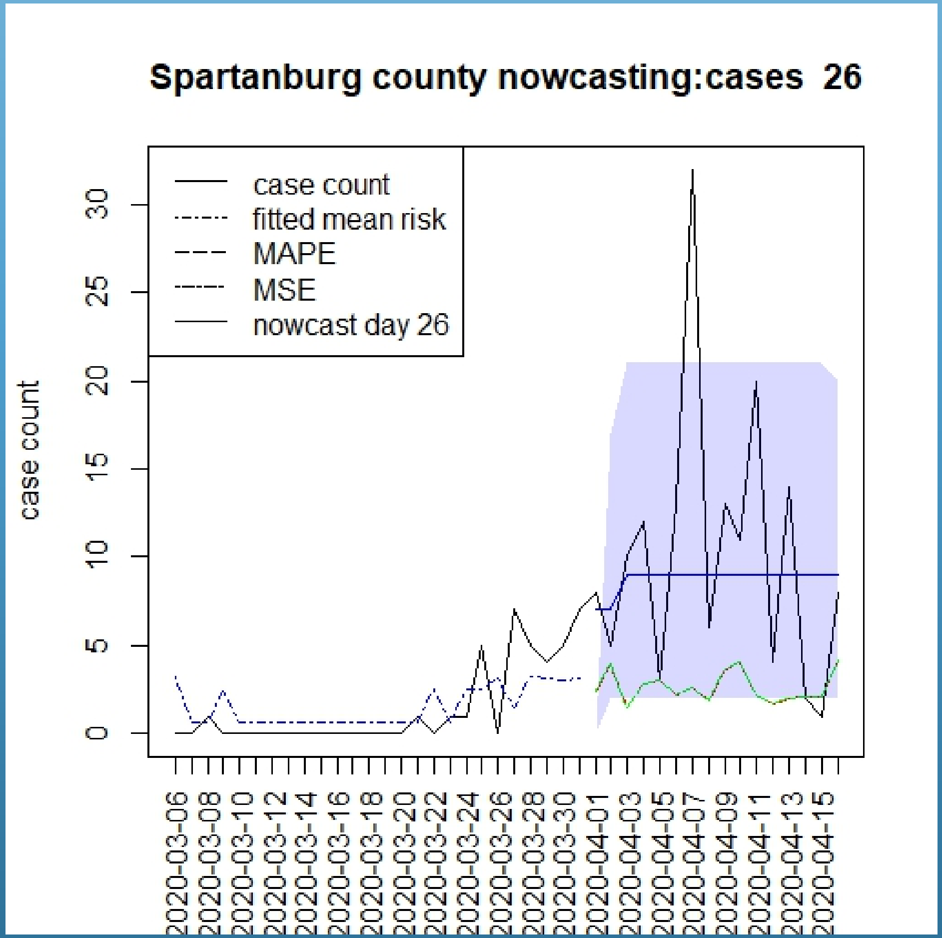
SC PARTIAL TO FULL LOCKDOWN MARCH 31ST –APRIL 16TH 2020



