HOW ACCURATELY MUST WE KNOW GRAIN SIZE IN ORDER TO RETRIEVE SWE?

Mike Durand and Jinmei Pan

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SnowEx 2017
Grand Mesa.
Near site 53W

The Ohio State University

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HOW ACCURATELY MUST WE KNOW GRAIN SIZE IN ORDER TO RETRIEVE SWE?

- Spaceborne radar (10-19 GHz/ X-Ku) remains a promising technique for global SWE
- Radar backscatter intensity (σ_0) from the land surface is a function of many properties besides SWE, e.g:
  - Snow grain size
  - Soil moisture
  - Soil freeze-thaw state

SCLP (NASA)

CoReH2O (European Space Agency)

WCOM (Chinese Space Agency)

❄ ❄ ❄ ❄ ❄ ❄ ❄ ❄

TSMM (Canadian Space Agency)

Ongoing proposal to NASA Explorer call led by Ana Barros

HOW ACCURATELY MUST WE KNOW GRAIN SIZE IN ORDER TO RETRIEVE SWE?

- The CoReH2O mission proposed years ago to ESA ~10 years ago specified equivalent grain size be known to within ±15% (Rott et al., 2012)

Status: a revised version of this preprint is currently under review for the journal TC.

Review Article: Global Monitoring of Snow Water Equivalent using High Frequency Radar Remote Sensing

Leung Tsang[1], Michael Durand[2], Chris Derksen[3], Ana P. Barros[4], Do-Hyuk Kang[5], Hans Lievens[6], Hans-Peter Marshall[7], Jiyue Zhu[1], Joel Johnson[8], Joshua King[3], Juha Lemmetyinen[9], Melody Sandells[10], Nick Rutter[10], Paul Siqueira[11], Anne Nolin[12], Batu Osmanoglu[13], Carrie Vuyovich[13], Edward J. Kim[13], Drew Taylor[14], Ioanna Merkouriadi[9], Ludovic Brucker[13], Mahdi Navari[13], Marie Dumont[15], Richard Kelly[16], Rhae Sung Kim[13], Tien-Hao Liao[17], and Xiaolan Xu[17]

Described in Tsang et al., in review.

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: DEFINITIONS

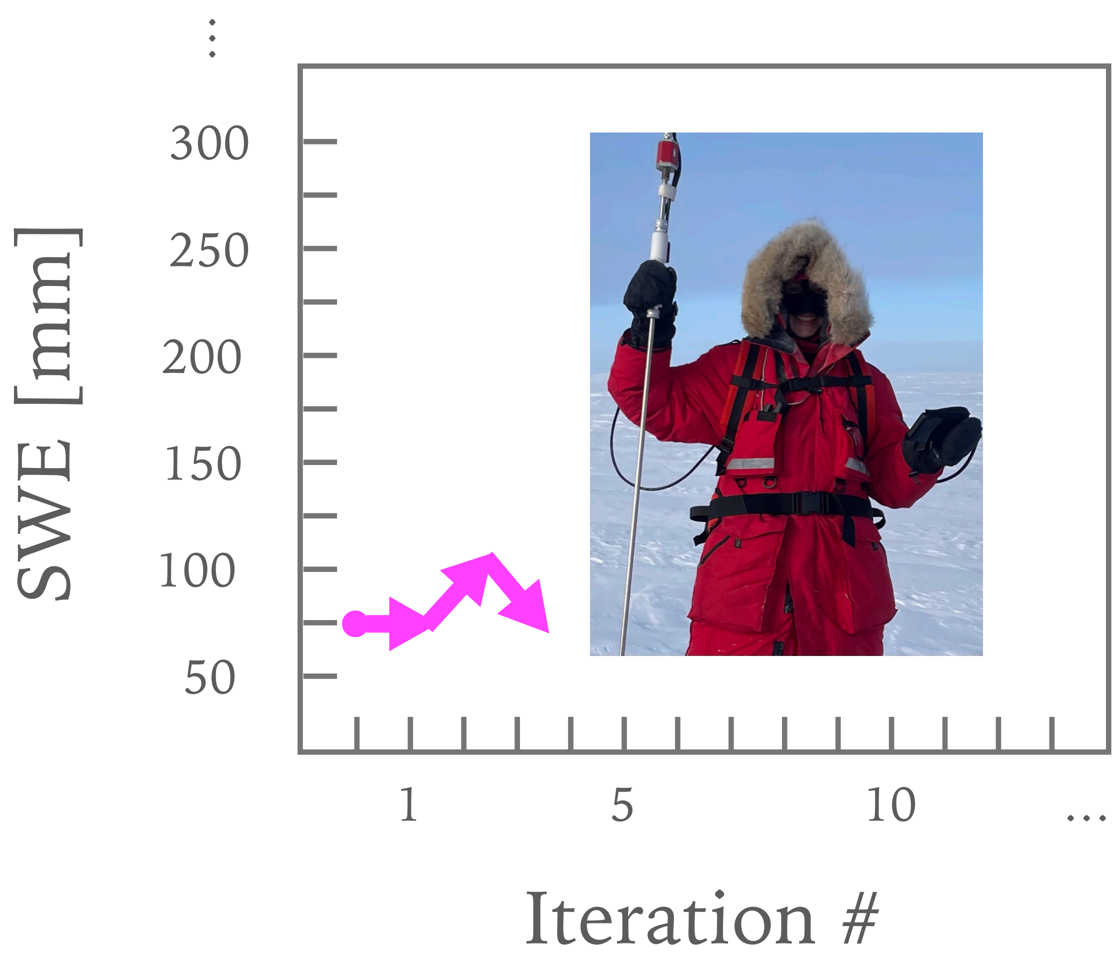
Random walk algorithms (such as MCMC) iteratively explore the optimal solution space for the parameters to estimate. They may have less stringent requirements for prior information.

x : *Parameters to estimate (SWE, grain size, …)*

y : *Radar observations (σ_0) for all frequencies & polarizations*

M : *Radiative transfer model:* $y = M[x]$

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: STARTING POINT



x_0 : *Starting values of SWE, grain size, etc.*

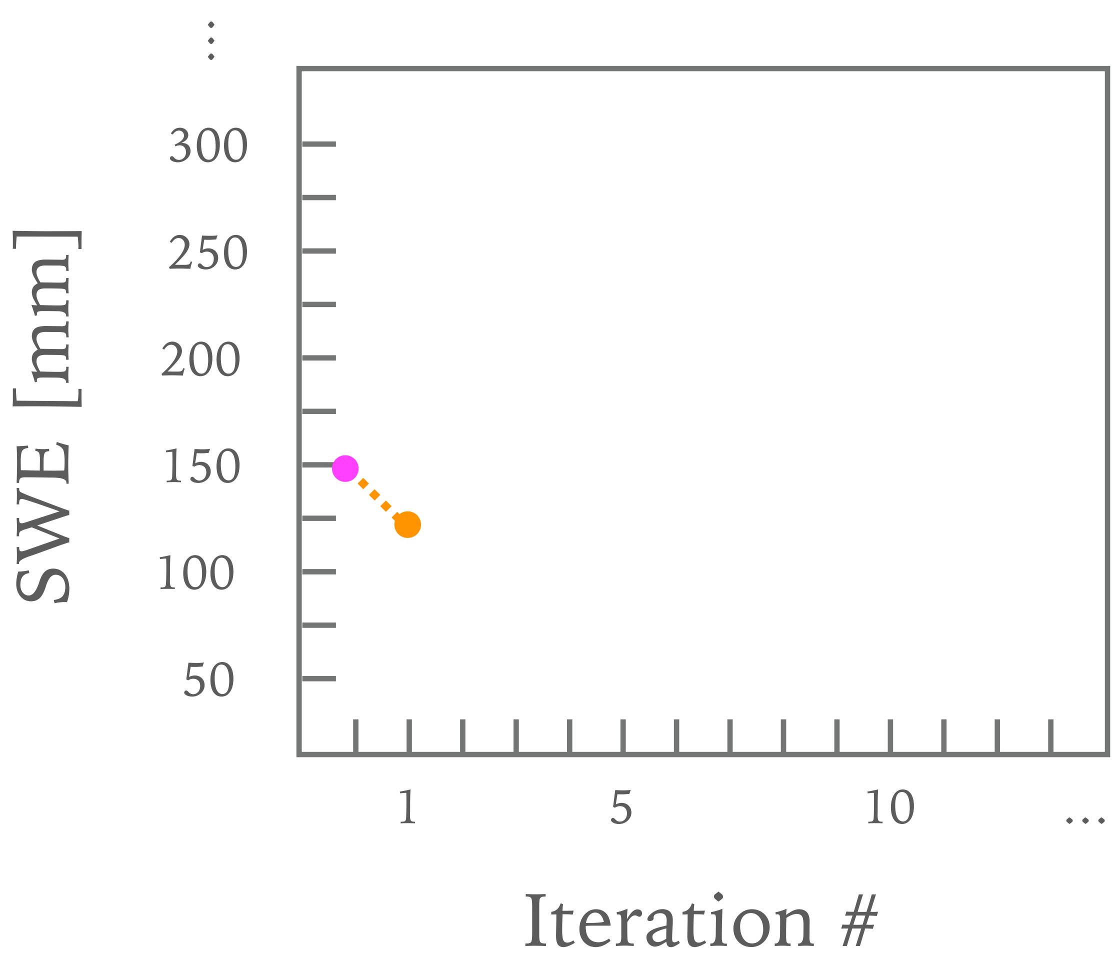
$\hat{y}_0 = M\left(x_0\right)$: *Corresponding predicted radar observations from radiative transfer model*

