Towards an Optimal Noise Versus Resolution Trade-off in Wind Scatterometry

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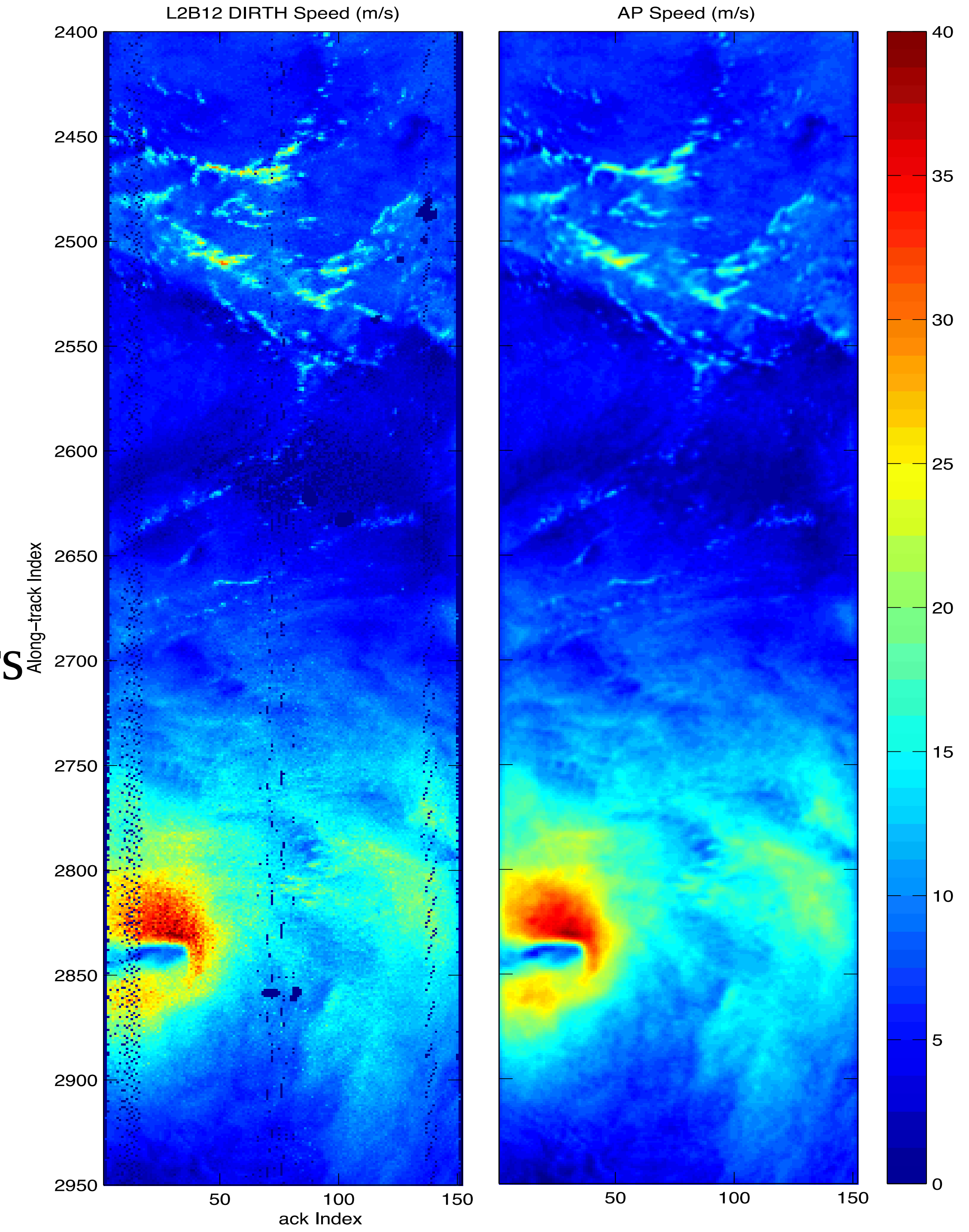
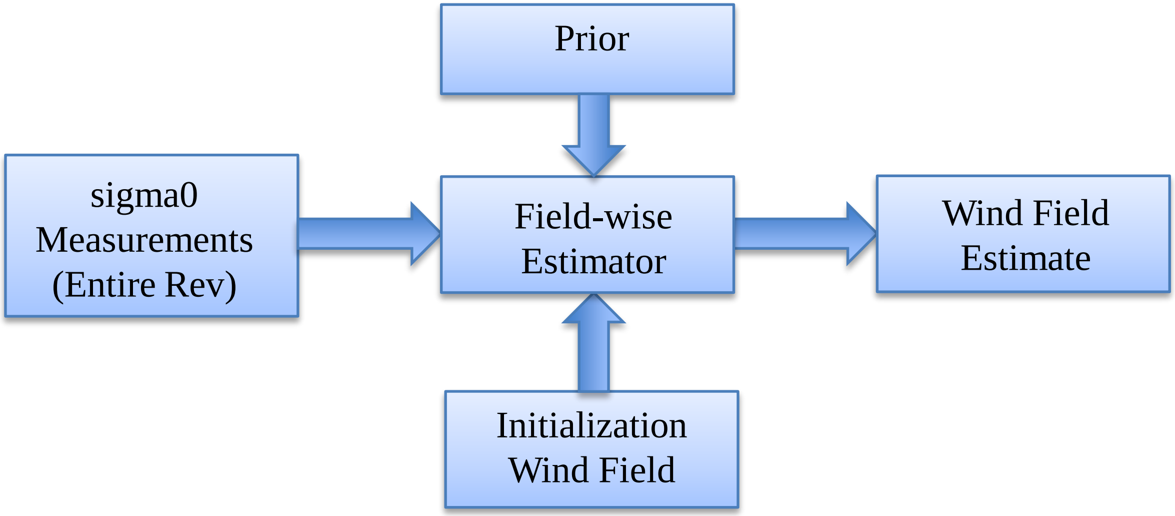
Overview