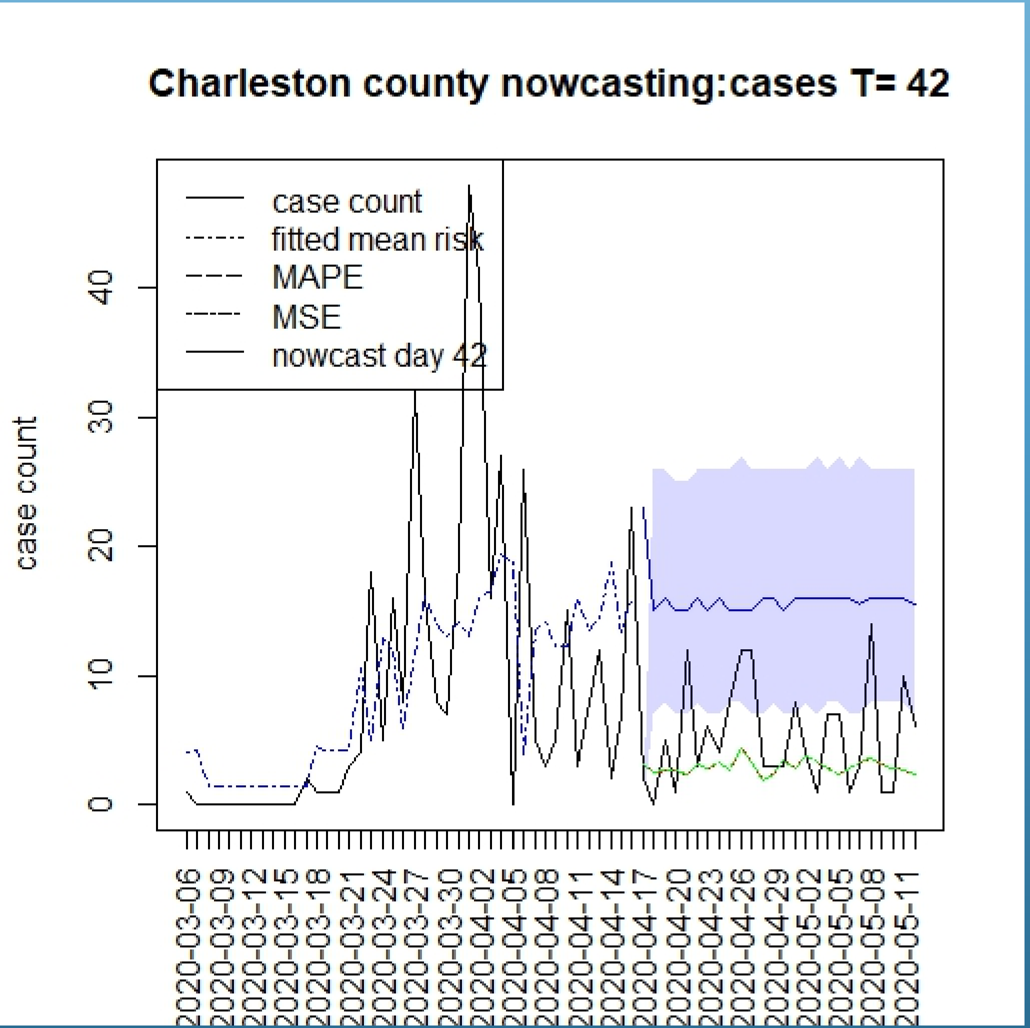


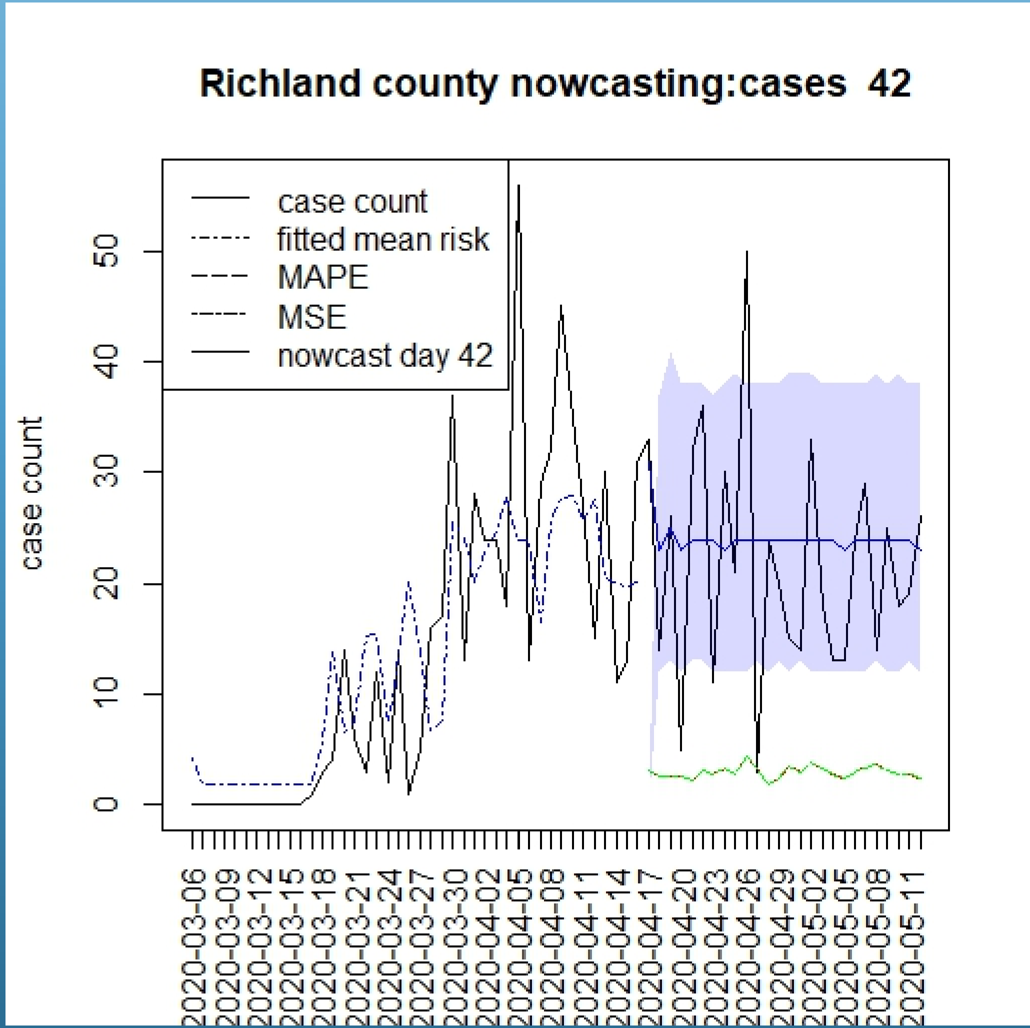
SAME PERIOD: GREENVILLE, SPARTANBURG



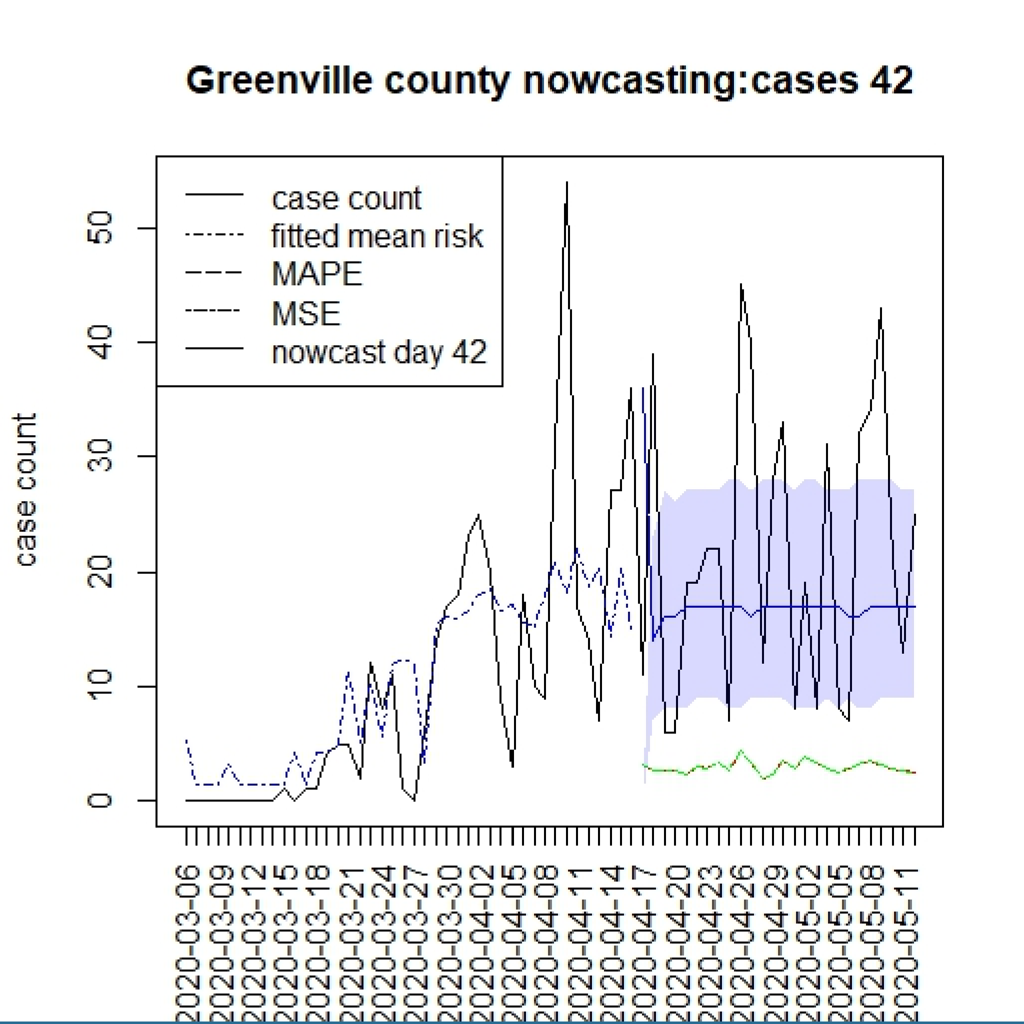


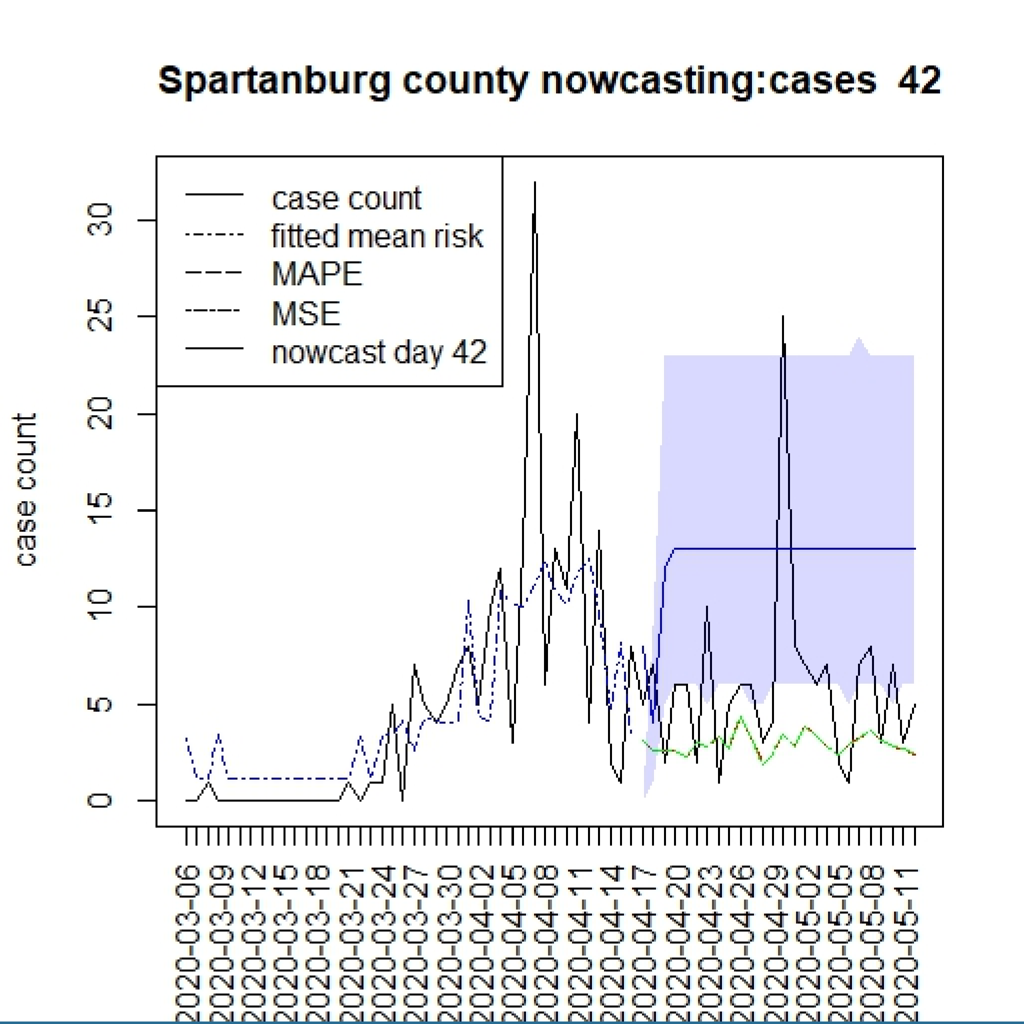
SC FULL LOCKDOWN: APRIL 16TH – MAY 12TH