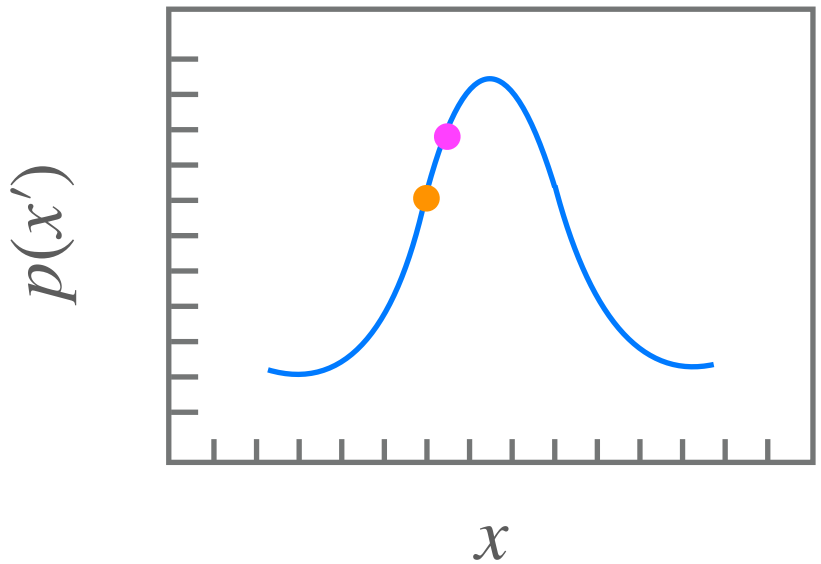
$p(x_0)$: *Probability of starting value: based on prior*

$p(\hat{y}_0 \,|\, x_0)$: *Probability of obtaining radar observation, given* x_0

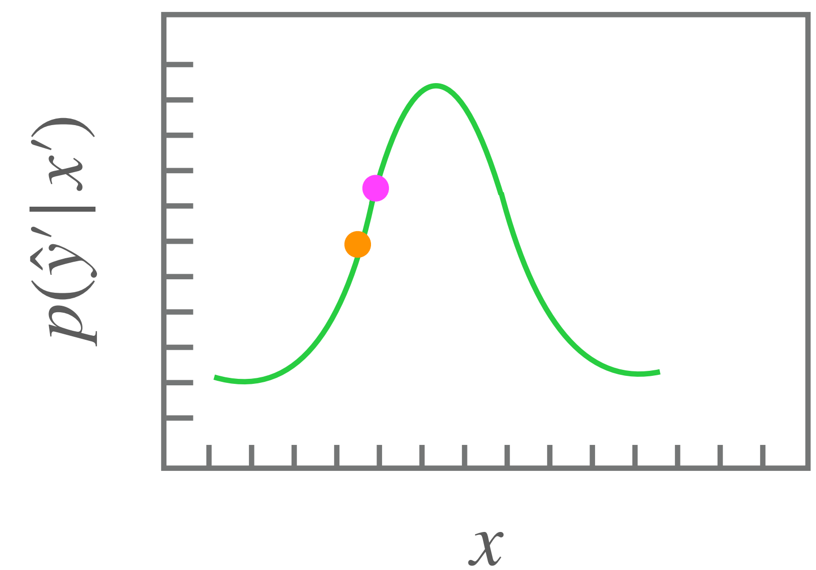
Random walk modifies snow property values, via candidates that can be either accepted or rejected

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: FIRST STEP





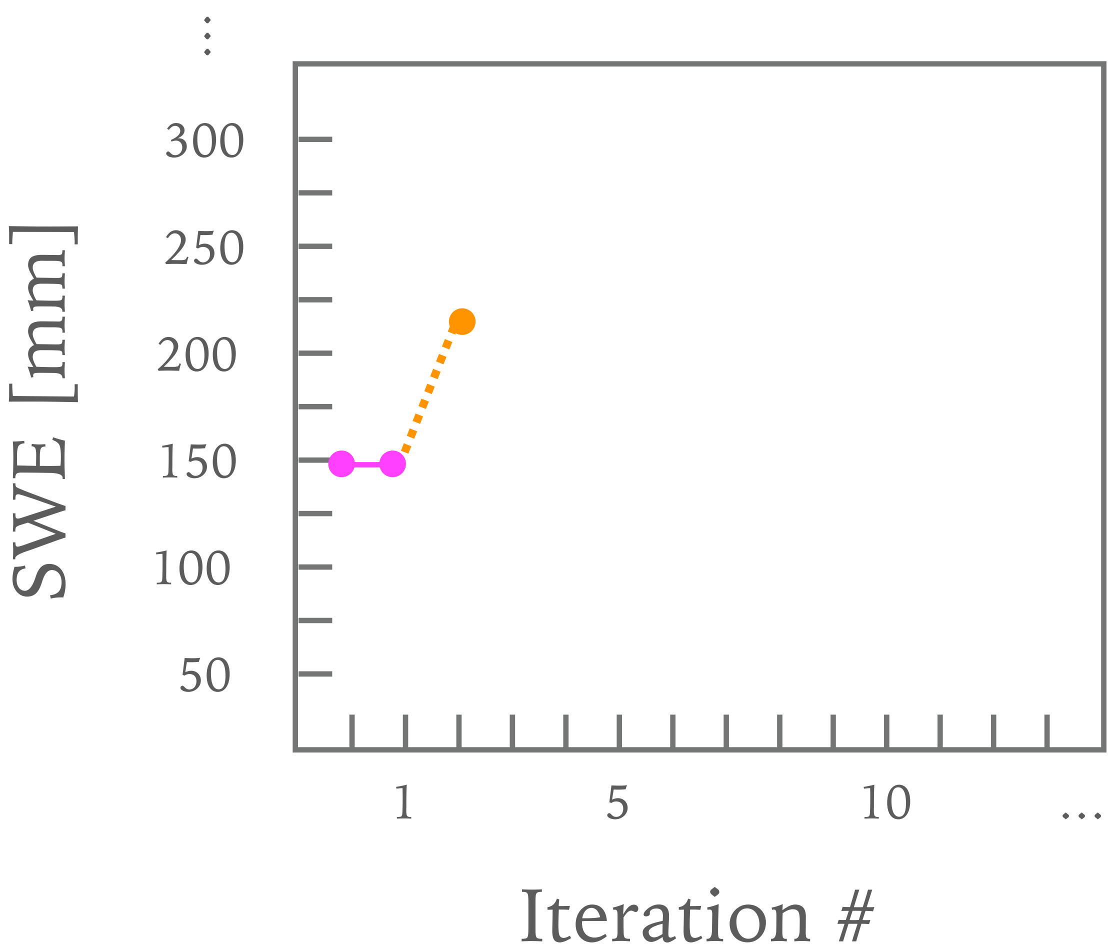
Probability of starting value: based on "prior distribution"

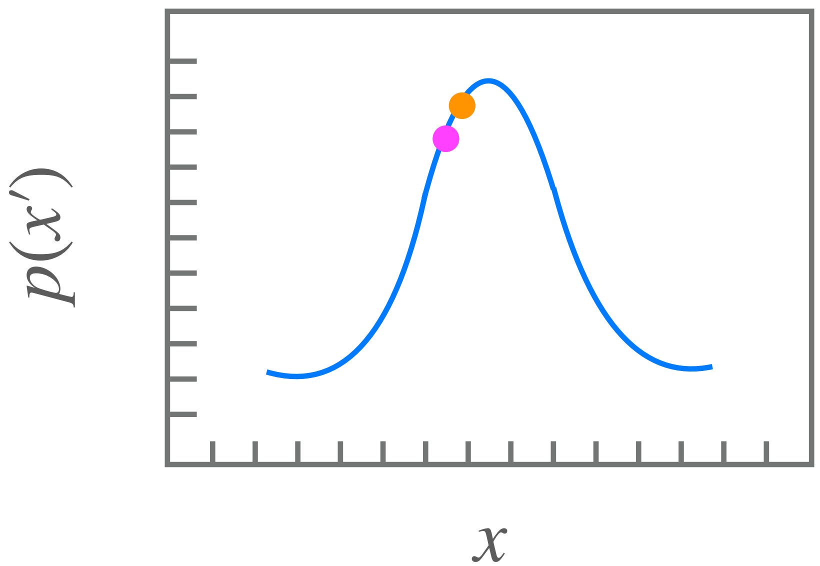


Probability of obtaining radar observation, given candidate, based on "likelihood distribution"

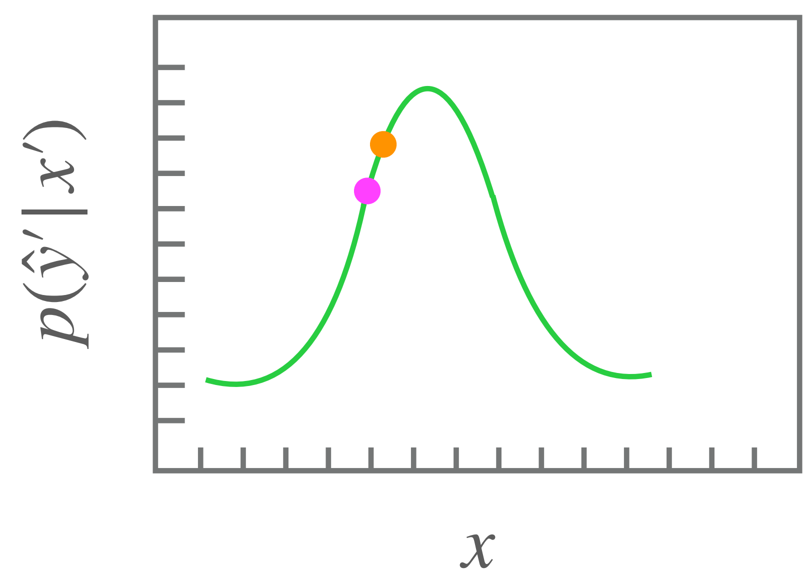
In this example, both likelihood and prior probability drops, and so candidate will be rejected.*

