Determining the AMSR-E SST Footprint from Co-Located MODIS SSTs

Brahim Boussidi[1], Peter Cornillon[1], Gavino Puggioni[2] and Chelle Gentemann[3]

[1] Graduate School of Oceanography, University of Rhode Island, Narragansett, RI 02882, USA
[2] Department of Computer Science and Statistics, University of Rhode Island, Kingston, RI 02881, USA
[3] Earth and Space Research, Seattle, WA 98121, USA

June 3, 2019

Acknowledgments

- Funding:
  - NASA Physical Oceanography Program (Grant #NNX16AI24G),
  - NOPP (80NSSC18K0837) and
  - Partial salary support for P. Cornillon from the .

Acknowledgments

- Funding:
  - NASA Physical Oceanography Program (Grant #NNX16AI24G),
  - NOPP (80NSSC18K0837) and
  - Partial salary support for P. Cornillon from the State of Rhode Island and Providence Plantations.

Acknowledgments

- Funding:
  - NASA Physical Oceanography Program (Grant #NNX16AI24G),
  - NOPP (80NSSC18K0837) and
  - Partial salary support for P. Cornillon from the State of Rhode Island and Providence Plantations.

Outline

The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

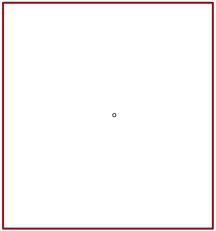
The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was 56 $\times$ 56 km^2 sampled every 10 km; i.e, oversampled

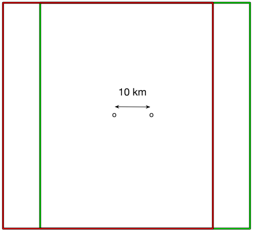
AMSR-E Sea Surface Temperature Footprint 56 x 56 km



The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

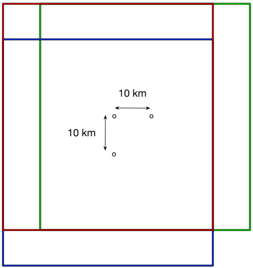
AMSR-E Sea Surface Temperature Footprint 56 x 56 km



The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

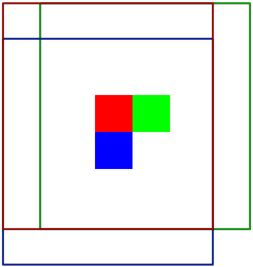
AMSR-E Sea Surface Temperature Footprint 56 x 56 km



The Problem

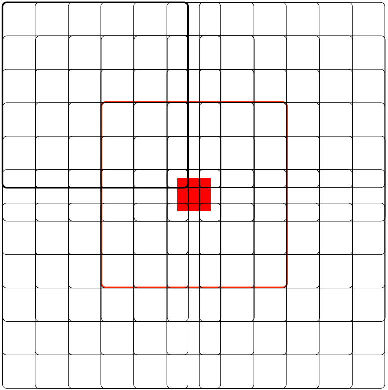
- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled

AMSR-E Sea Surface Temperature Footprint 56 x 56 km



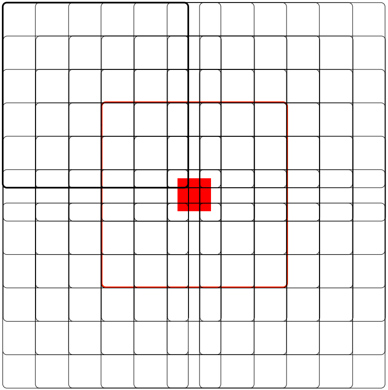
The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled



The Problem

- A microwave sensor, *AMSR-E*, carried on the *Aqua* spacecraft sampled the global ocean twice daily from 2002 through 2011.
- Sea surface temperature (SST) is estimated from the *AMSR-E* measurements.
- The putative SST footprint was $56 \times 56\,\mathrm{km}^2$ sampled every 10 km; i.e, oversampled



Our objective was to deconvolve the AMSR-E field to obtain a true 10x10 km resolution SST field

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

An Initial Approach

- A straight deconvolution requires some seed values.
- We have coincident $1 \times 1\,\mathrm{km}^2$ MODIS SSTs in cloud-free areas.
- So we used MODIS to seed the deconvolution
  - We selected a region with a large fraction of clear MODIS pixels
  - Averaged the pixels to the 10×10 km AMSR-E grid.
  - And inverted.
  - It didn't work so well! The resulting field was dominated by noise.
- We quickly determined there were two problems:
  - The solution was very sensitive to noise.
  - The putative AMSR-E footprint of 56×56 km was not correct.
- It was clear that we needed to:
  - Determine the AMSR-E footprint
  - Characterize the noise in the AMSR-E field.

Outline

The Idea is ...

to use the high-resolution MODIS SST fields with the AMSR-E fields to determine the AMSR-E footprint.

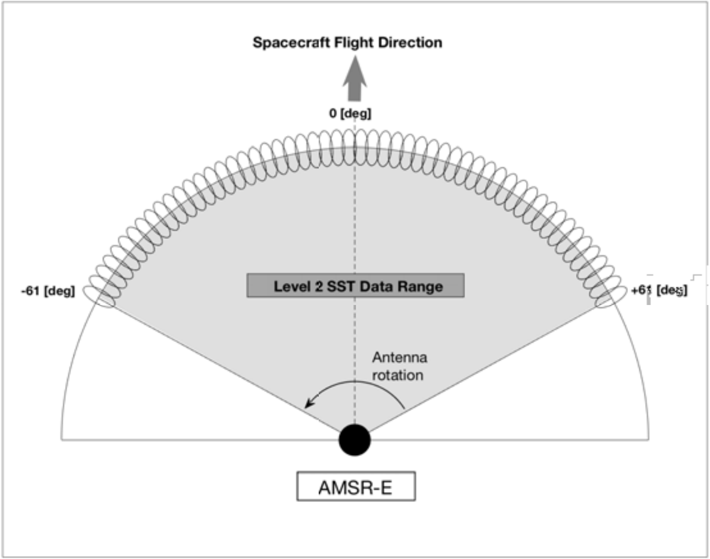
But first some more background.

The Idea is ...

