# Assessing incomplete sampling of disease transmission networks

PMI Monthly Meeting

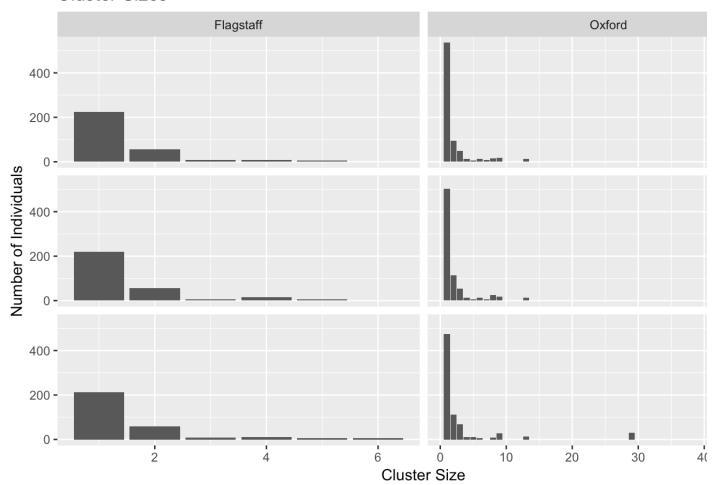
Derek Sonderegger, PhD - Northern Arizona University May 8, 2019

# Collaboration with NAU's Pathogen and Microbiome Institute



# **Cluster Size Distributions**

### Cluster Sizes



# Defining $\gamma$ = HAI rate from full data

- For each cluster, the first time a strain is observed it is considered environmentally acquired.
- The second (or third, or fourth, ..) time a strain is observed, it is healthcare acquired.

$$\gamma = \frac{N - ||\mathcal{I}||}{N} = 1 - \frac{||\mathcal{I}||}{N}$$

N = Number of Patients

 $\mathcal{I} = \text{Set of strain identifiers}$ 

 $||\mathcal{I}|| = \text{Actual Number of Clusters/Strains}$ 

• Knowing  $||\mathcal{I}||$  is the key to calculating HAI rate!

# Observed Number of Clusters/Strains under Simple Random Sampling

· Define the following

 $\alpha$  = proportion of the population sampled

 $n_i$  = actual size of the *i*th cluster

 $m_i$  = observed size of the *i*th cluster

Notice that

$$1 \leq m_i \leq n_i$$

and

$$\sum n_i = N$$

$$\sum m_i = \alpha N$$

5/20

# **Conditional Distribution**

 $m_i | n_i \sim \text{ZTHyperGeometric}(n_i, N - n_i, \alpha N) \text{ for } i$ 

- Zero Truncated HyperGeometric
- Assume approximate independence between observed cluster sizes
- Distribution requires working with hypergeometric terms

$$f(0|n_i) = \frac{\binom{n_i}{0}\binom{N-n_i}{\alpha N}}{\binom{N}{\alpha N}}$$

Notice that  $\alpha$  and  $f(0|n_i)$  are inversely related and we could crudely approximate

$$f(0|n_i) \approx 1 - \alpha$$

# **Critical Expectation**

$$E[m_i] = E[E(m_i|n_i)] = E[(1 - f(0|n_i))^{-1} \alpha n_i]$$

Utilizing this equation, can derive two different estimators.

- 1. The plug-in estimator that ignores the expectation, and approximates  $[1-f(0)]^{-1} \approx \alpha^{-1}$ . This results in  $\hat{n}_i = m_i$ .
- 2. Ignoring the expectations, we could utilize the actual hypergeometric function for  $f(0|n_i)$  and solve the following equation for  $\hat{n}_i$ . This solution needs to be solved via numerical methods because the "chooses" in  $f(0|n_i)$ .

# **Biased Estimator**

· Denoting

$$\widehat{n} = \sum \widehat{n}_i$$

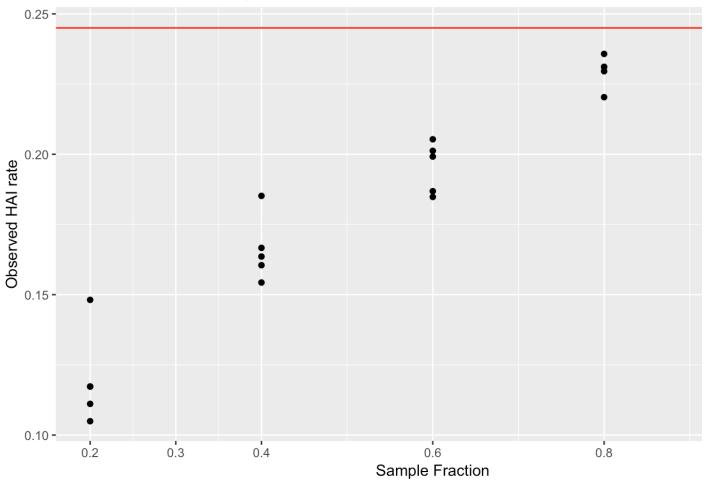
I =Set of observed strains

|I| = Observed Number of Clusters/Strains

$$\widehat{\gamma}^* = \frac{1}{\widehat{n}} \sum_{i \in I} (\widehat{n}_i - 1) = \frac{\widehat{n} - ||I||}{\widehat{n}} = 1 - \frac{||I||}{\widehat{n}}$$

