Bayesian inference of disparity maps for DEM generation and ground deformation

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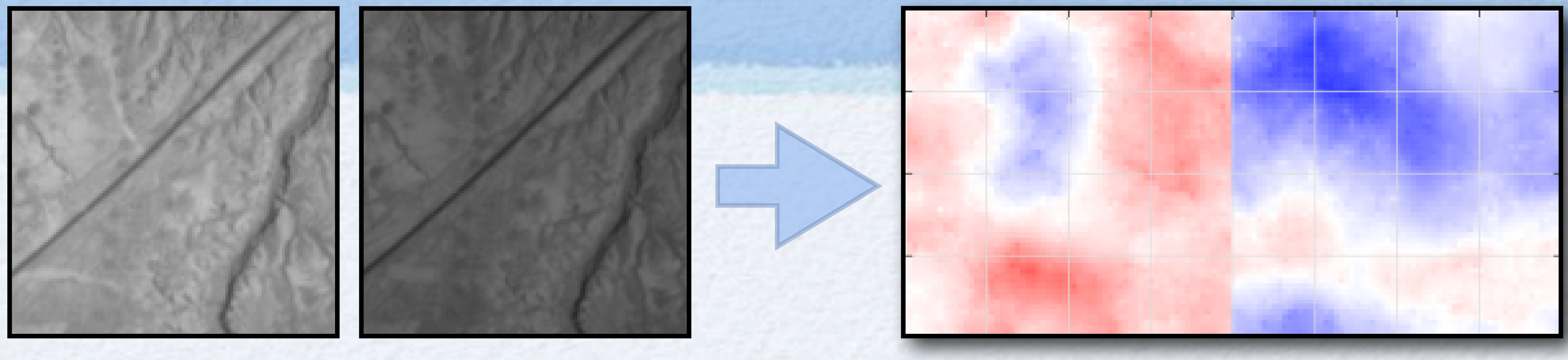
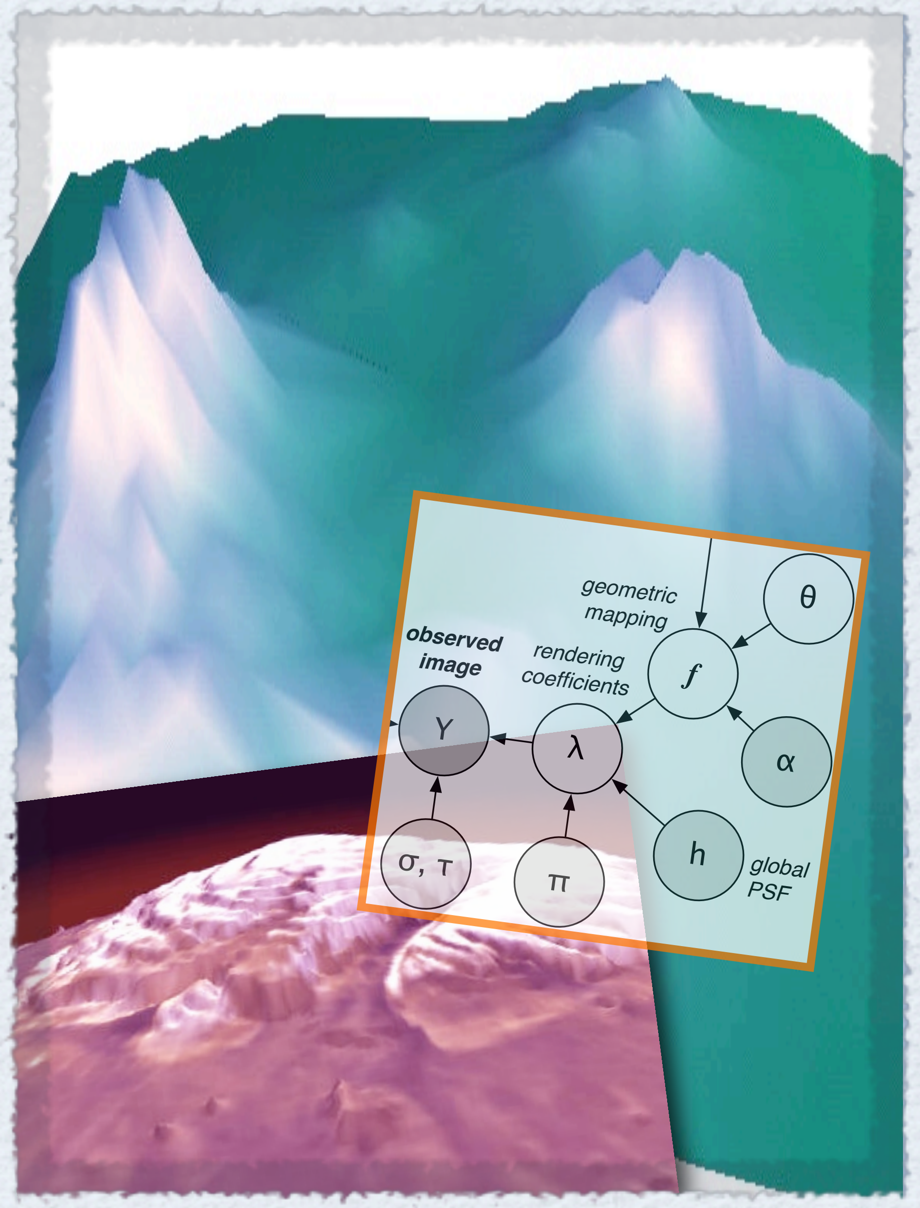


SPACEFUSION Project - Projet ANR "Jeunes Chercheurs" 2006-2008

Outline

- Background and objectives
- Problems with existing methods
- Bayesian inference
- Assumptions, forward model
- Smoothness priors
- Graphical model
- Preliminary tests
- Results from real data
- Future work



Background - the SpaceFusion project

- Science objectives - multisource data fusion
  - **Astronomical data fusion** and super-resolution
  - Digital Elevation Model (**DEM**) generation
  - By-product: ground **deformation map**
  - Fusion of optical images into **rectified reflectance maps**
  - Main contribution: **uncertainties**

- In practice
  - 3-year grant, funded by the French Research Agency (ANR)
  - 1 full-time PI, 3 part-time CO-I, 2 collaborators,
    1 postdoc, 1 invited professor, 3 master students
  - 2006 & 2007: LSIIT, Strasbourg, France
  - 2008: CGE Evora, Portugal

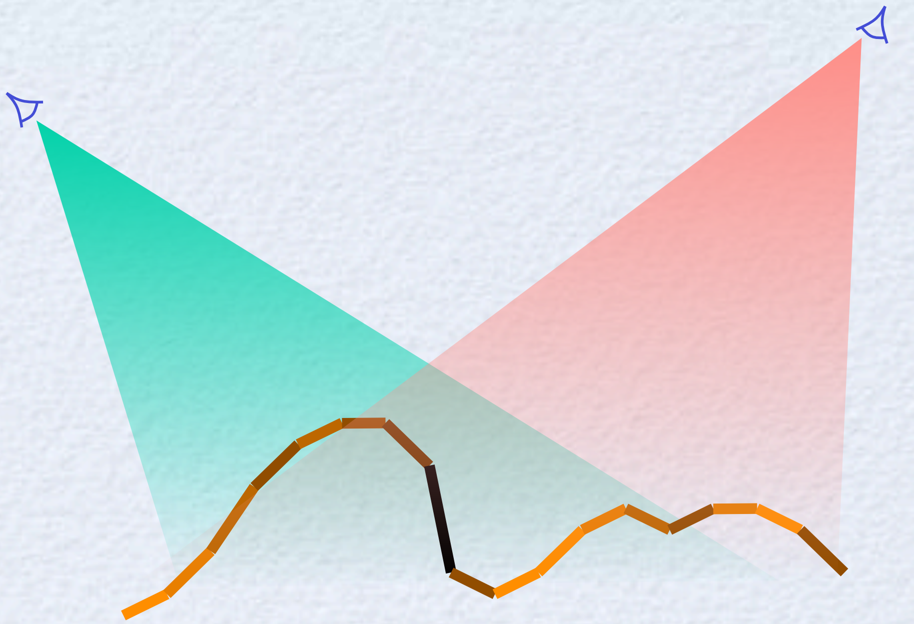
Summary

- Applications: Earth & planetary sciences
  - High-resolution ground deformation maps
  - Surface reconstruction: DEMs + reflectance of natural areas
- Our main objectives
  - **Dense vector disparity maps** with **sub-pixel accuracy**
  - Provide the **uncertainties** to allow for error propagation
- Why use optical images
  - Availability, coverage, redundancy, price
- Requirements
  - **Raw images, well-sampled**

- Necessary tools
  - Probability theory, signal processing, computer vision, applied math, and of course some Physics!

Some problems with existing methods for stereo 3D reconstruction

Shape from Stereo



Drawbacks :

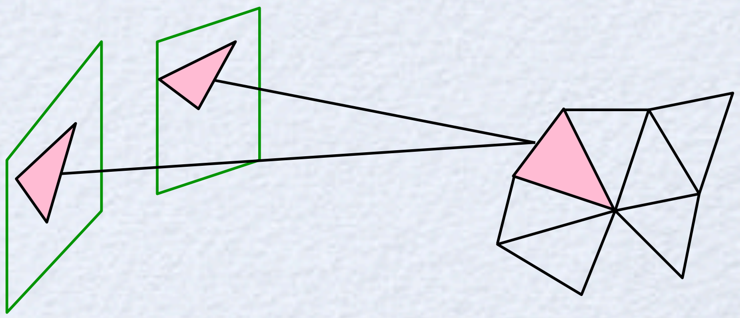
- Relies on finding point **matches** in both images
- The **density** of detected features is not uniform

Dense stereo via disparity maps

Drawbacks :

- Photometric **matching areas** in both images of minimum **size**
- Usually works in **1D** from **resampled** images!