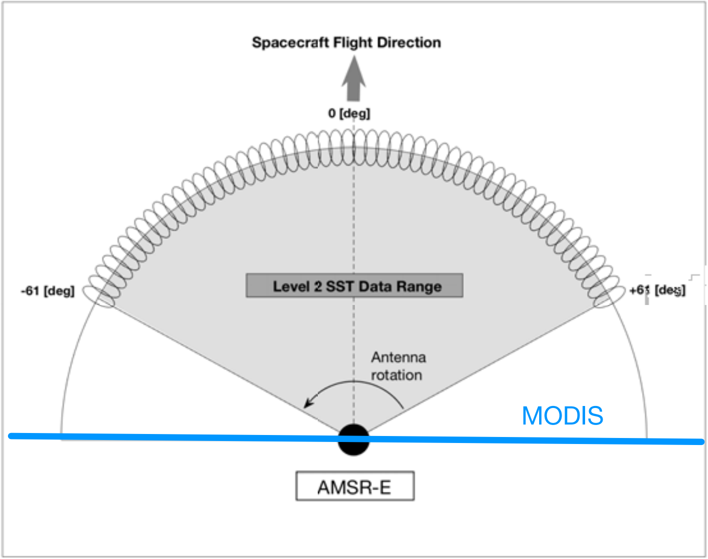
to use the high-resolution MODIS SST fields with the AMSR-E fields to determine the AMSR-E footprint.

But first some more background.

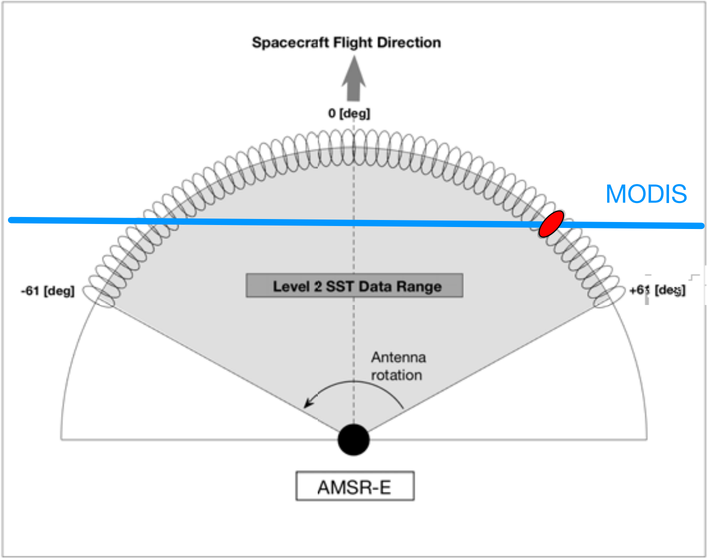
Scanning Geometry – AMSR-E was a Conical Scanner



Scanning Geometry – AMSR-E was a Conical Scanner



Scanning Geometry – AMSR-E was a Conical Scanner



Determining the AMSR-E Footprint

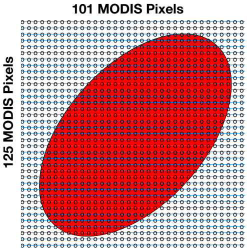
- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.

Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.

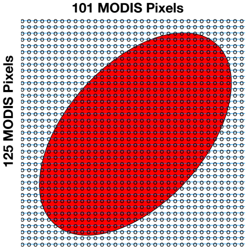
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



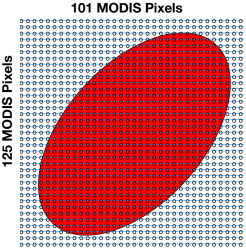
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



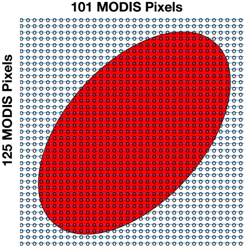
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



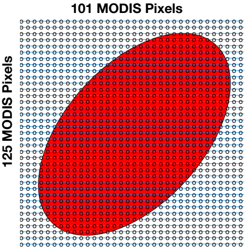
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



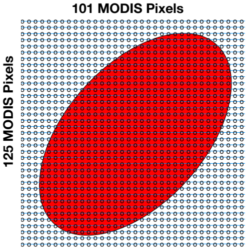
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 × 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 × 31) MODIS SST measurements/matchup
- ≈4,000,000 globally distributed AMSR-E – MODIS matchups.



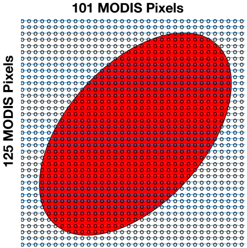
Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



Determining the AMSR-E Footprint

- Build the AMSR-E – MODIS matchups dataset.
  - Nighttime L2 AMSR-E SST pixel,
  - A 101 $\times$ 125 MODIS L2 SST pixel region.
    - centered on the AMSR-E pixel,
    - with the 125 element dimension is parallel to the nadir track.
    - with at least 90% of the MODIS pixels classified as clear.
  - We averaged the MODIS pixels into 4x4 pixel non-overlapping squares.
  - This resulted in a total of 775 (25 $\times$ 31) MODIS SST measurements/matchup
- $\approx$4,000,000 globally distributed AMSR-E – MODIS matchups.



Distribution of Matchups

- So the problem we want to solve is:

$$\underbrace{\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ \vdots \\ a_{N-1} \\ a_N \end{pmatrix}}_{A} = \underbrace{\begin{pmatrix} m_1^1 & m_2^1 & m_3^1 & \cdots & m_{775}^1 \\ m_1^2 & m_2^2 & m_3^2 & \cdots & m_{775}^2 \\ m_1^3 & m_2^3 & m_3^3 & \cdots & m_{775}^3 \\ m_1^4 & m_2^4 & m_3^4 & \cdots & m_{775}^4 \\ & & & \vdots & \\ m_1^{N-1} & m_2^{N-1} & m_3^{N-1} & \cdots & m_{775}^{N-1} \\ m_1^N & m_2^N & m_3^N & \cdots & m_{775}^N \end{pmatrix}}_{M} \underbrace{\begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ \vdots \\ h_{775} \end{pmatrix}}_{H} + \underbrace{\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \vdots \\ \epsilon_{N-1} \\ \epsilon_N \end{pmatrix}}_{\epsilon}$$

- Or more compactly: $A_{N\times 1} = M_{775\times N} H_{775\times 1} + \epsilon_{N\times 1}$

  where A are the AMSR-E values,
  M the MODIS values,
  H the AMSR-E footprint vector containing the weighting elements and
  ϵ noise in the data.