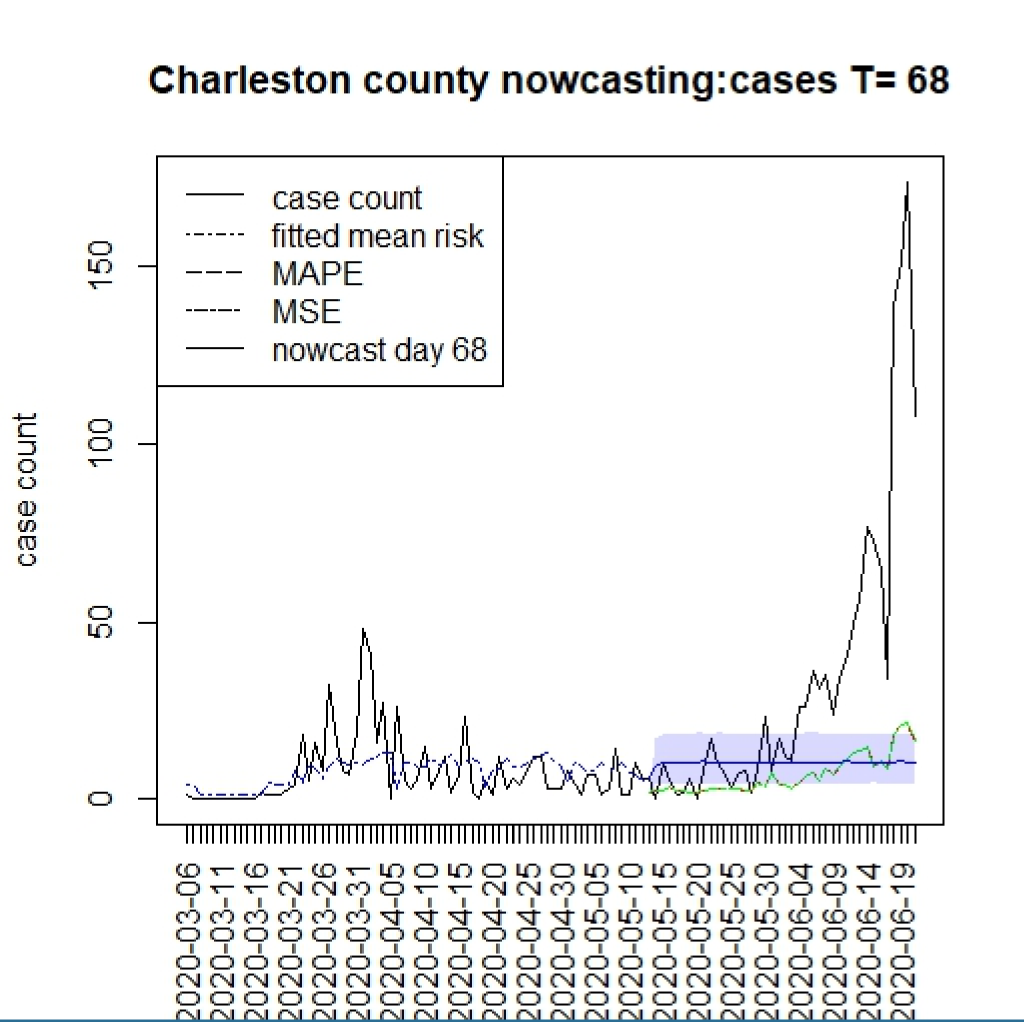


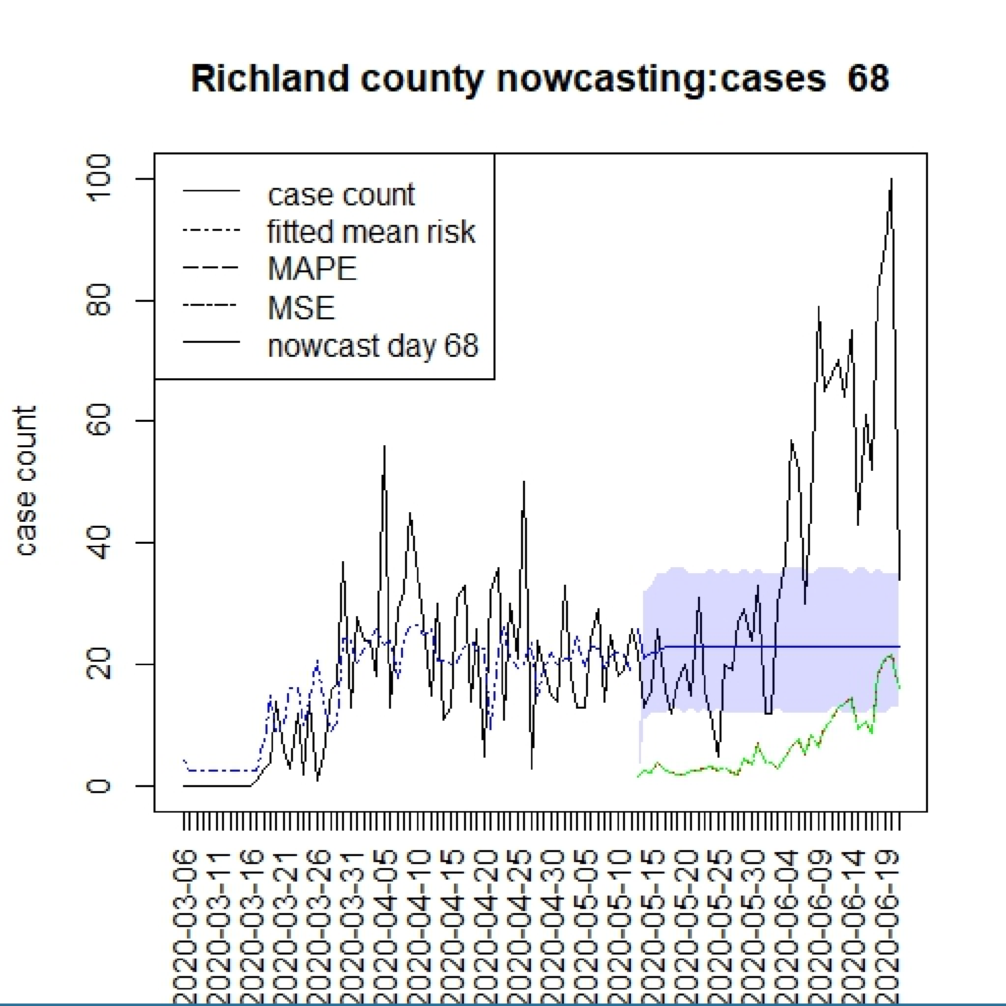
SAME PERIOD: GREENVILLE, SPARTANBURG



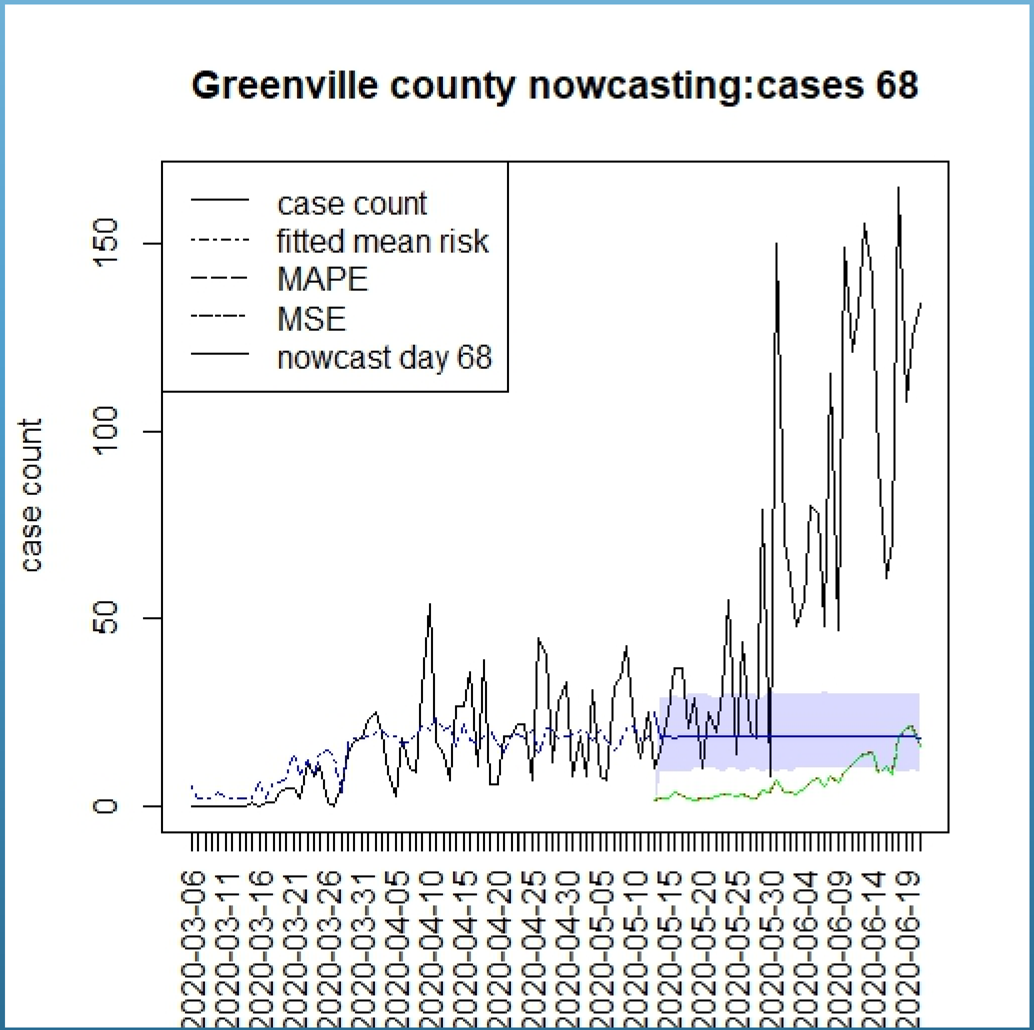


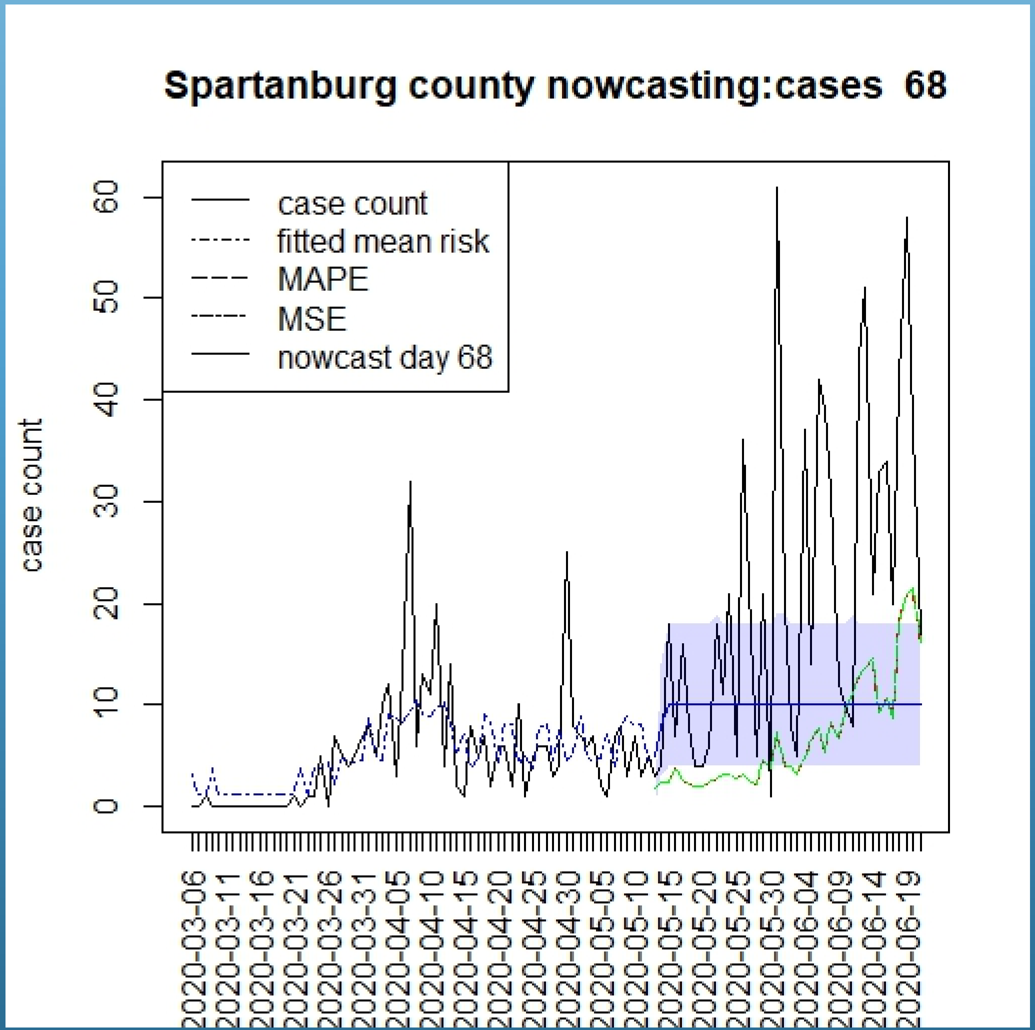
SC LIFTING: MAY 12TH – JUNE 21ST CHARLESTON AND RICHLAND





