

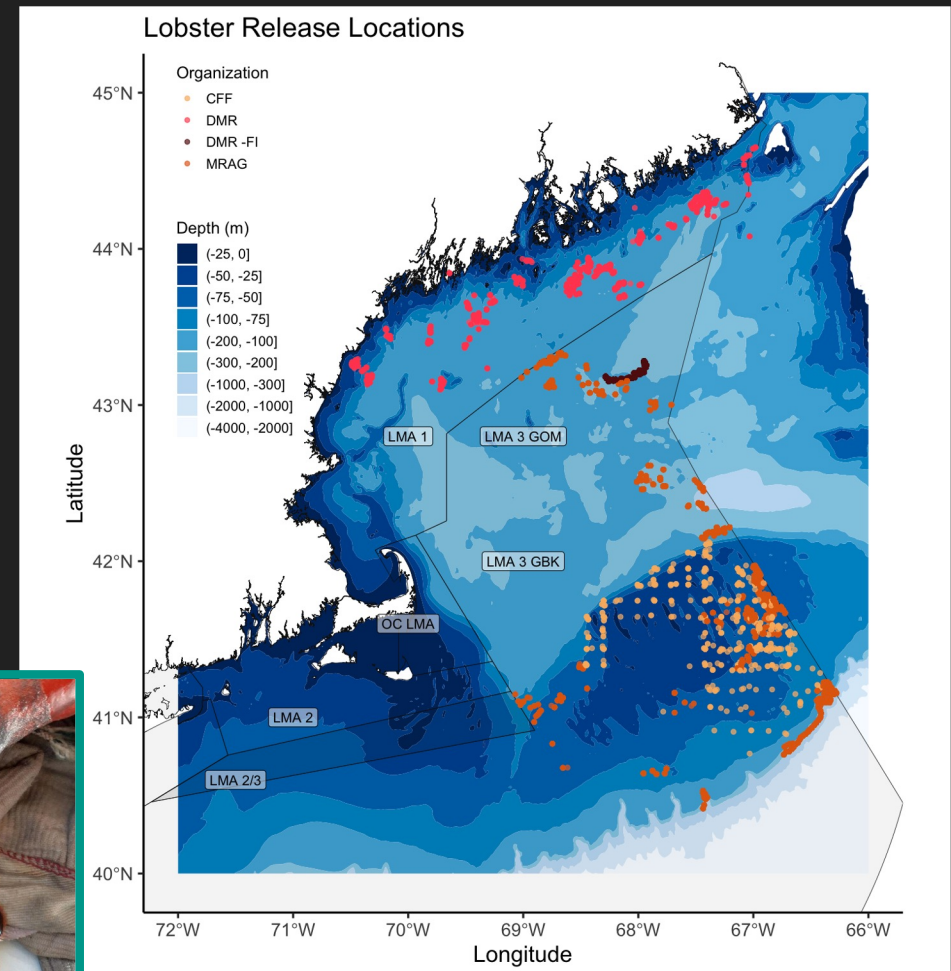
# Estimating Observation Errors from Tag Data

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# AOLA data collection

Project addressed 2015 ASMFC Stock Assessment research priorities.