- This is simply a regression relation between A and M.
- We want to determine the form of H, which minimizes

$$\arg\min_{H} ||A_{N\times 1} - M_{775\times N} H_{775\times 1}||^2$$

Distribution of Matchups

- So the problem we want to solve is:

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ \vdots \\ a_{N-1} \\ a_N \end{pmatrix}_A = \begin{pmatrix} m_1^1 & m_2^1 & m_3^1 & \cdots & m_{775}^1 \\ m_1^2 & m_2^2 & m_3^2 & \cdots & m_{775}^2 \\ m_1^3 & m_2^3 & m_3^3 & \cdots & m_{775}^3 \\ m_1^4 & m_2^4 & m_3^4 & \cdots & m_{775}^4 \\ & & & \vdots & \\ m_1^{N-1} & m_2^{N-1} & m_3^{N-1} & \cdots & m_{775}^{N-1} \\ m_1^N & m_2^N & m_3^N & \cdots & m_{775}^N \end{pmatrix}_M \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ \vdots \\ h_{775} \end{pmatrix}_H + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \vdots \\ \epsilon_{N-1} \\ \epsilon_N \end{pmatrix}_\epsilon$$

- Or more compactly: $A_{N\times 1} = M_{775\times N} H_{775\times 1} + \epsilon_{N\times 1}$

  where A are the AMSR-E values,
  M the MODIS values,
  H the AMSR-E footprint vector containing the weighting elements and
  ϵ noise in the data.

- This is simply a regression relation between A and M.
- We want to determine the form of H, which minimizes

$$\arg\min_H \| A_{N\times 1} - M_{775\times N} H_{775\times 1} \|^2$$

Distribution of Matchups

- So the problem we want to solve is:

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ \vdots \\ a_{N-1} \\ a_N \end{pmatrix}_A = \begin{pmatrix} m_1^1 & m_2^1 & m_3^1 & \cdots & m_{775}^1 \\ m_1^2 & m_2^2 & m_3^2 & \cdots & m_{775}^2 \\ m_1^3 & m_2^3 & m_3^3 & \cdots & m_{775}^3 \\ m_1^4 & m_2^4 & m_3^4 & \cdots & m_{775}^4 \\ & & & \vdots & \\ m_1^{N-1} & m_2^{N-1} & m_3^{N-1} & \cdots & m_{775}^{N-1} \\ m_1^N & m_2^N & m_3^N & \cdots & m_{775}^N \end{pmatrix}_M \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ \vdots \\ h_{775} \end{pmatrix}_H + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \vdots \\ \epsilon_{N-1} \\ \epsilon_N \end{pmatrix}_\epsilon$$

- Or more compactly: $A_{N\times 1} = M_{775\times N} H_{775\times 1} + \epsilon_{N\times 1}$

  where A are the AMSR-E values,
  M the MODIS values,
  H the AMSR-E footprint vector containing the weighting elements and
  ϵ noise in the data.

- This is simply a regression relation between A and M.
- We want to determine the form of H, which minimizes

$$\arg\min_H \| A_{N\times 1} - M_{775\times N} H_{775\times 1} \|^2$$

Distribution of Matchups

- So the problem we want to solve is:

$$\begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ \vdots \\ a_{N-1} \\ a_N \end{pmatrix}_A = \begin{pmatrix} m_1^1 & m_2^1 & m_3^1 & \cdots & m_{775}^1 \\ m_1^2 & m_2^2 & m_3^2 & \cdots & m_{775}^2 \\ m_1^3 & m_2^3 & m_3^3 & \cdots & m_{775}^3 \\ m_1^4 & m_2^4 & m_3^4 & \cdots & m_{775}^4 \\ & & & \vdots & \\ m_1^{N-1} & m_2^{N-1} & m_3^{N-1} & \cdots & m_{775}^{N-1} \\ m_1^N & m_2^N & m_3^N & \cdots & m_{775}^N \end{pmatrix}_M \begin{pmatrix} h_1 \\ h_2 \\ h_3 \\ \vdots \\ h_{775} \end{pmatrix}_H + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \vdots \\ \epsilon_{N-1} \\ \epsilon_N \end{pmatrix}_\epsilon$$

- Or more compactly: $A_{N\times 1} = M_{775\times N} H_{775\times 1} + \epsilon_{N\times 1}$

  where A are the AMSR-E values,
  M the MODIS values,
  H the AMSR-E footprint vector containing the weighting elements and
  ϵ noise in the data.

- This is simply a regression relation between A and M.
- We want to determine the form of H, which minimizes

$$\arg\min_H \|A_{N\times 1} - M_{775\times N} H_{775\times 1}\|^2$$

Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
  - Sample N values with replacement from the pool of data.
  - Solve
  - Repeat R times
- Average the solutions.
- Example simulation.

Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
    - Sample N values with replacement from the pool of data.
    - Solve
    - Repeat R times
- Average the solutions.
- Example simulation.

Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
    - Sample N values with replacement from the pool of data.
    - Solve
    - Repeat R times
- Average the solutions.
- Example simulation.

Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
  - Sample N values with replacement from the pool of data.
  - Solve
  - Repeat R times
- Average the solutions.
- Example simulation.

Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
  - Sample N values with replacement from the pool of data.
  - Solve
  - Repeat R times
- Average the solutions.
- Example simulation.

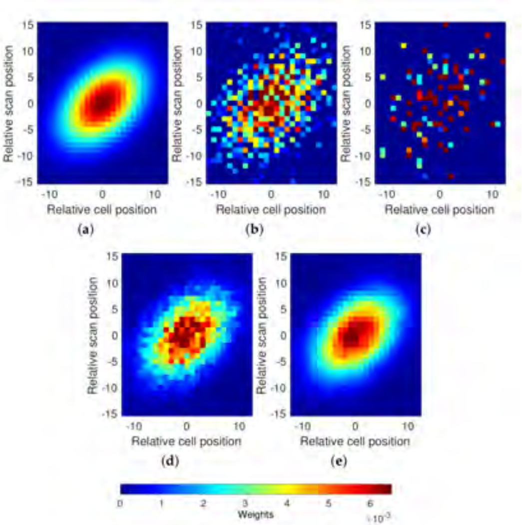
Bag-it

- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
  - Sample N values with replacement from the pool of data.
  - Solve
  - Repeat R times
- Average the solutions.
- Example simulation.

Bag-it

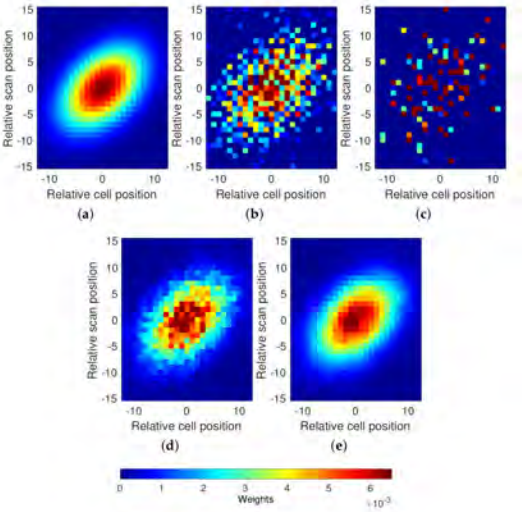
- A straight inversion does not work well.
- Bagging (a.k.a. bootstrapping) is a way of dealing with this.
  - Sample N values with replacement from the pool of data.
  - Solve
  - Repeat R times
- Average the solutions.
- Example simulation.

