Quantifying Uncertain Remotely-Sensed Rainfall Estimates using an Ensemble-Based Bayesian Approach

S. Hamed Alemohammad
Department of Civil and Environmental Engineering, Massachusetts Institute of Technology
hamed_al@mit.edu

Massachusetts Institute of Technology

Introduction

- Current remotely-sensed rainfall retrieval techniques are uncertain. Therefore, a *quantitative representation of retrieval uncertainties* is required for widespread adoption of satellite products.
- An elegant way to express these uncertainties is to *generate a realistic ensemble of rainfall replicates* that are conditioned on the current uncertain measurement.
- Our method quantifies uncertain spatial rainfall retrievals using a *non-parametric Bayesian* technique.
- Unlike previous studies, this method derives the error likelihood using an archive of historical measurements and provides an ensemble characterization of measurement error.
- Formulation of this approach in terms of *image attributes* makes it possible to use ensemble methods that would not otherwise be computationally feasible for problems of realistic size.

Dataset

- *Study Area*: the central part of continental US as shown in Figure 3.
- *Time Domain*: from Aug. 2003 until Dec. 2010.
- *Satellite Data*: rainfall retrievals from the Advanced Microwave Sounding Unit (AMSU-B) on-board NOAA-16.
- *Ground Validation*: Ground-based radar measurements from NEXRAD are used as benchmark product for the true rainfall.

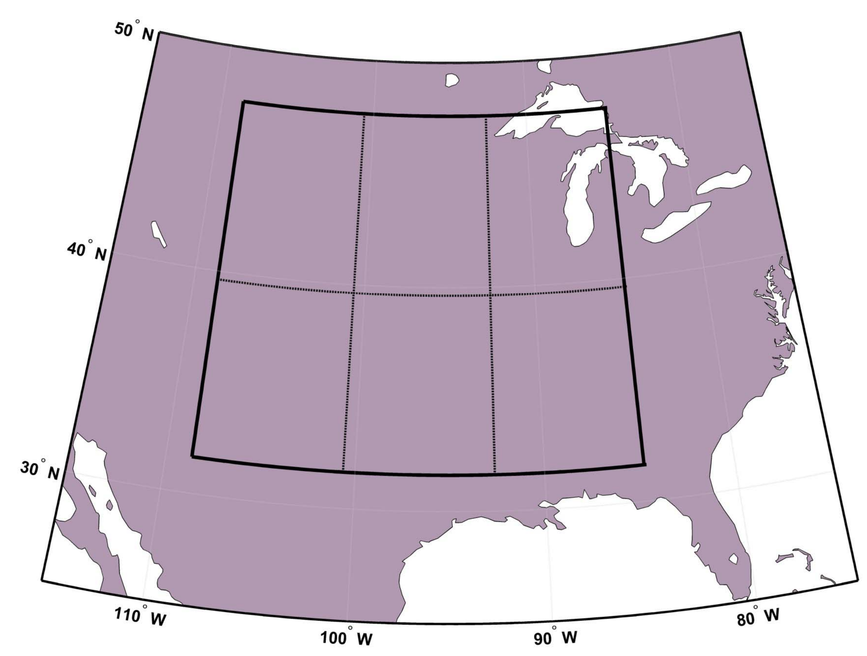


***Figure 3** – Study Area*

Methodology

- The characterization process is formulated as a Bayesian sampling problem and solved with a non-parametric version of *importance sampling*.
- It's impractical to implement the Bayesian sampling in *high-dimensional image space*. Therefore, a *dimensionality reduction* scheme is introduced to map all the images to a *low-dimensional attribute space.*
- From Bayes' rule we have:

$$\underbrace{P_{X|Z}\left[X(t)\,|\,Z(t)\right]}_{\text{Posterior Distribution}} \propto \underbrace{P_{Z|X}\left[Z(t)\,|\,X(t)\right]}_{\text{Likelihood Function}} \times \underbrace{P_X\left[X(t)\right]}_{\text{Prior Distribution}}$$

X(t): Vector representing true rainfall in the attribute space at time t.

Z(t): Vector representing uncertain satellite retrieval in the attribute space at time t.

- The likelihood function is derived from the historical observations of the satellite and ground-based radar, considered to be the true here.
- The prior distribution is derived from a set of prior replicates generated using a new stochastic method.