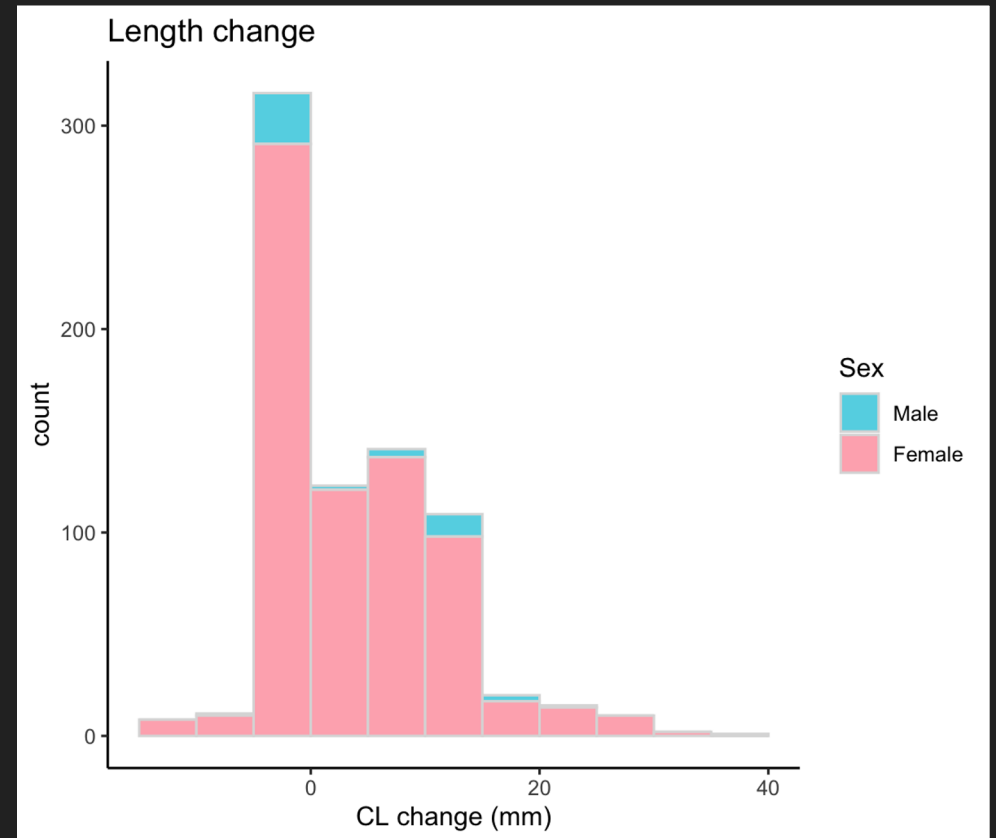
1. “Examine stock connectivity between GOM and GBK”
2. “Update information on growth and maturity”



Above: Lobster release locations by different organizations; Right: Example image used in industry outreach to fishermen.

## Recapture data

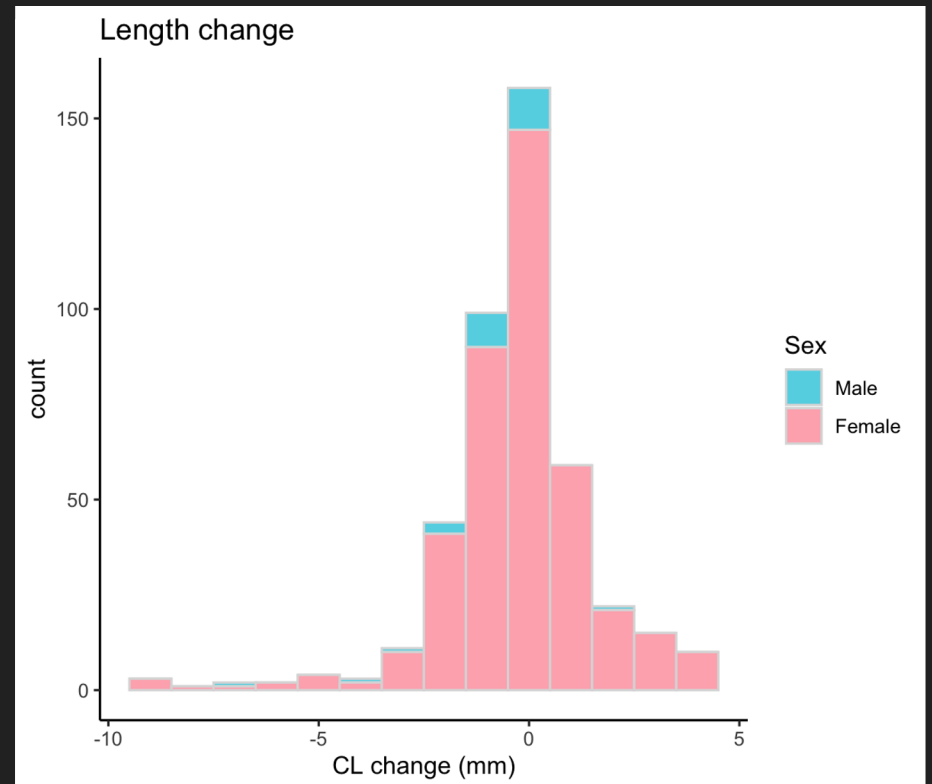
- 1800+ recaptures
  - 488 caliper only measurement
  - 270 caliper + ImageJ measurement
  - 251 ImageJ measurement
- Note: a large proportion of measurements are negative