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: SECOND STEP





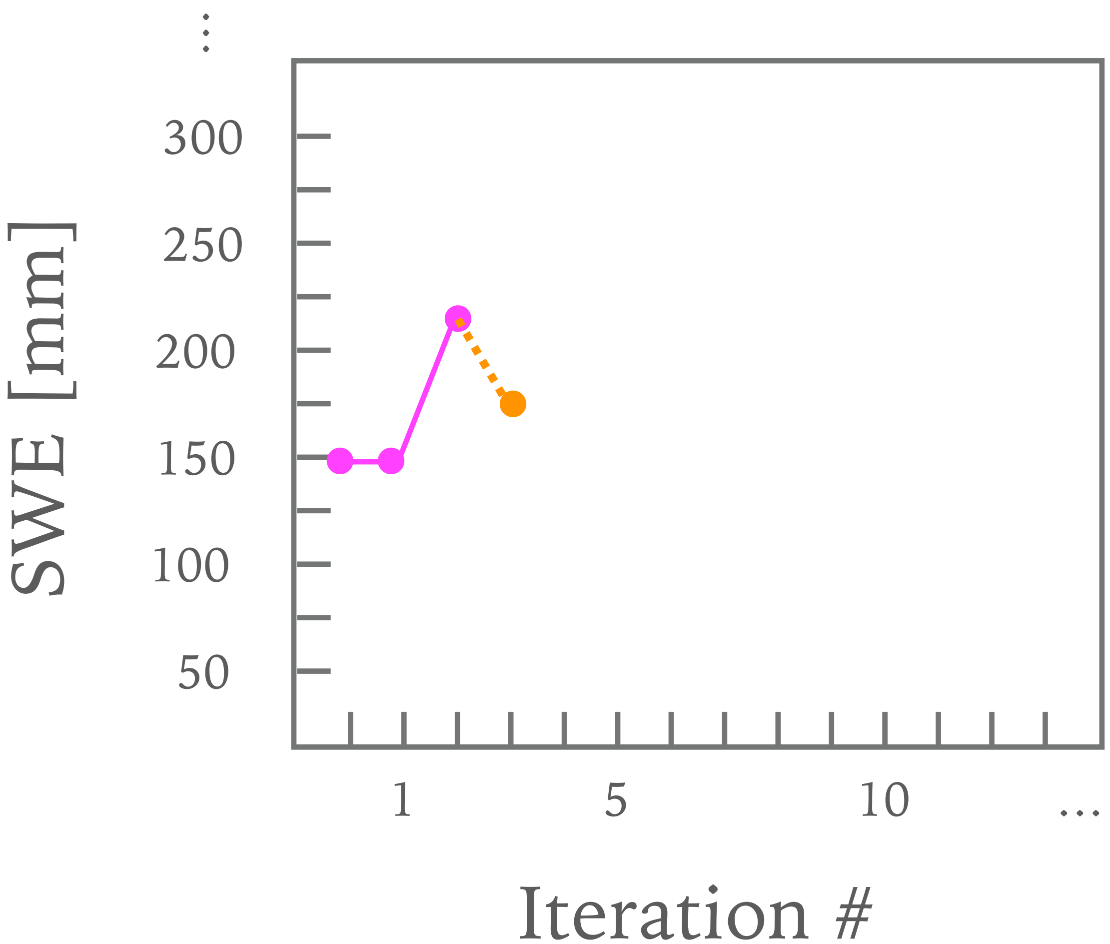
Probability of starting value: based on "prior distribution"

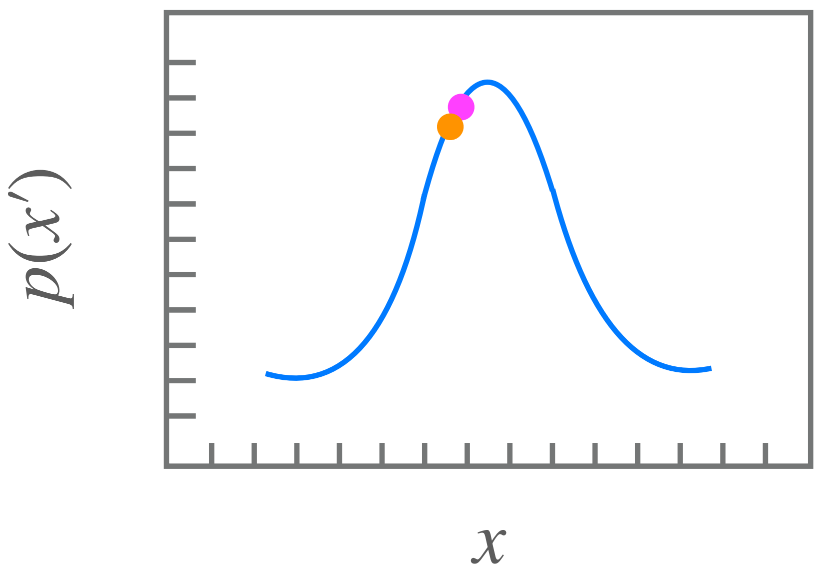


Probability of obtaining radar observation, given candidate, based on "likelihood distribution"

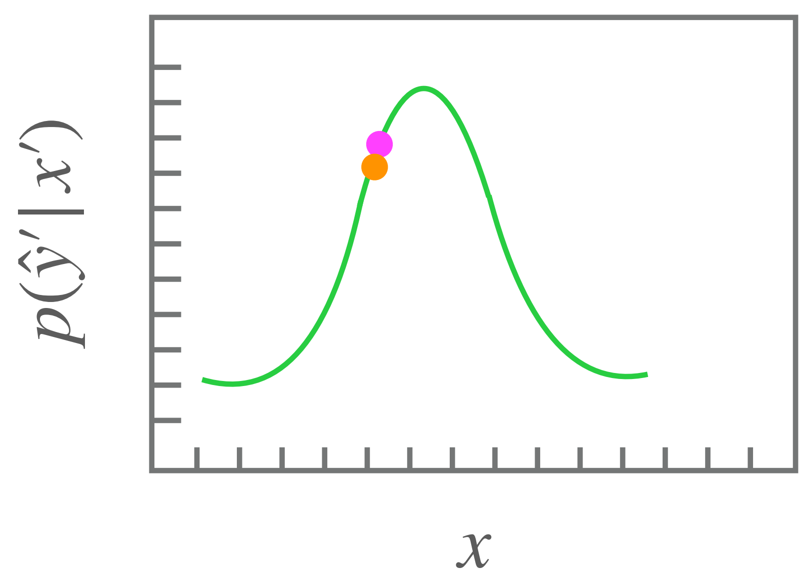
In this example, both likelihood and prior probability rises, and so candidate will be accepted.

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: THIRD STEP





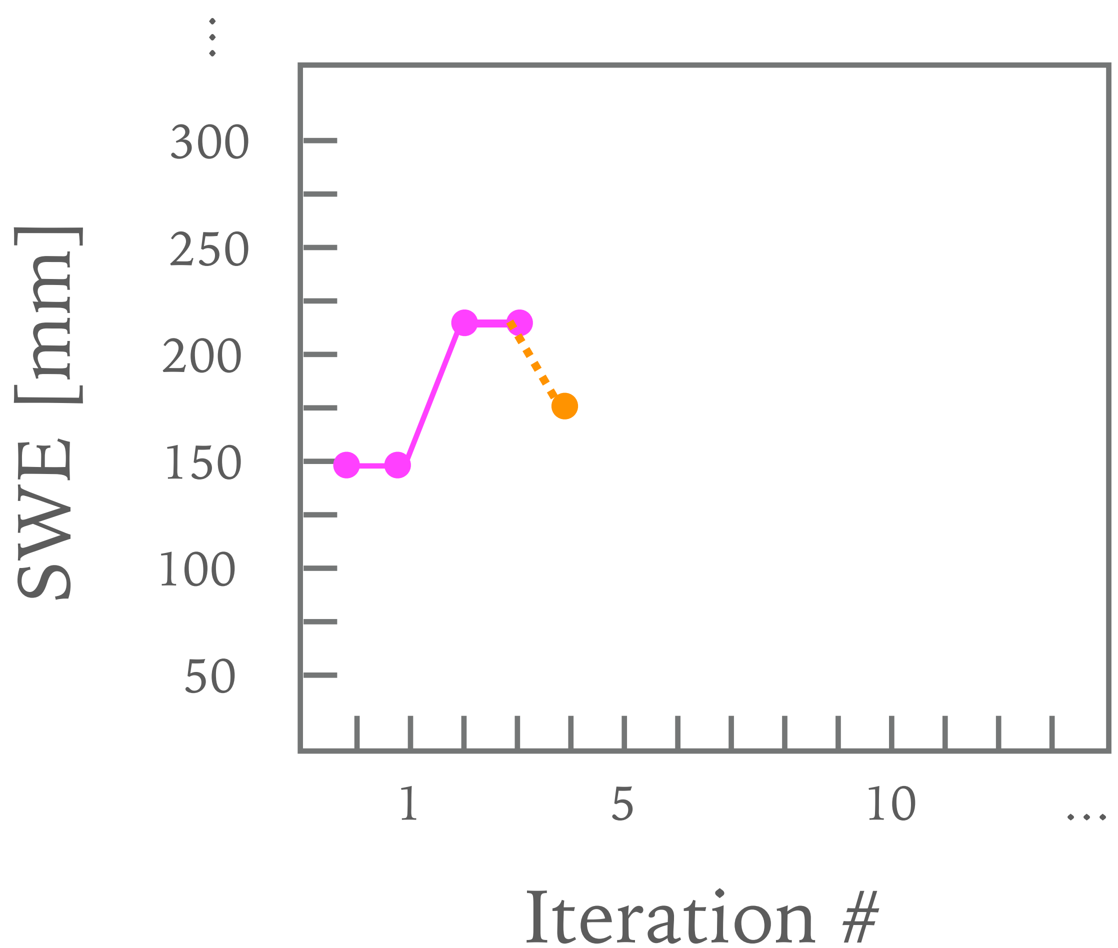
Probability of starting value: based on "prior distribution"



Probability of obtaining radar observation, given candidate, based on "likelihood distribution"

In this example, both likelihood and prior probability drops, and so candidate will be rejected.*