Prior Replicate Generation

- This is a stochastic-based method that uses an *orientation* and *scale-dependent spatial filter* to describe rainfall images in terms of a small number of random coefficients.
- The statistics of the random coefficients are derived from a *training image (TI).*
- It generates realistic spatially dis-continuous rainfall replicates.

Figure 1 shows a set of replicates generated using this method along with their TI.

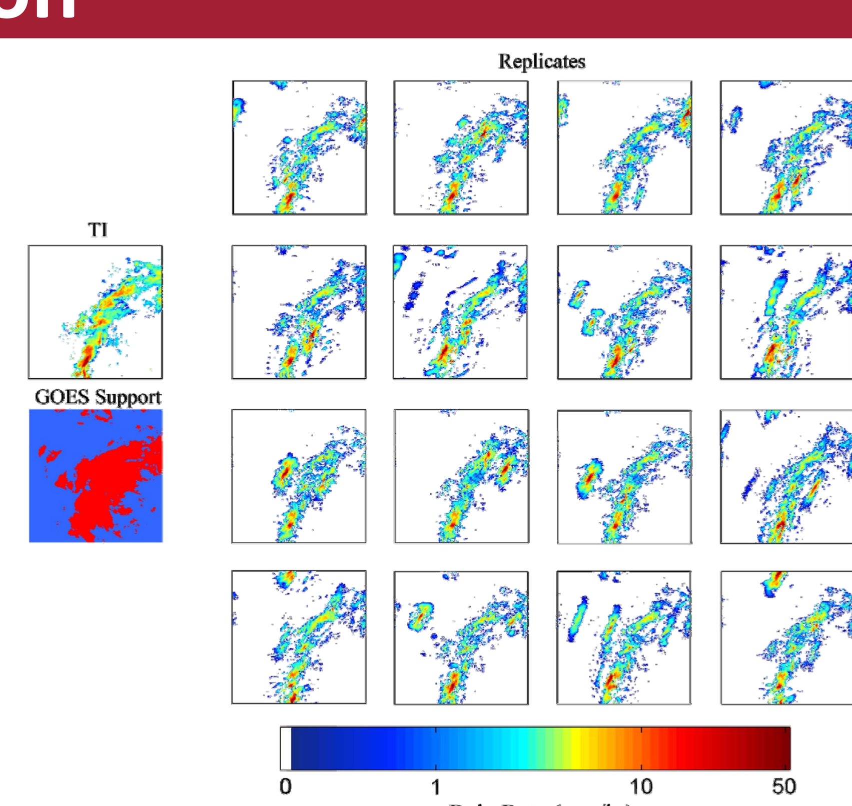


***Figure 1** – Sample replicates generated using the new stochastic method*

Dimensionality Reduction

A novel dimensionality reduction scheme using principle component analysis (PCA) is introduced to describe images in a problem-specific low-dimensional attribute space. Figure 2 shows the components of this scheme.