Calculated length change from caliper measurements (758 total)

## Low growth observations

- How can we use poor datapoints i.e. low, negative, zero length change?



Distribution of low length changes.

# Estimating error from obs. with $E[\text{Growth}] = 0$

Collect Recapture Length Obs.

Calculate Length Change, and Filter Growth to Minimum Molt Increment,  $E[G] = 0$

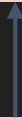
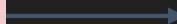
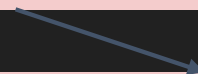
Generate a Normal Vector with Mean = 0, Standard Deviation  $p$

Round Randomized Error Vector to Match Obs. Error Structure

Minimize the D-statistic in KS by optimizing standard dev.  $p$

Compare error vectors with KS test, bootstrap to prevent staircase effect.

**ITERATE**



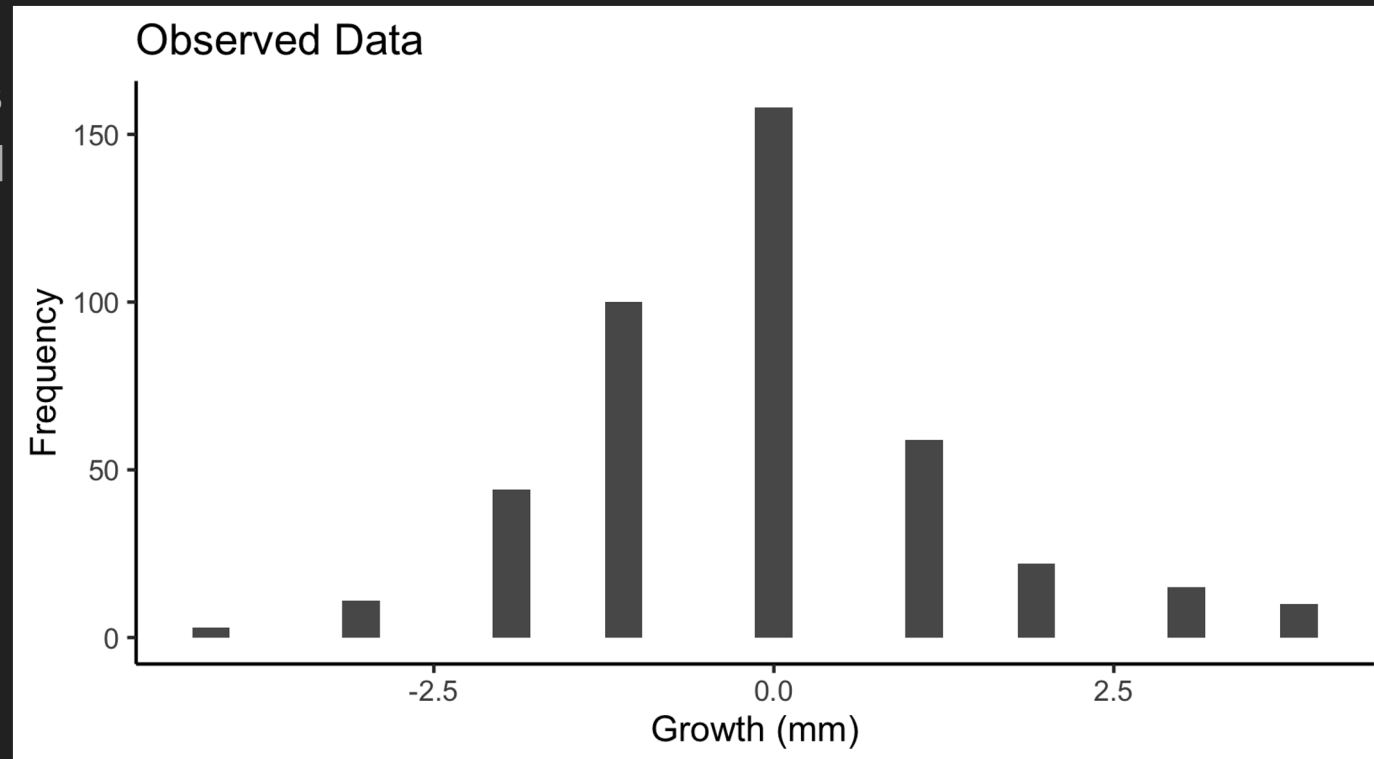
## Why estimate error in this way?