Bagging – A Simulation



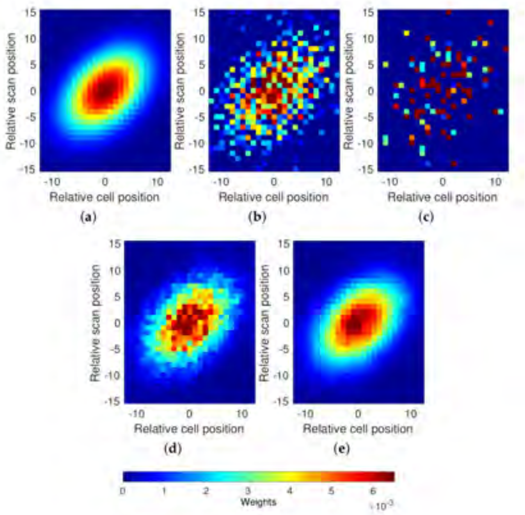
(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

Bagging – A Simulation



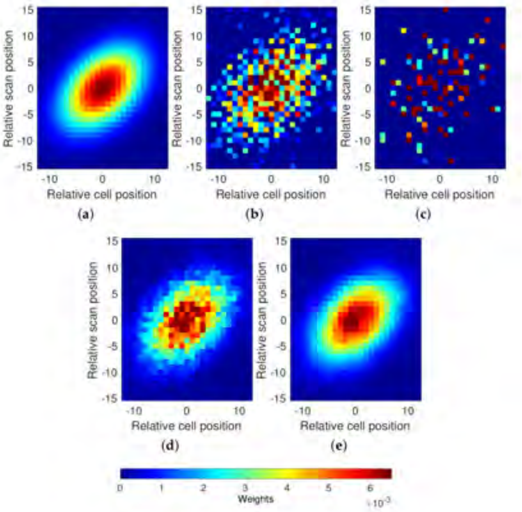
(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

Bagging – A Simulation



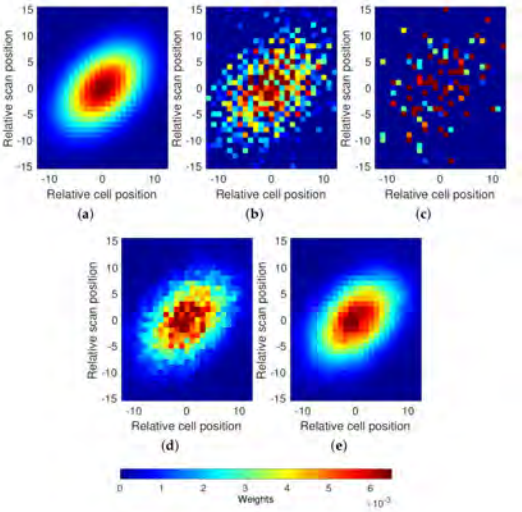
(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

Bagging – A Simulation



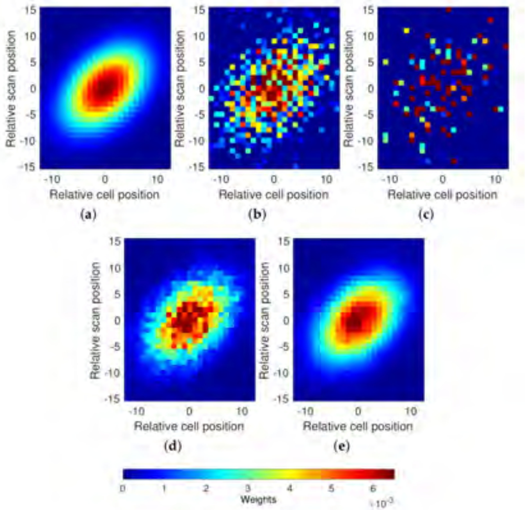
(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

Bagging – A Simulation



(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

Bagging – A Simulation



(a) Imposed footprint. Simulated 250,000 matchups with 0.2 K σ AMSR-E, 0.05 K σ MODIS.
(b) Retrieved footprint (R; N) = (1; 250,000) (c) (1; 2,000) (d) (2,000; 2,000)
(e) 4 $\times$ 4 moving average of (d).

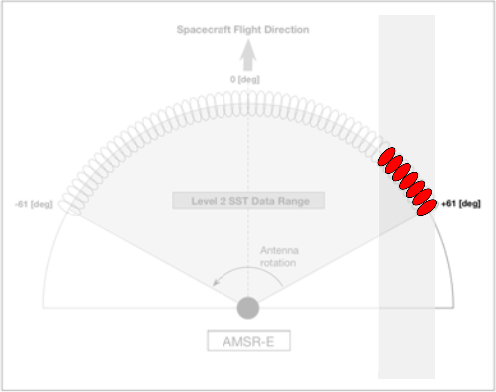
Outline

Footprint by Cell Position

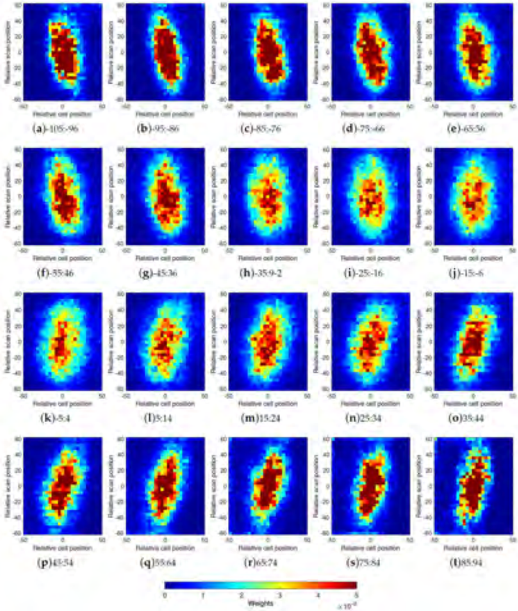
- Using 2,000 iterations of 2,000 samples (R; N) = 2,000; 2,000
- We obtained footprints for all matchups in ranges of 10 cell positions.

