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Assessing EARS' Ability to Locally Detect the 2009 H1N1 Pandemic

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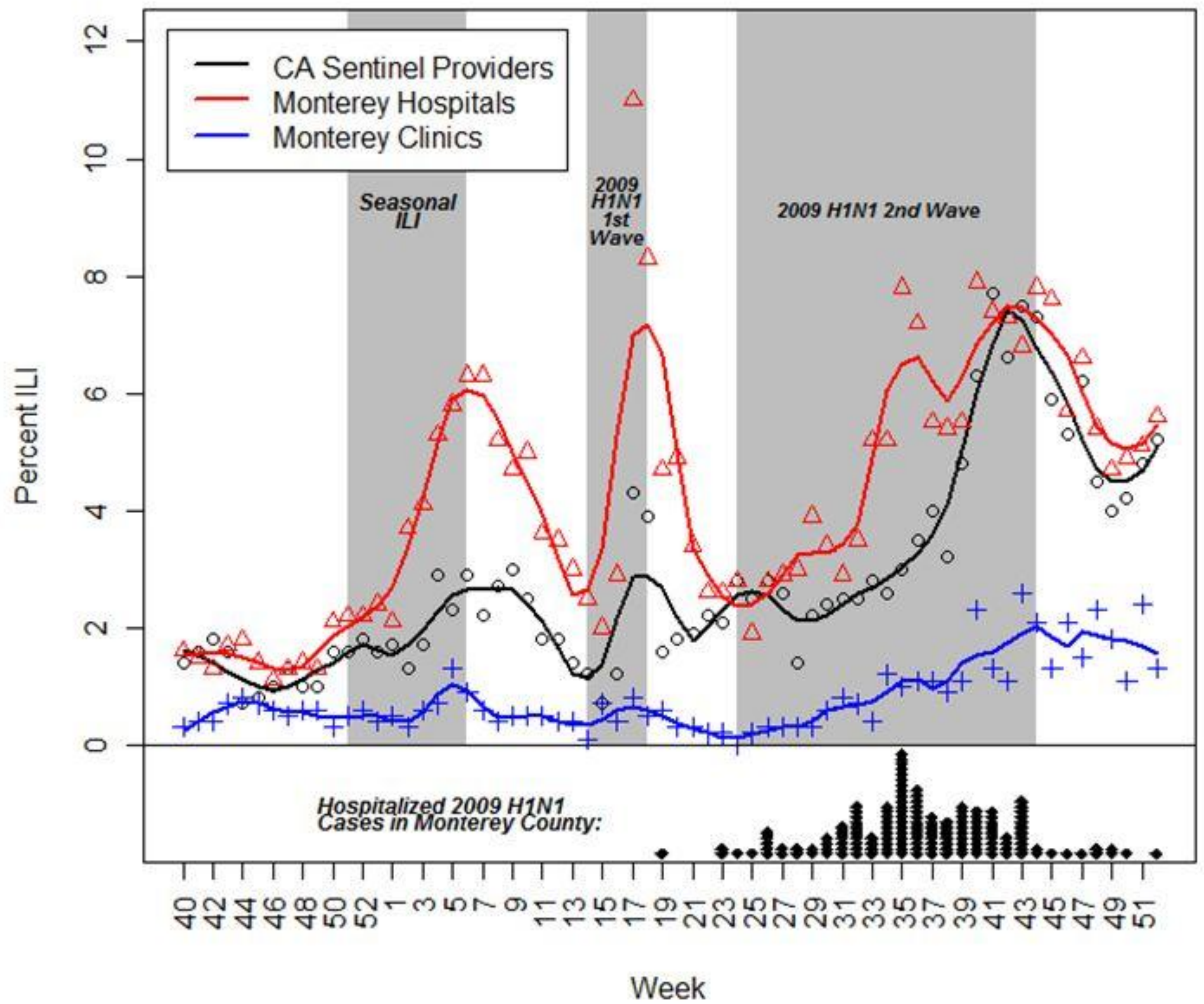
13th Biennial CDC Symposium on Statistical Methods
May 25, 2011

Research Questions

- How well can the Early Aberration Reporting System (v4.5) detect known outbreaks?
- Are there alternatives that improve performance?
  - ILI syndrome definitions
  - Detection algorithms

The Outbreak Periods



ILI Syndrome Definition Alternatives

- MCHD has used three definitions for ILI syndrome:

ILI Definitions	Symptom Combination Logic
EARS Baseline:	"cold" *or* "cough" *or* "sore throat"
MCHD Expanded:	"cold" *or* "cough" *or* "fever" *or* "chills" *or* "muscle pain" *or* "headache" *or* ("flu" *and not* "shot")
MCHD Restricted:	("fever" *and* "cough") *or* ("fever" *and* "sore throat") *or* ("fever" *and* "cough" *and* "sore throat") *or* ("flu" *and not* "shot")