SC SAME PERIOD: GREENVILLE-SPARTANBURG





COUNTERFACTUAL DIFFERENTIALS

- Measuring loss between cases and counterfactuals

$$e_{i,k} = y^{p}_{i,k} - y_{i,k}$$

$$(M)APE_{i,k} = abs(e_{i,k})$$

$$(M)SE_{i,k} = e^{2}_{i,k}$$

$$TotDiff_{i} = \sum_{k} e_{i,k}$$

$$AveDiff_{i} = \underset{k}{mean}(e_{i,k})$$

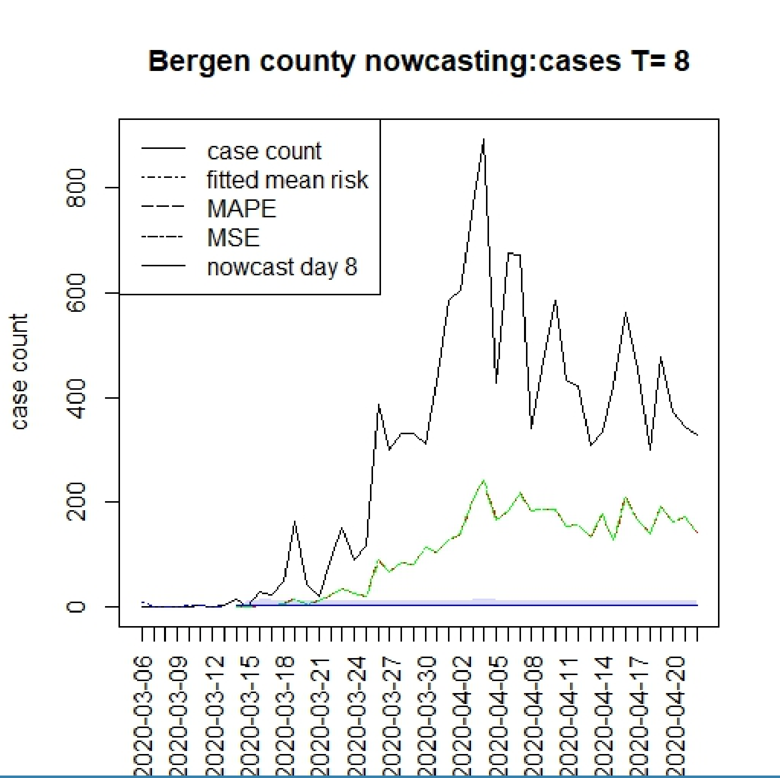
SC: COMPARISON OF DIFFERENTIALS

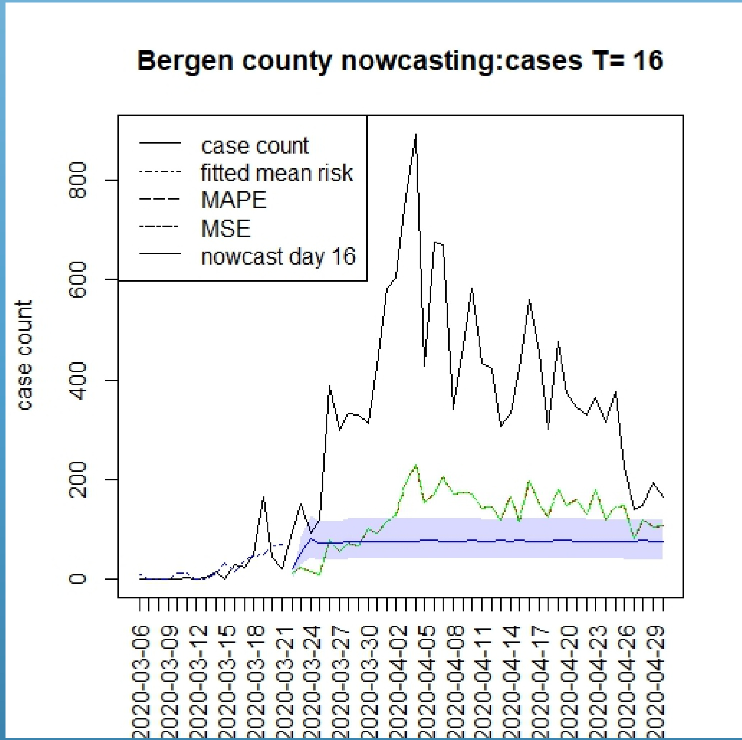
time	Charleston Total	Richland Total	Greenville