- Estimation approach
  - Field-wise estimation with statistical signal model
- Implementation
  - MAP estimation
  - Development of priors
- Analysis (QSCAT)
  - Speed histograms
  - Metrics vs. ECMWF
  - Spectra
  - Examples



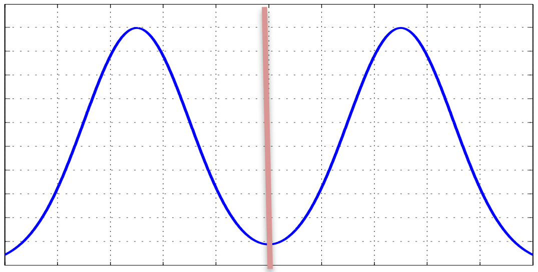
Estimation Approach

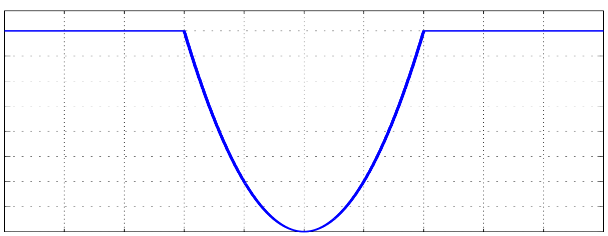
- Field-wise retrieval with statistical signal model (i.e., prior)
  - Simultaneously estimate every WVC for entire rev
  - Prior incorporates spatial covariance (k^{-2} spectrum)
  - No ambiguity removal post wind-retrieval
    - Effectively done by initialization



Estimation Approach

- Bayes Estimation
  - Multimodal => local quadratic loss
  - Impractical to implement unless local ball -> 0
  - Converges to the MAP estimate
- MAP Estimation
  - Practical to implement
  - Incorporates the spatial structure of prior
  - Trades off noise and resolution
  - May be biased





Maximize log of posterior distribution (gradient search)

$$\frac{\partial}{\partial \vec{U}(x)} \log f(\vec{U}(x)|\vec{\sigma}_m^0) = \frac{\partial}{\partial \vec{U}(x)}[\log f(\vec{\sigma}_m^0|\vec{U}(x)) + \log f(\vec{U}(x))]$$

ML portion   Prior

Implementation: MAP Estimation

- ML portion (left side)[1]

$$\frac{\partial}{\partial U_i(x)} \log f(\vec{\sigma}^0_m | \vec{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \mathrm{gmf}_n(\vec{U}(x))}{\partial U_i(x)}$$

- Prior indep Gaussian with spatial cov matrices[2]

$$f(\vec{U}(x)) = f(U_s(x)) f(U_d(x))$$

If signal covariance model is stationary, can be implemented as convolutions (fast computation with FFT)

$$\frac{\partial \log f(U_s(x))}{\partial U_s(x)} = \frac{-1}{2} \mathbf{R}_s^{-1} (U_s(x) - \mu_s(x))$$

$$\frac{\partial \log f(U_d(x))}{\partial U_d(x)} = \sin(U_d(x)) \circ \mathbf{R}_d^{-1} \cos(U_d(x)) - \cos(U_d(x)) \circ \mathbf{R}_d^{-1} \sin(U_d(x))$$

[1] B. A. Williams and D. G. Long, "A reconstruction approach to scatterometer wind vector field retrieval," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 49, no. 6, pp. 1850 – 1864, June 2011.
[2] B. A. Williams, "A field-wise retrieval approach to the noise versus resolution trade-off in wind scatterometry," *IEEE Transactions on Geoscience and Remote Sensing*, to be submitted.

