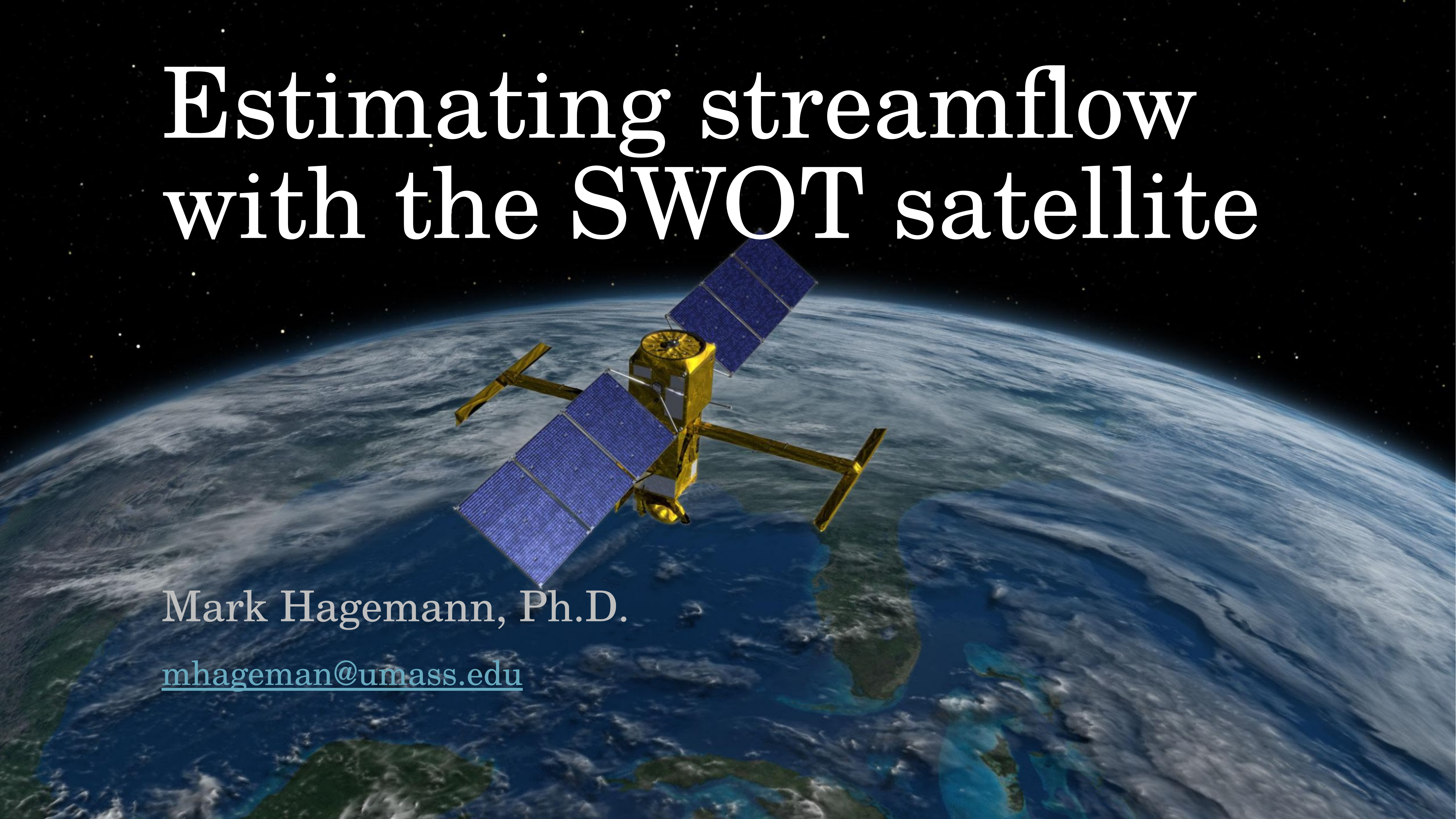

Estimating streamflow with the SWOT satellite

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Acknowledgments

- NASA Jet Propulsion Lab
- UMass Fluvial hydrology group, Dr. Colin Gleason

Overview

- SWOT satellite mission
- Bayesian model for river discharge using SWOT observations
- HydroSWOT proxy dataset
- Results

Bayes and data assimilation

SWOT satellite mission

- **S**urface **W**ater & **O**cean **T**opography
- NASA, CNES
- 2021 Launch

Measurements

- Height (H) via RADAR interferrometry
- Width (W) via ####
- Slope via height / distance
- dA via integration of W dH

The model (1)

$$Q = \frac{1}{n} A^{5/3} W^{-2/3} S^{1/2}$$

- Manning's equation

The model (2)

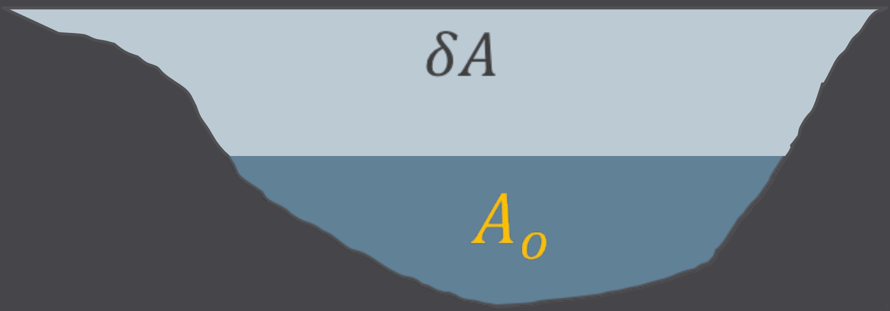
$$\log Q = -\log n + \frac{5}{3}\log A - \frac{2}{3}\log W + \frac{1}{2}\log S$$

- Manning’s equation
- Log-transform

The model (3)

$$\log Q = -\log n + \frac{5}{3}\log(A_0 + \delta A) - \frac{2}{3}\log W + \frac{1}{2}\log S$$

