Towards a gridded best estimate of accumulated precipitation from quantitative precipitation estimates (QPE) and forecasts (QPF) in mountainous regions:

A simplified Kalman Filter approach

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# OUTLINE

- Motivation
- Objectives
- The simplified Kalman Filter: what is it?
- The simplified Kalman Filter: construction of **B** and **R**
- Eastern US cases
- Western US cases
- Comments on future directions and how to evaluate these products.

# MOTIVATION

Estimates of precipitation (quantitative precipitation estimates or QPE) are important for a broad range of applications including:

Aftermath of Spring Creek flash flood 28 July 1997

- Flood monitoring and forecasting
- Inputs to hydrologic models
- Seasonal precipitation estimates for water resource quantification
- Agriculture
- Fire risk outlooks

And yet QPE is often poorly known, especially in remote complex terrain regions.



# **OBJECTIVES**

- We want to take account of strengths and weaknesses
- of the many different QPE/QPF datasets to
- (1) quantify QPE uncertainty and
- (2) get a best estimate deterministic QPE.

# Multi-Radar Multi-Sensor (MRMS) Products:

- Radar-only QPE
- Gauge-only QPE
- Gauge-corrected QPE
- Mountain Mapper based QPE (based on PRISM)
- **Stage IV:** Generated by RFCs as the final "analysis of record" for the National Weather Service; generating methodologies vary by RFC. CCPA is a bias-corrected Stage IV. **Others:** satellite-based QPE, reanalyses, etc.

**CAM guidance:** may be our **ONLY** source of quantitative precipitation information in remote, observation-sparse regions.



#### THE SIMPLIFIED KALMAN FILTER

The community still generally uses deterministic QPE datasets as "truth". However, the uncertainty associated with the various QPE/QPF products argues for an explicit treatment of uncertainty in a final, merged QPE dataset. A data assimilation framework is well-suited to this problem. In this work, we examine how a simplified Kalman Filter could be applied for this purpose.

$$x_a = x_f + (B^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1} (y - H x_f), \qquad P^{-1} = B^{-1} + H^T R^{-1} H$$

For this problem,  $x_f$  can be considered the CAM QPF at any given time. So it is a vector of length N (where N = number of model gridpoints). y is the vector of QPE datasets (interpolated to CAM QPF scale for simplicity), of length jN (where j is the number of QPE datasets considered).

**B** will be an N x N matrix which contains information on QPF errors, as well as spatial correlations in QPF. **R** will be a jN x jN matrix which contains information on QPE errors, as well as spatial correlations in QPE.

**B** and **R** determine how information is combined from the different sources.

## THE SIMPLIFIED KALMAN FILTER

For this talk, I am only showing simple, illustrative examples:

- QPF is HRRR 6h QPF (3km grid spacing).
- QPE is MRMS 6h radar-only QPE (interpolated to HRRR scale).
- **R** is based on the MRMS radar quality index (RQI), and is a diagonal matrix (i.e., MRMS radar-only
- QPE should not have any precipitation location errors)
- **B** is a static value with an inverse distance weighting to take account of HRRR QPF location errors. **H** is the identity matrix.
- The actual calculation is carried out for small subdomains at a time (localization).

# CASES:

Two non-complex terrain cases: Midwest Heavy Rain (15 July 2018) TS Imelda (19 Sep 2019) Two complex terrain cases: Globe, AZ, flash flood (23 July 2019) Southern CA cutoff low (6 April 2020) **Relatively smooth terrain cases: Stage IV QPE** 

00-06 UTC 15 July 2018

10.0

15.0

20.0

25.0

37.5

50.0

75.0

mm

1.0

5.0

06-12 UTC 19 Sep 2019



100.0

125.0

150.0

Relatively smooth terrain cases: MRMS radar-only QPE

00-06 UTC 15 July 2018

10.0

15.0

20.0

25.0

37.5

50.0

75.0

mm

1.0

5.0

06-12 UTC 19 Sep 2019



100.0

125.0

150.0

Relatively smooth terrain cases: HRRR 6h QPF



06-12 UTC 19 Sep 2019

75.0



100.0

125.0

150.0

#### **Relatively smooth terrain cases: MRMS RADAR QUALITY INDEX**

## 00-06 UTC 15 July 2018



### 06-12 UTC 19 Sep 2019



mm												
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00-06 UTC 15 July 2018

1.0

5.0

10.0

15.0

20.0

25.0



R: 17.5 – 75mm

06-12 UTC 19 Sep 2019



00-06 UTC 15 July 2018

1.0

5.0

10.0

15.0

20.0

25.0

37.5

50.0

75.0



R: 17.5 – 137.5mm

06-12 UTC 19 Sep 2019



100.0

125.0

150.0

00-06 UTC 15 July 2018

1.0

5.0

10.0

15.0

20.0

25.0

37.5

50.0

75.0



R: 17.5 – 262.5mm

06-12 UTC 19 Sep 2019



100.0

125.0

150.0

00-06 UTC 15 July 2018

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10.0

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R: 17.5 – 262.5mm

06-12 UTC 19 Sep 2019



100.0

125.0

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00-06 UTC 15 July 2018



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00-06 UTC 15 July 2018



10.0

15.0

20.0

25.0

37.5

50.0

75.0

1.0

5.0

R: 17.5 – 262.5mm

06-12 UTC 19 Sep 2019



100.0

125.0

150.0

Relatively smooth terrain cases: MRMS gauge-only QPE





100.0

125.0

150.0

200.0

**Complex terrain cases: Stage IV QPE** 

00-06 UTC 23 July 2019





#### **Complex terrain cases: MRMS radar-only QPE**

00-06 UTC 23 July 2019





#### **Complex terrain cases: MRMS radar-only QPE**

00-06 UTC 23 July 2019





#### **Complex terrain cases: HRRR 6h QPF**

00-06 UTC 23 July 2019





#### **Complex terrain cases: MRMS RADAR QUALITY INDEX**

00-06 UTC 23 July 2019





R: 17.5 – 75mm

00-06 UTC 23 July 2019





00-06 UTC 23 July 2019

R: 17.5 – 137.5mm





R: 17.5 – 262.5mm

00-06 UTC 23 July 2019





R: 17.5 – 262.5mm

00-06 UTC 23 July 2019





00-06 UTC 23 July 2019

R: 17.5 – 262.5mm





R: 17.5 – 262.5mm

00-06 UTC 23 July 2019





#### **Complex terrain cases: MRMS gauge-only QPE**

00-06 UTC 23 July 2019





### **DISCUSSION AND CONCLUSIONS**

This is very much a work in progress. Cannot conclude much about the performance of the framework without quantitative verification. Comparison against high-quality rain gauges, over a large number of cases.

The framework really needs to account for the non-Gaussian nature of precipitation. This may be possible through a Gaussian transformation (as proposed by Lien et al. 2013).

$$y_{\text{trans}} = G^{-1}[F(y)]$$
 1  $G^{-1}(x) = \sqrt{2} \operatorname{erf}^{-1}(2x-1), 2$ 

#### Future work:

Inclusion of additional QPE datasets (being careful to maintain independent verification)

More advanced specifications of **B** and **R** (better quantification of uncertainty)

Can this framework be expanded to other time intervals (i.e., 1h precip)?

How to deal with snow?

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