Generalized stereo (deformable models)



Drawbacks :

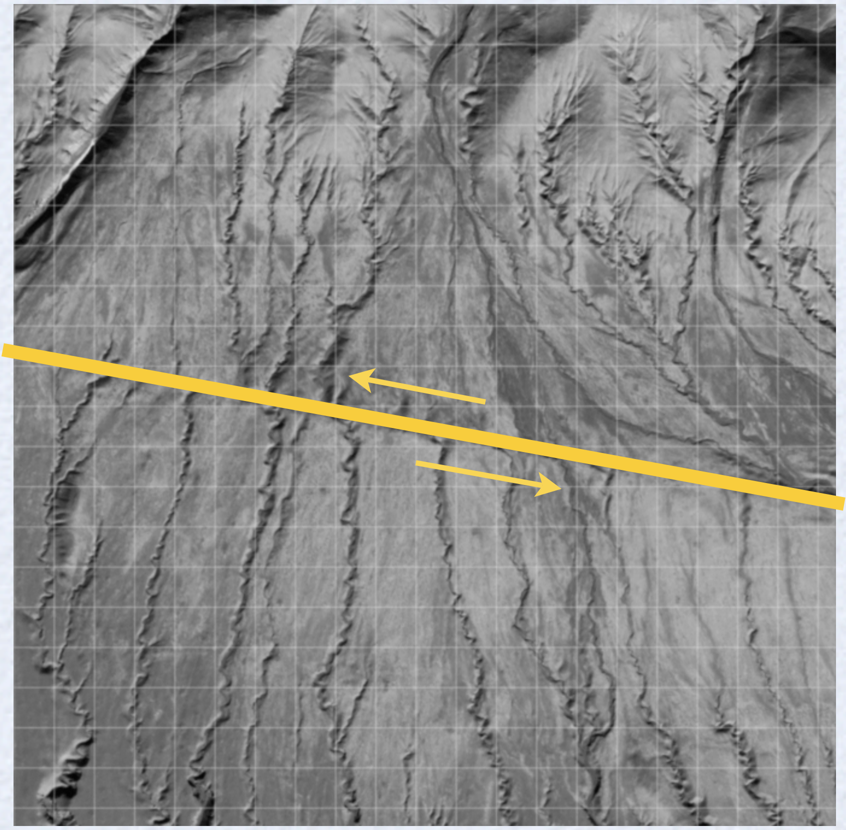
- **Not Bayesian:** difficult to estimate model parameters...

Sub-pixel accuracy, uncertainty map, 2D vector?

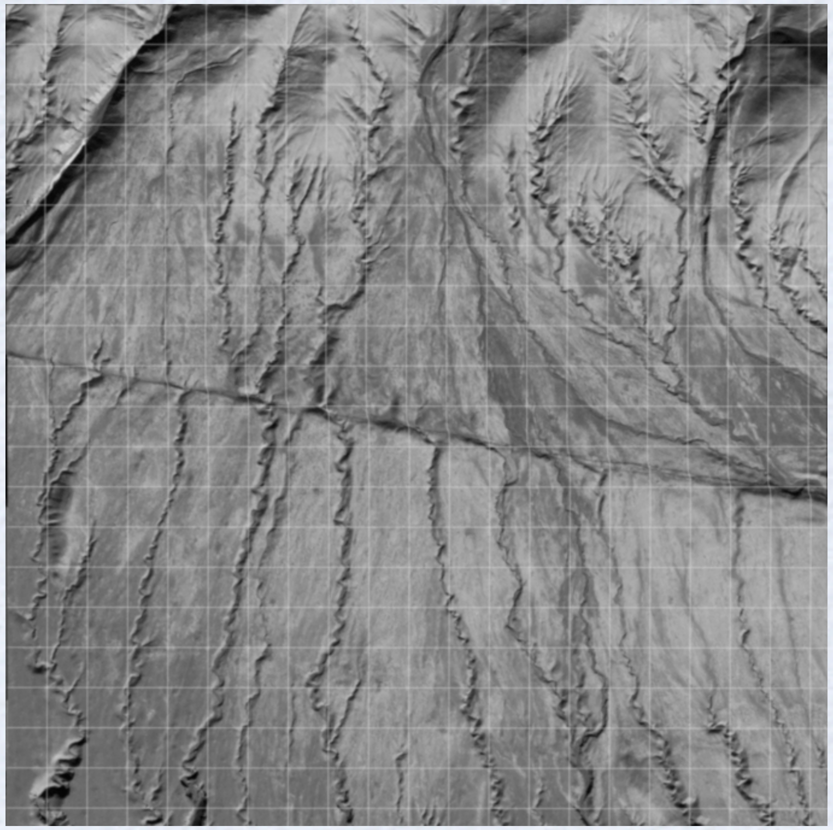
Deformation fields in Earth Sciences

D. Fitzenz, J. Van der Woerd - **IPG Strasbourg**

- Infer the parameters of a dense deformation field
  2 images: one before, one after earthquake/deformation/event...
  - Deformation field = **spatially variable** translation vectors
  - **Challenge: subpixel accuracy** (0.1 pixel to detect a 30 cm shift)
  - Allow for discontinuities on segments (faults)



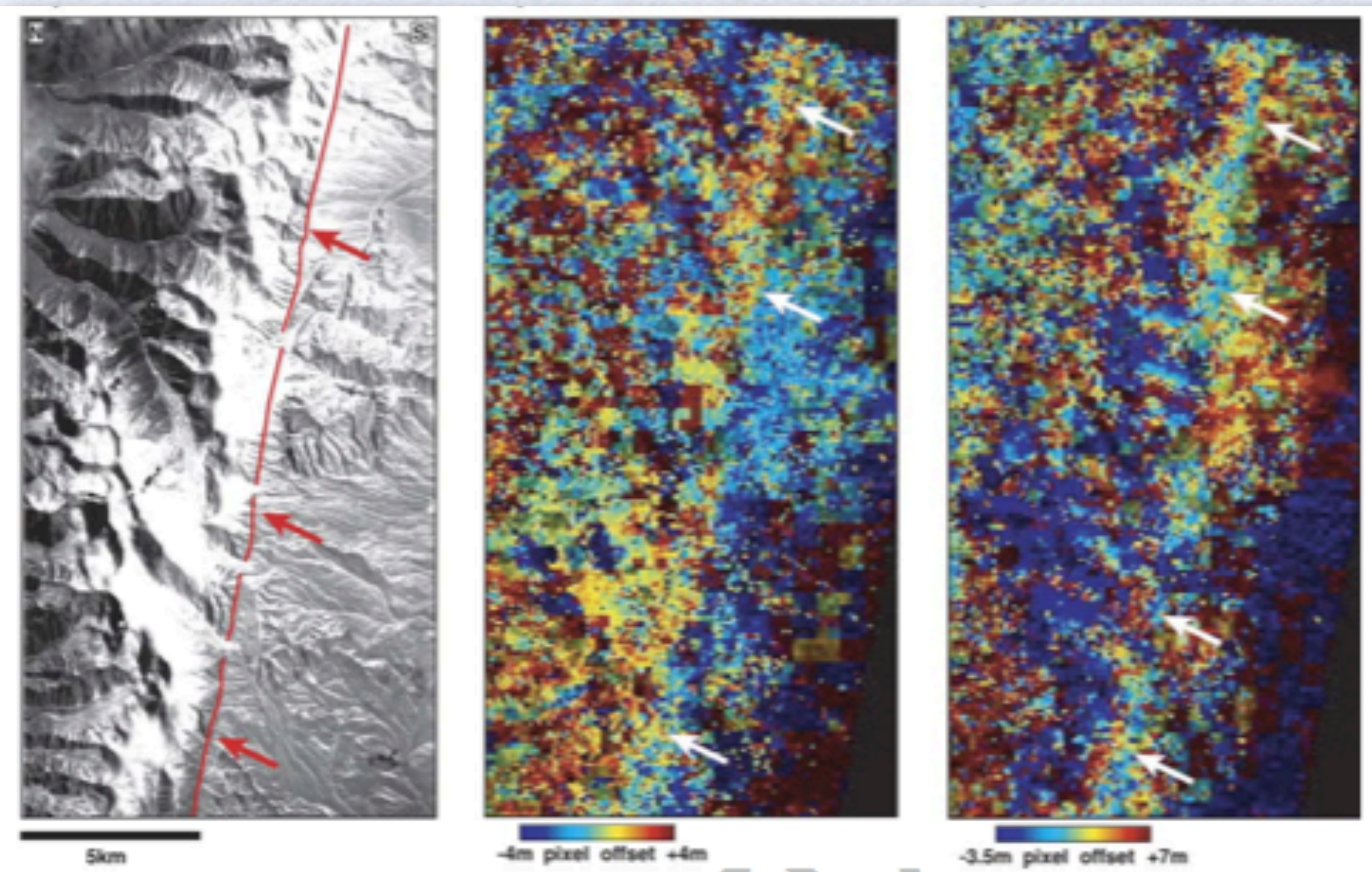
Before EQ (simulation)



After EQ (simulation)

Tests: existing methods for ground deformation measurement

Real remote sensing data

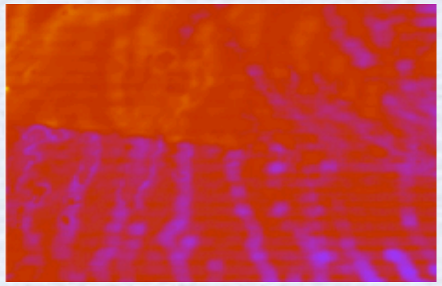


Klinger et al, 2006, Kunlun fault.
1m accuracy, 320m resolution
“optical image correlation”

➤ **High resolution? Uncertainty map?**

Simulations

Reference



Fourier 32x32
(correlation)

Fourier 128x128
(correlation)

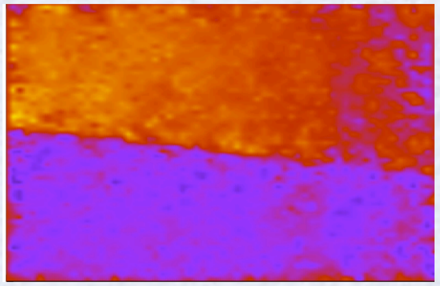


Image space,
nonrigid
(least squares)

Bayesian inference

***OBJECTIVE*:**
***posterior** probability density function (pdf)*

likelihood
image formation model

prior model
(a priori knowledge about the observed object)