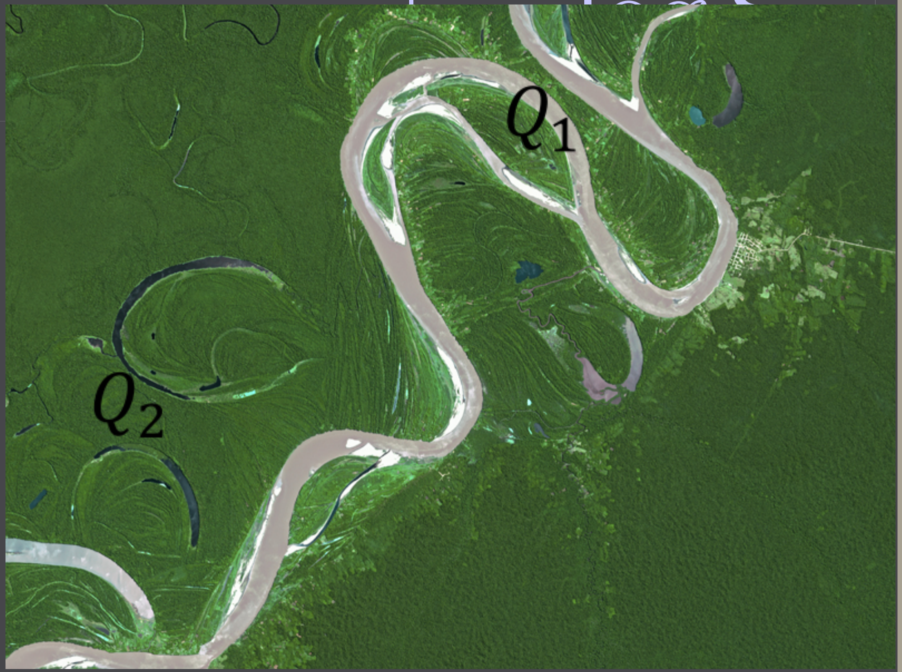
- Manning's equation
- Log-transform
- Adjust for SWOT observables



The model (4)

$$\log Q_{it} = -\log n + \frac{5}{3}\log(A_{0,i} + \delta A_{it}) - \frac{2}{3}\log W_{it}$$

- Manning's equation
- Log-transform
- Adjust for SWOT observables
- Index in time and space



The model (5)

$$\log Q_t = -\log n + \frac{5}{3}\log(A_{0,i} + \delta A_{it}) - \frac{2}{3}\log W_{it}$$

$$+ \frac{1}{}\log S$$

- Manning's equation
- Log-transform
- Adjust for SWOT observables
- Index in time and space
- Mass conservation

The model (6)

$$\frac{2}{3}\log \mathsf{W}_{\mathsf{it}} - \frac{1}{2}\log \mathsf{S}_{\mathsf{it}} = -\log \mathsf{n} + \frac{5}{3}\log(\mathsf{A}_{0,\mathsf{i}} + \delta \mathsf{A}_{\mathsf{it}}) - \log \mathsf{Q}_{\mathsf{t}} + \epsilon_{\mathsf{it}}$$

- Manning's equation
- Log-transform
- Adjust for SWOT observables
- Index in time and space
- Mass conservation
- Rearrange, acknowledge error

The model (7)

$$\underbrace{\frac{2}{3}\log W_{it} - \frac{1}{2}\log S_{it}} = -\log n + \frac{5}{3}\log(A_{0,i} + \delta A_{it}) - \log Q_t + \epsilon_{it}$$

$$f(y_{it} | n, Q_t, A_{0,i}, \delta A_{it}) = N(\mu = \mathrm{RHS}, \sigma)$$

- Observables vary in time and space
- Quantities of interest vary in time or space (not both)
- Random error

The model (8)

$$f(y_{it}, \delta A_{it} | n, Q_t, A_{0,i})$$

$$f(y_{it} | n, Q_t, A_{0,i}, \delta A_{it}) = N(\mu = \mathrm{RHS}, \sigma)$$

- Observables vary in time and space
- Quantities of interest vary in time or space (not both)
- Random error

The model (9)

$$f(y_{it}, \delta A_{it} | n, Q_t, A_{0,i}) = f(y_{it} | n, Q_t, A_{0,i}, \delta A_{it}) \times f(\delta A_{it} | n, Q_t, A_{0,i})$$

$$f(y_{it} | n, Q_t, A_{0,i}, \delta A_{it}) = N(\mu = \mathrm{RHS}, \sigma)$$

- Observables vary in time and space
- Quantities of interest vary in time or space (not both)
- Random error

$$f(\delta A_{it} | n, Q_t, A_{0,i})$$

$$f(\delta A_{it}|n, Q_t, A_{0,i}) = f(\delta A_{it}|A_{0,i}) = f(\delta A_{it}|A_{0,i}, \sigma_A)$$

$$= \frac{1}{(\delta A + A_0)\sqrt{2\pi}\sigma_A} \times \exp\left(-\frac{1}{2\sigma_A^2}[\log(\delta A + A_0) - \log A_0]^2\right),$$