Total	Spartanburg Total	Charleston Mean	Richland Mean	Greenville Mean	Spatanburg Mean
T26 K16	-27	-179	-145	-22	-1.68	-11.1	-9.06	-1.37
T42 K26	277	61	-105	171	10.6	2.34	-4.0	6.57
T68 K40	-952	-611	-1941	-456	-23.8	-15.3	-48.6	-11.4
Counterfactuals at different times (T) and extents (K): assumes the best fitting model 5A								

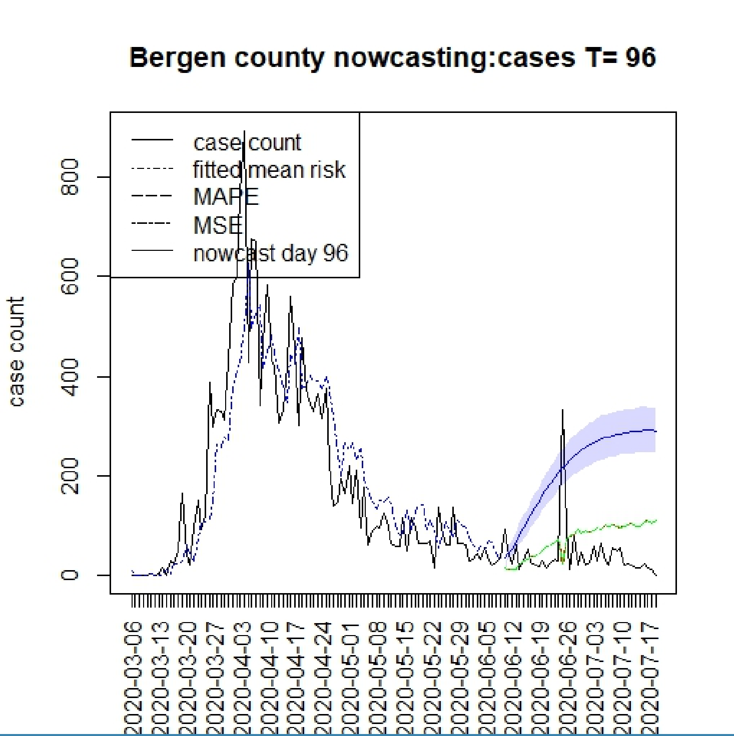
NEW JERSEY

- Evaluating model 5B (best daily case model)
- Time periods of interest:
- T=8
- T=16 lockdown
- T= 96 lifting