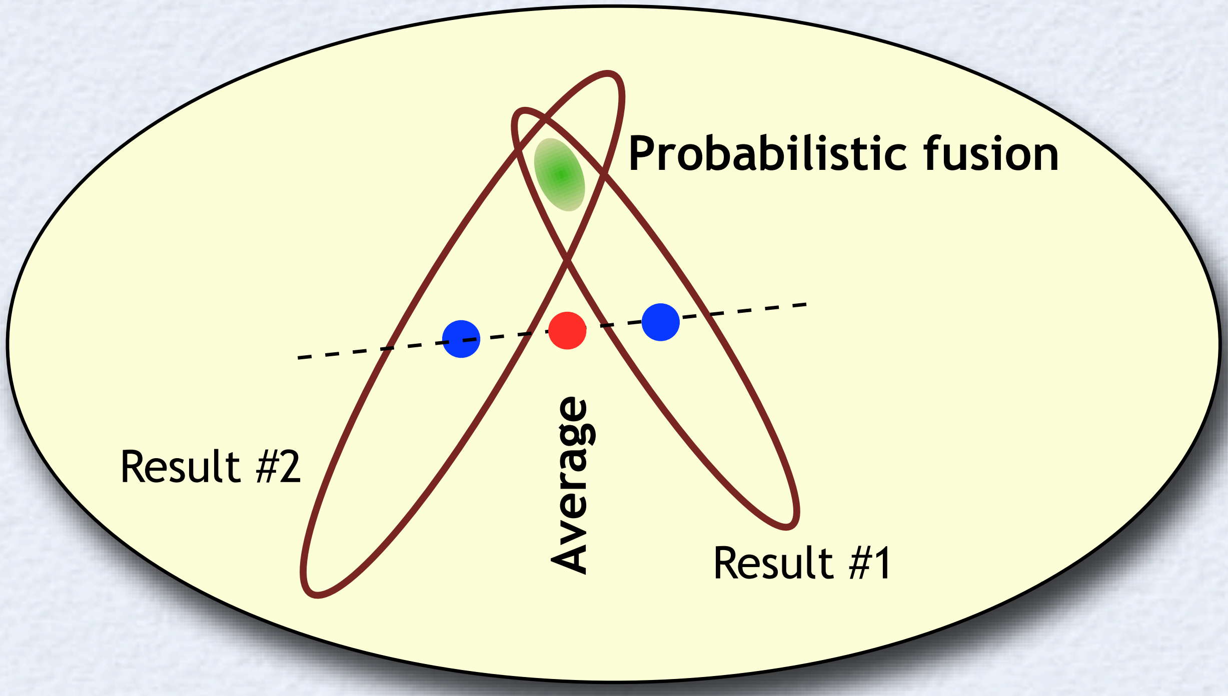
$$p\,(\theta \mid \text{observations}) = \frac{p\,(\text{observations} \mid \theta) \times p\,(\theta)}{p\,(\text{observations})}$$

parameters of interest
(unknown solution)

evidence
(useful for model comparison)

- **Eliminate the unwanted parameters (integration)**
- **Compute the optimal parameters of interest (optimization)**
- **Compute the related uncertainties (derivatives)**
- **Model selection and assessment (comparison)**

Probabilistic data fusion vs. averaging



- **Take into account uncertainties: variance, correlations**
  Formal framework for the combination of multiple observations
- **Propagate uncertainties**
  From the observation noise to the end result!
  Downside: algorithms ought to account for input uncertainties

Basic ingredients & mathematical tools

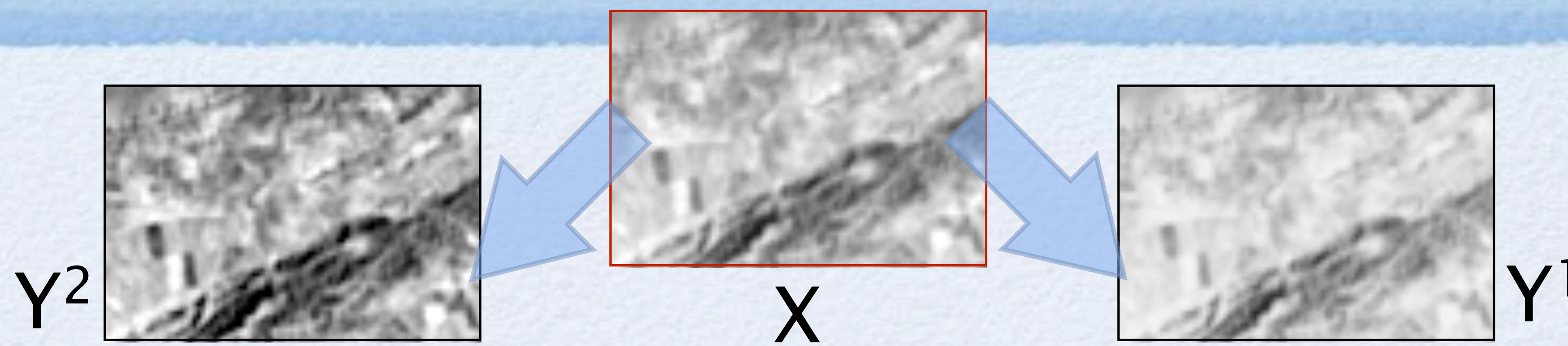
Forward modeling:

- **All parameters are random variables**
- **Data - image formation model** (rendering + degradations)
- **Prior - object modeling** (disparities, 3D, etc.)
- **Graphical models** convenient for design and understanding

Bayesian inference scheme:

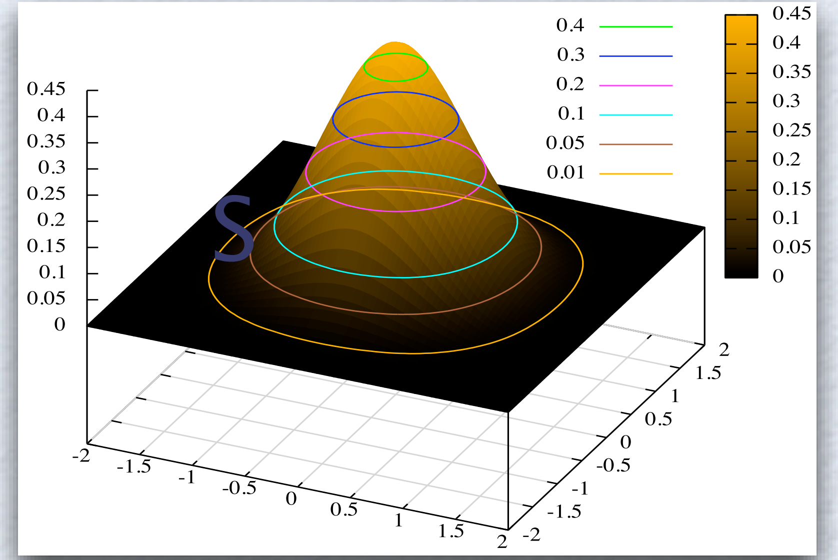
- **Integration w.r.t. nuisance parameters** (aka. marginalization)
- **Deterministic functional optimization** - for speed
- **Error propagation / uncertainty evaluation** (covariance matrix)
- **Approximations required** (otherwise intractable)

Forward model
1. Underlying 2D “reflectance map”



- Common reflected radiance map

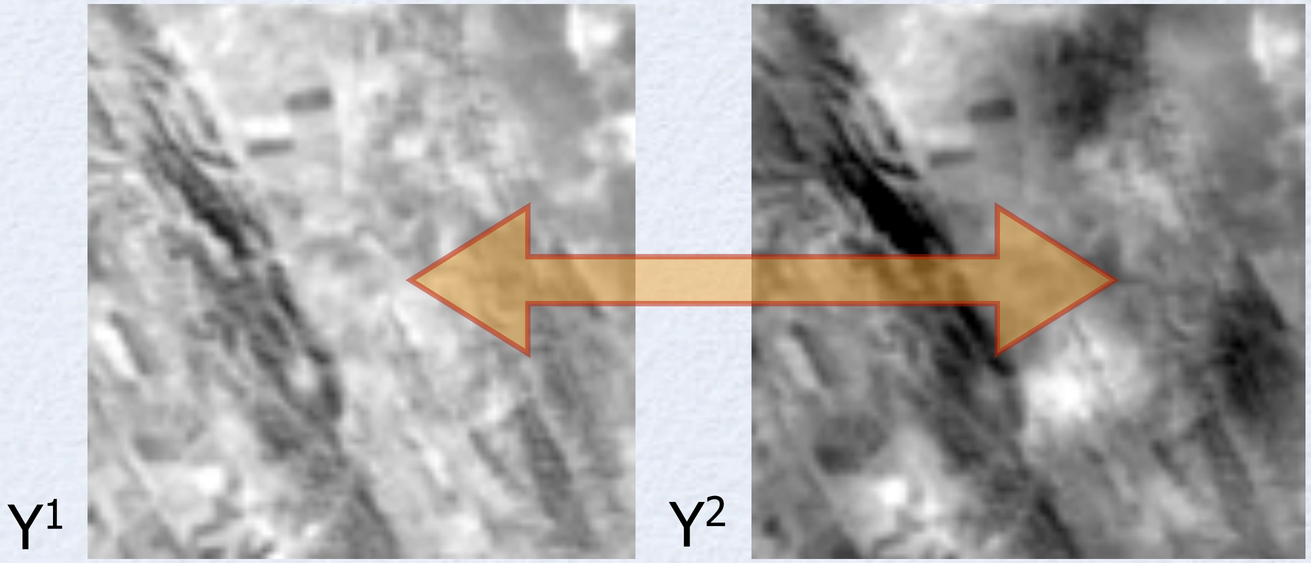
- Model this map as a 2D image:
  - Choose an appropriate **parametrization** and topology
    - Sampling **grid size** ε
    - **Rectangular** lattice
  - Use the **sampling theorem**
    - **Frequency cut-off** (optical resolution)
    - **Well-sampled images** (wrt. Nyquist rate)
    - **Near-optimal representation using Splines:**



Target PSF (B-Spline 3)

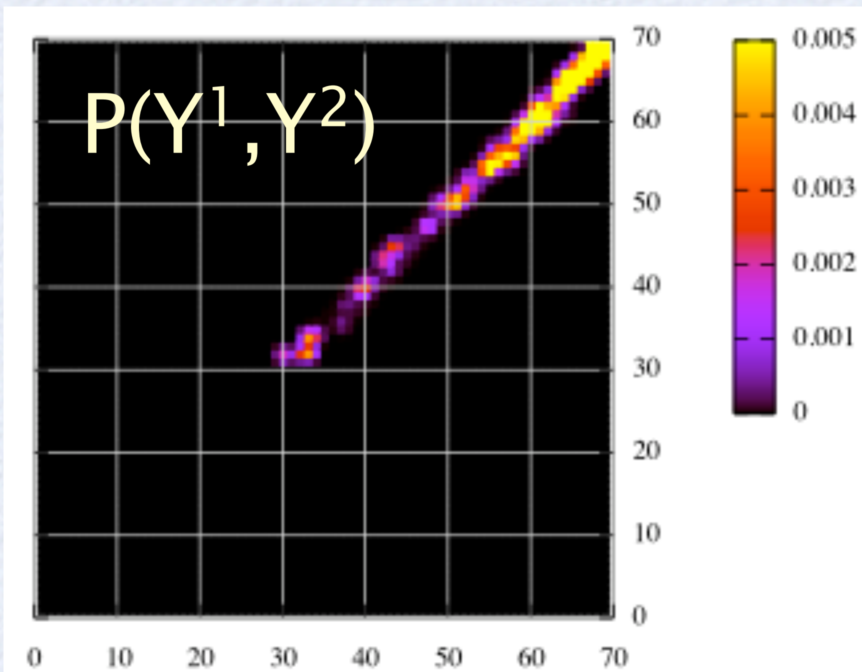
2. Modeling radiometric changes

- **Parametric**
  - **Multiplicative** changes - include reflectance effects (non-Lambert, lighting variations), shadows, atmospheric attenuation, instrumental artifacts...
  - **Additive** changes - include atmospheric haze, clouds, instrumental biases...
  - **Additive noise** - approx. Gaussian, independent pixels