- Each length measurement has the potential to introduce error
- Combining length estimates may cancel or compound this error → error distribution
- If we can estimate a stable stochastic term for this error, we can add noise to GTM growth increment parameter
- Running the assessment model with and without this additional noise can inform as to the level of compound measurement bias and its impact on results

# Distribution of low growth measurements

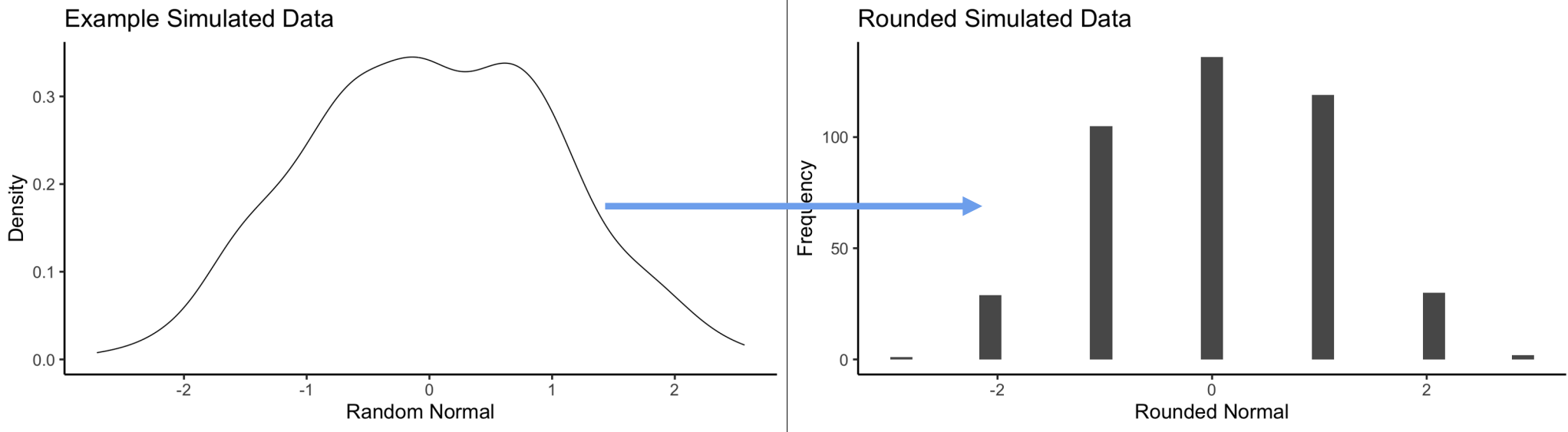
Low growth measurements are not normally distributed due to the discrete structure of observer measurements.

Confirmed with Shapiro-Wilk.