$$(\delta A > -A_0)$$

HydroSWOT database

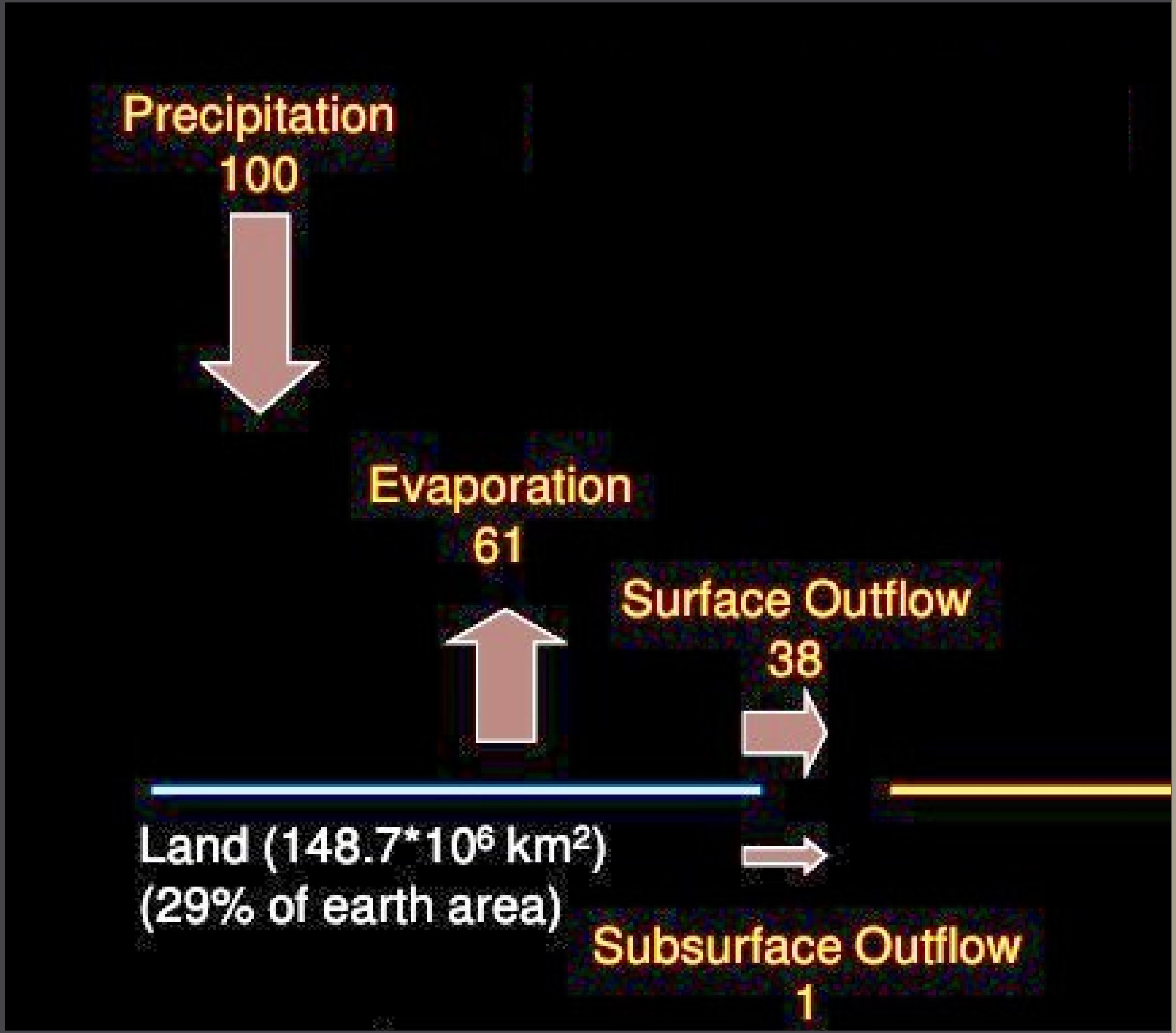
- Direct measurement
- Stream gages

Results

How is Q measured?

- Direct measurement
- Stream gages
  - Great for USA
  - Less great for Africa

$$Q = P - ET$$



How is Q measured?

- Direct measurement ← Labor-intensive
- Stream gages ← Labor-, $-intensive
- Water-balance models ← Imprecise

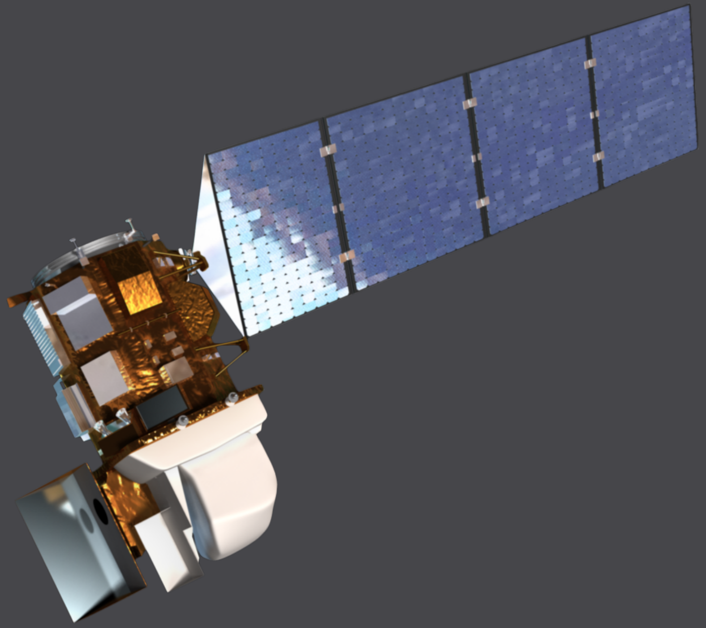
← Insufficient data

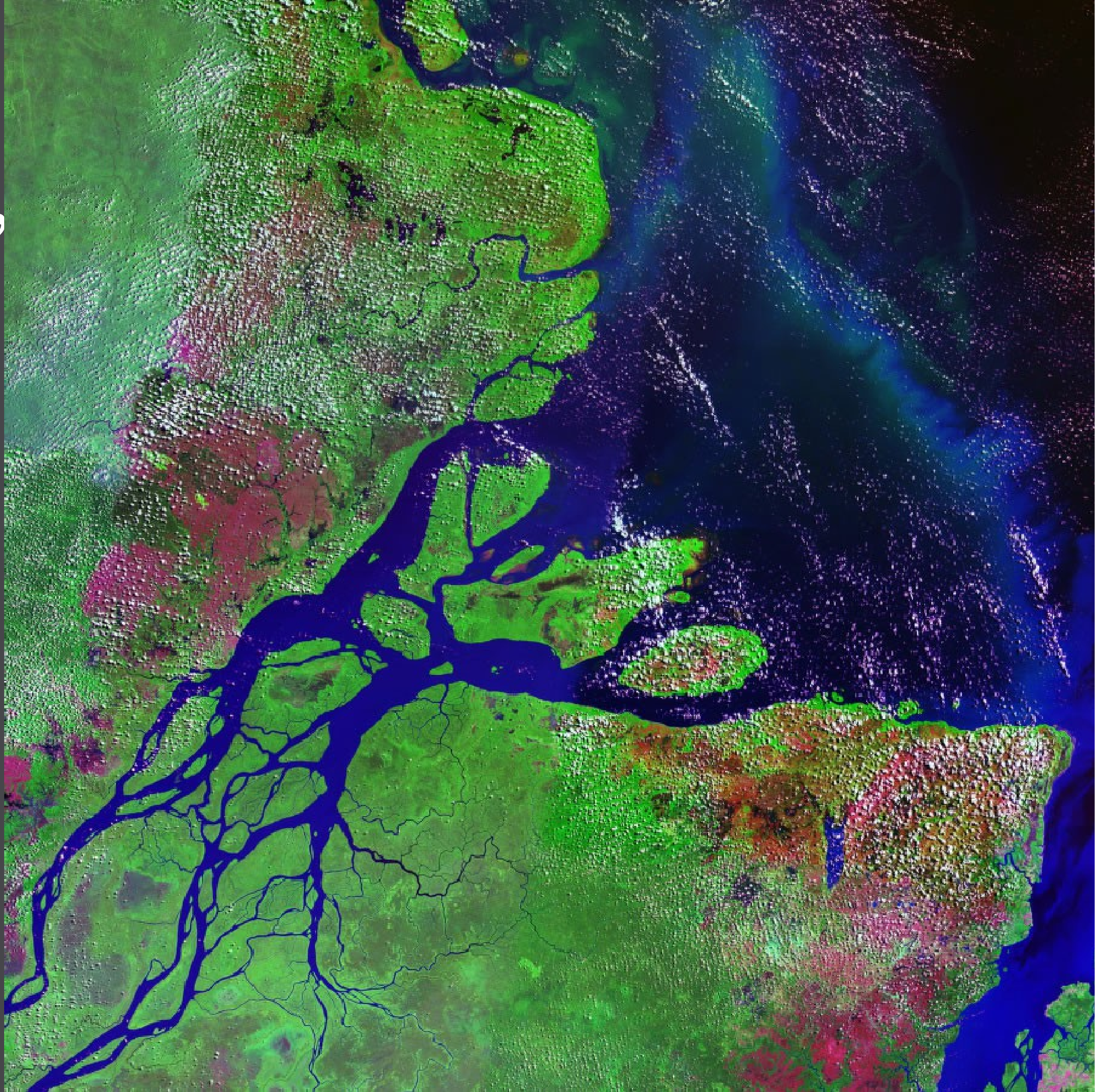
How is Q measured?