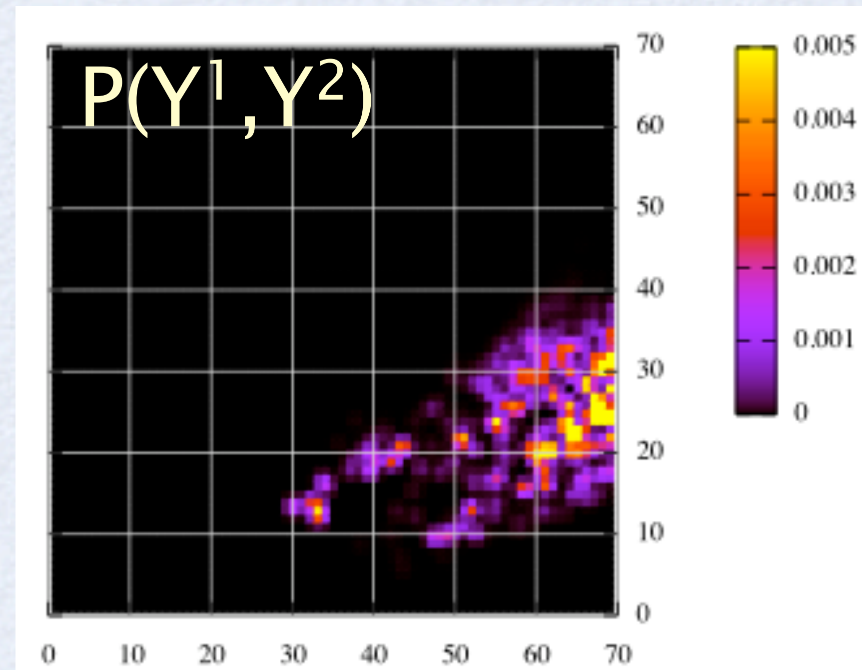


Why use a spatially adaptive change model

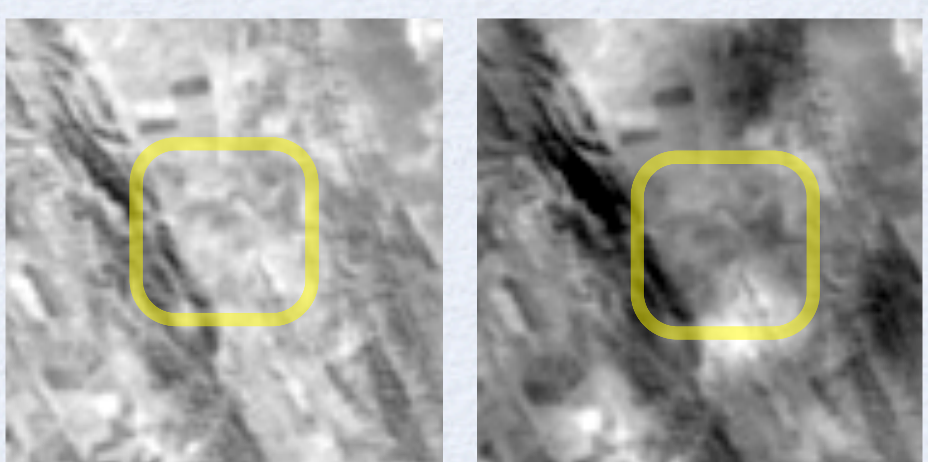
Test - global joint histograms after registration:



No changes: diagonal



Add. and mul. changes



Test area and simulated changes

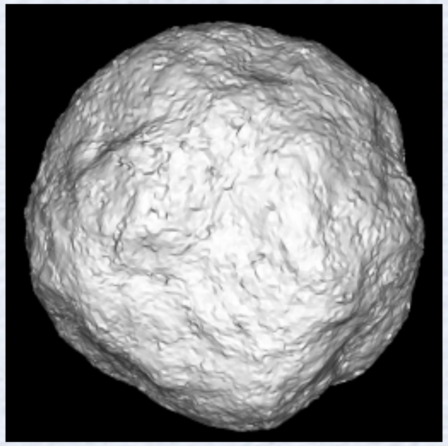
change model parameters should be spatially adaptive!

3. A smoothness prior model for disparity maps

- **Arbitrary** disparity maps: surface deformation
  - Depends on the application (earthquakes, erosion...)

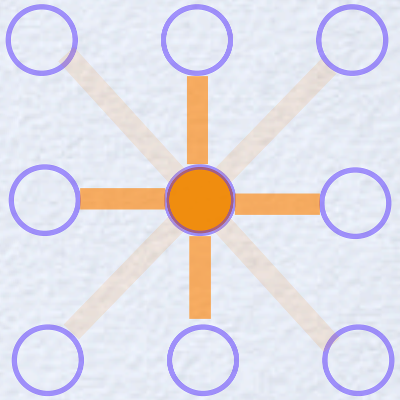
- **Constrained** disparity maps: 3D reconstruction
  - **Epipolar lines... *if known!***
  - **d_x:** very smooth
  - **d_y:** related to the topography