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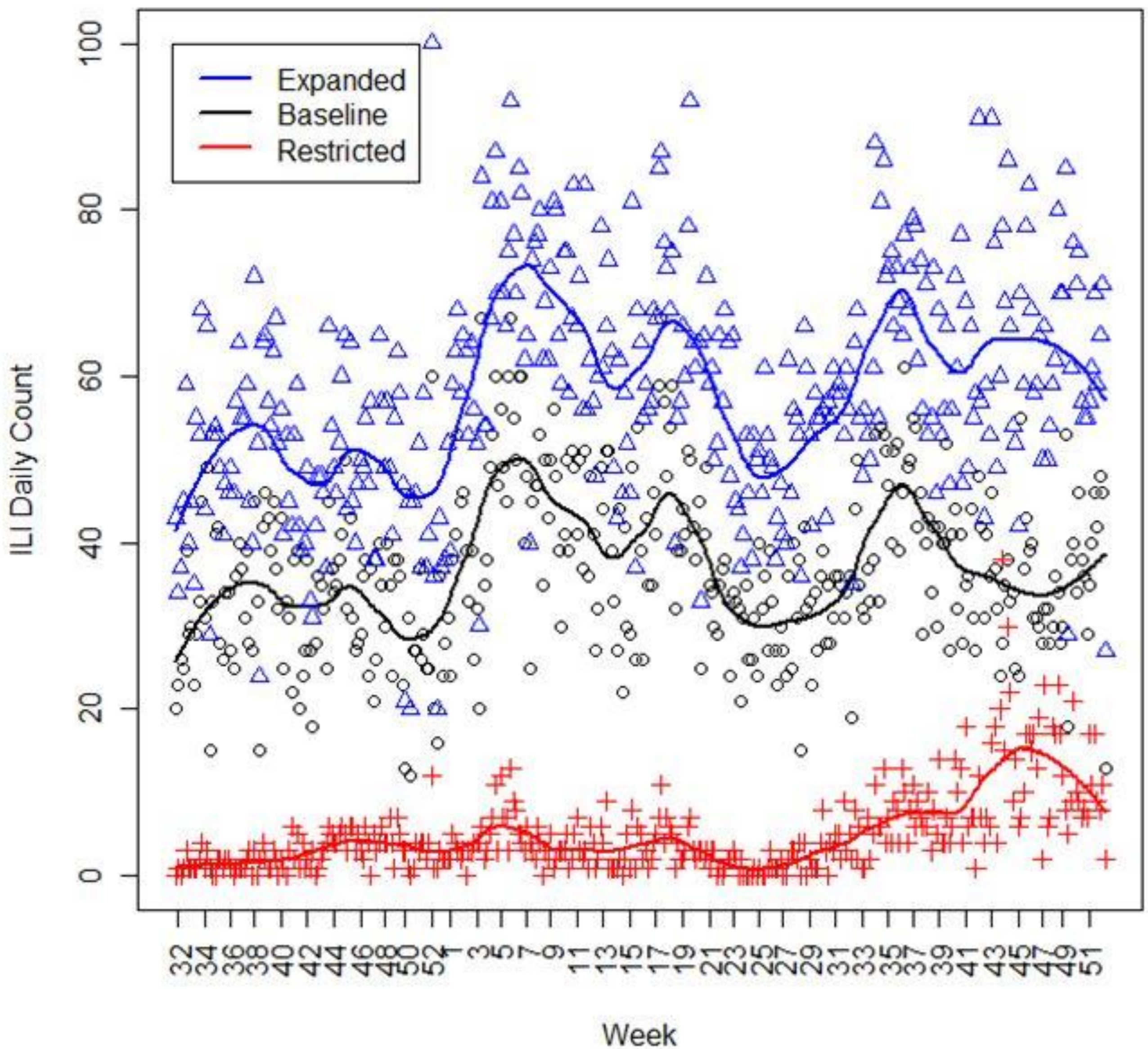
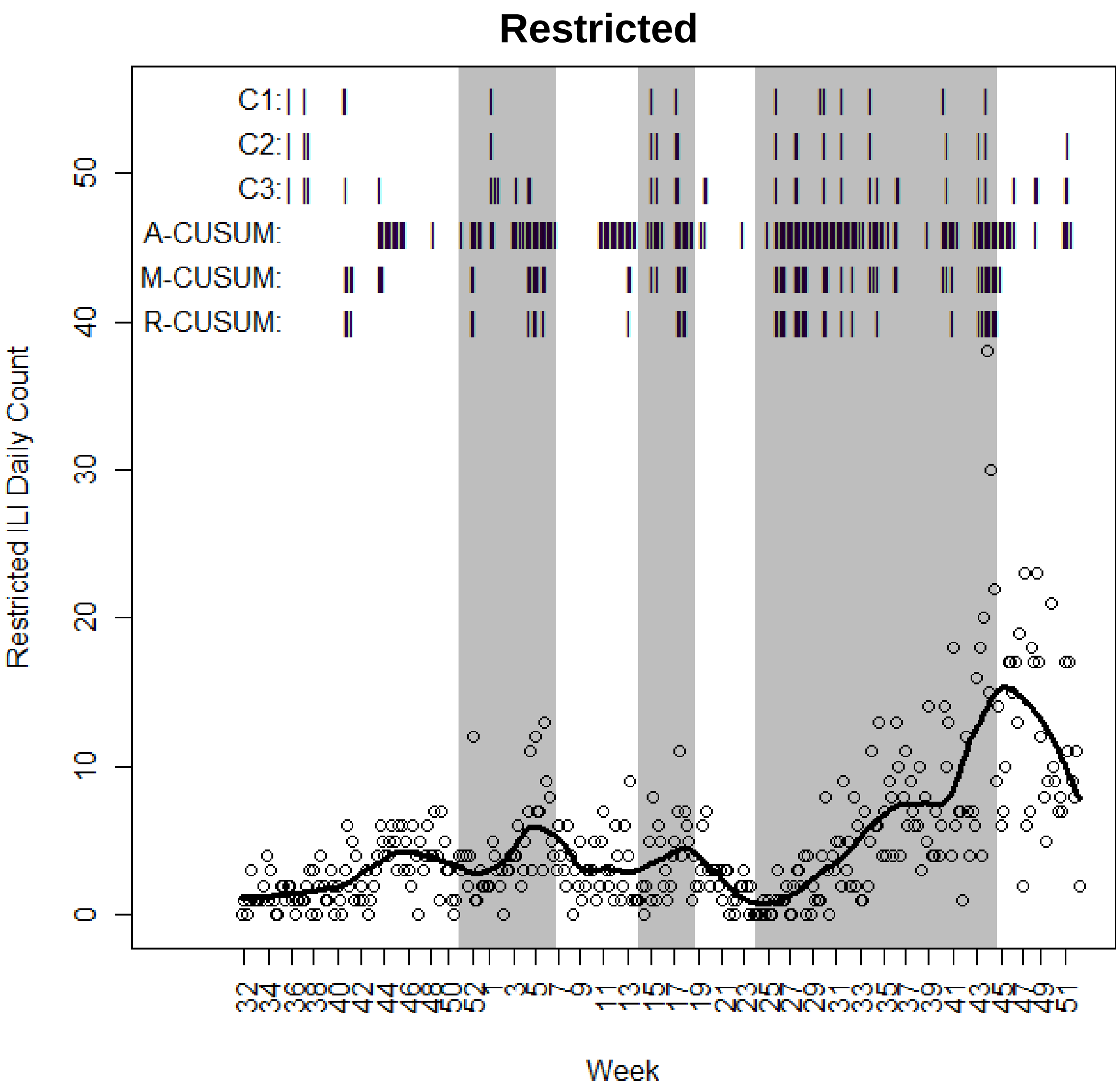
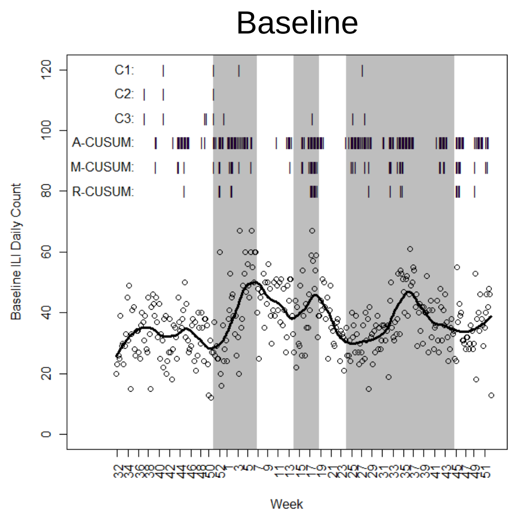
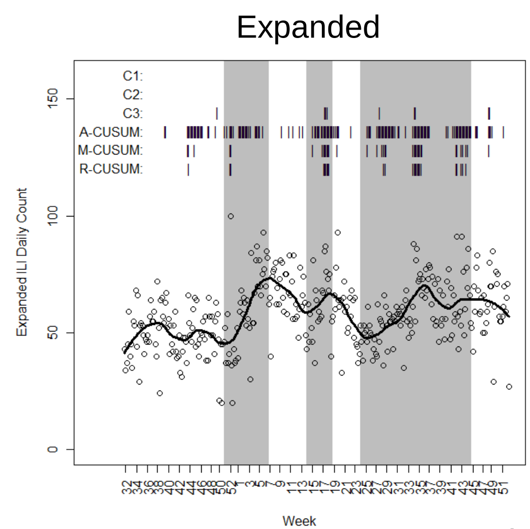
Definitions Affect Daily Counts