- Direct measurement
- Stream gages
- Water-balance models
- "Flow laws"
  - Relate Q to slope, bed material, channel geometry

- Manning's equation: $Q = \frac{1}{n}\frac{A^{5/3}}{W^{2/3}}S^{1/2}$
  - A: cross-sectional area
  - n: "manning's n" (relates to bed roughness)
  - W: stream width
  - S: stream slope
- At-a-station hydraulic geometry: $Q = aW^{b}$
  - W: stream width
  - a, b: parameters relating to channel geometry

More on ”flow laws”



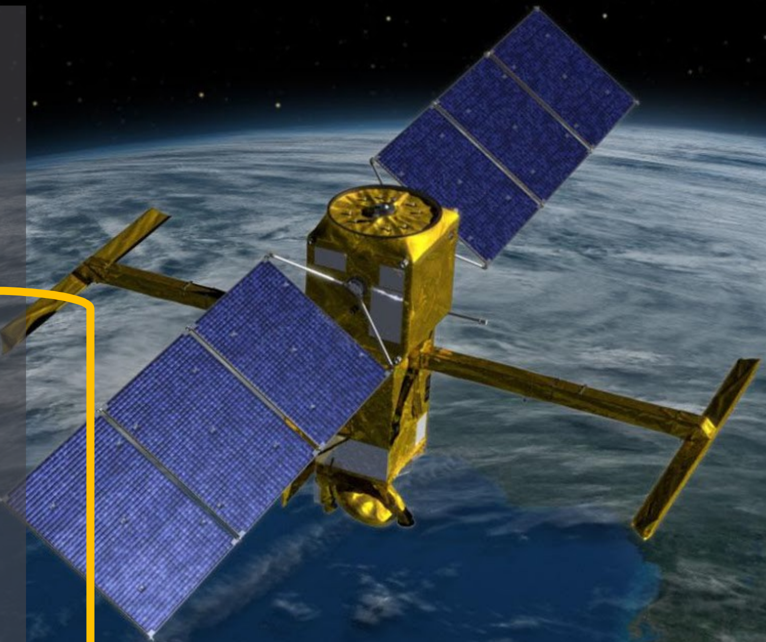


Satellite Remote Sensing

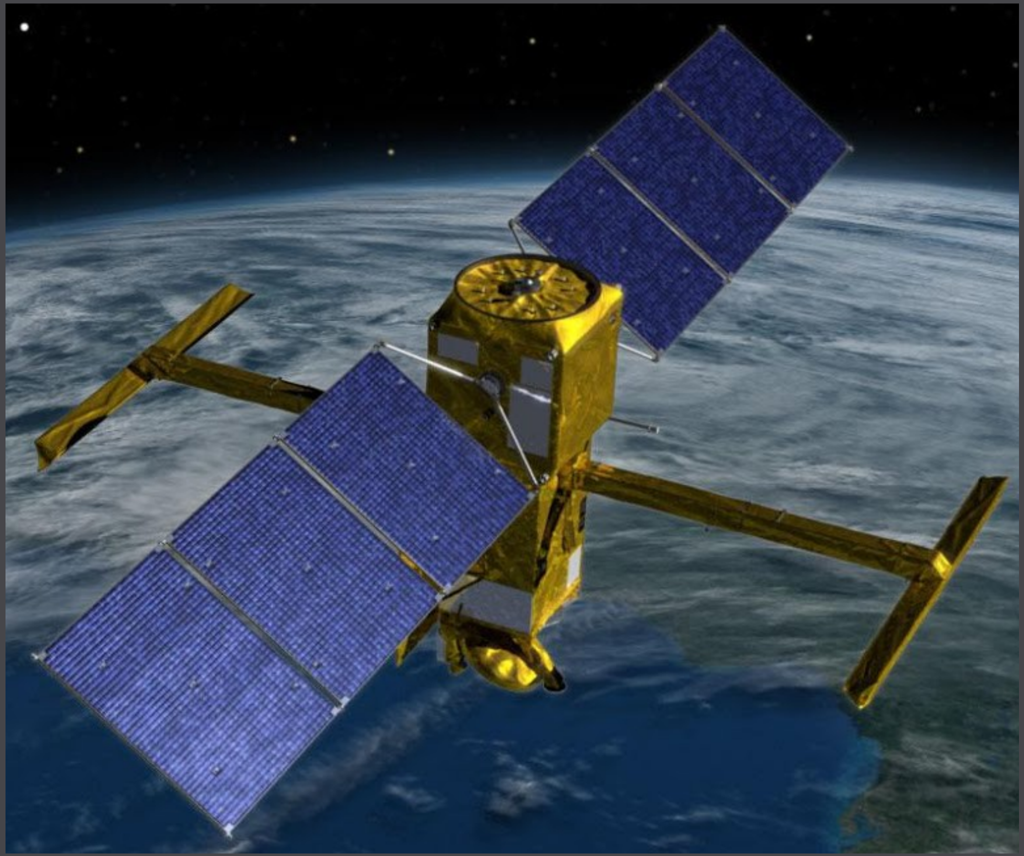
- Pictures of Earth from space
- E.G. LANDSAT (1972-present)

- Upcoming NASA satellite mission (2020 launch)
- Stream width $\pm 15m$
- Stream height $\pm 10\ cm$
- Stream slope $\pm 2\ cm/km$

For any stream reach worldwide!