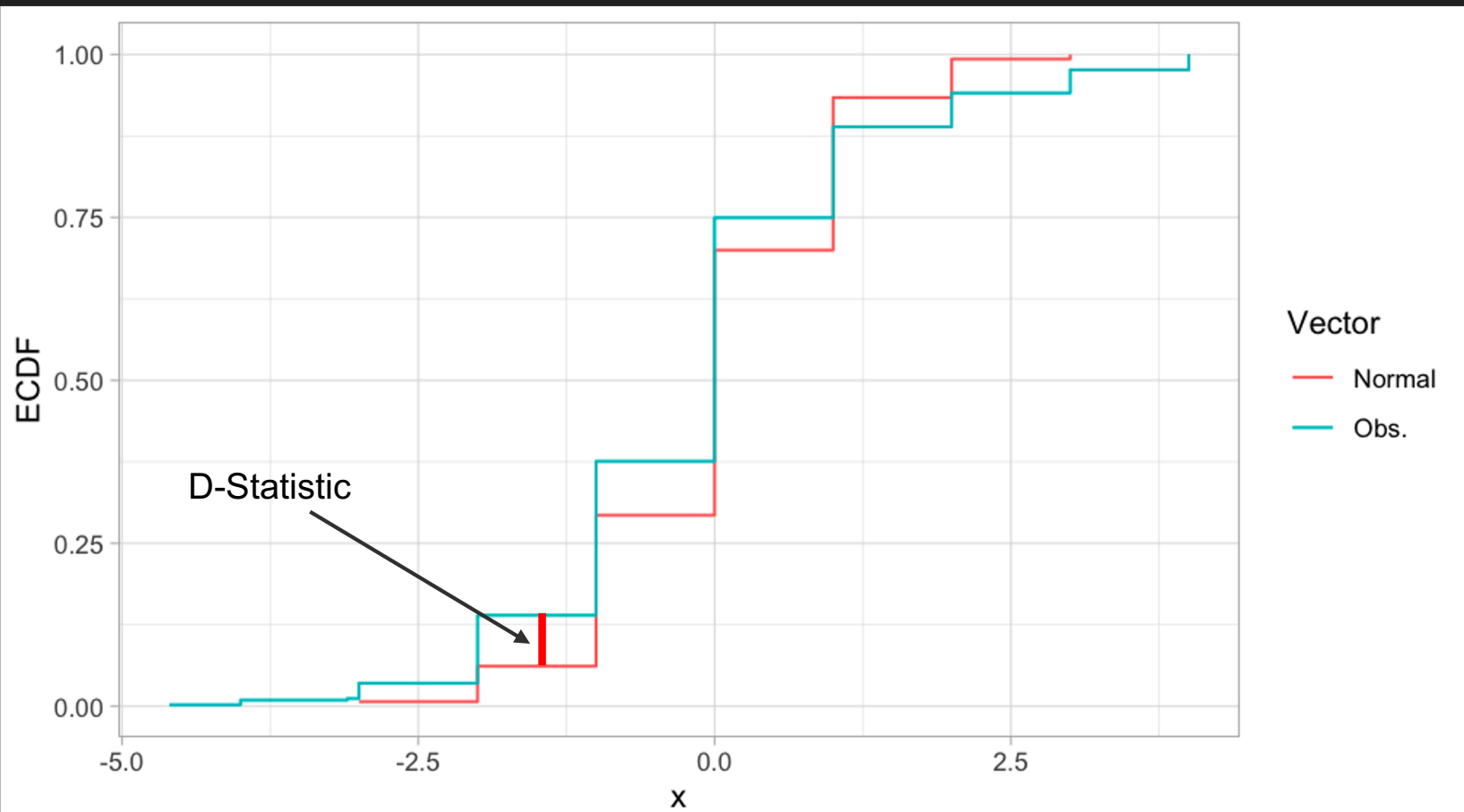
# The normal vector, discretization and the D-statistic

Generate random normal, discretize to match growth data, compare distributions via KS D-statistic