Footprint by Cell Position

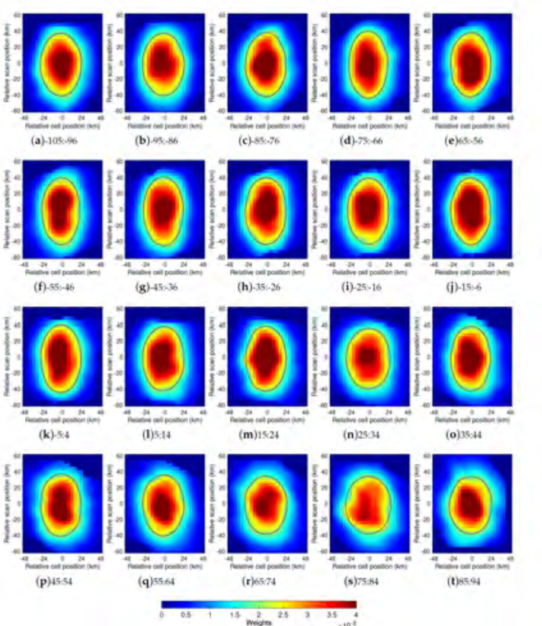
- Using 2,000 iterations of 2,000 samples (R; N) = 2,000; 2,000
- We obtained footprints for all matchups in ranges of 10 cell positions.



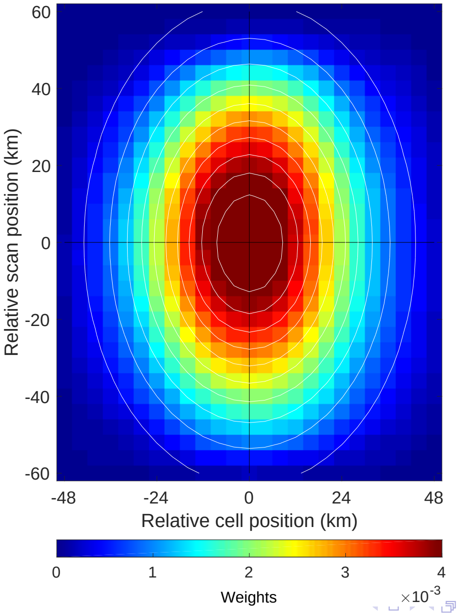
Raw Footprints



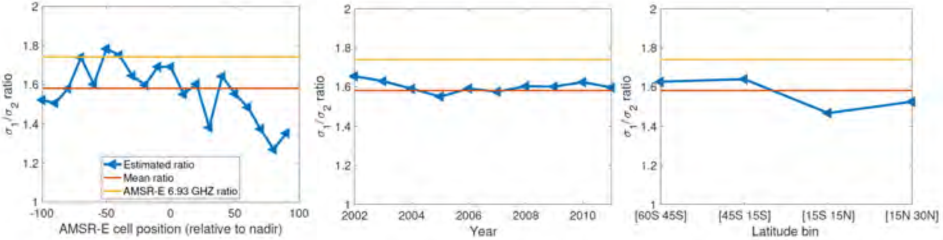
Corrected Footprints



Mean (Reference) Footprint



Footprint as a Function of Cell Position, Year and Latitude



Impact of Footprint on Comparisons with Other Satellite-Derived SSTs

If you average a cloud-free MODIS field to the corresponding AMSR-E field with our footprint you would expect the difference field to be white noise with AMSR-E sigma

YOU DON'T $\Leftarrow$ Note shouting

Impact of Footprint on Comparisons with Other Satellite-Derived SSTs

If you average a cloud-free MODIS field to the corresponding AMSR-E field with our footprint you would expect the difference field to be white noise with AMSR-E sigma

YOU DON'T ⇐ Note shouting

Impact of Footprint on Comparisons with Other Satellite-Derived SSTs

If you average a cloud-free MODIS field to the corresponding AMSR-E field with our footprint you would expect the difference field to be white noise with AMSR-E sigma

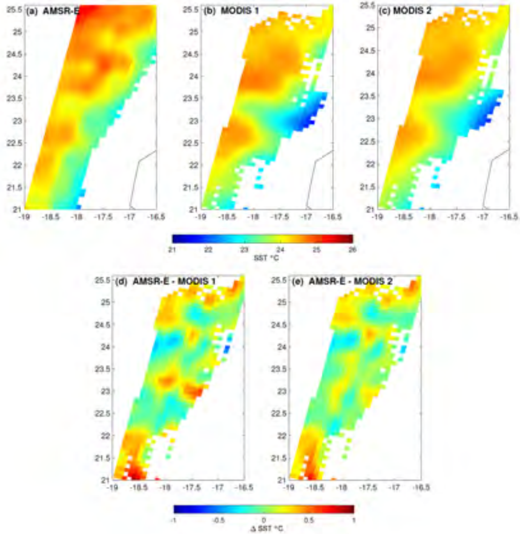
YOU DON'T $\Leftarrow$ Note shouting

Impact of Footprint on Comparisons with Other Satellite-Derived SSTs

If you average a cloud-free MODIS field to the corresponding AMSR-E field with our footprint you would expect the difference field to be white noise with AMSR-E sigma

YOU DON'T $\Leftarrow$ Note shouting

Impact of Footprint on Comparisons with Other Satellite-Derived SSTs



MODIS-1 - average MODIS to AMSR-E with 56 × 56 km footprint.
MODIS-2 - average MODIS to AMSR-E with our footprint.

Outline

1. Motivation
2. The AMSR-E Footprint
3. Results
4. Deconvolution
5. Conclusions

The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

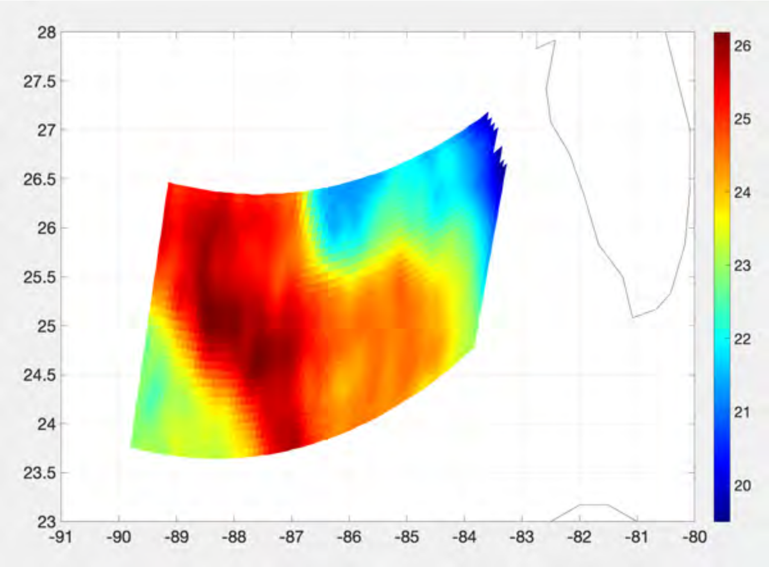
The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