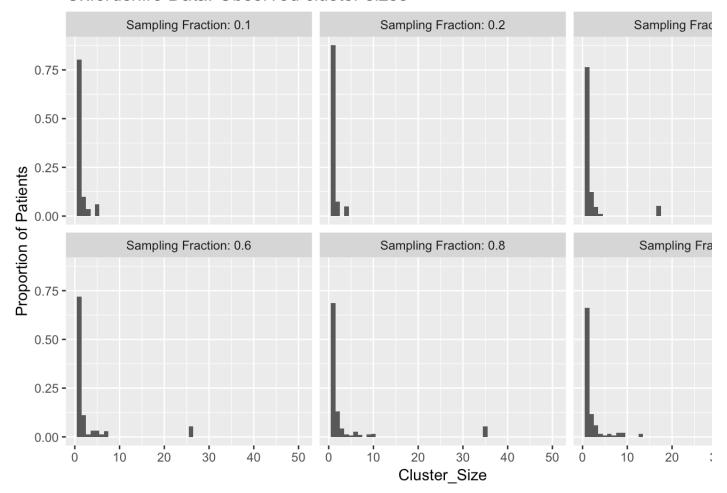
# Does the plug-in Estimator Work?

### Oxfordshire Data - Plugin Estimator



# Why doesn't this work?

### Oxfordshire Data: Observed cluster sizes



# **Bias Correction Procedure**

- 1. Calculate the sample HAI rate.
- 2. Repeatedly subsample the sample at the designated  $\alpha$  fraction.
- 3. For each subsample, calculate the subsample's HAI rate
- 4. Look at the average discrepancy and use that to adjust the sample HAI rate estimate.
- 5. The adjustments are made on the logit scale to force the resulting rate to remain in the [0, 1] interval.

# Bias Correction Procedure - Math!

By repeatedly sub-sampling at  $\alpha$  rate J times and calculating  $\hat{\gamma}_j^*$  for the jth sub-sample,

$$\bar{\delta} = \frac{1}{J} \sum_{j} \left[ \operatorname{logit}(\hat{\gamma}^*) - \operatorname{logit}(\hat{\gamma}^*_j) \right]$$

$$\hat{\gamma} = \operatorname{ilogit}\left( \operatorname{logit}(\hat{\gamma}^*) + \bar{\delta} \right)$$

We performed the bias correction step on the logit scale to ensure the resulting estimator is in [0, 1].

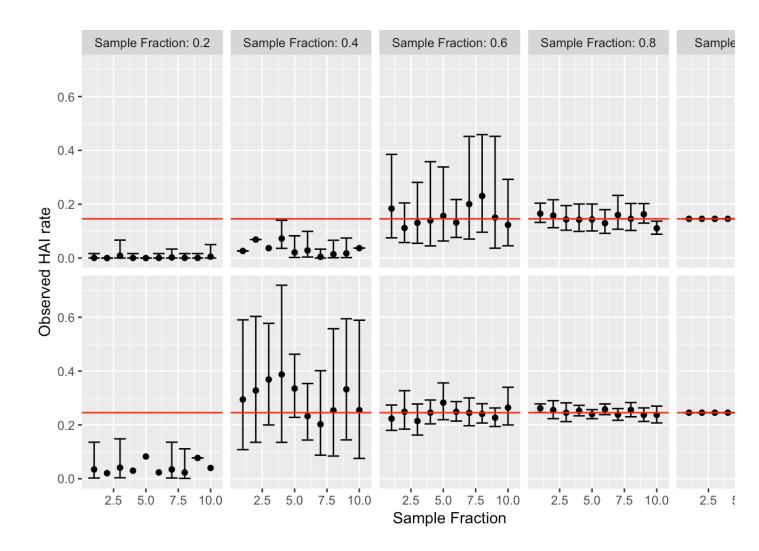
# Get approximate Confidence Intervals too!