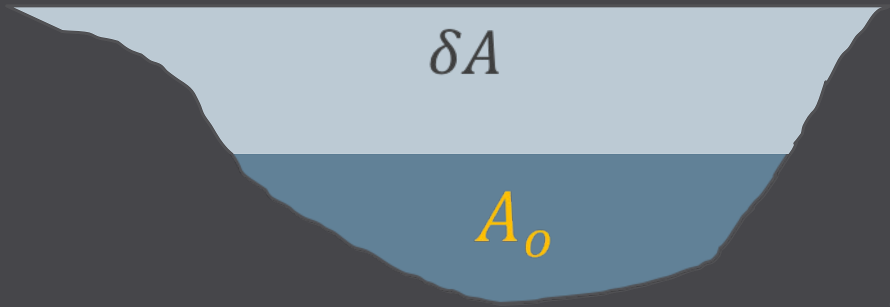


Surface Water and Ocean Topography (SWOT)



Can we get Q from SWOT measurements?

- (Using flow-law equations)
- Manning's equation: $Q = \frac{1}{n}\frac{(A_o+\delta A)^{5/3}}{W^{2/3}}S^{1/2}$
  - A_o: cross-sectional area at smallest measured width
  - δA: change in area from A_o
  - n: "manning's n" (relates to bed roughness)
  - W: stream width
  - S: stream slope

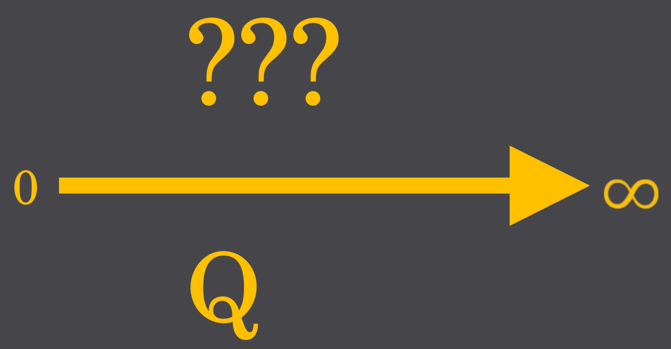


Can we solve the flow-law equations?

- Manning's equation: $Q = \frac{1}{n}\frac{(A_o+\delta A)^{5/3}}{W^{2/3}}S^{1/2}$
  - Multiple cross-sections
- Conserve flow in reach: $Q_1 = Q_2$
- More unknowns than equations!

Can we solve the flow-law equations?

Bayes, briefly $\mathrm{p}(A|B) \propto p(B|A)p(A)$



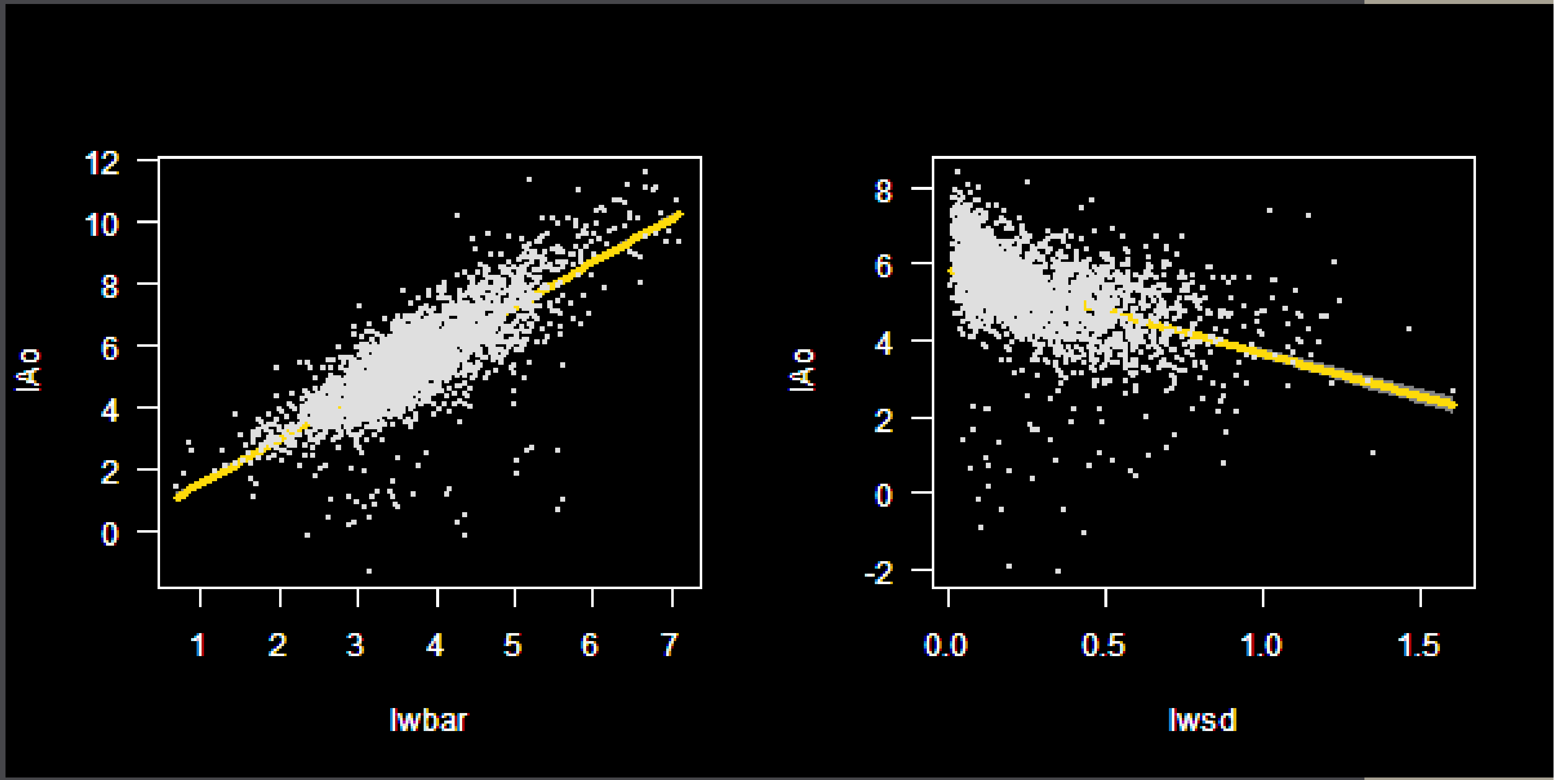
- Describe and constrain uncertain quantities
- Get a *distribution* for unknowns
- Computationally expensive

```
parameters {
  vector[nt] logQ;
  real logn;
  real<lower=30> Ao[nx];
}

model {
  logn ~ normal(logn_hat, logn_sd);
  logQ ~ normal(logQ_WBM,
cv2sigma(cvQ));
  for (i in 1:nx) {
    man_lhs[i] ~ normal(man_rhs[i],
sigma_man);
  }
  Ao ~ lognormal(logAo_hat, logAo_sd);
}
```