RANDOM WALK ALGORITHM FOR SWE ESTIMATION: FUTURE STEPS

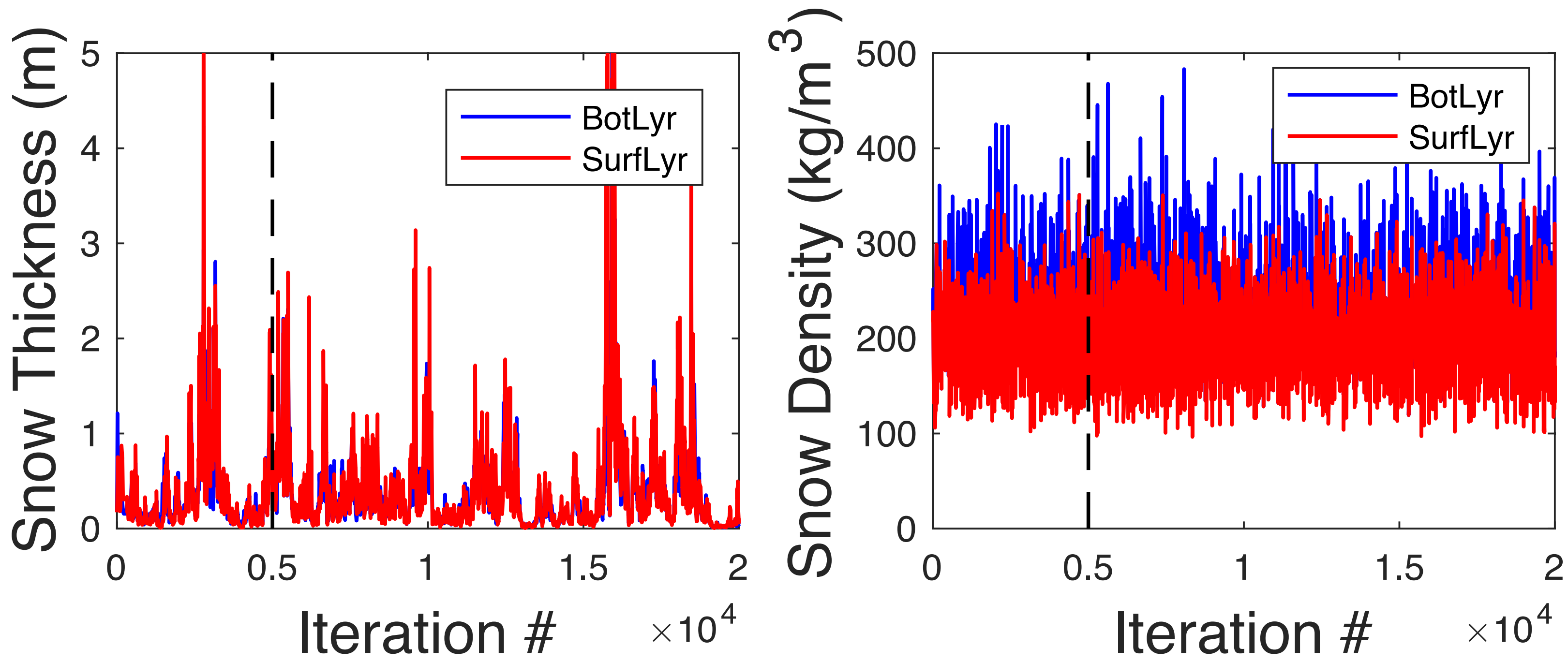


$p(x')$: *Probability of starting value: based on "prior distribution"*

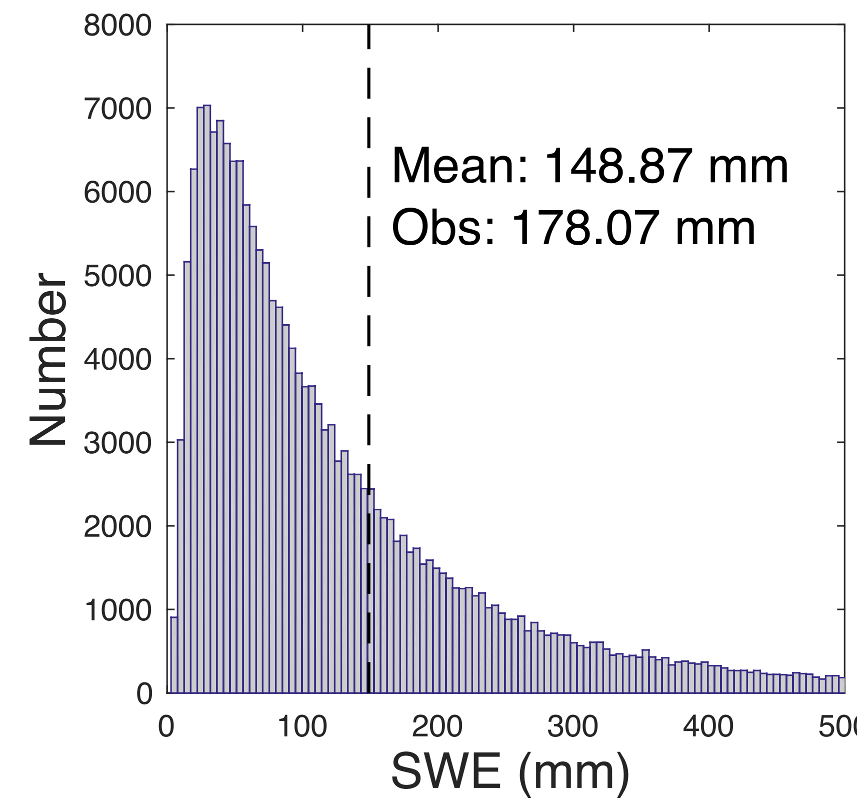
$p(\hat{y}'|x')$: *Probability of obtaining radar observation, given candidate step, based on "likelihood distribution"*

This process continues, typically on the order of 10,000 times…

EXAMPLE RANDOM WALK CHAINS



Multi-layer case builds separate layer thickness & density chains



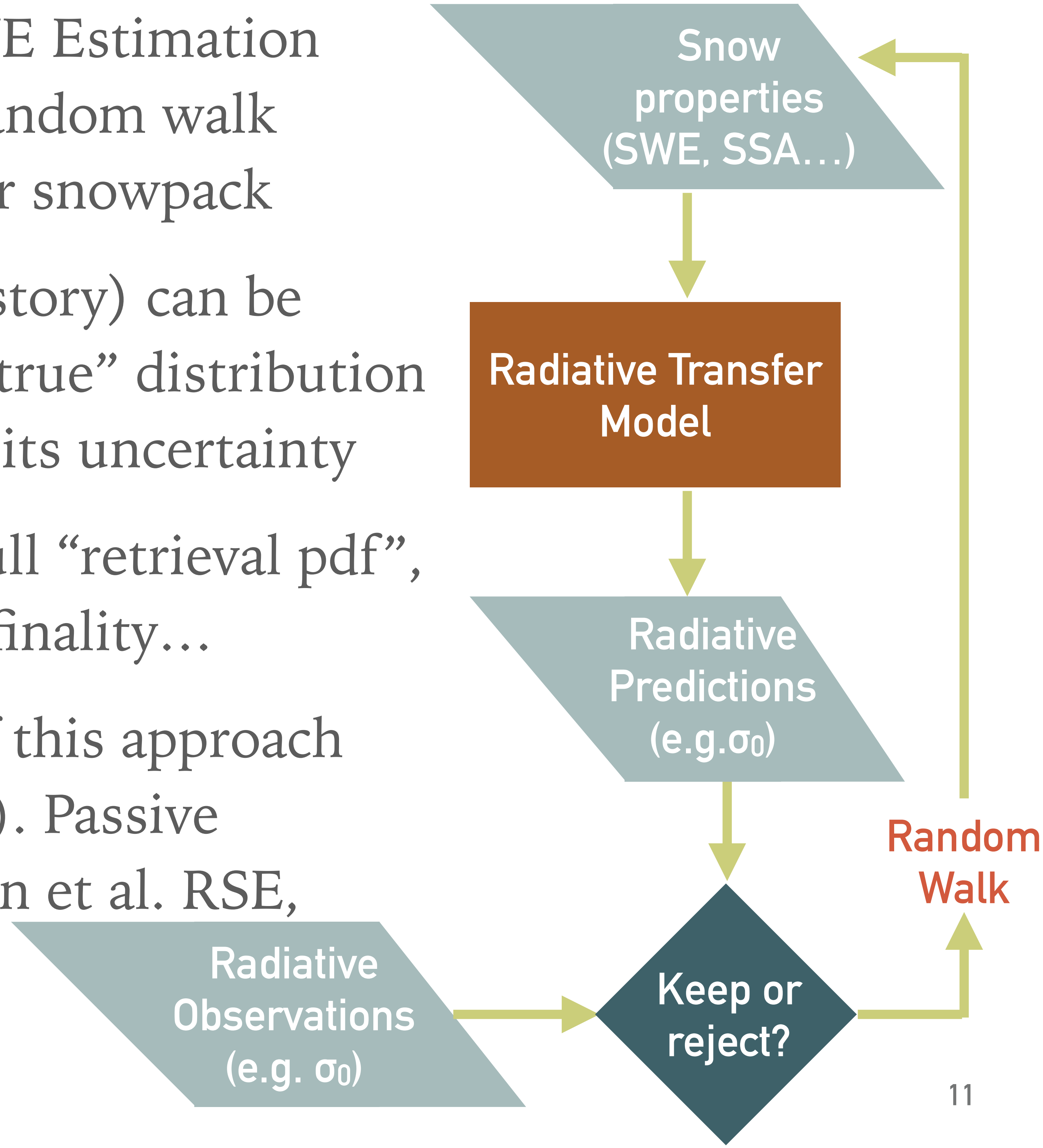
This algorithm is much different than minimizing a cost function.

Could this approach be more forgiving in terms of required grain size precision a priori?

Estimate & uncertainty summarized from "retrieval PDF"