...*planetary surface modeling*

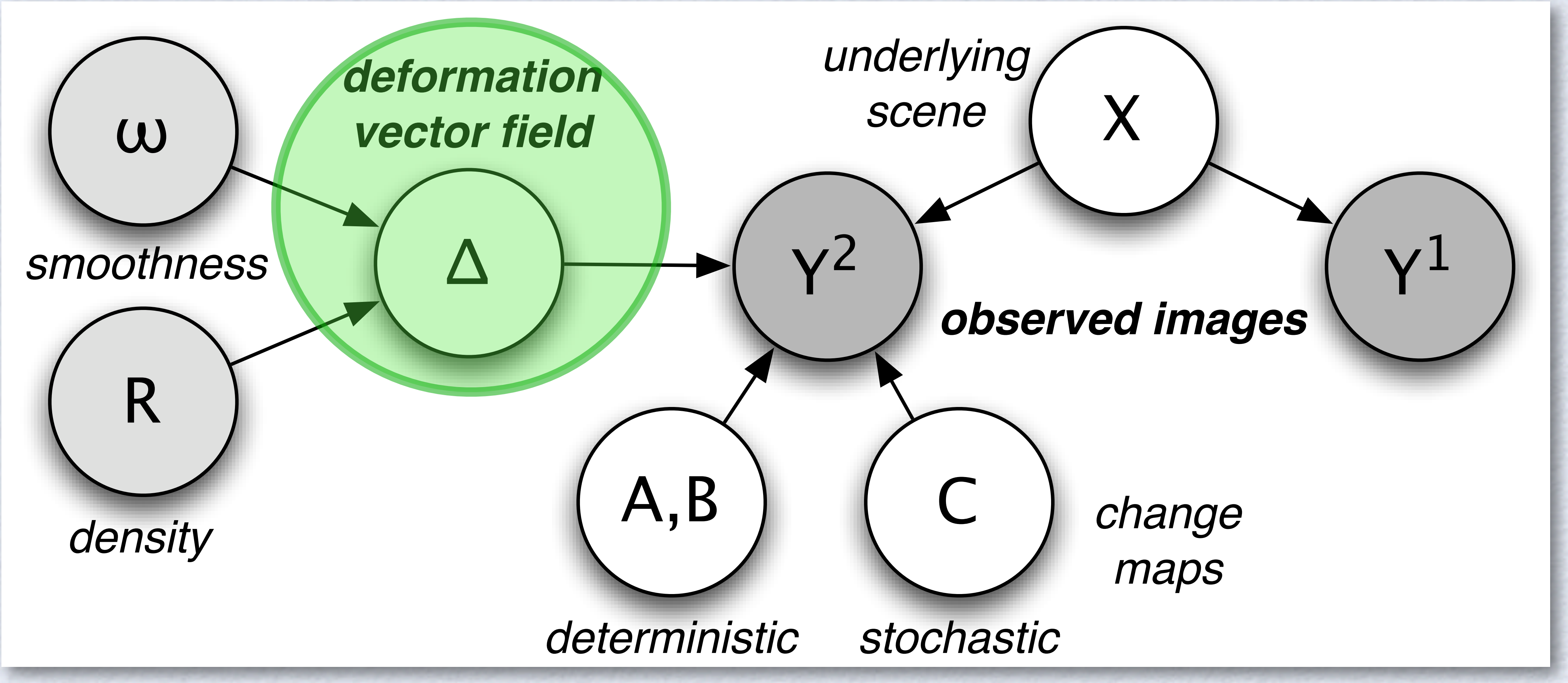


Self-similar process based on image gradient operators

Markov Random Field:
spatial interactions
btw. neighbor parameters

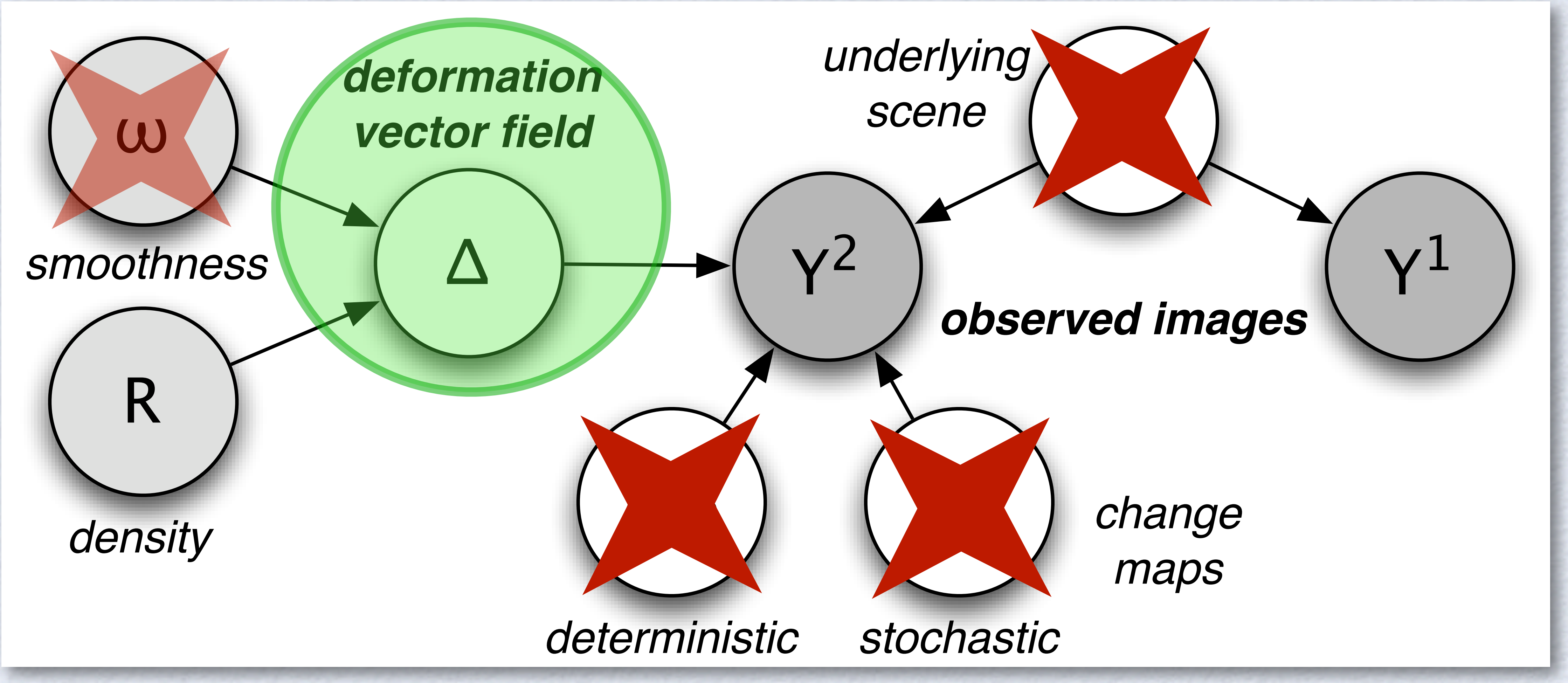


Bayesian inference from 2 observations



- **Graphical model:** build the joint probability density function (pdf)
- **Marginalization:** integrate the joint pdf w.r.t. nuisance variables

Inference Method M3



- **Marginalize** all change model parameters
- Use **explicit** values for prior model parameters
- Use the evidence framework to **estimate** them automatically, then **plug in** the estimated values

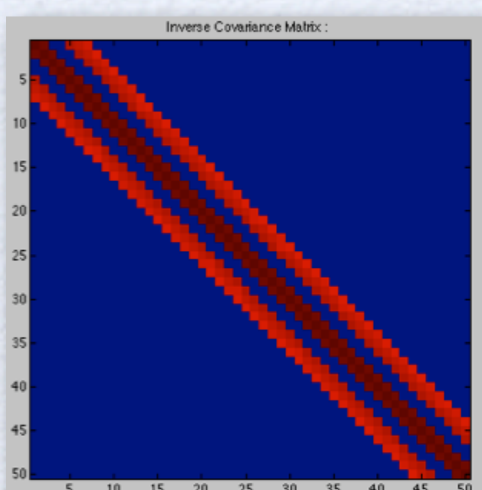
How the inference algorithm works

Compute the marginal Maximum A Posteriori, and a Gaussian approximation around the optimum

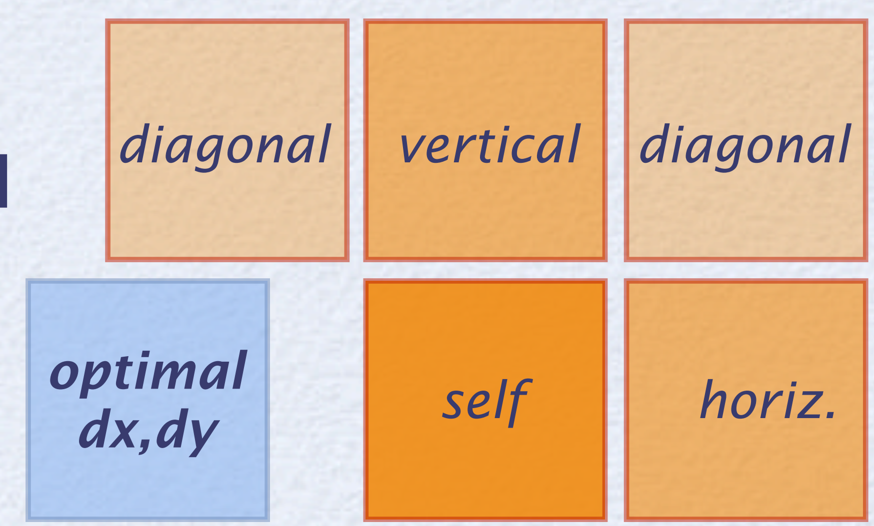
Iterative optimization of an energy functional
(nonlinear search: conjugate gradient, ...)

$$\log P(d_x,d_y \mid Y^1,Y^2) = \underbrace{\boxed{D(d_x,d_y,Y^1,Y^2)}}_{\textit{data term}} + \underbrace{\boxed{Prior(d_x)+Prior(d_y)}}_{\textit{smoothness penalty}}$$

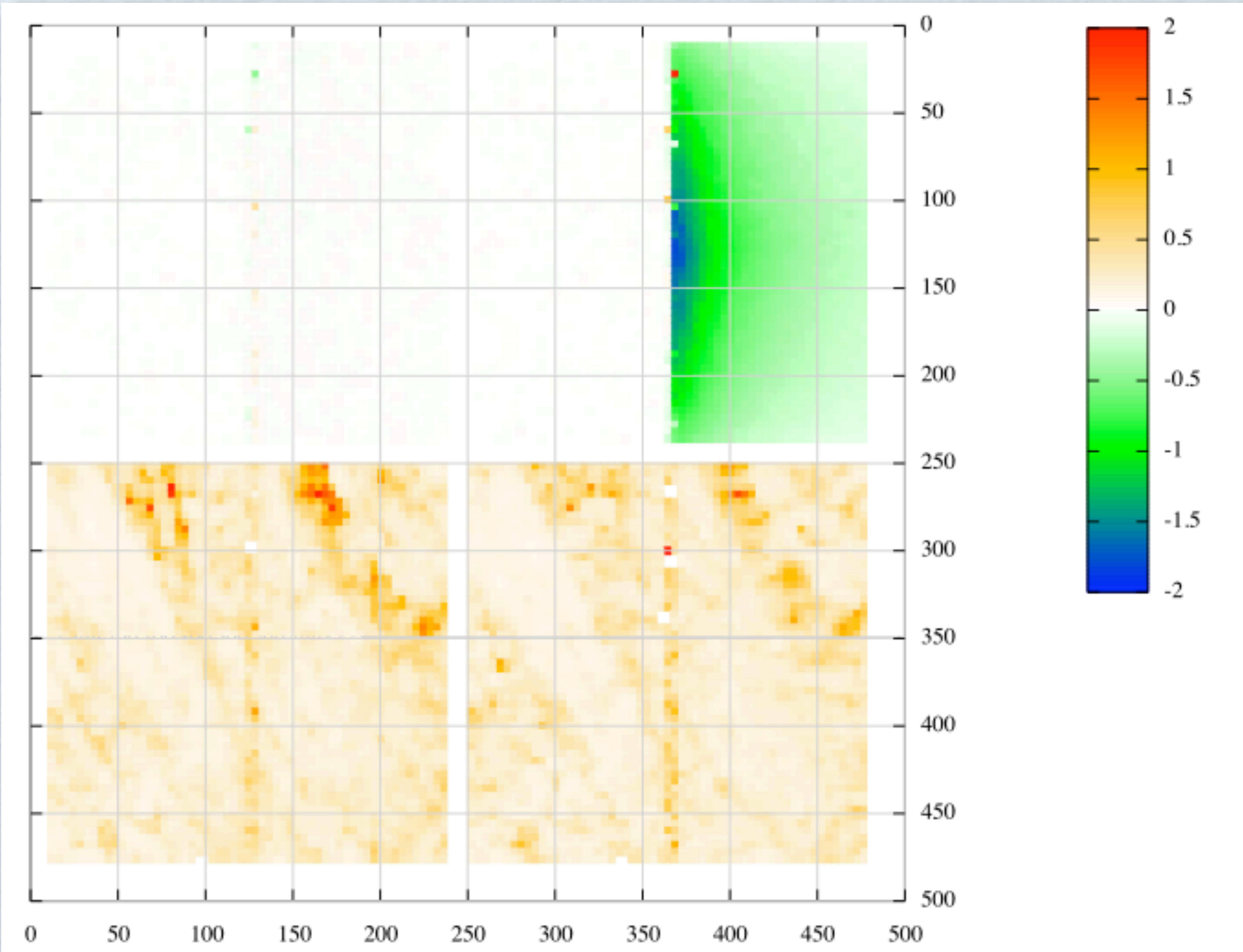
- Inverse covariance matrix: **uncertainties**
  - **Second derivatives** of the energy U at the optimum
  - **Sparse matrix**



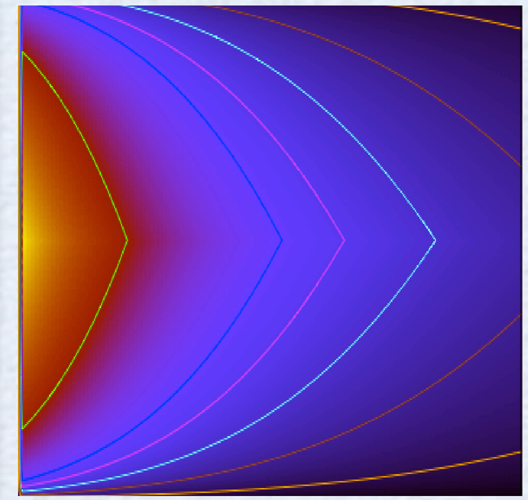
compound result storage



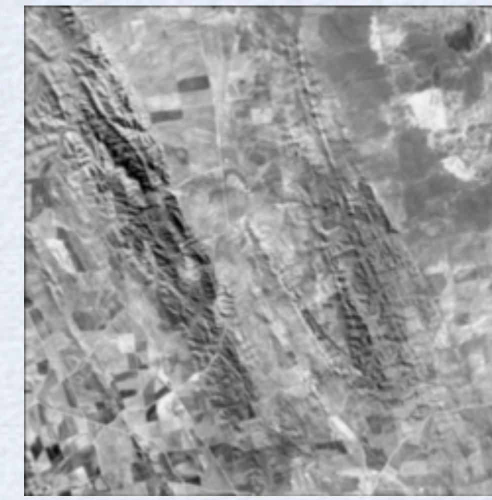
Bayesian inference: preliminary tests
(change = iid Gaussian noise, window-based estimation)