Restricted Definition Performed Best







Quantifying Performance

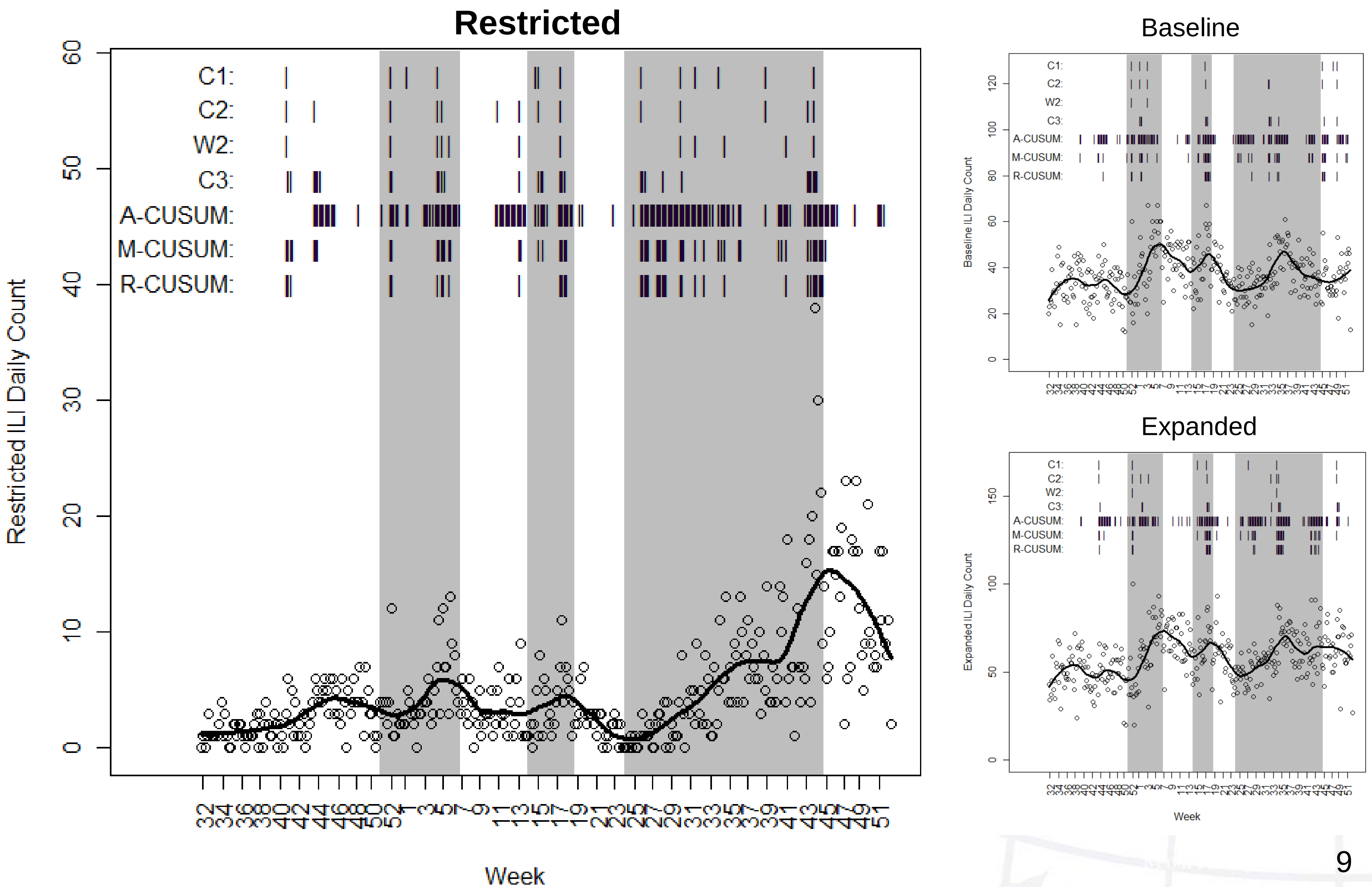
- Metrics:
  - *Sensitivity*: # outbreak days with signal / # outbreak days
  - *Specificity*: # non-outbreak days without signal / # non-outbreak days
  - *Average delay*:
    - $\bar{d}_1$ average time to signal from start of outbreak period
    - $\bar{d}_2$ average time to signal from earliest signal
- Results:

	Baseline				Expanded				Restricted			
Algorithm	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$
C1	0.02	0.99	14+	11+	0.00	1.00	57+	52+	0.06	0.98	9.7	6.0
C2	0.01	0.99	43+	40+	0.00	1.00	57+	52+	0.08	0.98	9.7	6.0
C3	0.03	0.98	8.7	5.7	0.04	0.98	26+	21+	0.13	0.93	9.7	6.0
A-CUSUM	0.55	0.75	3.0	0.0	0.58	0.77	4.7	0.0	0.62	0.76	3.7	0.0
M-CUSUM	0.21	0.93	4.7	1.7	0.18	0.97	6.3	1.7	0.28	0.95	7.0	3.3
R-CUSUM	0.09	0.97	14.7	11.7	0.14	0.99	14.7	10.0	0.21	0.98	10.7	7.0

Results

- Restricted ILI definition gave best performance
  - For both EARS and CUSUM methods
  - For details, see Hagen, K.S., R.D. Fricker, Jr., K. Hanni, S. Barnes, and K. Michie, Assessing the Early Aberration Reporting System's Ability to Locally Detect the 2009 Influenza Pandemic, *Statistics, Politics, and Policy*
- Suggests performance gains to be had by improving syndrome definitions
  - "Low-hanging fruit"
- Results beg the question: which algorithm should be preferred?
  - Can't compare results directly – CUSUM had advantages

EARS' Methods Marginally Improved by Removing Weekend Zeros



EARS' Methods Marginally Improved by Removing Weekend Zeros

	Algorithm	Baseline Sens.	Baseline Spec.	Baseline $\bar{d}_1$	Baseline $\bar{d}_2$	Expanded Sens.	Expanded Spec.	Expanded $\bar{d}_1$	Expanded $\bar{d}_2$	Restricted Sens.	Restricted Spec.	Restricted $\bar{d}_1$	Restricted $\bar{d}_2$
Weekends Removed	C1	0.02	0.98	41+	38+	0.03	0.99	9.3	4.6	0.07	0.99	6.3	2.6
	C2	0.04	0.99	21.3	18.3	0.04	0.99	22.0	17.3	0.06	0.98	7.0	3.3
	W2	0.01	1.00	45+	42+	0.01	1.00	26+	22+	0.06	0.99	17.3	13.6
	C3	0.06	0.99	25	22	0.05	0.98	36.3	31.6	0.14	0.96	7.0	3.3
With 0s	C1	0.02	0.99	14+	11+	0.00	1.00	57+	52+	0.06	0.98	9.7	6.0
	C2	0.01	0.99	43+	40+	0.00	1.00	57+	52+	0.08	0.98	9.7	6.0
	C3	0.03	0.98	8.7	5.7	0.04	0.98	26+	21+	0.13	0.93	9.7	6.0

- Remember the metrics:
  - *Sensitivity*: # outbreak days with signal / # outbreak days
  - *Specificity*: # non-outbreak days without signal / # non-outbreak days
  - *Average delay*:
    - $\bar{d}_1$ average time to signal from start of outbreak period
    - $\bar{d}_2$ average time to signal from earliest signal

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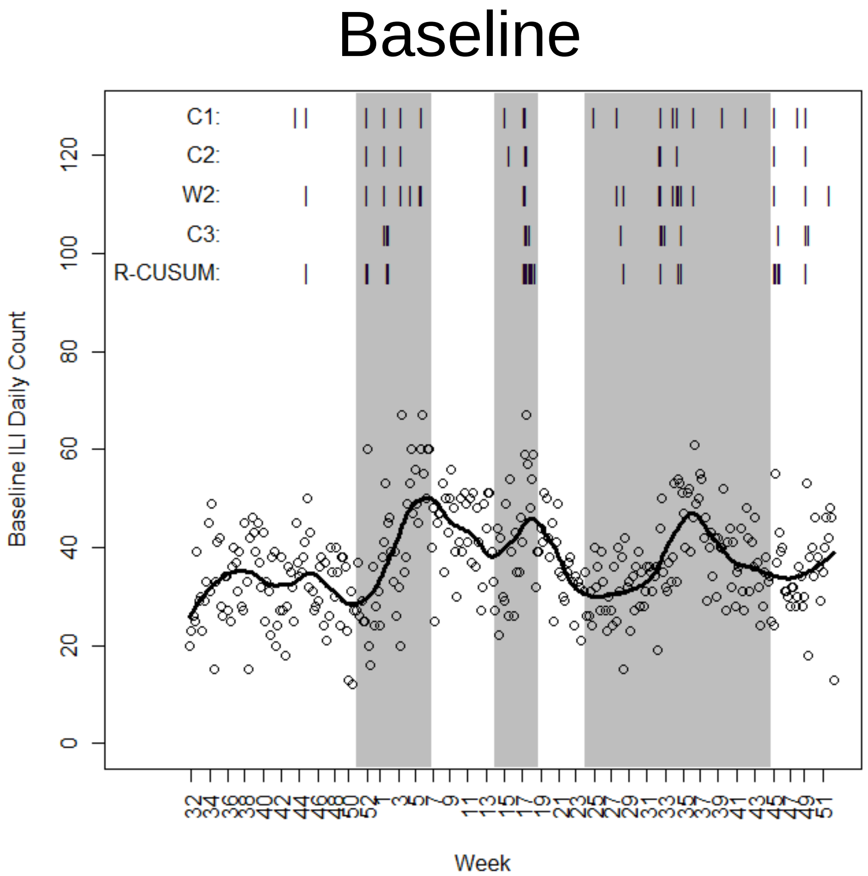
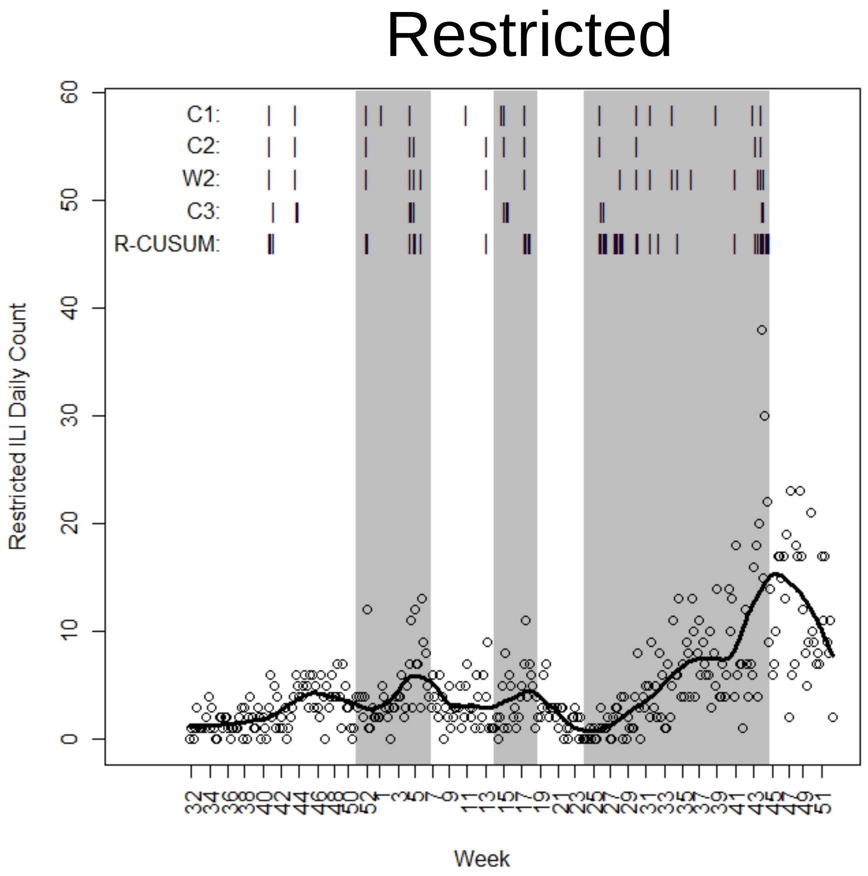
EARS Performance *Much* Improved by Adjusting Signal Thresholds