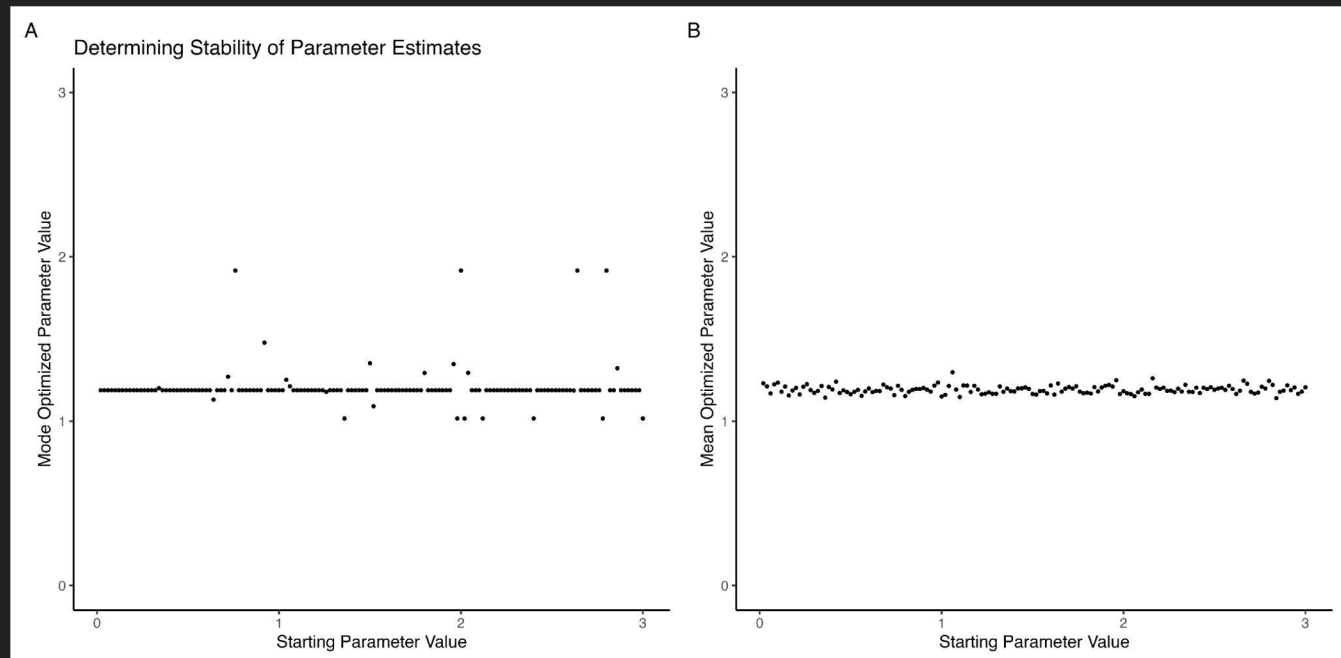


# The normal vector, discretization and the D-statistic



# Testing Across Starting Parameters

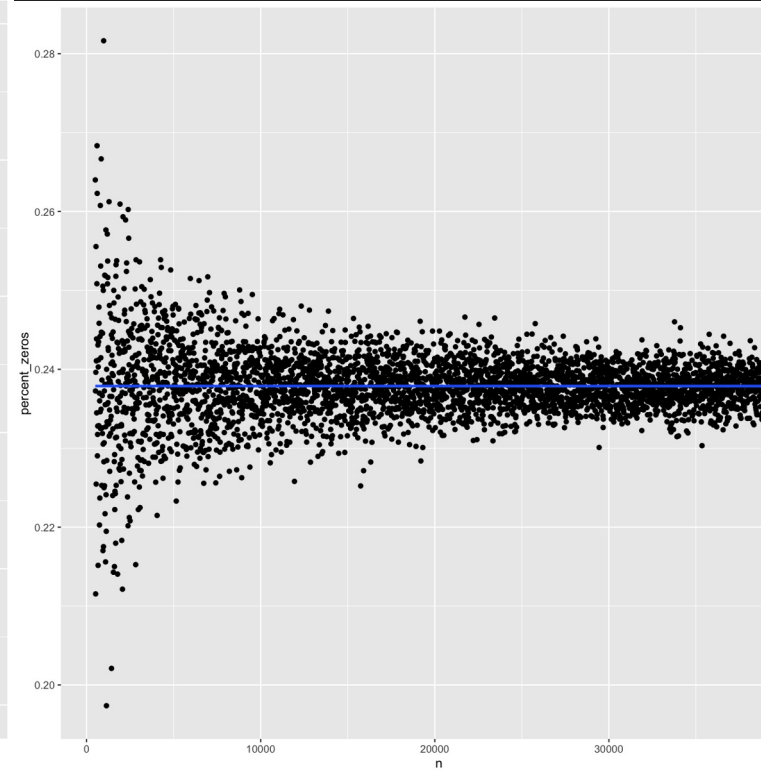
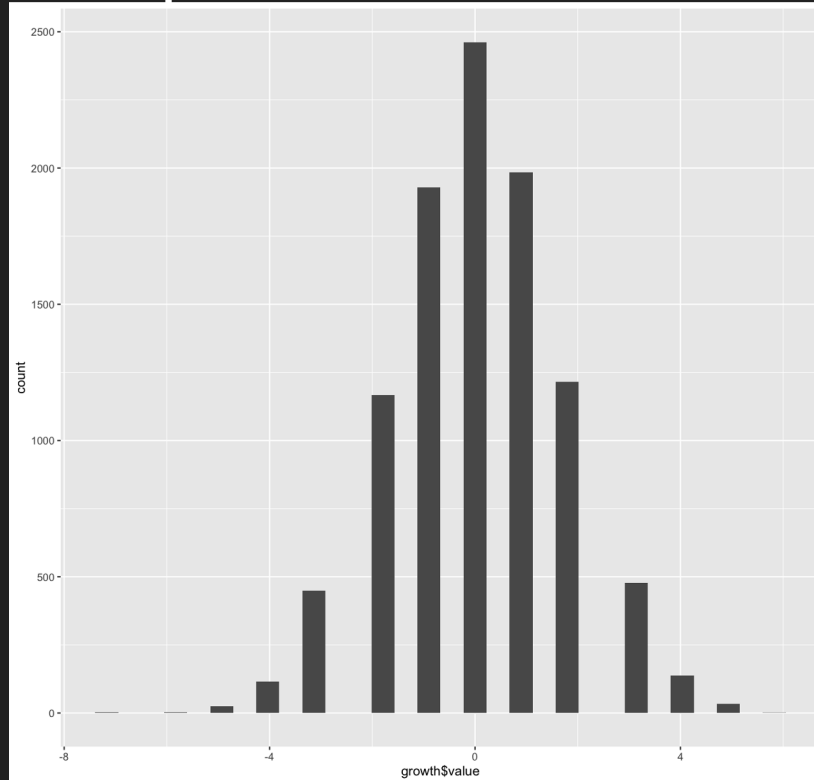
- 150 starting standard deviation values from 0.02 to 3.00
- Standard deviation is optimized over 100 iterations, mode and mean are reported to determine stability
- $N(0, 1.19)$  is identified as the stochastic term.