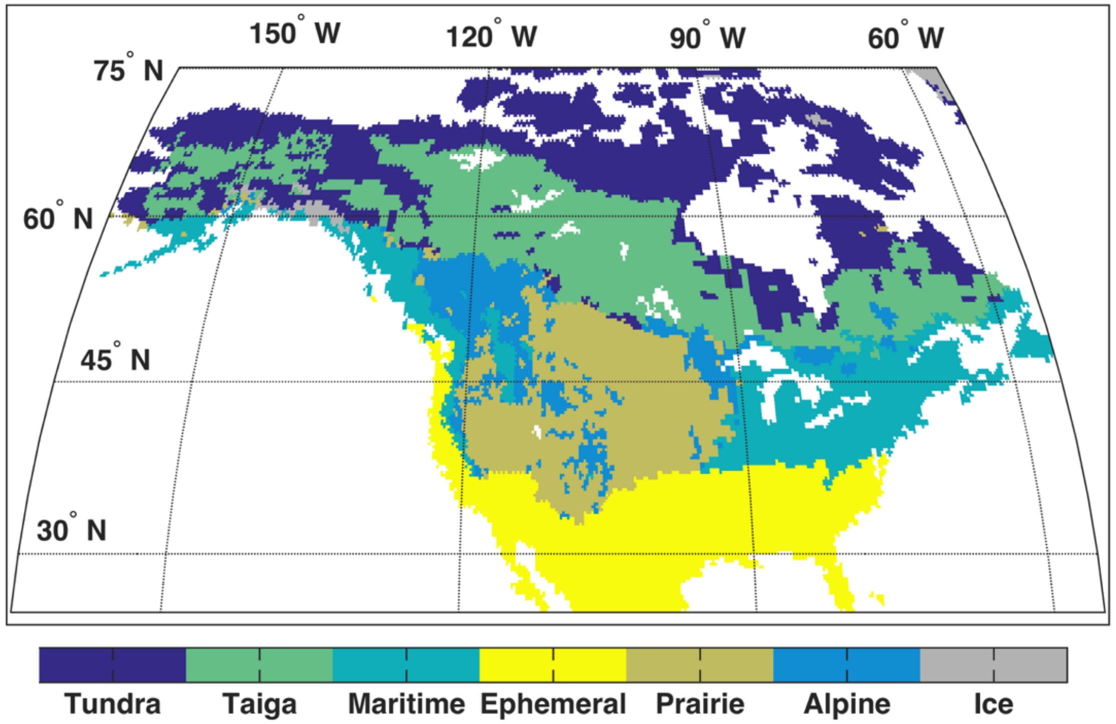
THE BASE-R ALGORITHM: BACKGROUND

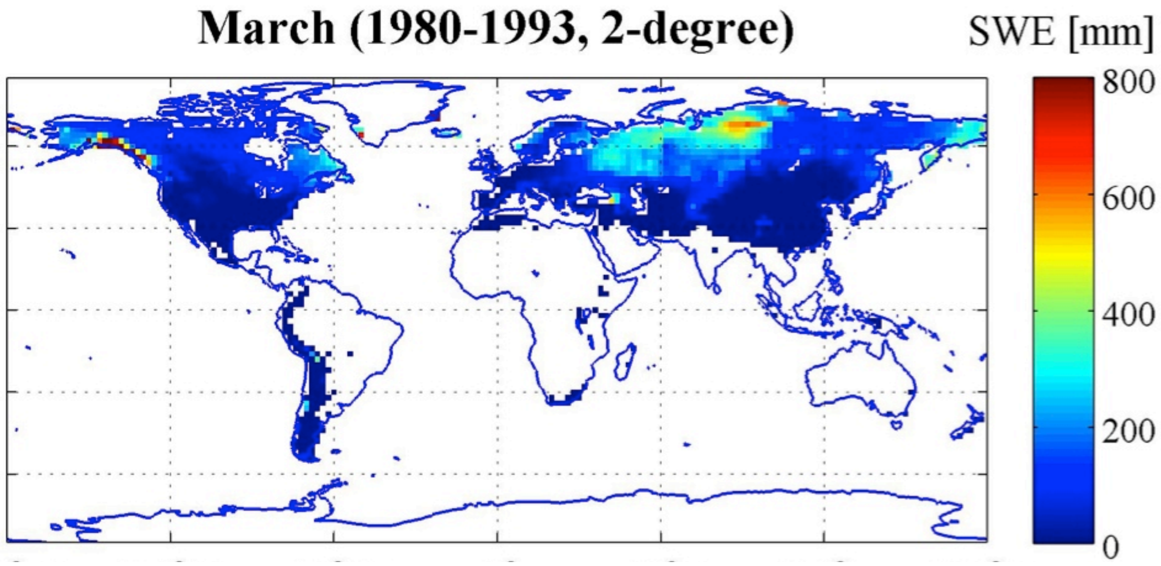
- Bayesian Algorithm for SWE Estimation with radar (BASE-R) is a random walk algorithm for multiple-layer snowpack
- The chain (i.e. its entire history) can be shown to converge to the “true” distribution of the SWE: an estimate & its uncertainty
- Iterative evaluation gives full “retrieval pdf”, including uncertainty, equifinality…
- BASE-R is an adaptation of this approach using radar backscatter (σ_0). Passive microwave validation by Pan et al. RSE, 2017.



BASE-R IMPLEMENTATION

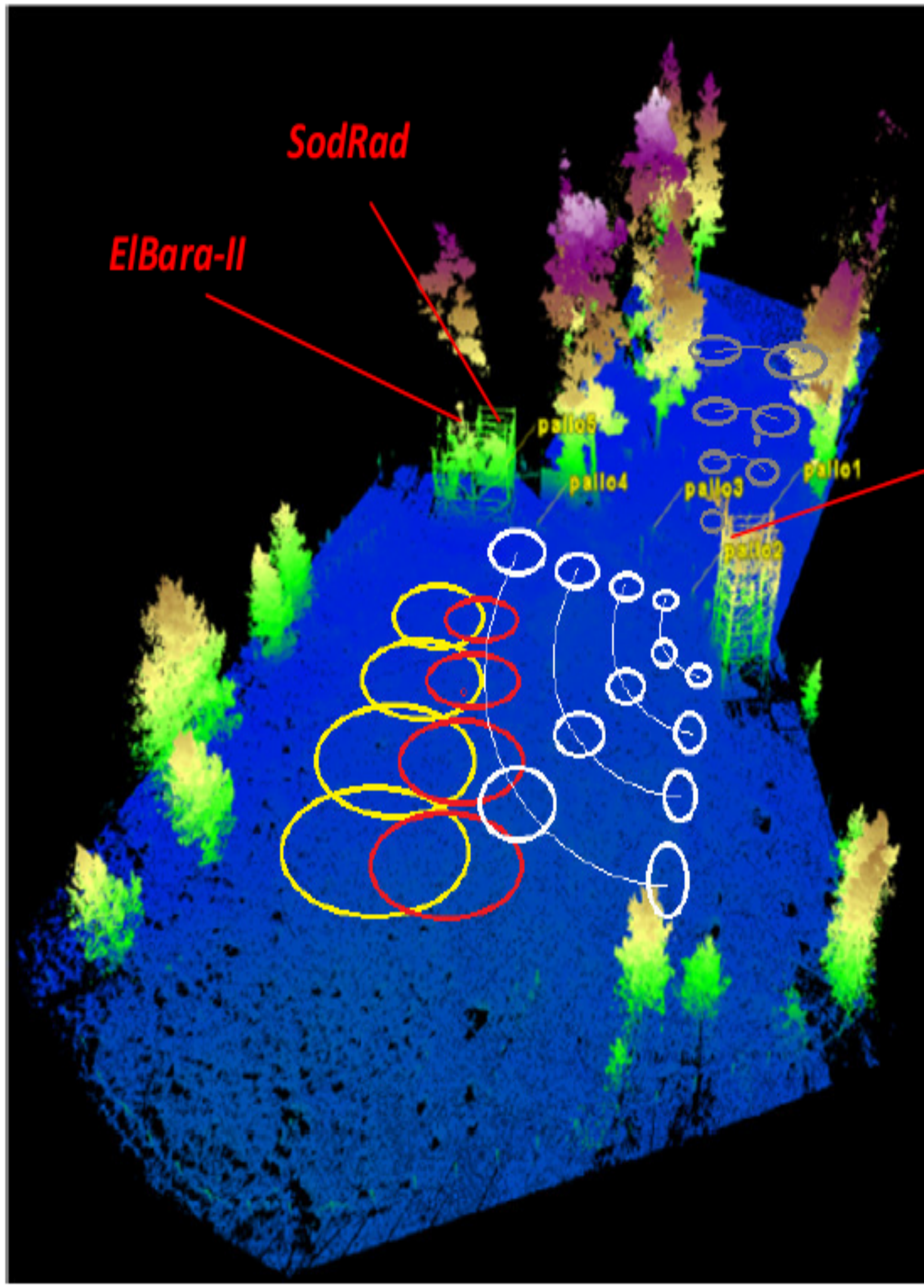
- For each snow layer, BASE-R estimates density, grain size autocorrelation length, temperature, layer thickness. Also soil moisture, roughness and temperature
- First guess / prior info: global SWE climatology (VIC), Sturm density. Assume large grain size uncertainty.
- Easy to objectively add better site-specific prior information if available (e.g. from modeling, past snowpits, etc.)
- Radiative transfer model: MEMLS3&a (Proksch et al., 2015) for snow + modified Mironov for soils





Pan et al., 2017

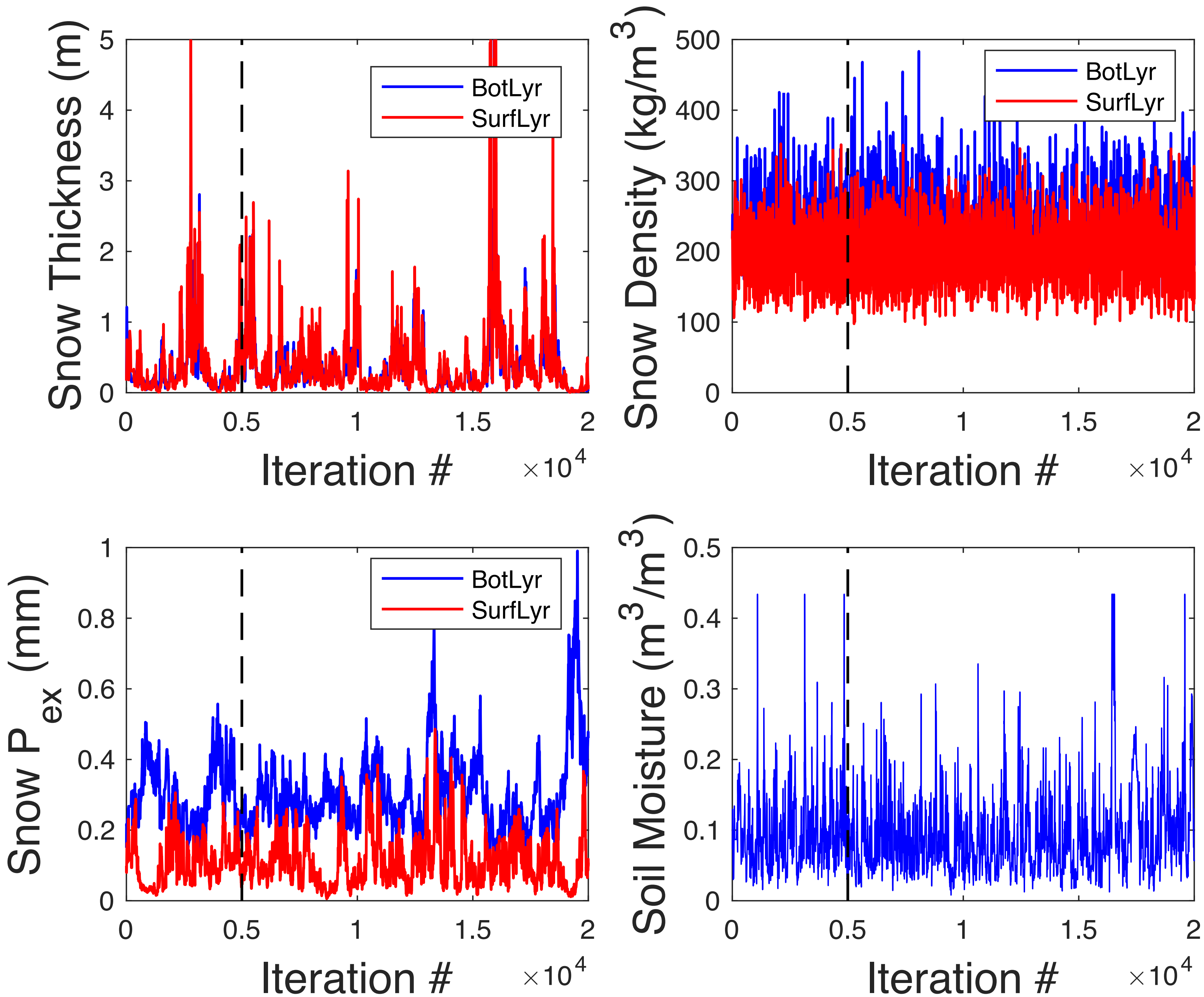
BASE-R: VALIDATION EXPERIMENT WITH NOSREX