Bayes with Stan language

- Code looks like math!
- Bayes-specific, Bayes-optimized
- Open-source
- Plays nice with scientific computing environments



Constraining "prior distributions"

- Ao relates to width statistics
  - Wider rivers are deeper on average
  - More width-variable rivers are shallower on average
- n: from literature

AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

10.1002/2015WR018434

Key Points:
- SWOT discharge algorithms were tested on synthetic observations for 19 rivers
- Algorithms accurately characterized temporal dynamics of river discharge
- At least one algorithm estimated discharge to <35% relative RMSE on 14/16 of nonbraided rivers

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An intercomparison of remote sensing river discharge estimation algorithms from measurements of river height, width, and slope

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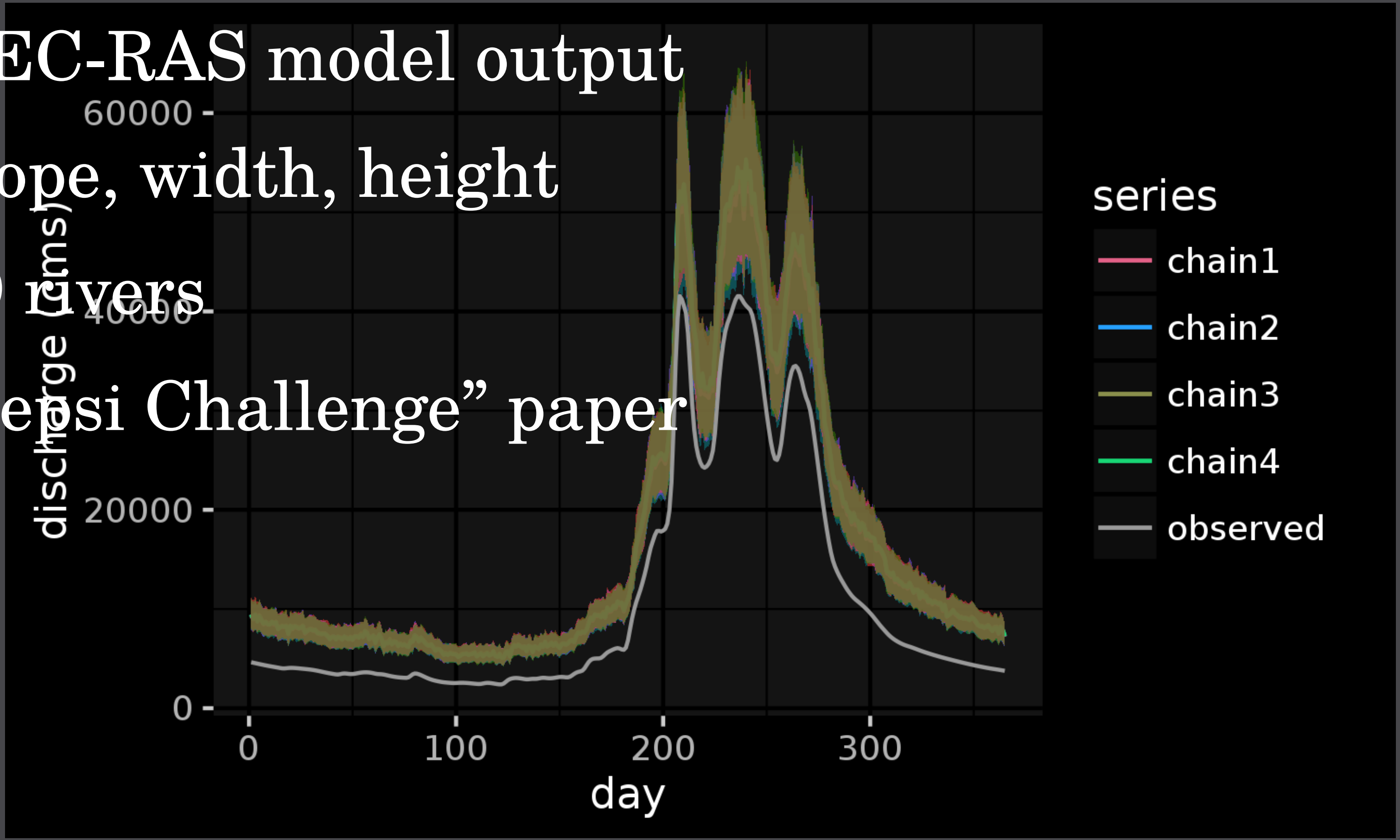
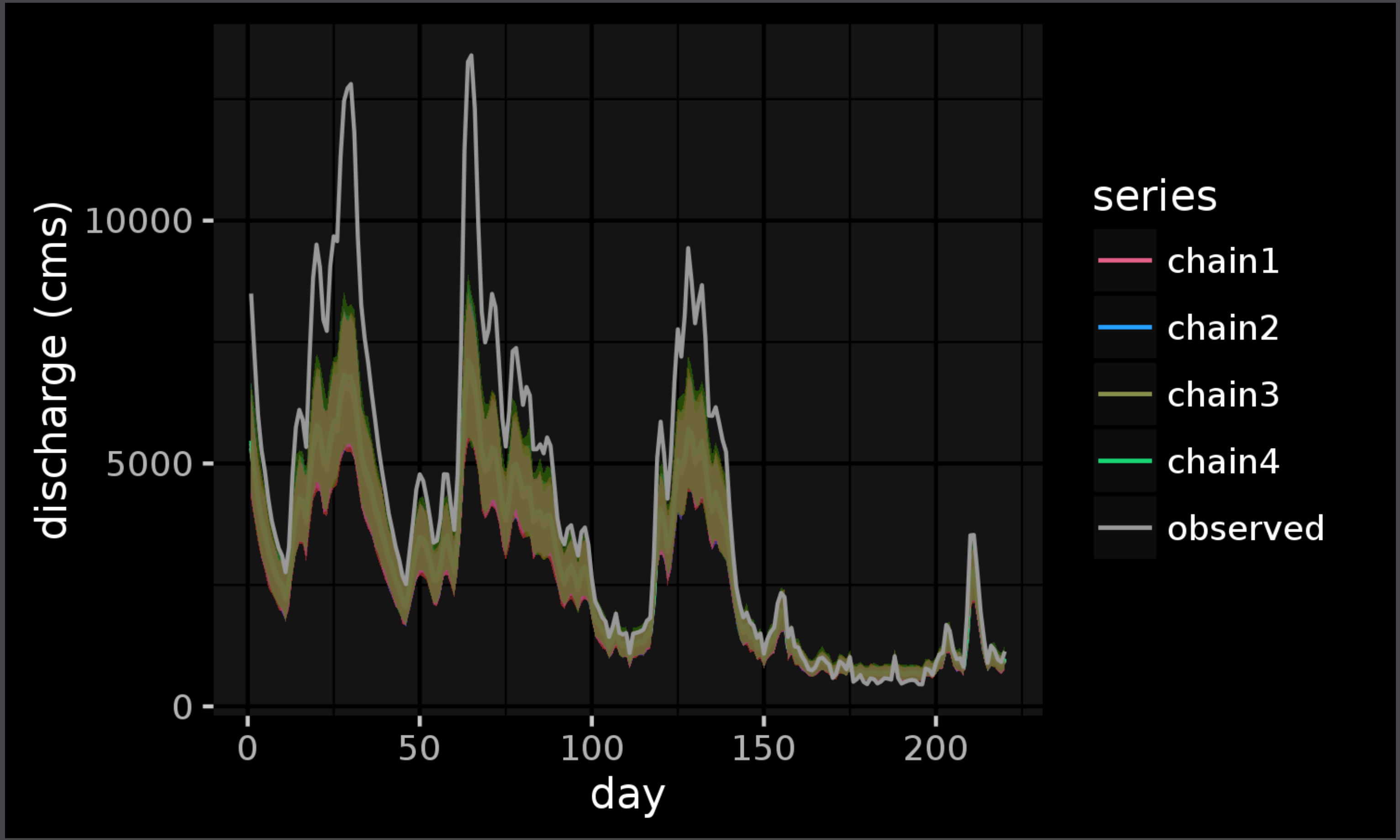
Abstract The Surface Water and Ocean Topography (SWOT) satellite mission planned for launch in 2020 will map river elevations and inundated area globally for rivers >100 m wide. In advance of this launch, we