- Standard deviation of the  $logit(\widehat{\gamma}_j^*)$  values gives a estimated standard error of  $logit(\widehat{\gamma})$  value.
- An approximate 95 confidence interval for  $\gamma$  we use is to add/subtract

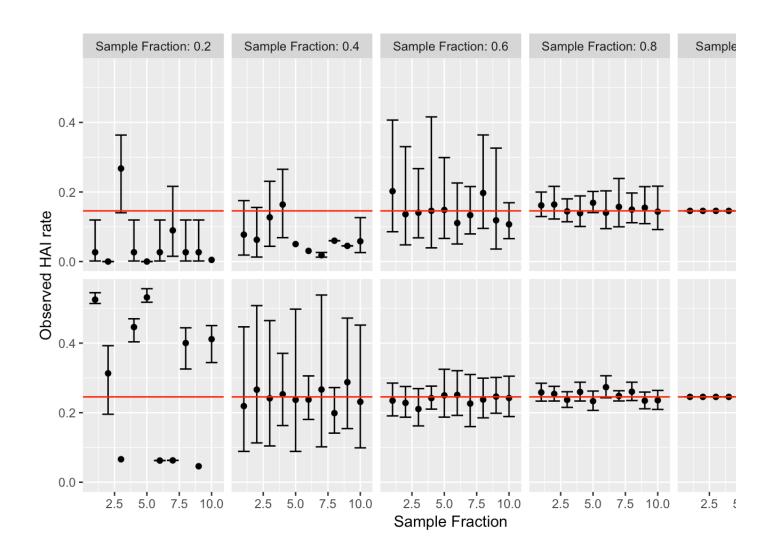
ilogit 
$$\left[ logit(\hat{\gamma}) \pm Z_{0.975} * SE(logit(\hat{\gamma})) \right]$$

# Results

# Plugin Results - Clinical Data



# Hypergeometric Results - Clinical Data



# Results - Simulated Populations

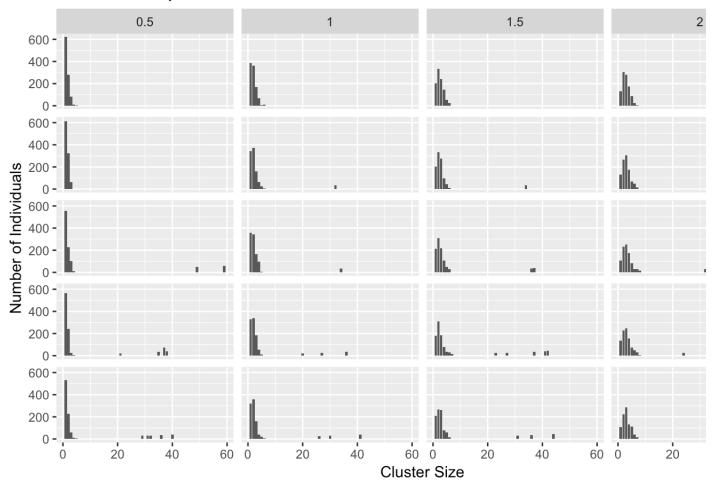
The Oxfordshire data could be reasonably modeled using a mixture of two distributions to separate the small clusters sizes from the large. We chose to model the small clusters sizes using a truncated Poisson distribution with the zero truncated out. The large cluster sizes were modeled from a logNormal distribution.

$$n_i \sim \begin{cases} \text{TPoisson}(\lambda) & \text{with probability } 1 - \rho \\ \text{logNormal}(\mu, \sigma) & \text{with probability } \rho \end{cases}$$

for i in  $\mathcal{I}$ .

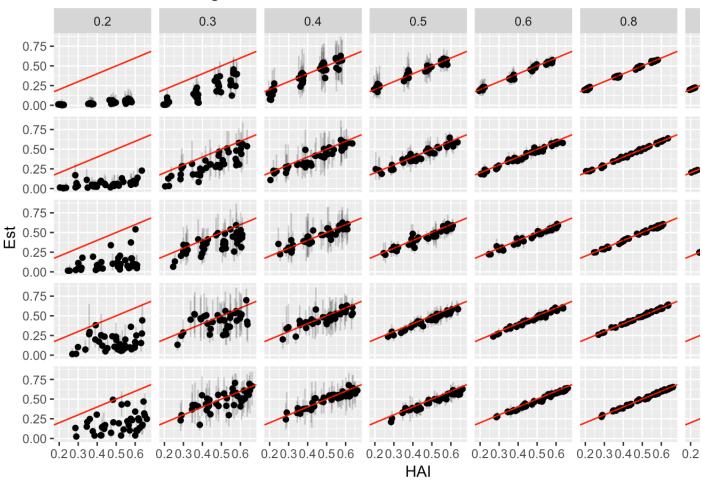
# Simulated Data Populations

## Simulated Populations



# Simulated Data Populations: Results

## Bias Corrected Plugin Estimator



# Simulated Data Populations: Results

### Bias Corrected Hypergeometric Estimator