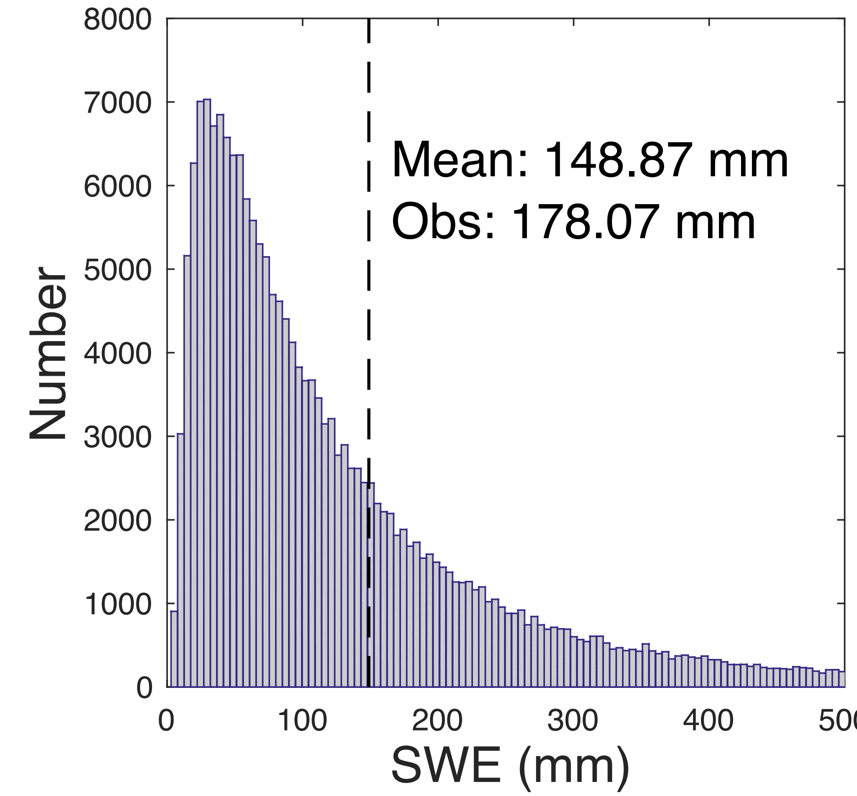


NoSREx: Lemmetyinen et al., 2016

- Nordic Snow Radar Experiment (NoSREx) data from Sodankyla, Finland (67°22' latitude).
- Taiga snow, typical peak accumulation ~200 mm SWE
- Continuous in situ radar observations with weekly snowpits
- Four years of data: Winter 2010-2013. Each year very different
- 10.2, 13.3, 16.7 GHz, vv-pol were used

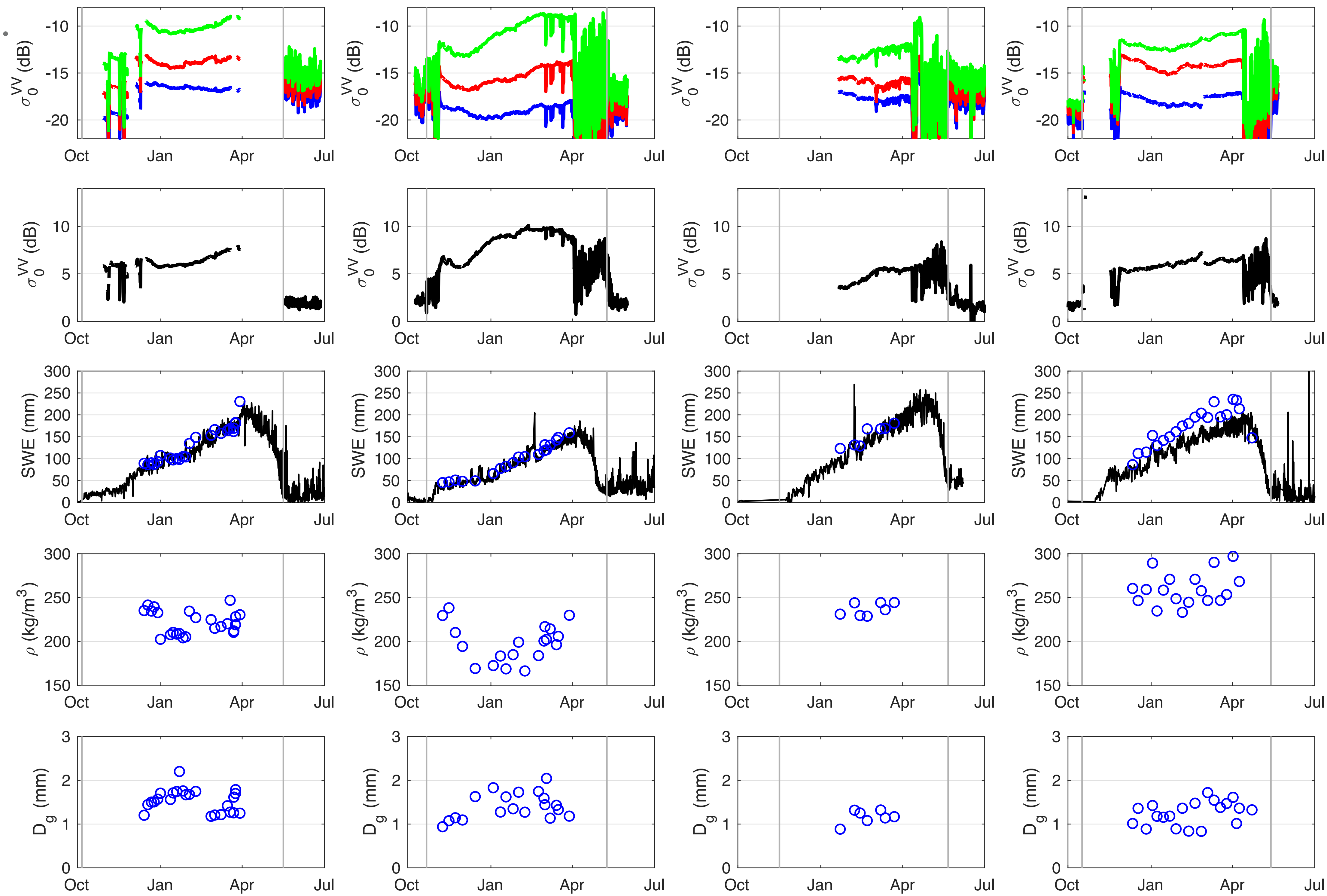
EXAMPLE BASE-R RESULTS: SODANKYLA, MARCH 23, 2012





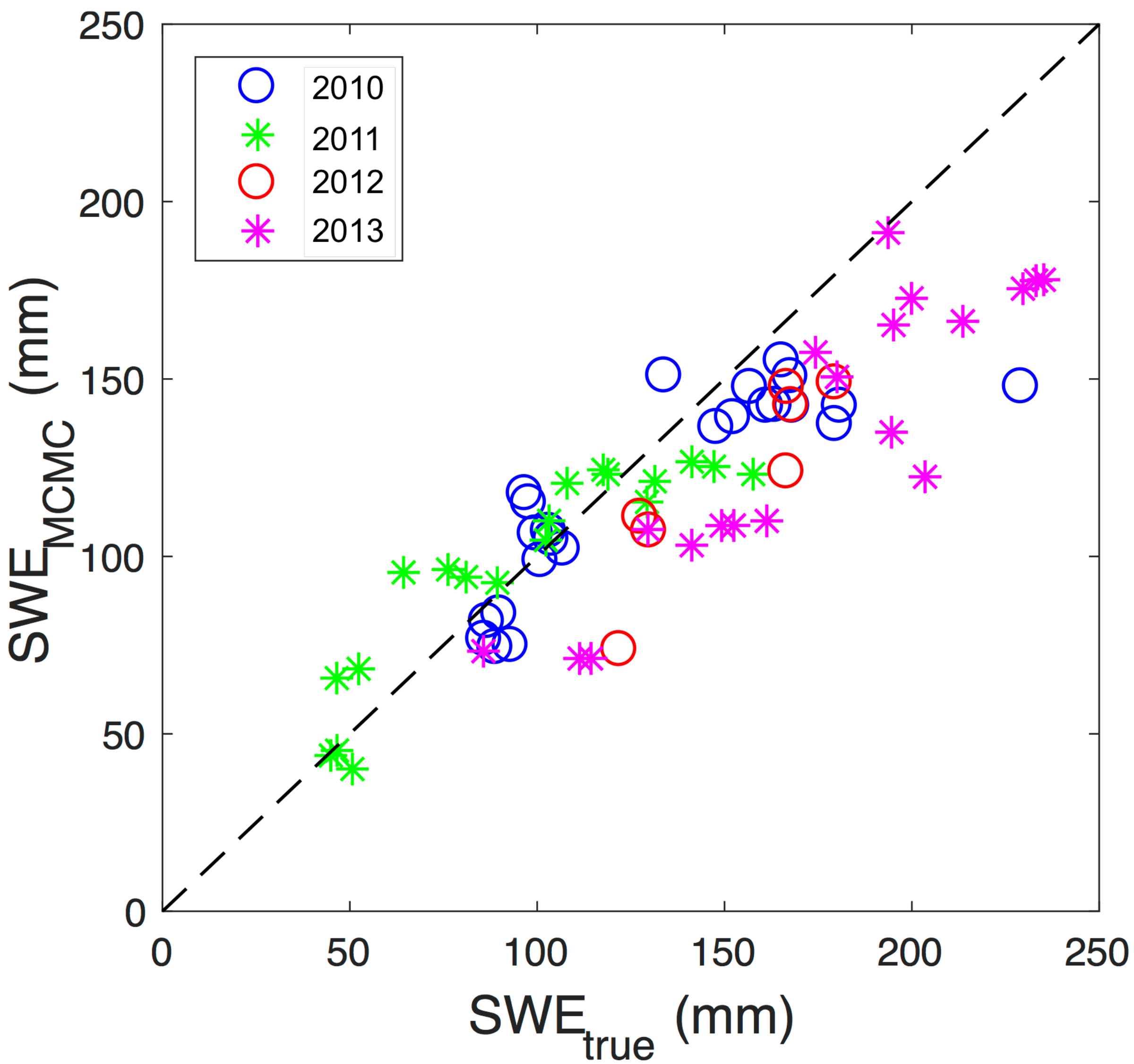
Estimate & uncertainty summarized from "retrieval PDF"