	Baseline				Expanded				Restricted			
Algorithm	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$
C1	0.09	0.97	5.7	0.0	0.04	0.99	9.3	0.0	0.08	0.98	6.3	0.0
C2	0.09	0.97	11.3	5.6	0.05	0.99	21.3	12.0	0.05	0.98	7.0	0.7
W2	0.10	0.97	13.3	7.6	0.06	0.99	14.6	5.3	0.09	0.98	14.3	8.0
C3	0.09	0.97	10.0	4.3	0.03	0.99	37+	28+	0.06	0.98	15.3	9.0
R-CUSUM	0.09	0.97	14.7	9.0	0.14	0.99	14.7	5.4	0.21	0.98	10.7	4.4

	Baseline				Expanded				Restricted			
Algorithm	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$	**Sens.**	**Spec.**	$\bar{d}_1$	$\bar{d}_2$
C1	0.26	0.75	2.3	0.0	0.28	0.77	3.3	0.0	0.29	0.76	4.7	1.0
C2	0.26	0.75	4.0	1.7	0.29	0.77	4.7	1.4	0.35	0.76	5.0	1.3
W2	0.39	0.75	4.0	1.7	0.41	0.77	8.3	5.0	0.41	0.76	6.3	2.6
C3	0.16	0.89	9.7	9.4	0.19	0.93	7.7	4.4	0.24	0.91	7.0	3.3
A-CUSUM	0.55	0.75	3.0	0.7	0.58	0.77	4.7	1.4	0.62	0.76	3.7	0.0