Implementation: Prior Covariance

- Exponential covariance function

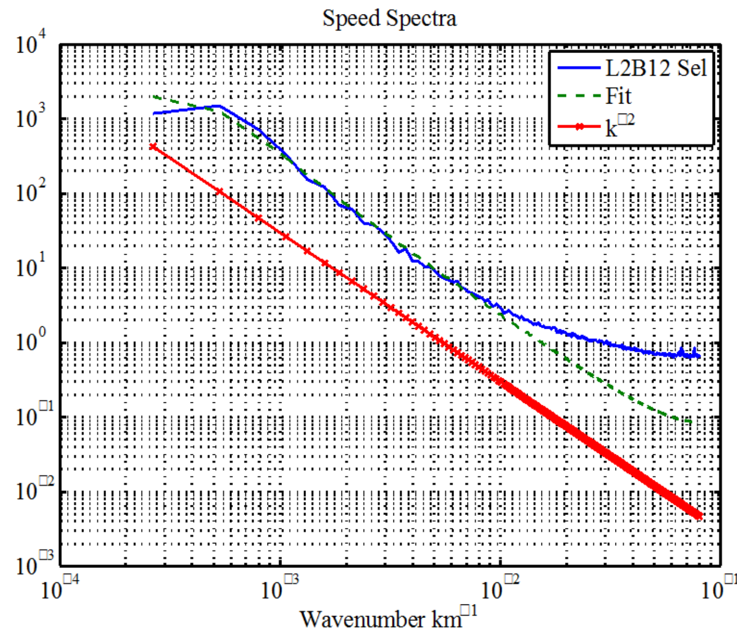
$$c(x) = e^{-2\pi k_0 |x|} \qquad \mathcal{F}\{c(x)\} = \frac{2k_0}{k^2 + k_0^2}$$

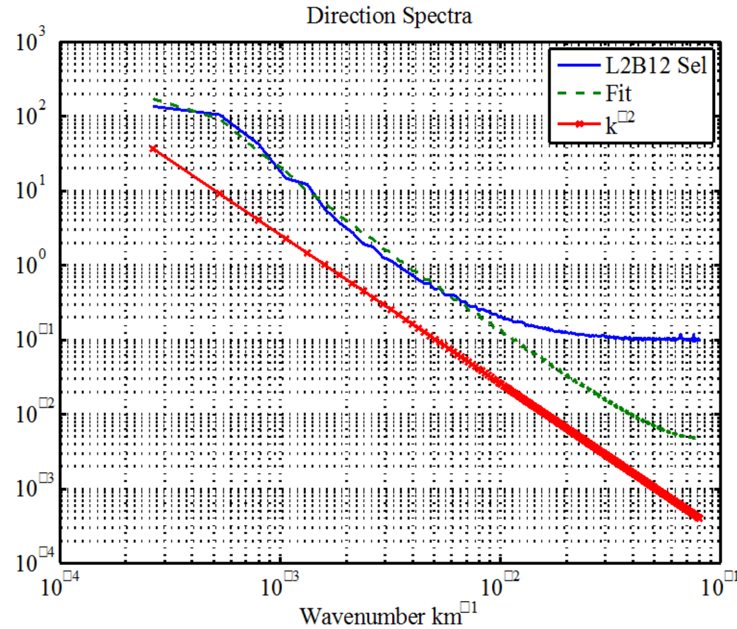
- Estimate parameters from L2B12 selected ambiguity using signal and noise model (direction cov of $\psi = e^{id}$)