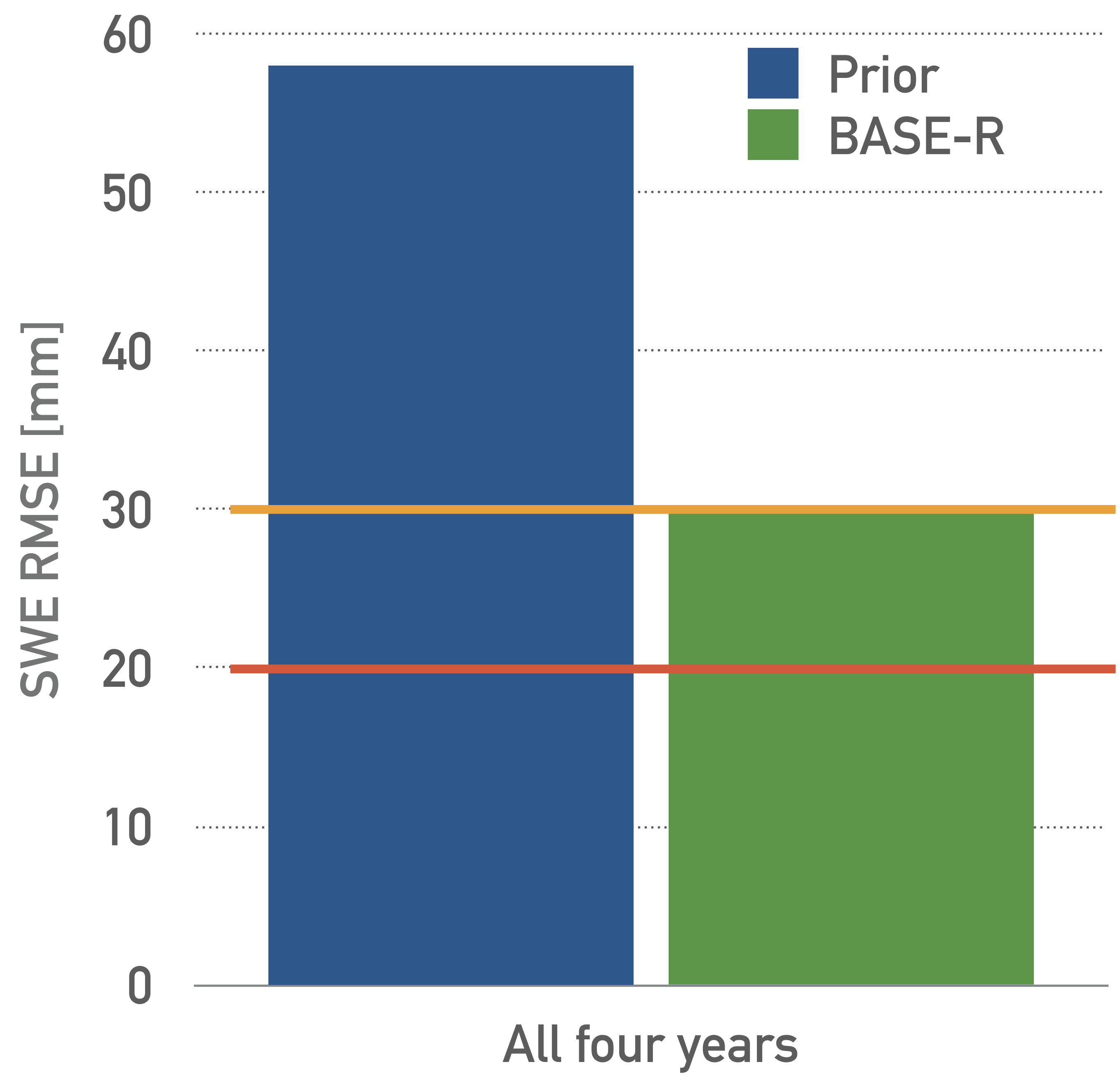
P_{ex} ~ snow grain size correlation length



σ_0^{VV} (dB)
-10
-15
-20
Oct
Jan
Apr
Jul
10
5
0
SWE (mm)
300
250
200
150
100
50
0
ρ (kg/m^3)
D_g (mm)
3
2
1