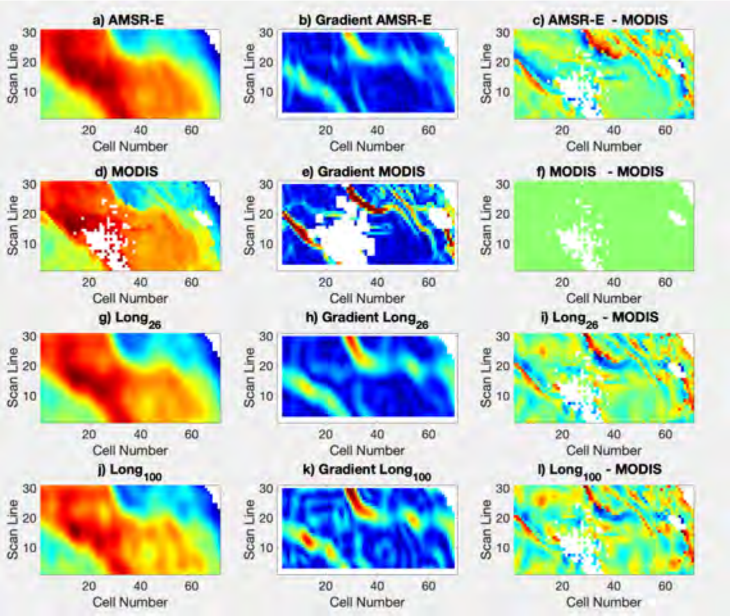
The Approaches

- Lagrange Multipliers - a way of constraining the inversion (not shown)
- David Long solution - a more sophisticated constraint
- Artificial Neural Network (ANN)
- Convolutional Neural Network (CNN) – will not discuss; results $<$ ANN
- Training
  - With AMSR-E – MODIS matchups
  - With LLC-4320 simulated fields.

AMSR-E Test Field



Results – David Long Solution



Artificial Neural Network (ANN)

- 3 layers: 54 node input layer, 10 neuron hidden layer & 1 node output layer.

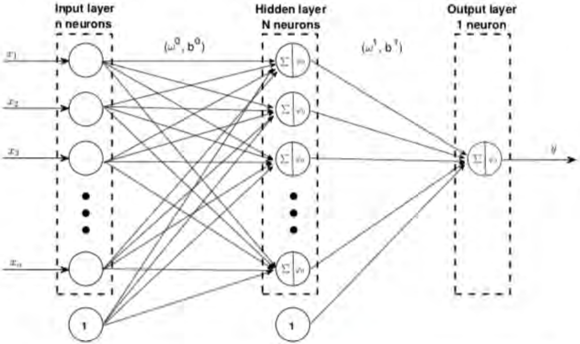
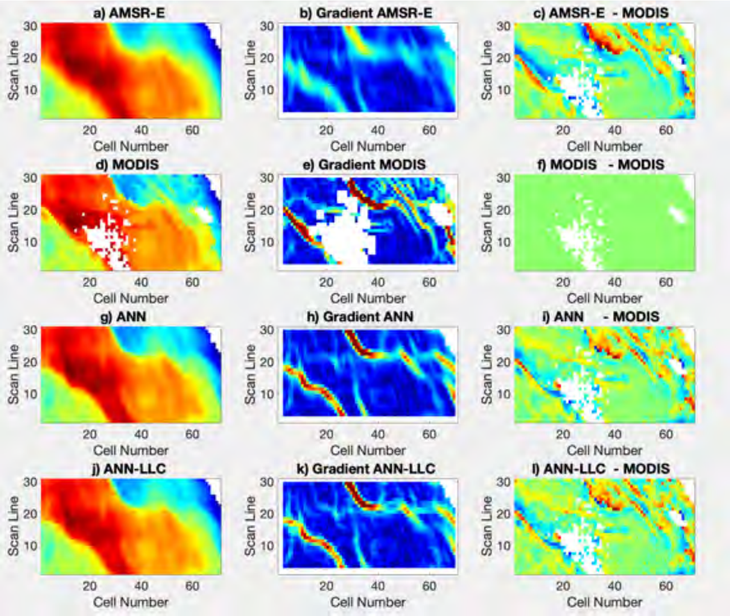


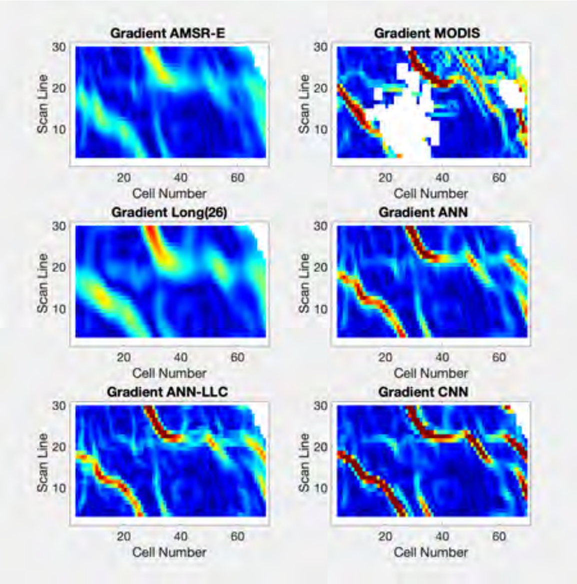
Figure 1. A three-layer Multi-layer perceptron (MLP) feedforward neural network.

LLC-4320

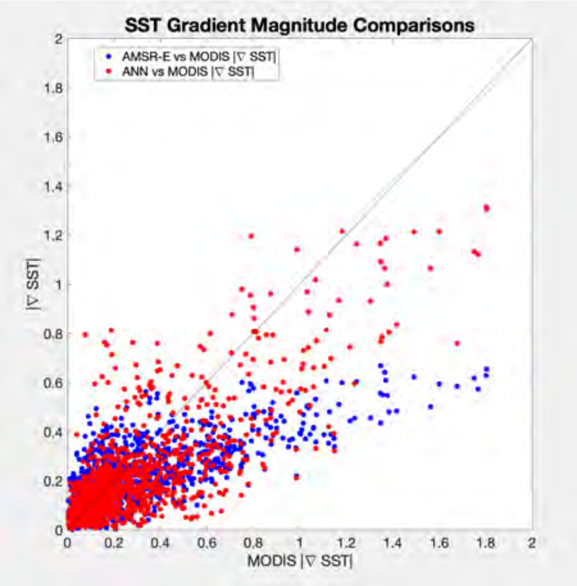
Results – ANN Solution



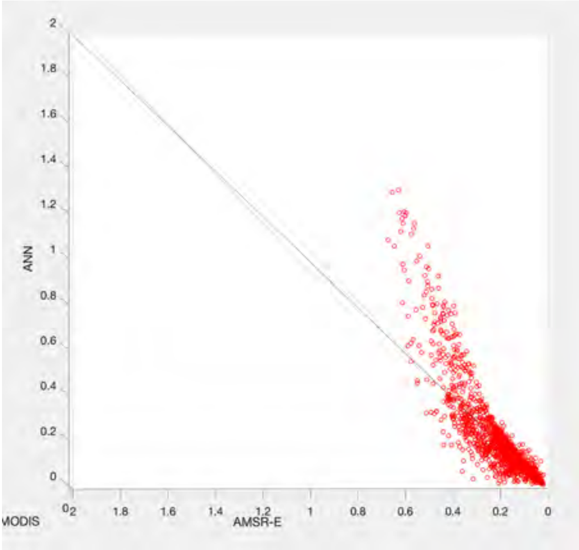
Results – Gradient Fields



What are the neural nets doing?