“Data”

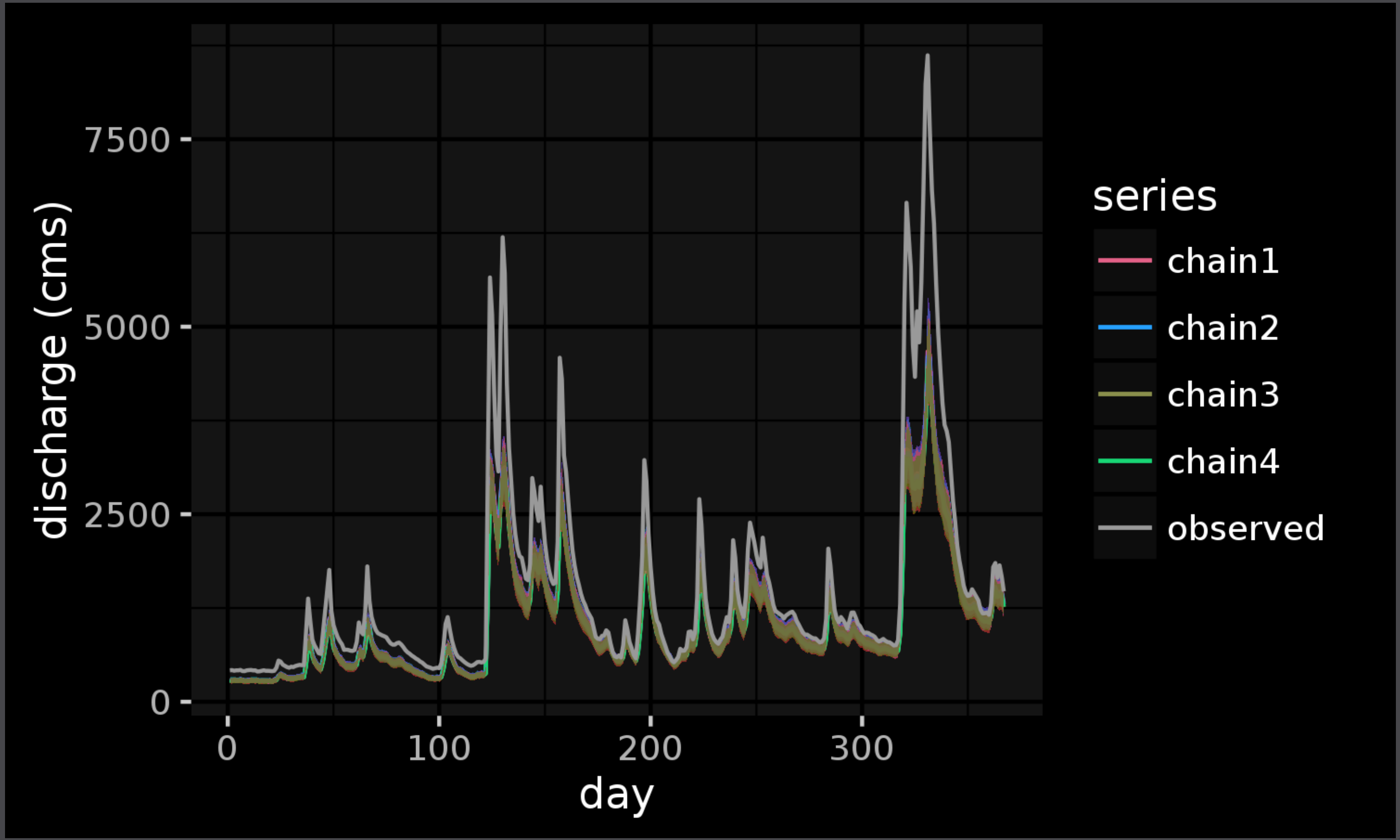
- HEC-RAS model output
- Slope, width, height
- 19 rivers
- “Pepsi Challenge” paper