BASE-R VALIDATION: ACROSS 69 SNOWPITS

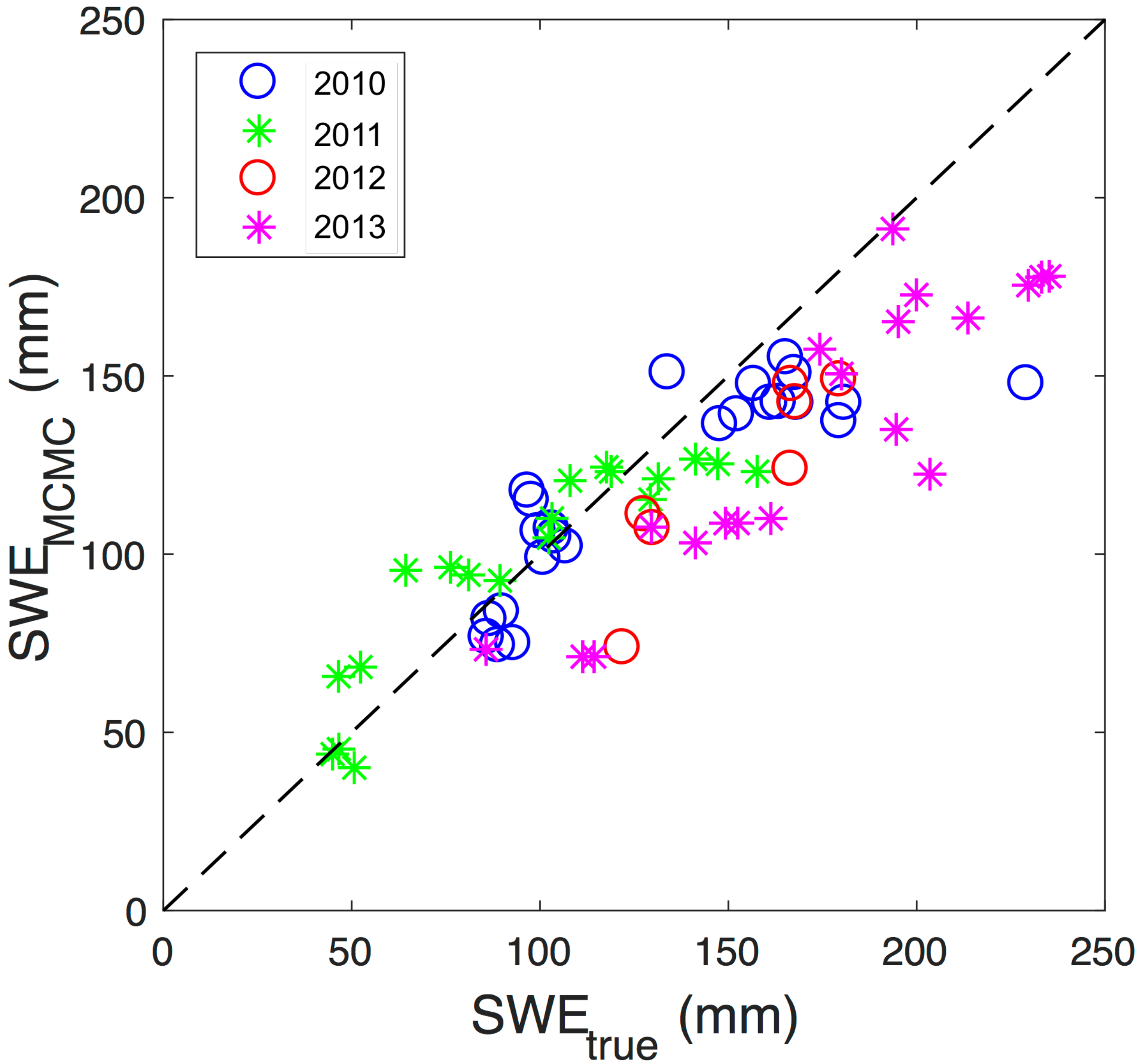


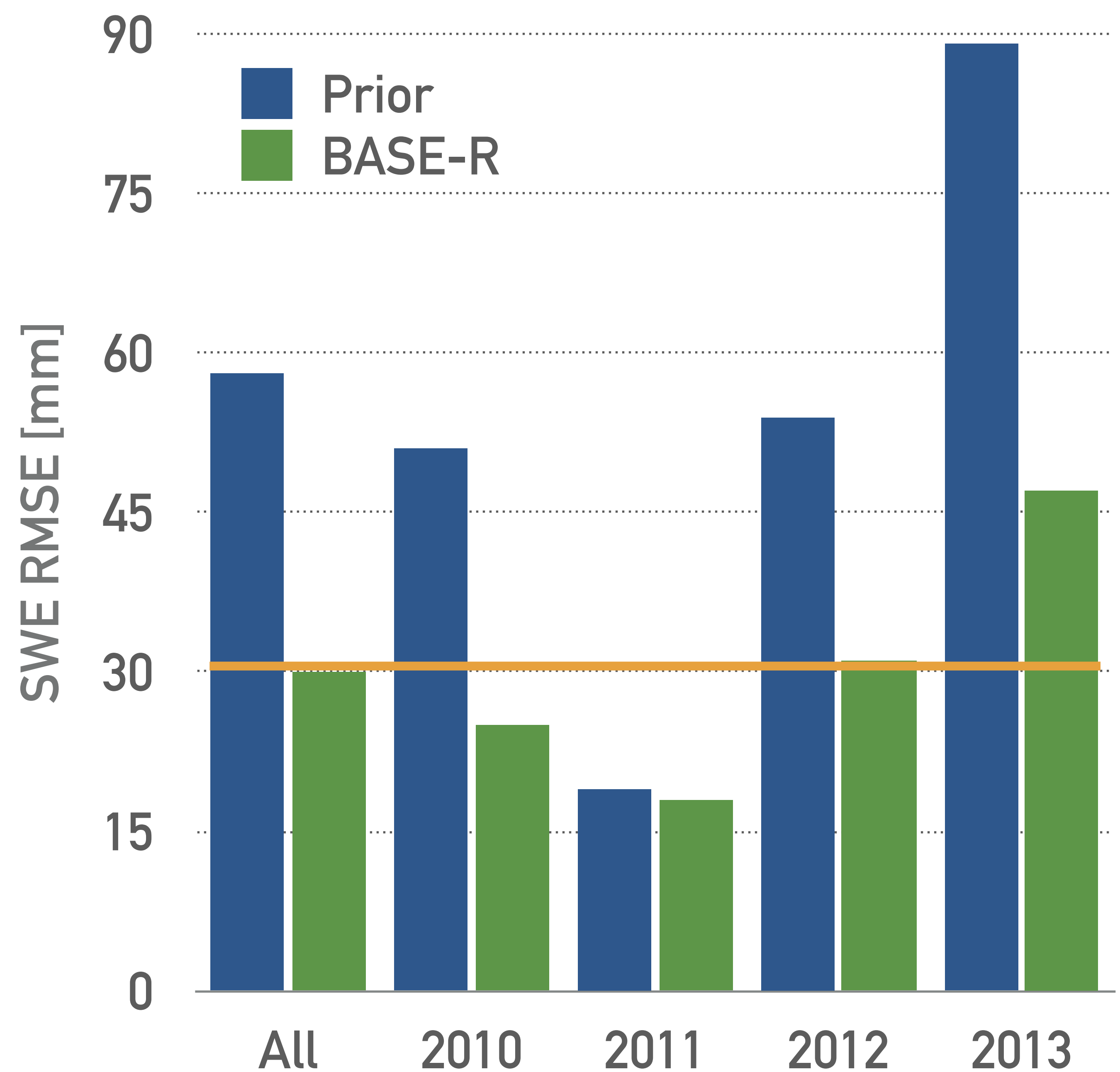


30 mm is the IGOS "threshold" requirement for shallow snow

20 mm is the IGOS "objective" requirement. BASE-R still has 10 mm to go!

BASE-R VALIDATION: PERFORMANCE VARIES ACROSS YEARS



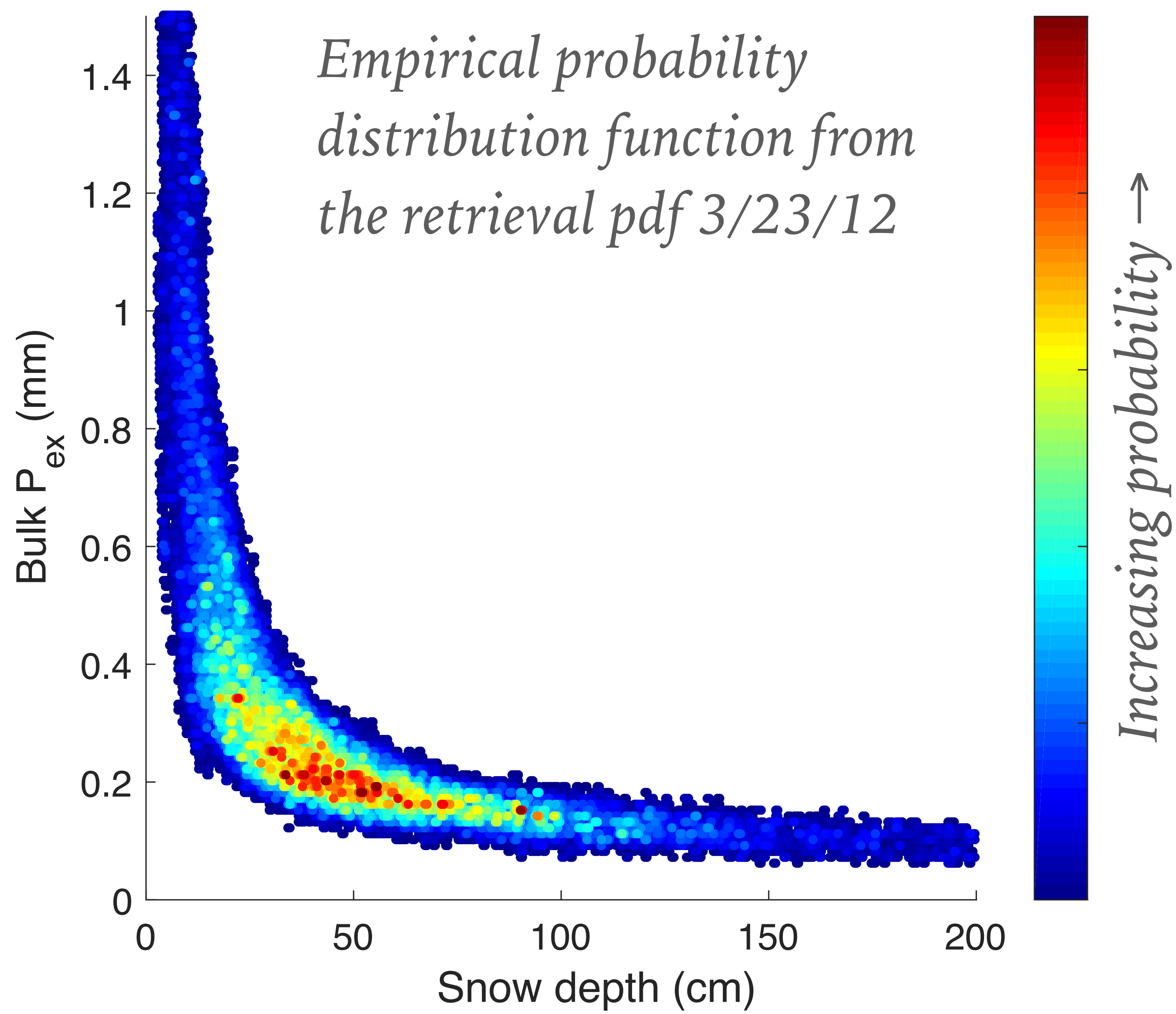


2012: warmest.

2012 & 2013: high measured densities led to SWE underestimation by BASE-R

BASE-R VALIDATION: LIMITATIONS

- BASE-R MCMC joint pdf visualization indicates tradeoff between grain size (P_{ex}) and depth
- Snow models could be used to provide additional prior information on grain size (P_{ex})



SUMMARY

- **This work demonstrates possibility of retrieval with uncertain grain size**
    - In contrast to previous work using error propagation (e.g. CoReH2O), this shows requirement for high precision grain size a priori is **algorithm dependent**
    - This conclusion is in agreement with Zhu et al. (2017) algorithm (presented earlier in this session by Ed)
- The high computational expense means we could not run this as is as an online algorithm for a global mission. However, we could in principle train a neural net to reproduce MCMC results over a wide range of conditions. You could also use a LUT to replace the RTM, with some modifications

REFERENCES

- Pan, J., Durand, M. T., Jagt, B. J. V., and Liu, D.: Application of a Markov Chain Monte Carlo algorithm for snow water equivalent retrieval from passive microwave measurements, Remote Sens Environ, 192, 150 165, https://doi.org/10.1016/j.rse.2017.02.006, 2017.
- Rott, H., Duguay, C., Etchevers, P., Essery, R., Hajnsek, I., Macelloni, G., Malnes, E., and Pulliainen, J.: CoReH2O: Report for mission selection, 2012.
- Rutter, N., Sandells, M. J., Derksen, C., King, J., Toose, P., Wake, L., Watts, T., Essery, R., Roy, A., Royer, A., Marsh, P., Larsen, C., and Sturm, M.: Effect of snow microstructure variability on Ku-band radar snow water equivalent retrievals, Cryosphere, 13, 3045–3059, https://doi.org/10.5194/tc-13-3045-2019, 2019.
- **Tsang, L., Durand, M., Derksen, C., Barros, A., and many others: Review Article: Global Monitoring of Snow Water Equivalent using High Frequency Radar Remote Sensing, *The Cryosphere*, in 2nd round of review, minor revisions.**
- Zhu, J., Tan, S., King, J., Derksen, C., Lemmetyinen, J., and Tsang, L.: Forward and Inverse Radar Modeling of Terrestrial Snow Using SnowSAR Data, Ieee T Geosci Remote, 56, 7122–7132, https://doi.org/10.1109/tgrs.2018.2848642, 2018.

QUESTIONS?

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BASE-R: OTHER LIMITATIONS

- Predicted SWE uncertainty in this experiment is very high.
- NoSRex scatterometry had relatively low dynamic range, making observation precision very important. Also not very sensitive to density, and is quite sensitive to soils, and forests. Does not work for wet snow. Highlight need for models!

BASE-R VALIDATION: OBSERVATION & MODEL ERROR

- Lowering assumed observation+model error too far leads to unrealistic results
- We suspect MEMLS3&a precision is around 0.5 dB
- Searching for a more precise model, including one that handles co-pol

Not shown: estimate explodes (310 mm error) when error assumed to be .1 dB