Results – ANN ∇SST vs AMSR-E ∇SST



Outline

Conclusions

- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

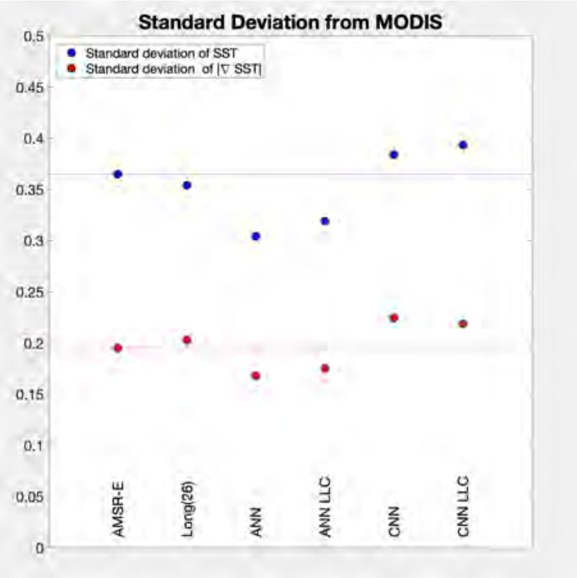
- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields

Conclusions

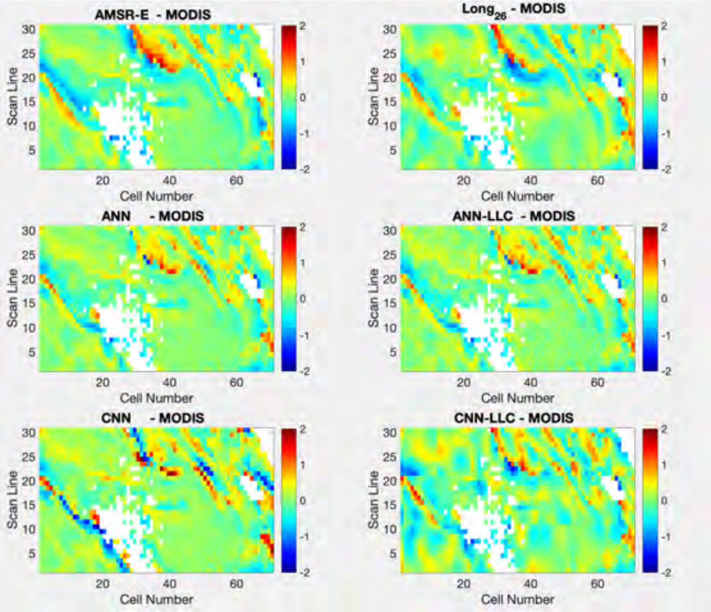
- We have characterized the AMSR-E SST footprint
- The footprint is stable
- Use of the correct footprint is necessary for comparison with other SST fields.
- Neural Networks show promise in deconvolving the fields – but not there yet.
  - Seems to be doing the right thing with gradients above the noise level.
  - May benefit from a time series.
  - Training with numerical model output seems to work quite well.
- AMSR-E/MODIS/Model output offers an ideal suite of 'data' with which to explore deconvolution of passive microwave geophysical fields with neural networs.
- Poster 9C: AMSR-E, MODIS, In situ Three-way Analysis of SST Error Variance
- Poster 13A: Pixel-to-Pixel Variability of AVHRR and MODIS L2 SST Fields


That's all Folks!
66

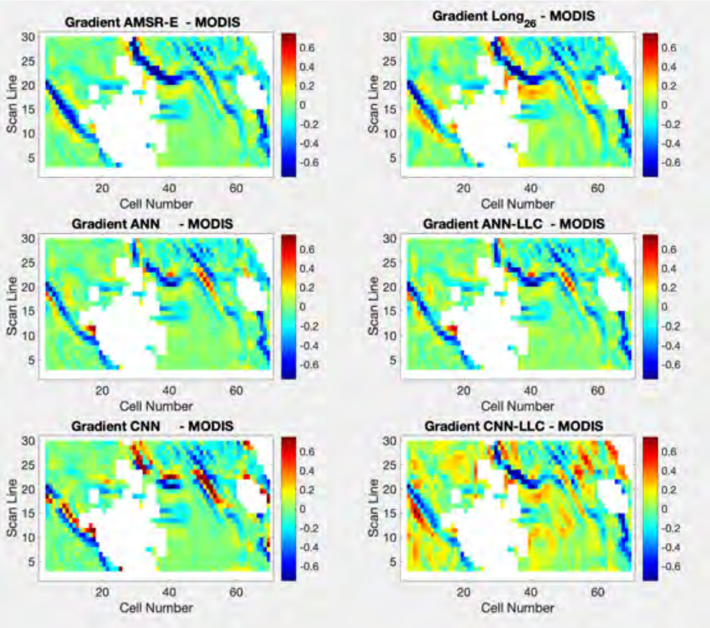
A Figure of Merit



Results – SST Differences



Results – SST Gradient Differences



AMSR-E Observed in 12 Spectral Bands

Table: AMSR-E Spectral Characteristics

Band (GHz)	Polarization	Beam Width (°)	Spatial Resolution (3-dB footprint size) [km x km]	Most sensitive to
6.93	V,H	2.2	75×43	SST
10.65	V,H	1.5	51×29	SST, wind speed
18.7	V,H	0.8	27×16	Columnar water vapor
23.8	V,H	0.9	32×18	Columnar water vapor
36.5	V,H	0.4	14×8	Columnar liquid water, rain
89.0	V,H	0.2	6×4	Rain (Flag)

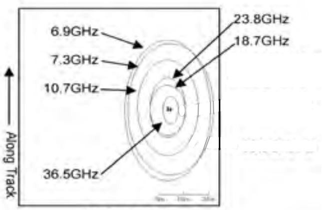
- 6.9 - 36.5 GHz channels mapped to common grid.
- SST, wind speed, water vapor, liquid water & rain rate retrieved simultaneously
- SST is determined from a combination of brightness temperatures obtained from pixels of differing spatial extent.
- The shape and size of the SST footprint is not obvious.