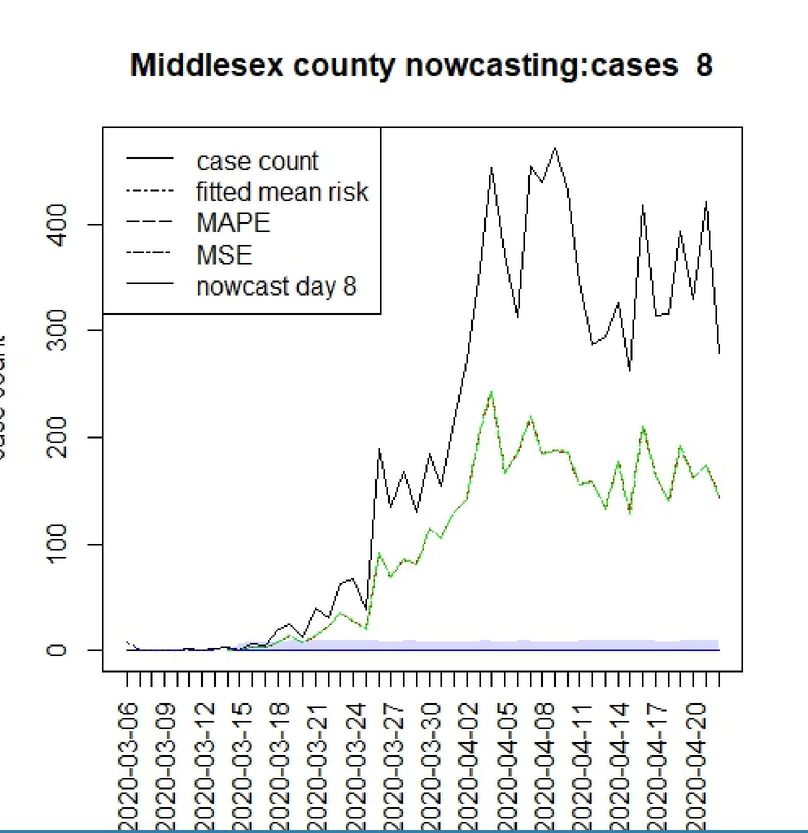
NEW JERSEY: BERGEN COUNTY

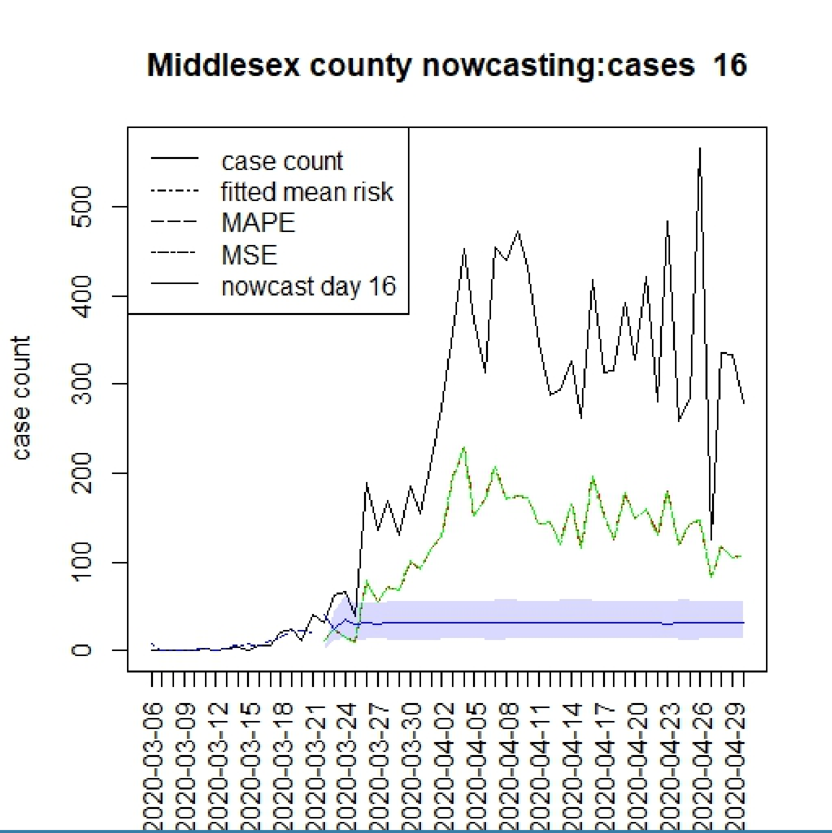


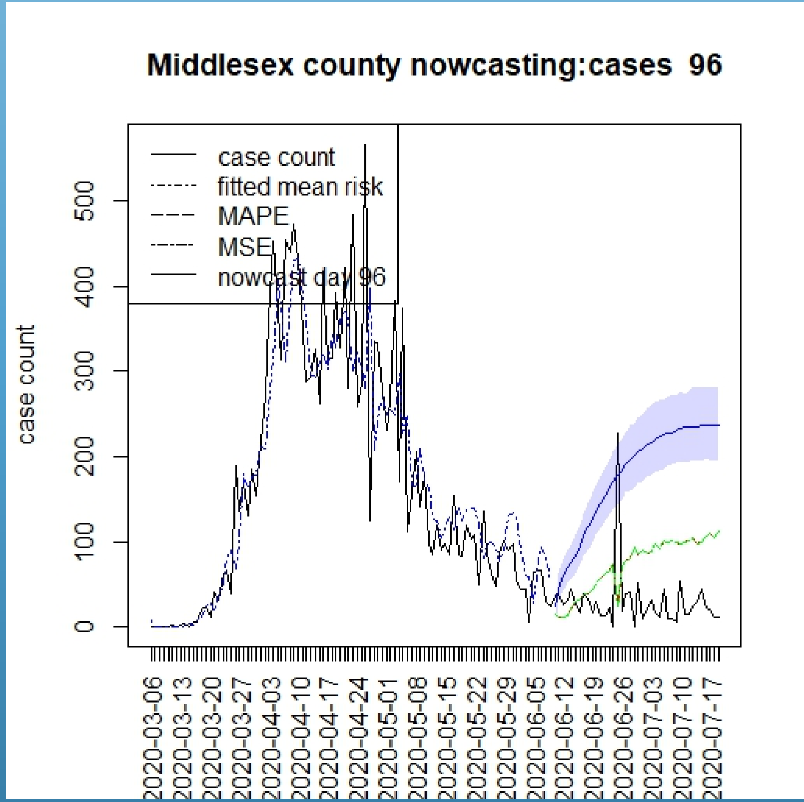




NEW JERSEY: MIDDLESEX COUNTY







NJ: COMPARISON OF DIFFERENTIALS

time	Bergen Total	Gloucester Total	Hunterdon Total	Middlesex Total	Bergen Mean	Gloucester Mean	Hunterdon Mean	Middlesex Mean
T8 K40	-13546	-856	-434	-9002	-338.6	-21.4	-10.9	-225.1
T16 K40	-12249	-1166	-432	-10354	-306.2	-29.2	-10.8	-258.8
T96 K40	6889	680	313	5897	172.2	17	7.8	147.4
Counterfactuals at different times (T) and extents (K): assumes the best fitting model 5B								

DISCUSSION & CONCLUSIONS

- Nowcasting and counterfactual estimation is possible in the context of ID spatio-temporal modeling
  - Confidence bounds can also be computed
- Can be used to assess the effects of lockdowns
- Sensitivity to cut off points is a major issue:
  - One step prediction behavior changes over time and different ‘good’ models appear at different times
- Sensitivity to reporting error is also a major Covid-19 issue.

RECENT REFERENCES

- Lawson, A. B. and Kim, J. (2021) Space-time Covid-19 Bayesian SIR Modeling in South Carolina *PlosOne* https://doi.org/10.1371/journal.pone.0242777
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PAPER AND QUESTIONS

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