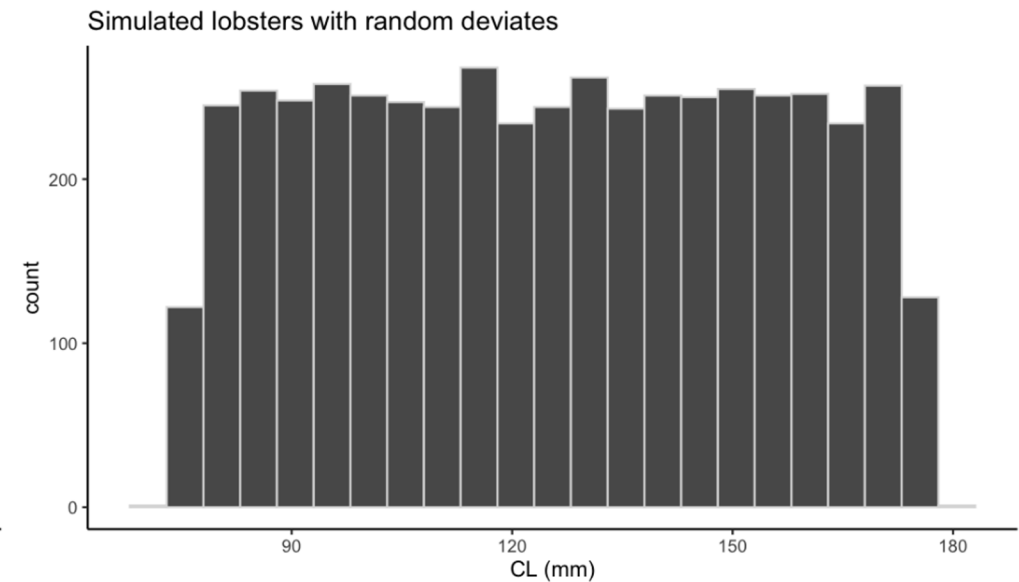
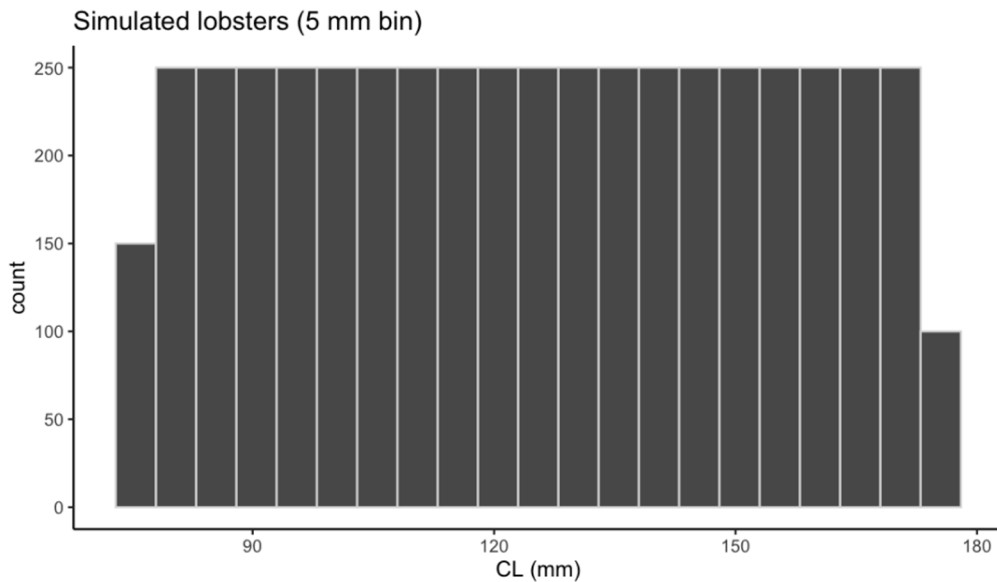
# Adding error components

If we assume both  
observer obs. have  
the same error  
structure,

Error cancels itself  
23.8 % of the time.



# Simulation bin change, $n = 5000$ “lobsters”



In simulation where lobsters are equally distributed across 5 mm bins, adding the stochastic term changes lobster size 19% of the time.

## Take Home Points

1. When we expect Growth = 0 we can use observations to calibrate an error term for growth.
2. Optimization of this term across parameter values finds  $N(0, 1.19)$  to be an appropriate stochastic term to model introduced observation error.
3. This stochastic term changes a lobsters size bin 19 % of the time in simulation.

This could be used to add noise to GTM growth increments and determine if observer error impacts our understanding of stocks by changing growth.

Next step: Fit as max likelihood through TMB

Questions!