AMSR-E Observed in 12 Spectral Bands

Table: AMSR-E Spectral Characteristics

Band (GHz)	Polarization	Beam Width (°)	Spatial Resolution (3-dB footprint size) [km x km]	Most sensitive to
6.93	V,H	2.2	75×43	SST
10.65	V,H	1.5	51×29	SST, wind speed
18.7	V,H	0.8	27×16	Columnar water vapor
23.8	V,H	0.9	32×18	Columnar water vapor
36.5	V,H	0.4	14×8	Columnar liquid water, rain
89.0	V,H	0.2	6×4	Rain (Flag)

- 6.9 - 36.5 GHz channels mapped to common grid.
- SST, wind speed, water vapor, liquid water & rain rate retrieved simultaneously
- SST is determined from a combination of brightness temperatures obtained from pixels of differing spatial extent.
- The shape and size of the SST footprint is not obvious.

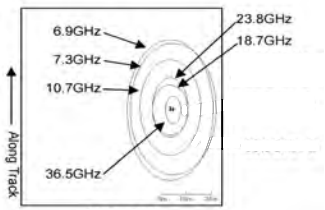


AMSR-E Observed in 12 Spectral Bands

Table: AMSR-E Spectral Characteristics

Band (GHz)	Polarization	Beam Width (°)	Spatial Resolution (3-dB footprint size) [km x km]	Most sensitive to
6.93	V,H	2.2	75 × 43	SST
10.65	V,H	1.5	51 × 29	SST, wind speed
18.7	V,H	0.8	27 × 16	Columnar water vapor
23.8	V,H	0.9	32 × 18	Columnar water vapor
36.5	V,H	0.4	14 × 8	Columnar liquid water, rain
89.0	V,H	0.2	6 × 4	Rain (Flag)

- 6.9 - 36.5 GHz channels mapped to common grid.
- SST, wind speed, water vapor, liquid water & rain rate retrieved simultaneously
- SST is determined from a combination of brightness temperatures obtained from pixels of differing spatial extent.
- The shape and size of the SST footprint is not obvious.

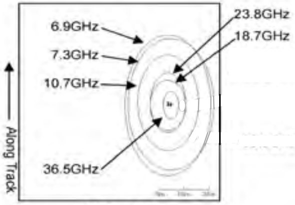


AMSR-E Observed in 12 Spectral Bands

Table: AMSR-E Spectral Characteristics

Band (GHz)	Polarization	Beam Width (°)	Spatial Resolution (3-dB footprint size) [km x km]	Most sensitive to
6.93	V,H	2.2	75 × 43	SST
10.65	V,H	1.5	51 × 29	SST, wind speed
18.7	V,H	0.8	27 × 16	Columnar water vapor
23.8	V,H	0.9	32 × 18	Columnar water vapor
36.5	V,H	0.4	14 × 8	Columnar liquid water, rain
89.0	V,H	0.2	6 × 4	Rain (Flag)

- 6.9 - 36.5 GHz channels mapped to common grid.
- SST, wind speed, water vapor, liquid water & rain rate retrieved simultaneously
- SST is determined from a combination of brightness temperatures obtained from pixels of differing spatial extent.
- The shape and size of the SST footprint is not obvious.

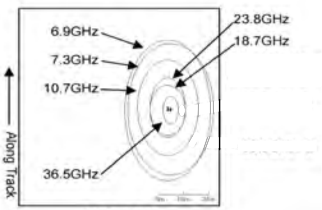


AMSR-E Observed in 12 Spectral Bands

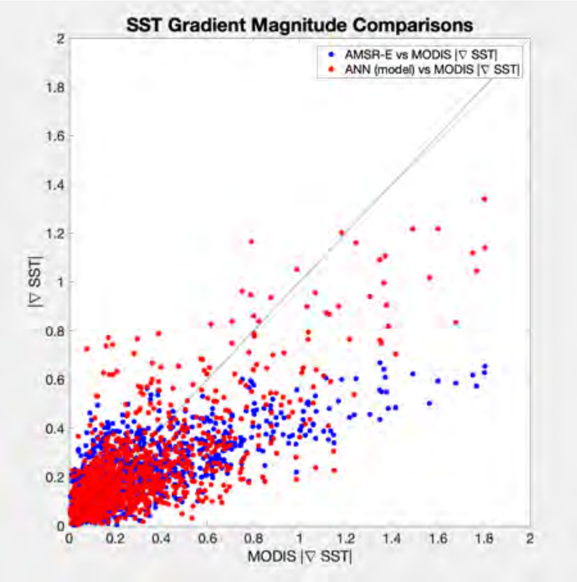
Table: AMSR-E Spectral Characteristics

Band (GHz)	Polarization	Beam Width (°)	Spatial Resolution (3-dB footprint size) [km x km]	Most sensitive to
6.93	V,H	2.2	75 × 43	SST
10.65	V,H	1.5	51 × 29	SST, wind speed
18.7	V,H	0.8	27 × 16	Columnar water vapor
23.8	V,H	0.9	32 × 18	Columnar water vapor
36.5	V,H	0.4	14 × 8	Columnar liquid water, rain
89.0	V,H	0.2	6 × 4	Rain (Flag)

- 6.9 - 36.5 GHz channels mapped to common grid.
- SST, wind speed, water vapor, liquid water & rain rate retrieved simultaneously
- SST is determined from a combination of brightness temperatures obtained from pixels of differing spatial extent.
- The shape and size of the SST footprint is not obvious.

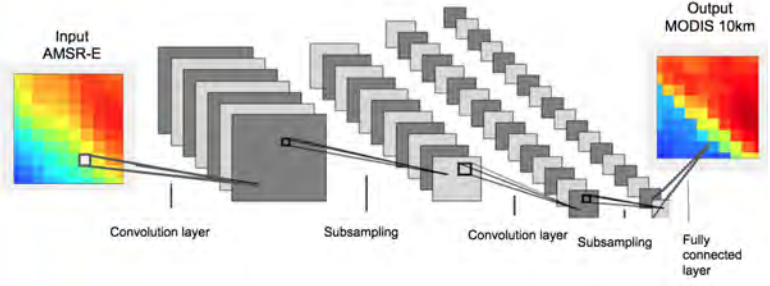


What are the neural nets doing?



Convolutional Neural Network (ANN)

- Input: a 10 × 10 AMSR-E pixel region and the output is the 10 × 10 target field minus the AMSR-E field.



Results – CNN Solution