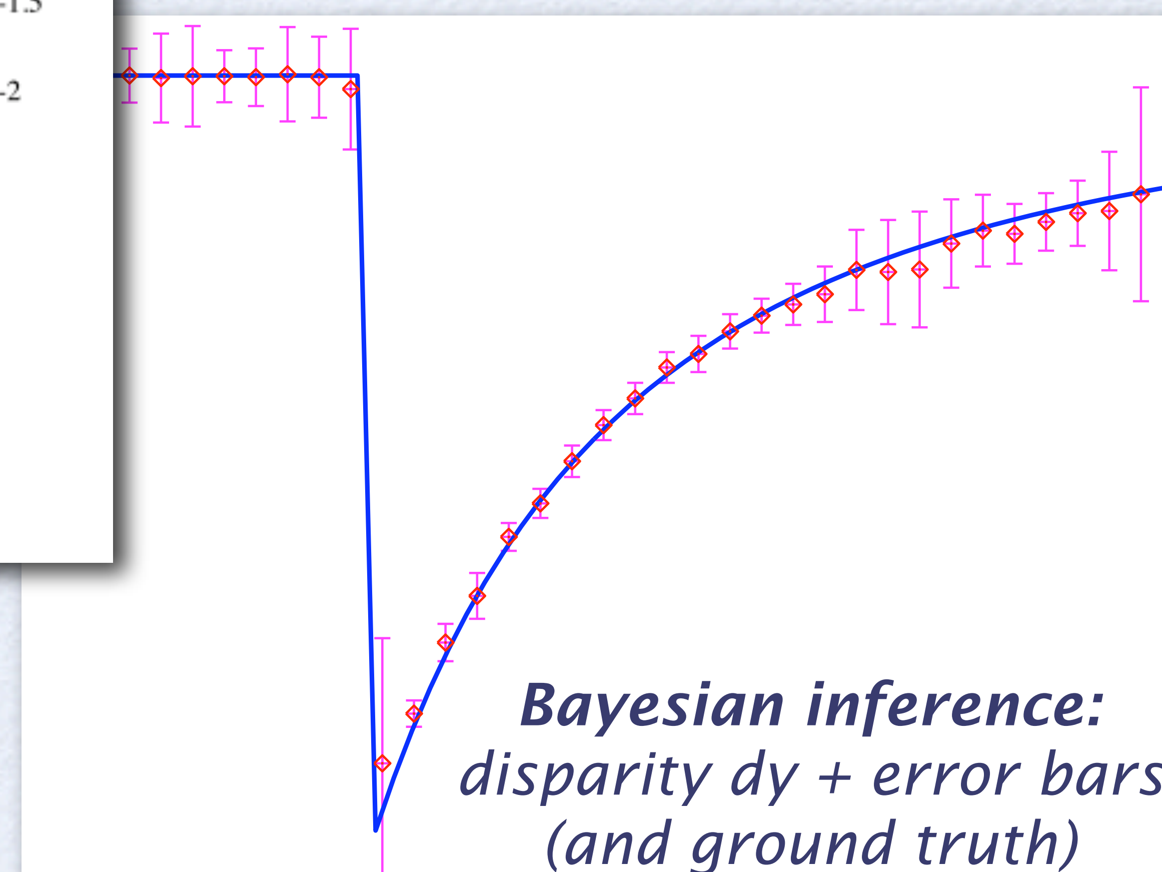
Bayesian inference:
disparity dx,dy
variance of dx,dy



reference dy



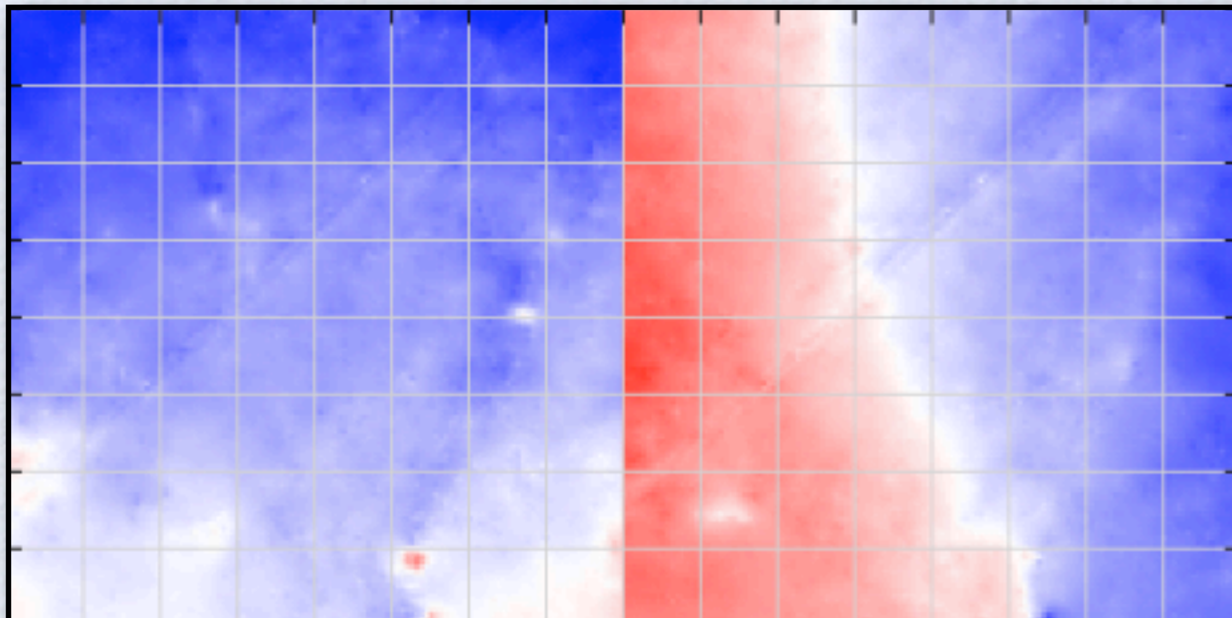
source image



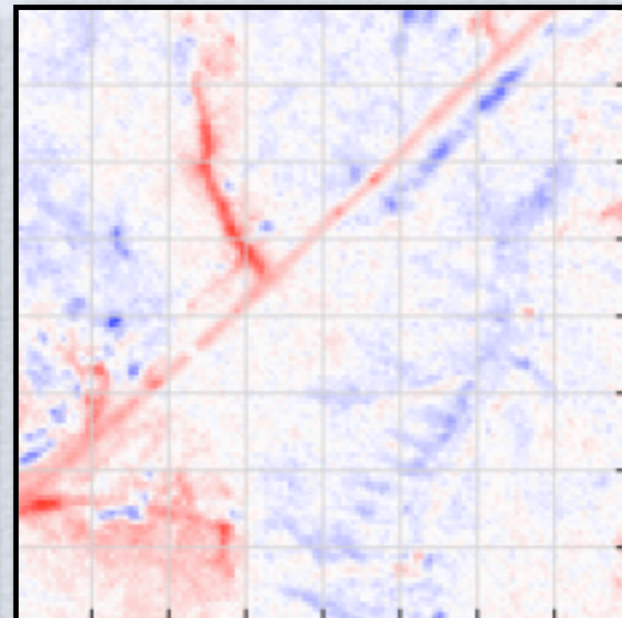
Bayesian inference:
disparity dy + error bars
(and ground truth)

Results - real data, method M2

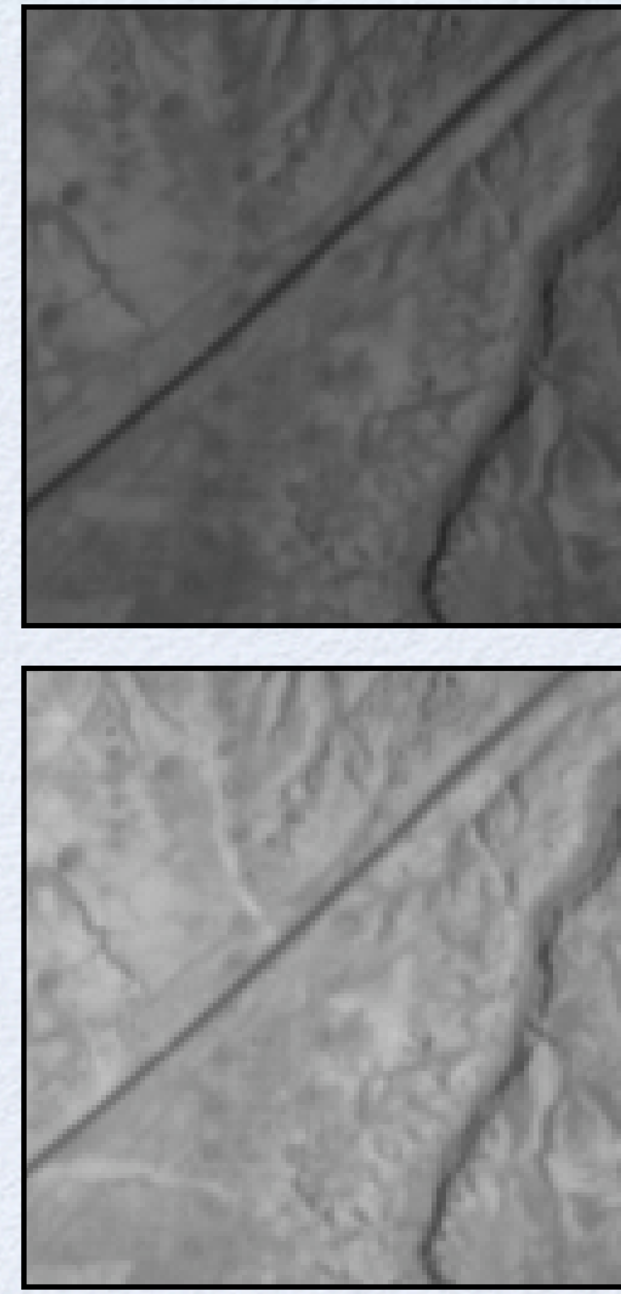
RAW SPOT 5, multidate, 128x128 pixels @ 3.5m, 1 disparity vector / pixel