EARS Performance *Much* Improved by Adjusting Signal Thresholds

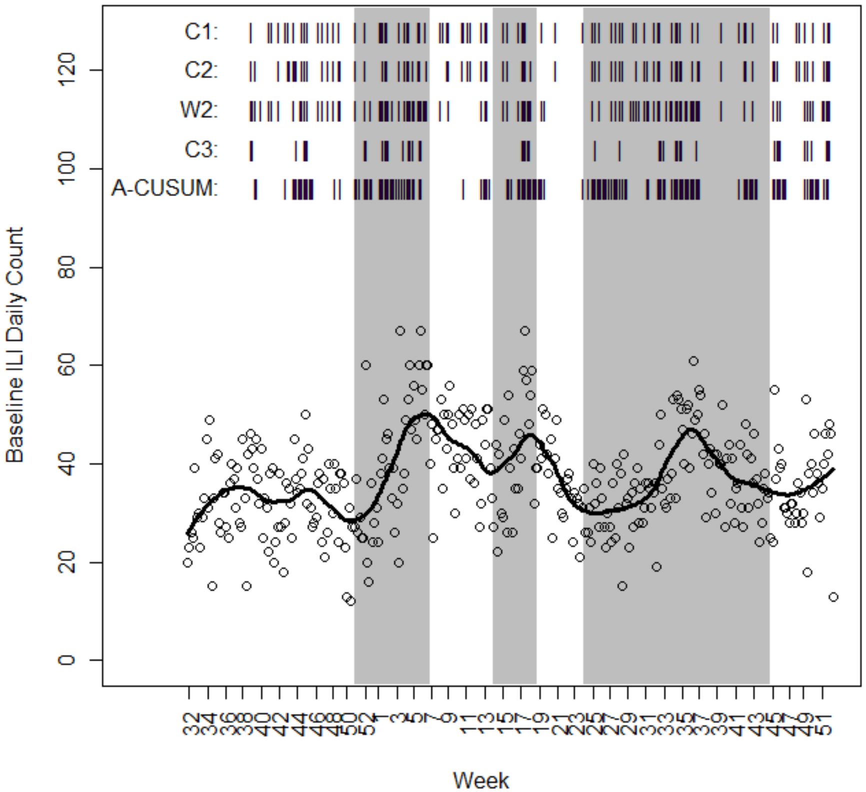




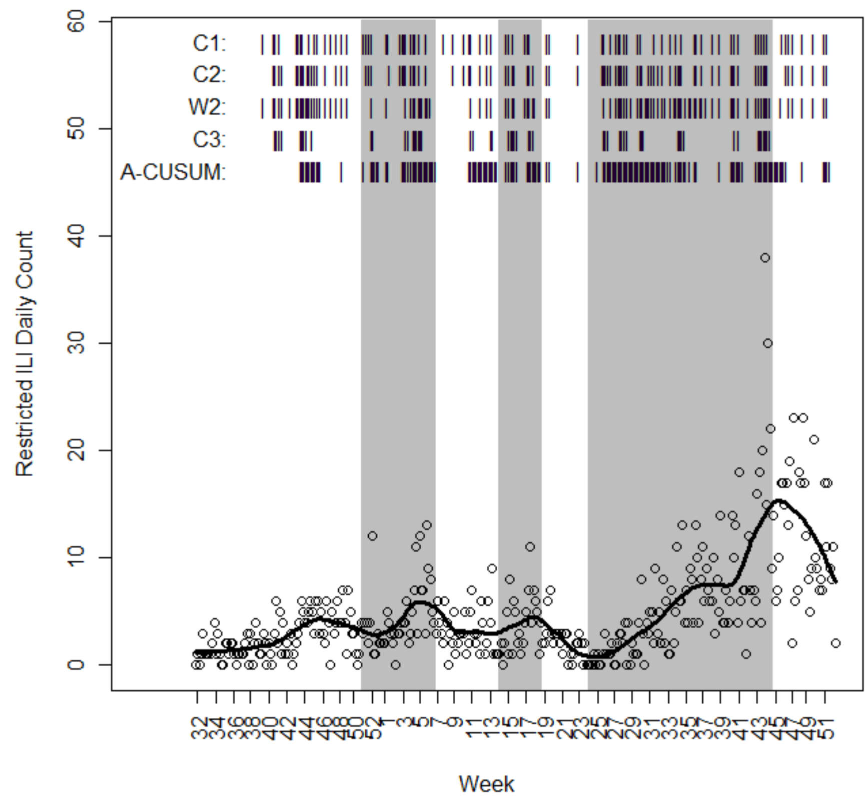
Performance when EARS thresholds set so methods match R-CUSUM specificity

EARS Performance *Much* Improved by Adjusting Signal Thresholds

Baseline



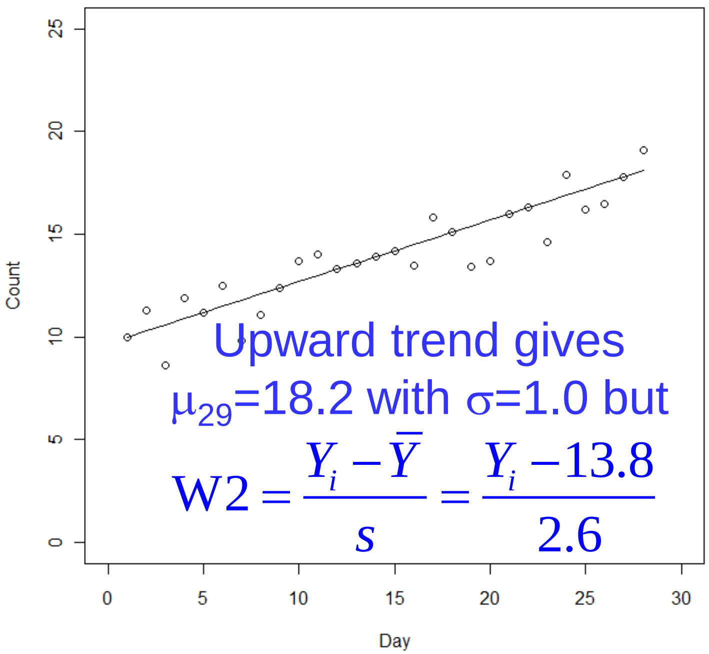
Restricted

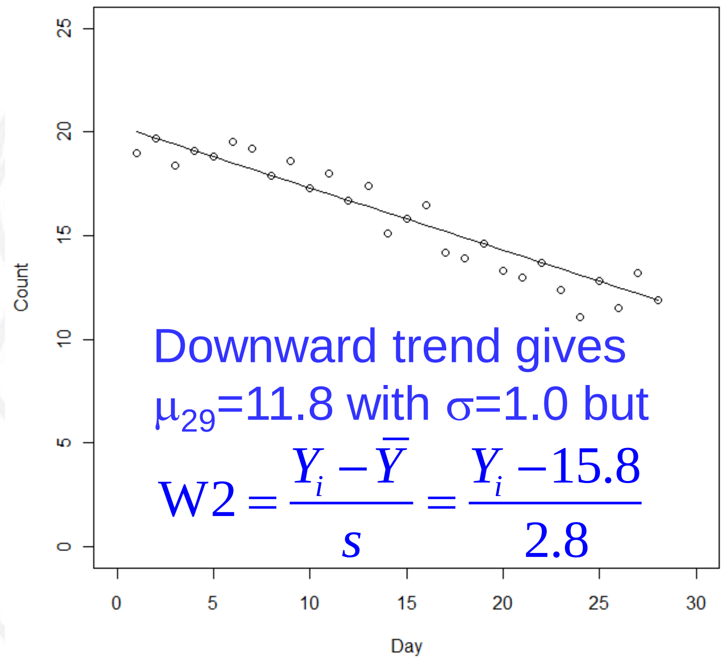


Performance when EARS thresholds set so methods match A-CUSUM specificity

Why Does W2 Average Delay Performance Lag?