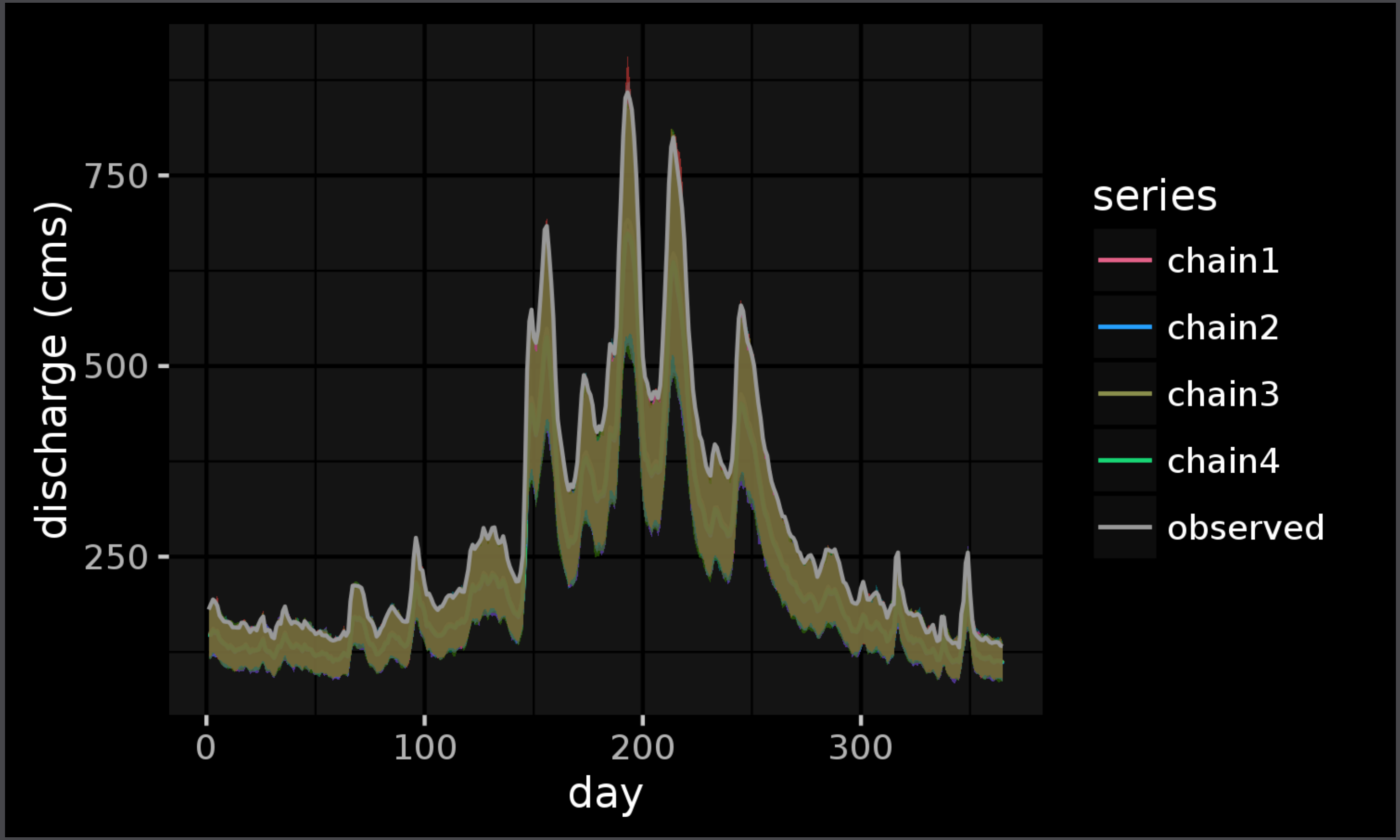
Results - Ganges



Results - Ohio



Results - Po


discharge (cms)
750
500
250
0
100
200
300
day
series
chain1
chain2
chain3
chain4
observed

Results – Seine

Worse

Better

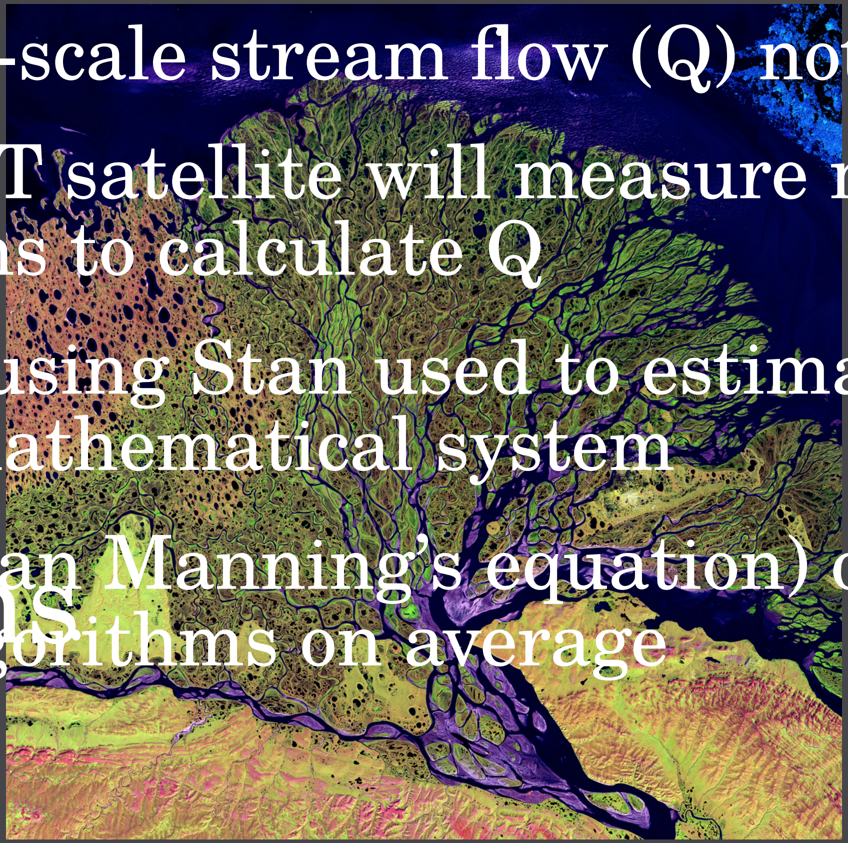
Comparing different algorithms (Pepsi Challenge)


AirSWOT

Next steps

- Validate using *actual* data
  - Field datasets
  - airSWOT
- Better constrain Manning’s n
  - Not actually constant
- Computer vision / deep learning for Q

Conclusions



- Global-, continental-scale stream flow (Q) not well constrained
- The upcoming SWOT satellite will measure many quantities used by flow-law equations to calculate Q
- Bayesian inference using Stan used to estimates Q in an underconstrained mathematical system
- Our method (Bayesian Manning's equation) outperforms other SWOT discharge algorithms on average

Thanks!

Thanks!