Bayesian inference:
estimated disparity dx,dy [-1,1]

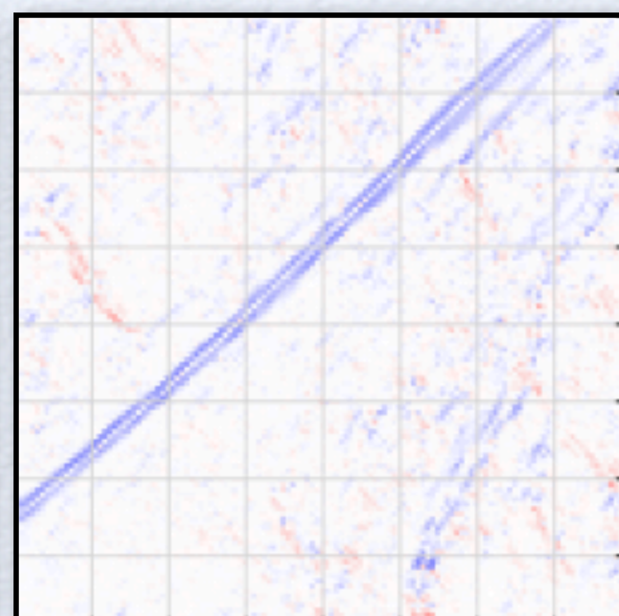


change map
[-10,10]



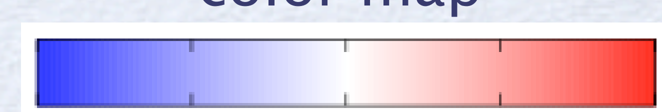
images Y1, Y2 [0,255]

standard deviation maps [-0.2,0.2]



correlation map [-1,1]

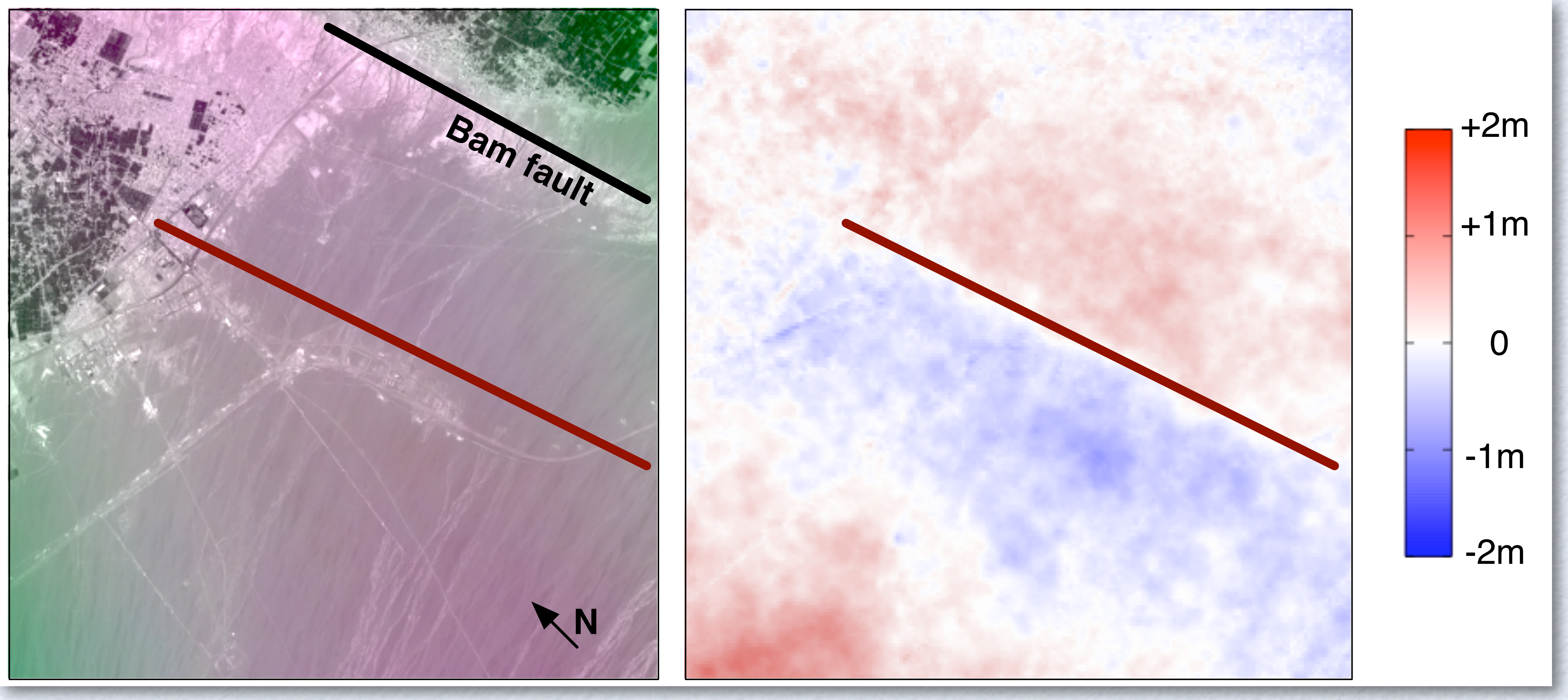
color map



Results - real data, method M3

RAW SPOT 5, multidate, 4096x4096 pixels @ 3.5m, 1 disparity vector / 4x4 pixels

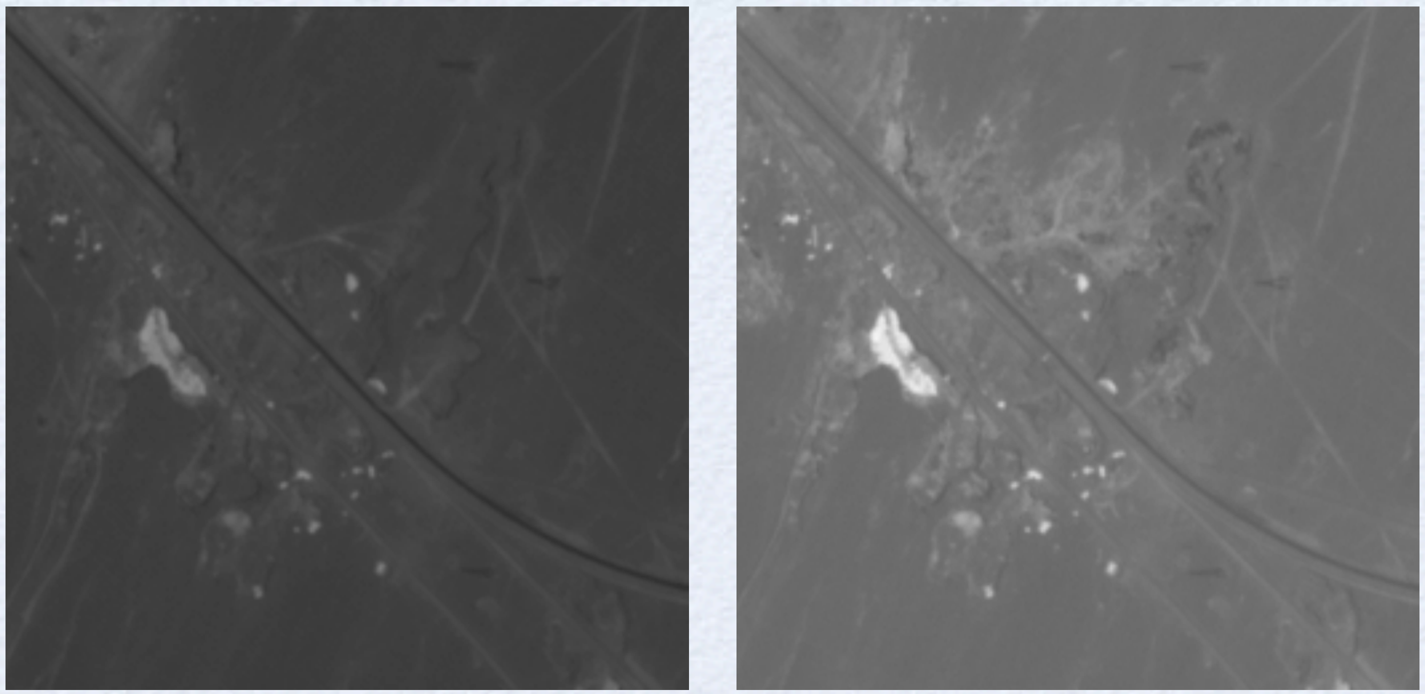
Data: images of Bam, Iran - before and after earthquake (10/03 and 02/04)