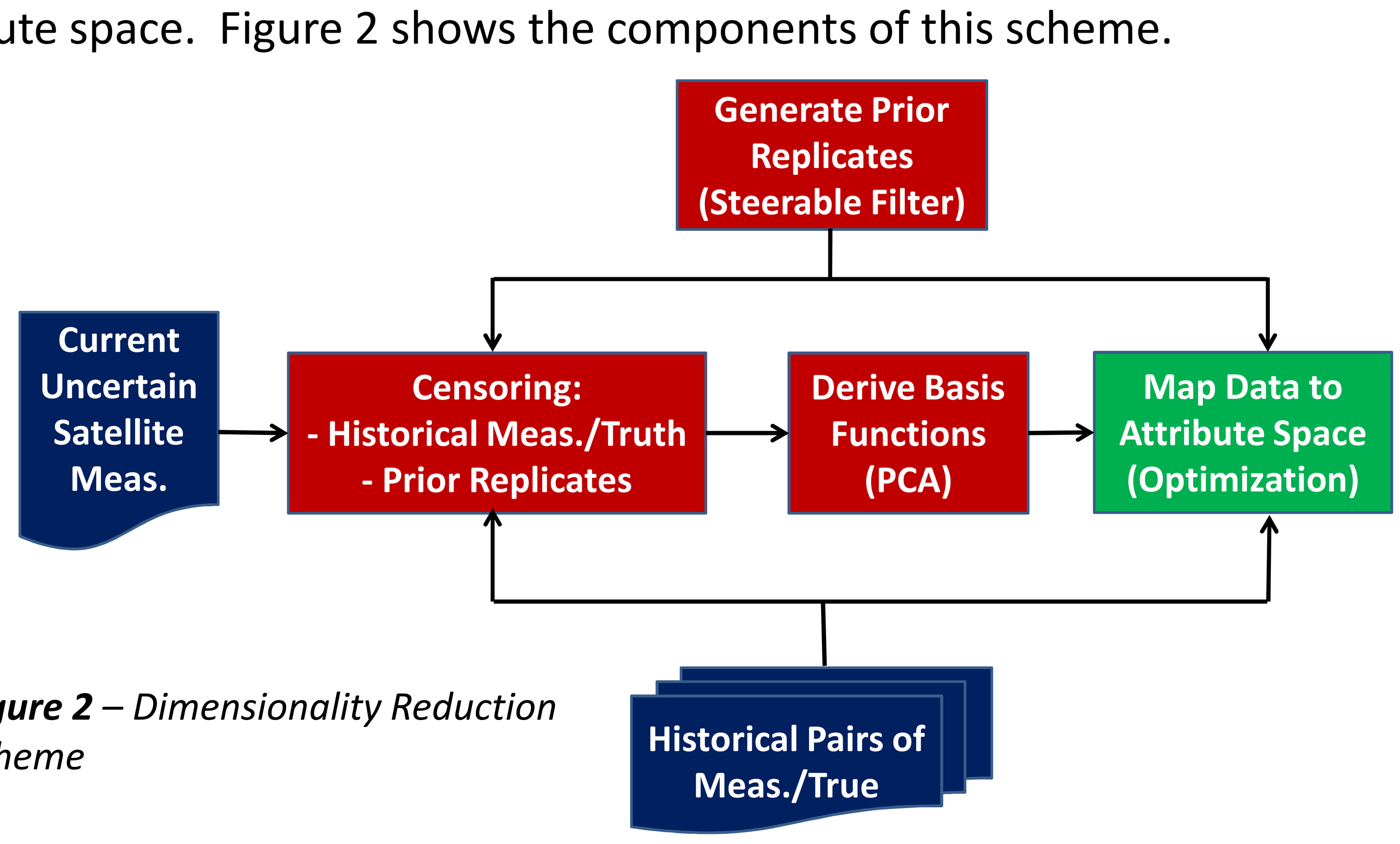
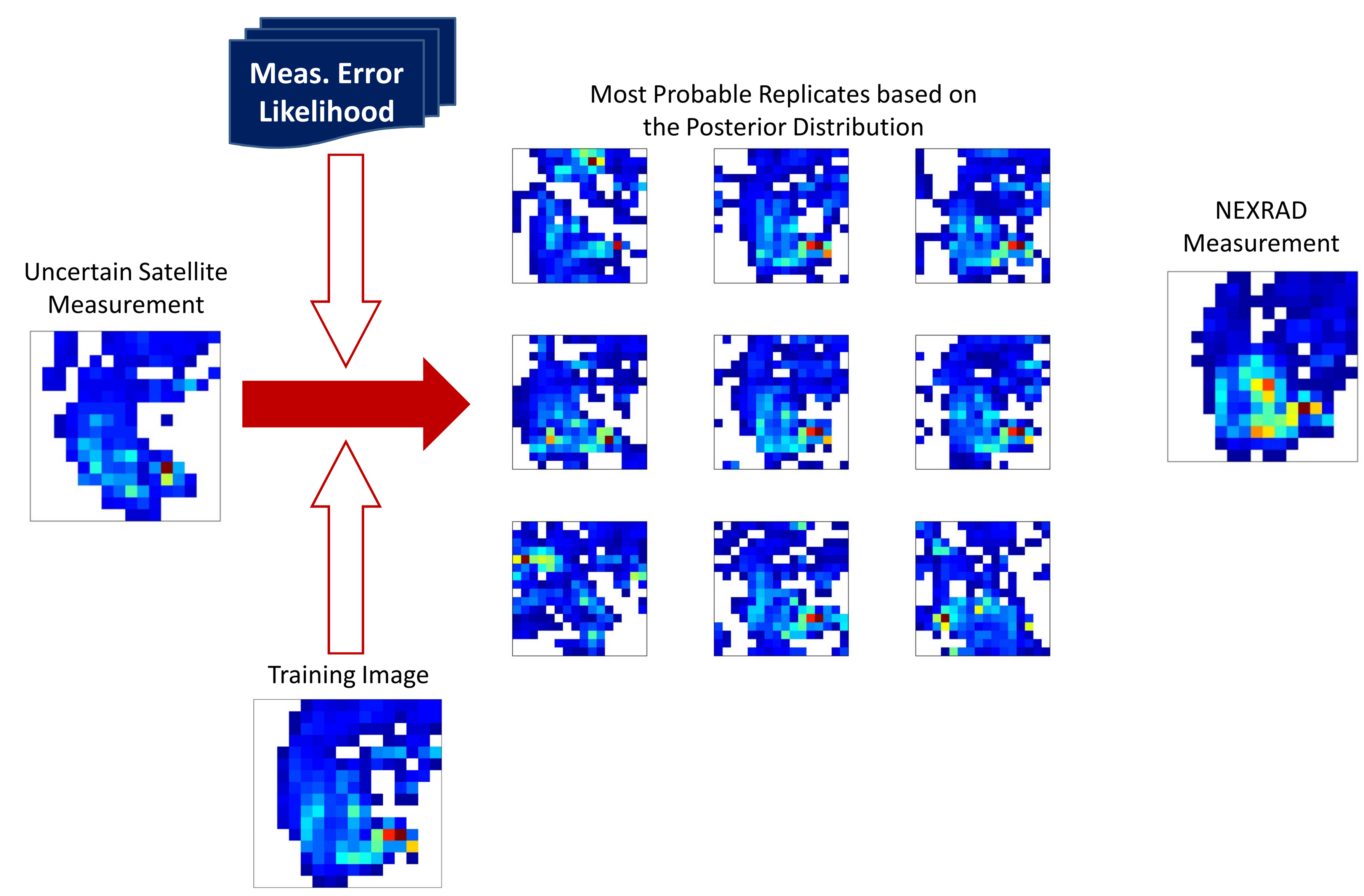
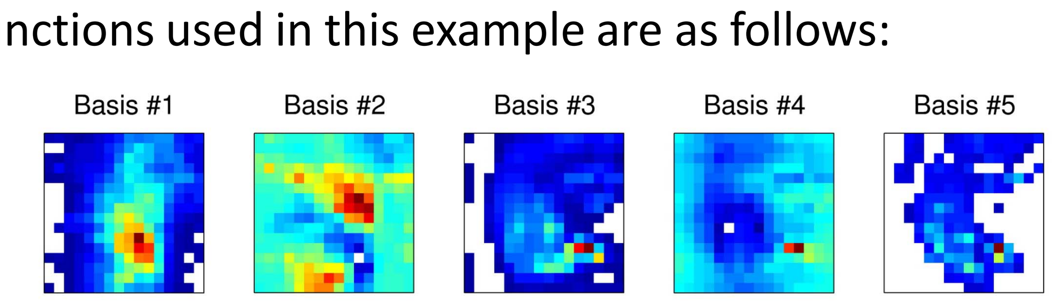


***Figure 2** – Dimensionality Reduction Scheme*

Results



The set of basis functions used in this example are as follows:



Evaluation

- The following index is defined to evaluate the quality of posterior samples:

$$R = \frac{D(Truth, MAP\ estimate)}{D(Truth, Uncertain\ Measurement)}$$

- Values of $R \leq 1$ indicates that the estimation provided by our method is better than the current satellite retrieval.
- Running this method on 100 sample measurements from AMSU-B on NOAA-16 and evaluating the index showed that in 90% of the samples *R* is less than or equal to 1.

Summary

1) The experiment indicates that our ensemble estimation approach is able to provide an improved description of rainfall features by giving a posterior ensemble that is narrower than the prior.
2) Measurement errors are derived from non-parametric probability densities estimated from historical pairs of satellite and ground-based radar measurements.
3) The proposed dimensionality reduction scheme properly describes high-dimensional images in a low-dimensional attribute space.
4) The primary limitation is the inevitable information loss that occurs in mapping the images to attribute space. (compromise between accurate mapping and accurate estimation of probabilities).

References:

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