- For non-stationary data, longer baselines can result in mis-estimation of mean and standard deviation
  - Thus, probability of signaling <u>for an equivalent deviation from current conditions</u> depends on past trends
- Consider:



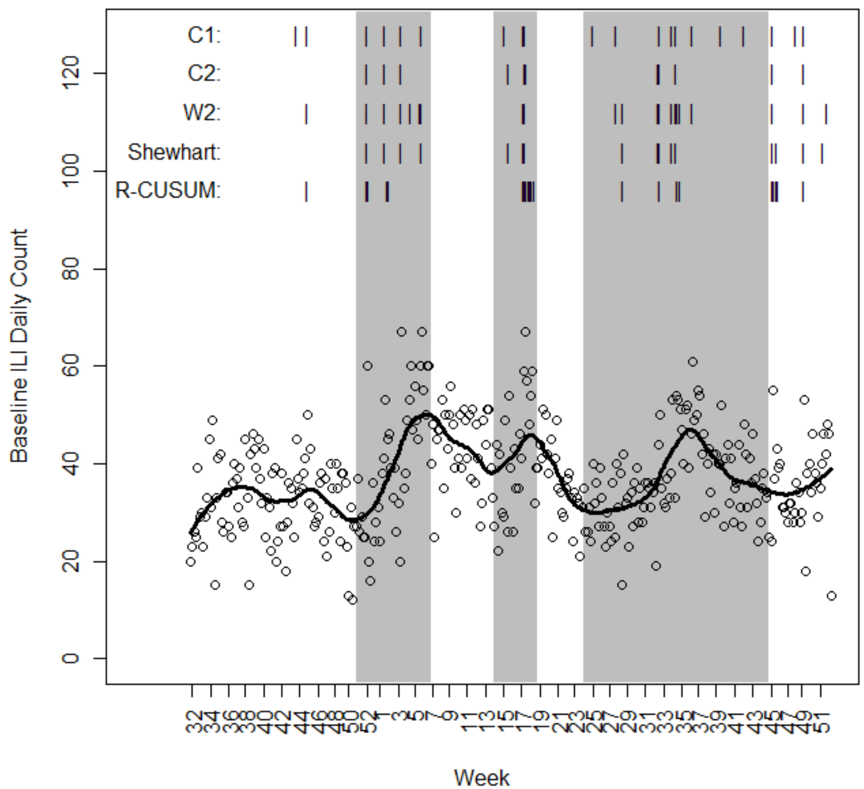


Improving on the W2 Method

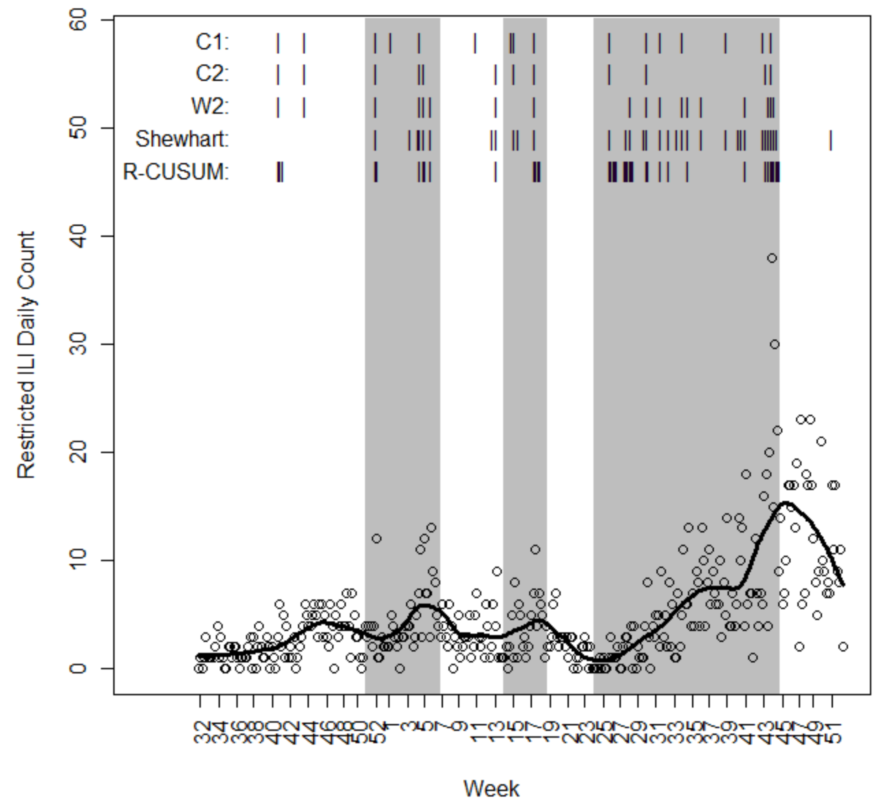
- Apply C1 and C2 methods to residuals from model (such as adaptive regression)
- Benefits:
  - Allows for longer baseline, but should give better estimation of daily means and standard deviations
  - In this work, adaptive regression residuals normally distributed, so easy to choose thresholds
- In quality control terms, it's applying Shewhart method to a model's standardized residuals
  - Model does not require years of data
  - In this work, we used 35 days (seven weeks)

Shewhart Method Applied to Adaptive Regression Residuals Performs Well

Baseline



Restricted



Performance when EARS thresholds set so methods match R-CUSUM specificity

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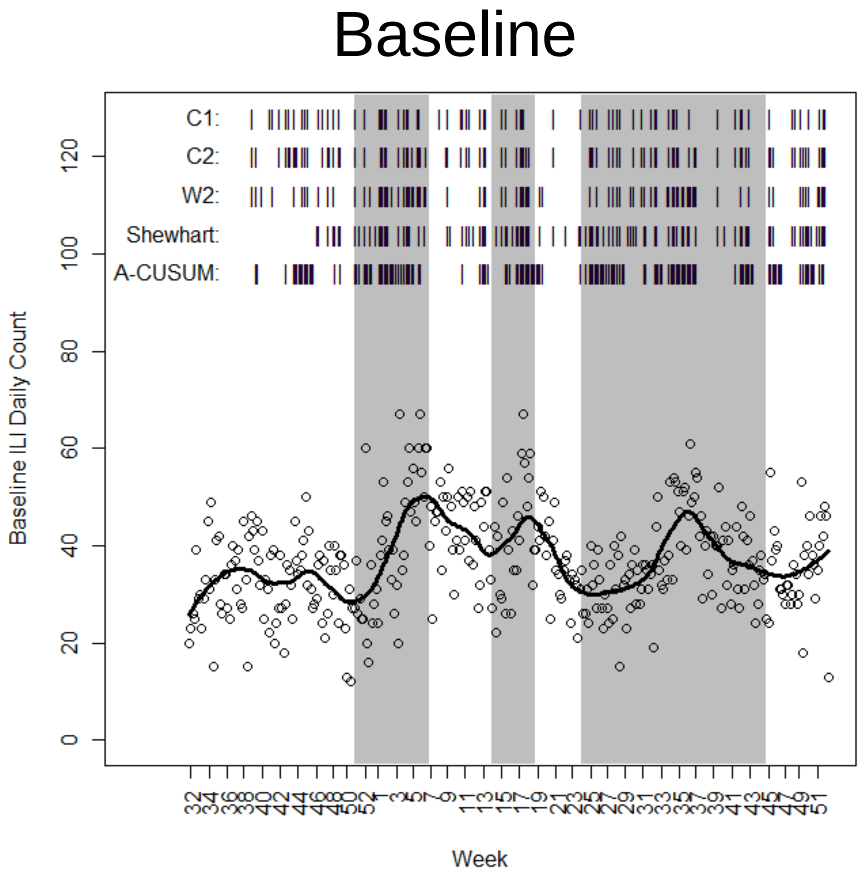