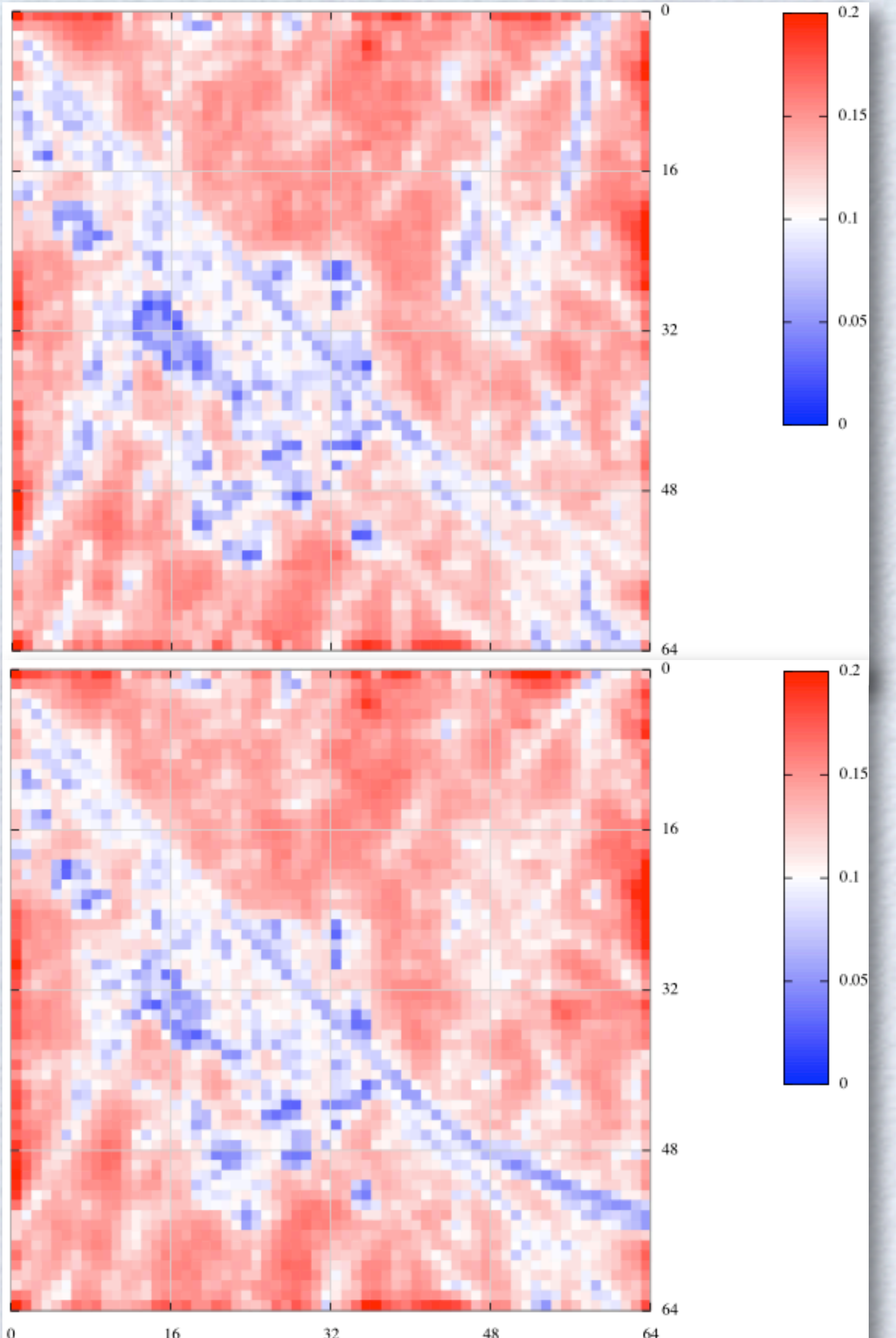
N-S projection of the displacement map eliminating most topographic artifacts (residual geometric effects not removed)

Results - real data, method M3

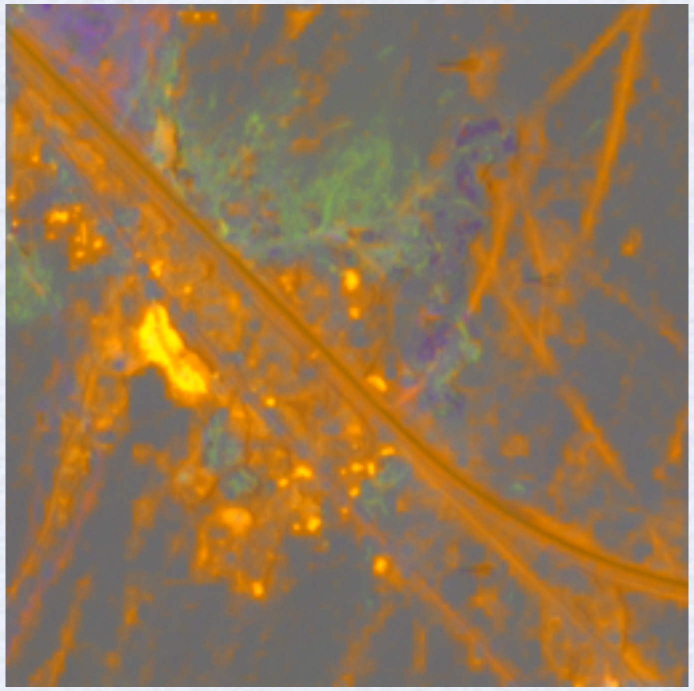
RAW SPOT 5, multidate, 128x128 pixels @ 3.5m, 1 disparity vector / 4x4 pixels



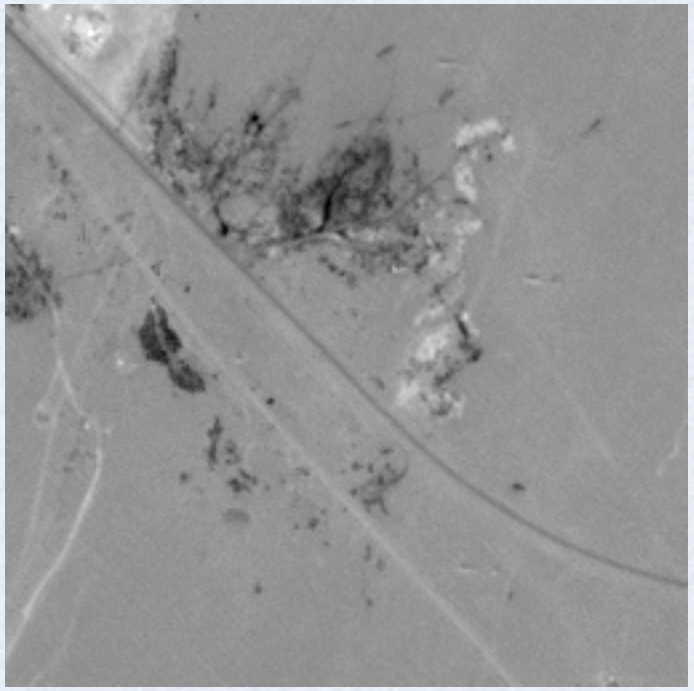
images Y1, Y2 [0,255]



x and y standard deviation maps



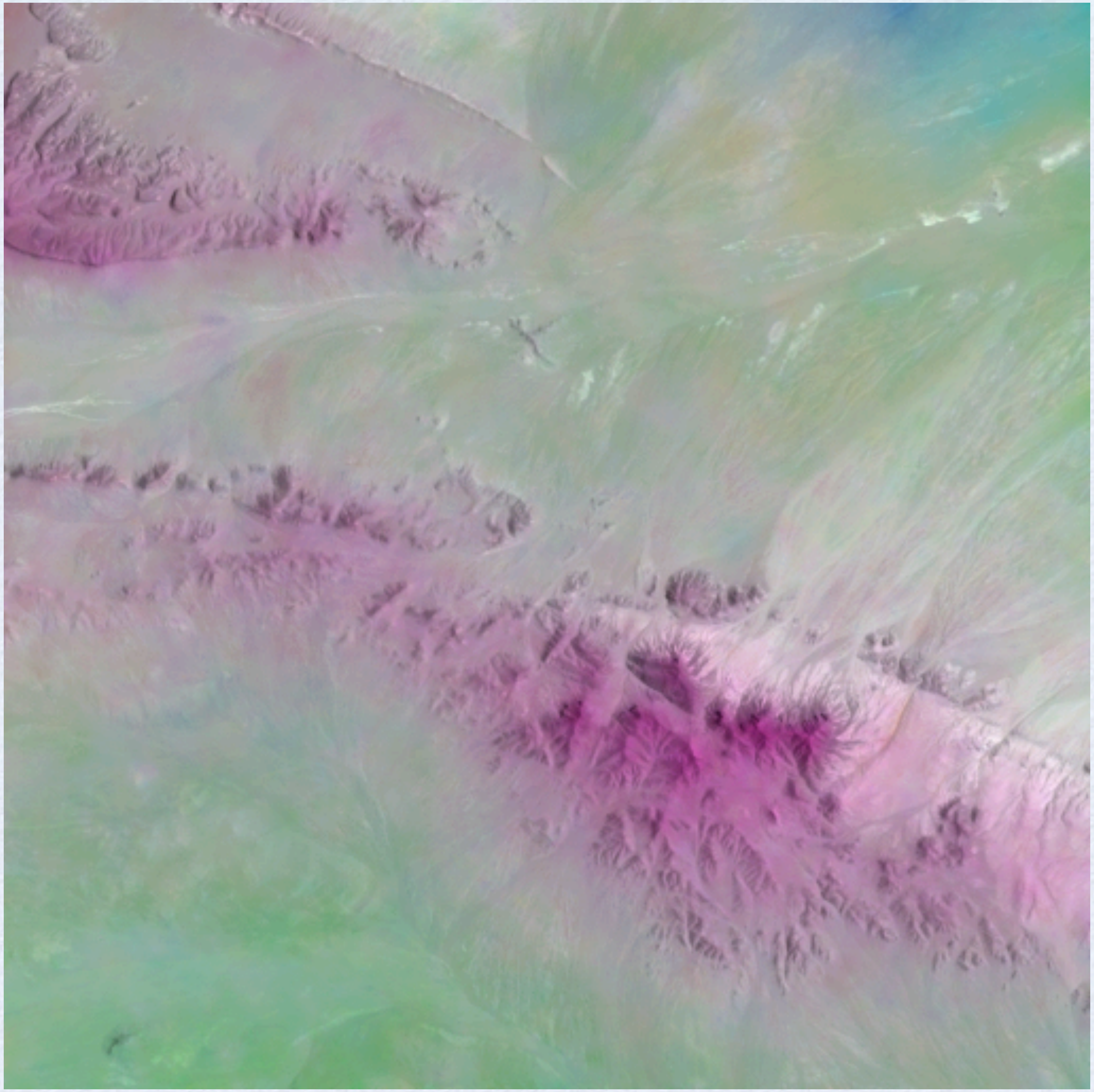
correlation map



change map

Results - real data, method M3

RAW SPOT 5, multidate, 1024x1024 pixels @ 3.5m, 1 disparity vector / 2x2 pixels



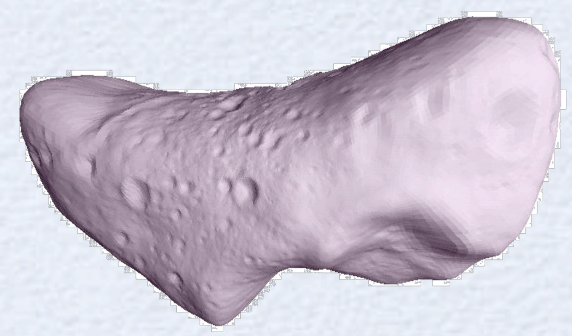
Color-coded disparity map, linear correction applied

(area near Bam, Iran; across-track stereo pair)

Future work

- **To do...**
  - Push-broom **camera calibration** using the disparity map
  - Disparity map conversion into an **elevation model**
  - Generation of rectified **fused reflectance maps**

  - Full 3D surface recovery **from n images**:
    - Rendering: take into account possible **occlusions**
    - **Reflectance** map inference



  - **Validation** on real data (raw images required)
    - Along-track (simultaneous): HRSC on Mars Express, ASTER
    - Across-track (multidate): SPOT 5
    - Ground truth? sparse GCP, LIDAR points, SRTM DEM...