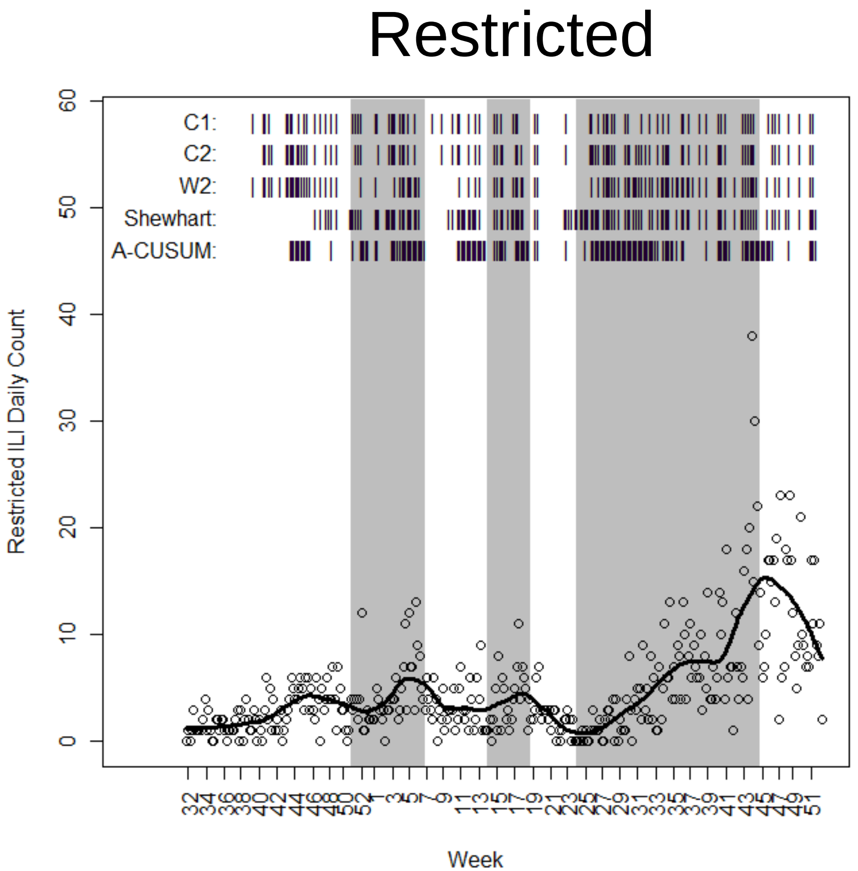

Performance when EARS thresholds set so methods match A-CUSUM specificity

Shewhart Method Applied to Adaptive Regression Residuals Performs Well

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W2	0.10	0.97	13.3	7.6	0.09	0.98	14.3	8.0
Shewhart	0.07	0.97	12.0	6.3	0.17	0.98	7.0	0.7
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W2	0.39	0.75	4.0	2.7	0.41	0.76	6.3	5.0
Shewhart	0.40	0.75	1.3	0.0	0.52	0.76	1.3	0.0
A-CUSUM	0.55	0.75	3.0	1.7	0.62	0.76	3.7	2.4

Conclusions

- More research into syndrome definitions would likely provide real benefits
- EARS C1 method performed quite well with appropriately set thresholds
- W2 performance improved with better estimation of mean and std. deviation
- Shewhart methods preferred (signal fast) when outbreak is rapid
  - CUSUM will do better for gradual increases

Back-up Slides

Early Aberration Reporting System

- EARS' detection algorithms:

$$C_1(t) = \frac{Y(t) - \bar{Y}_1(t)}{s_1(t)}$$

- Sample statistics calculated from previous 7 days' data
- Signal when $C_1 > 3$

$$C_2(t) = \frac{Y(t) - \bar{Y}_3(t)}{s_3(t)}$$

- Sample statistics calculated from 7 days' of data prior to 2 day lag
- Signal when $C_2 > 3$

$$C_3(t) = \sum_{i=t}^{t-2} \max\left[0, C_2(i) - 1\right]$$

- Signal when $C_3 > 2$

- Often referred to as CUSUMs, but not true
- In SPC parlance, C_1 and C_2 are Shewhart variants

CUSUM on Adaptive Regression Forecast Errors

- Adaptive regression: regress a sliding baseline of observations on time relative to current observation
  - I.e. regress $Y(t-1),\ldots,Y(t-n)$ on $n,\ldots,1$
- Calculate standardized residuals from one day ahead forecast, $Z(t)=R(t)/\hat{\sigma}_Y$, where

$$R(t)=Y(t)-\left[\hat{\beta}_0+\hat{\beta}_1\times(n+1)+\hat{\beta}_j\right]$$

and $\hat{\sigma}^2=\frac{1}{33}\sum_{i=t-35}^{t-1} R_i^2\left(1+\mathbf{x}_0'(\mathbf{X}'\mathbf{X})^{-1}\mathbf{x}_0\right)$

- CUSUM:

$$S(t)=\max\left[0,S(t-1)+Z(t)-k\right]$$

where a signal is generated if $S(t)>h$

Three CUSUMs Evaluated

- We looked at the performance of three CUSUMs based on choices of k and h:
  - Smaller k: Can detect smaller increases in mean
  - Larger h: Fewer false positive signals (i.e., larger ATFS) but slower to signal

Type	**Label**	k	h	**ATFS**
Aggressive:	CUSUM1	0.5	0.365	5
Moderate:	CUSUM2	1.0	0.695	20
Routine:	CUSUM3	1.0	1.200	60