$$\mathrm{cov}(x) = ae^{-b|x|} + c\delta(x)$$

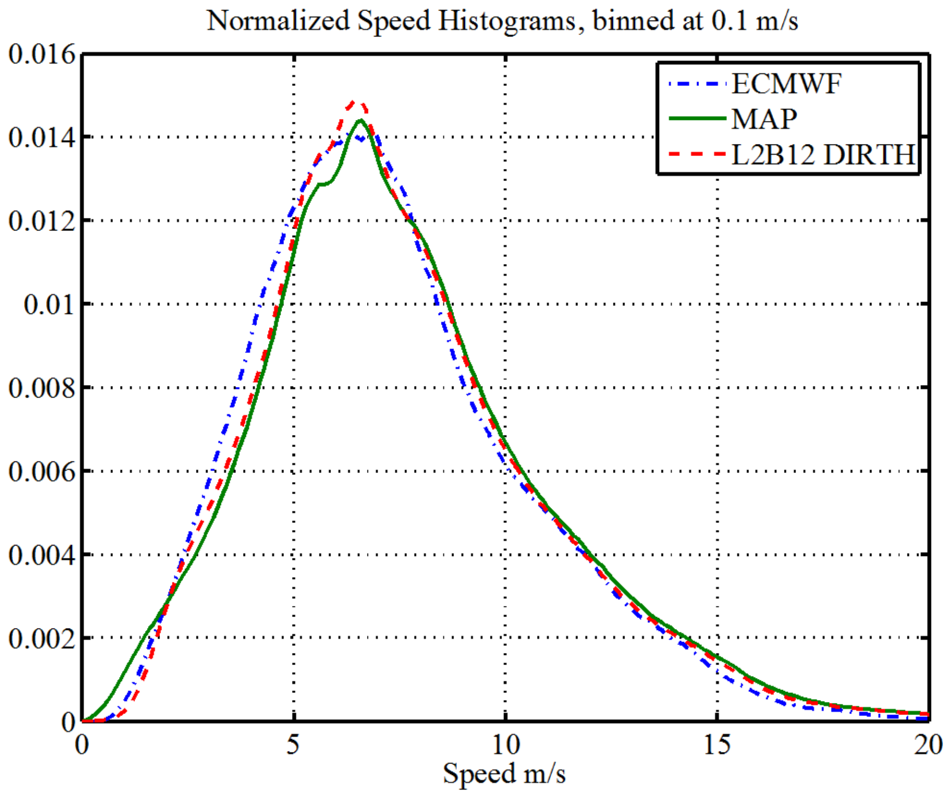
TABLE I
ESTIMATED MODEL PARAMETERS

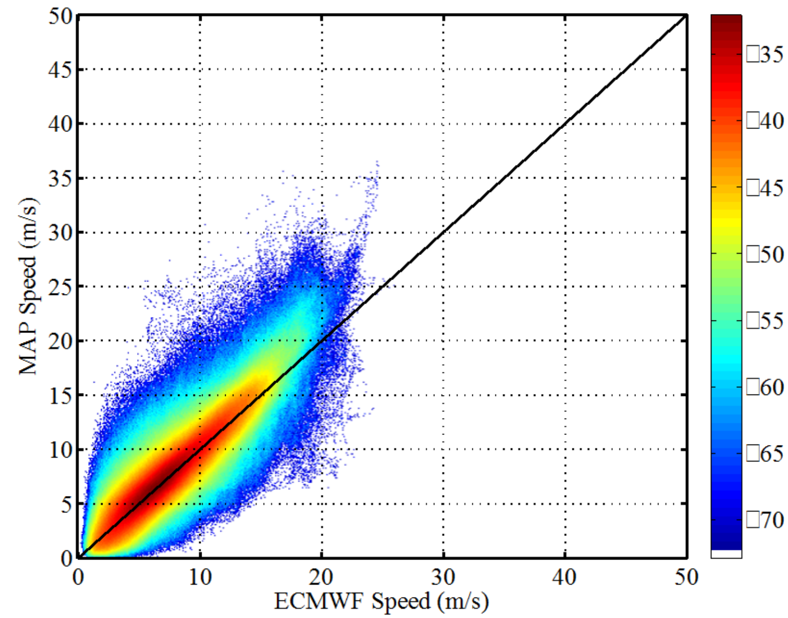
Parameter	Value	
	Speed	Direction
a	12.58	0.924
b	0.01238	0.01029
c	0.678	0.074

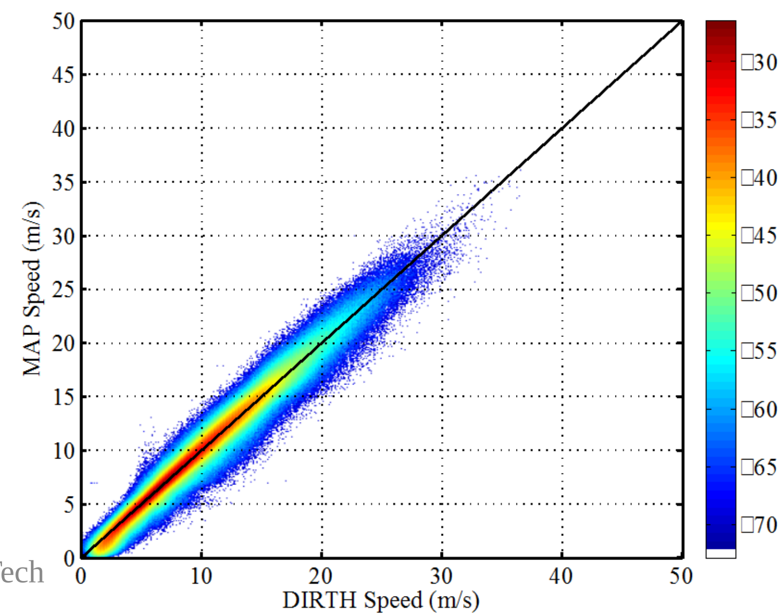




Analysis: Speed Histograms

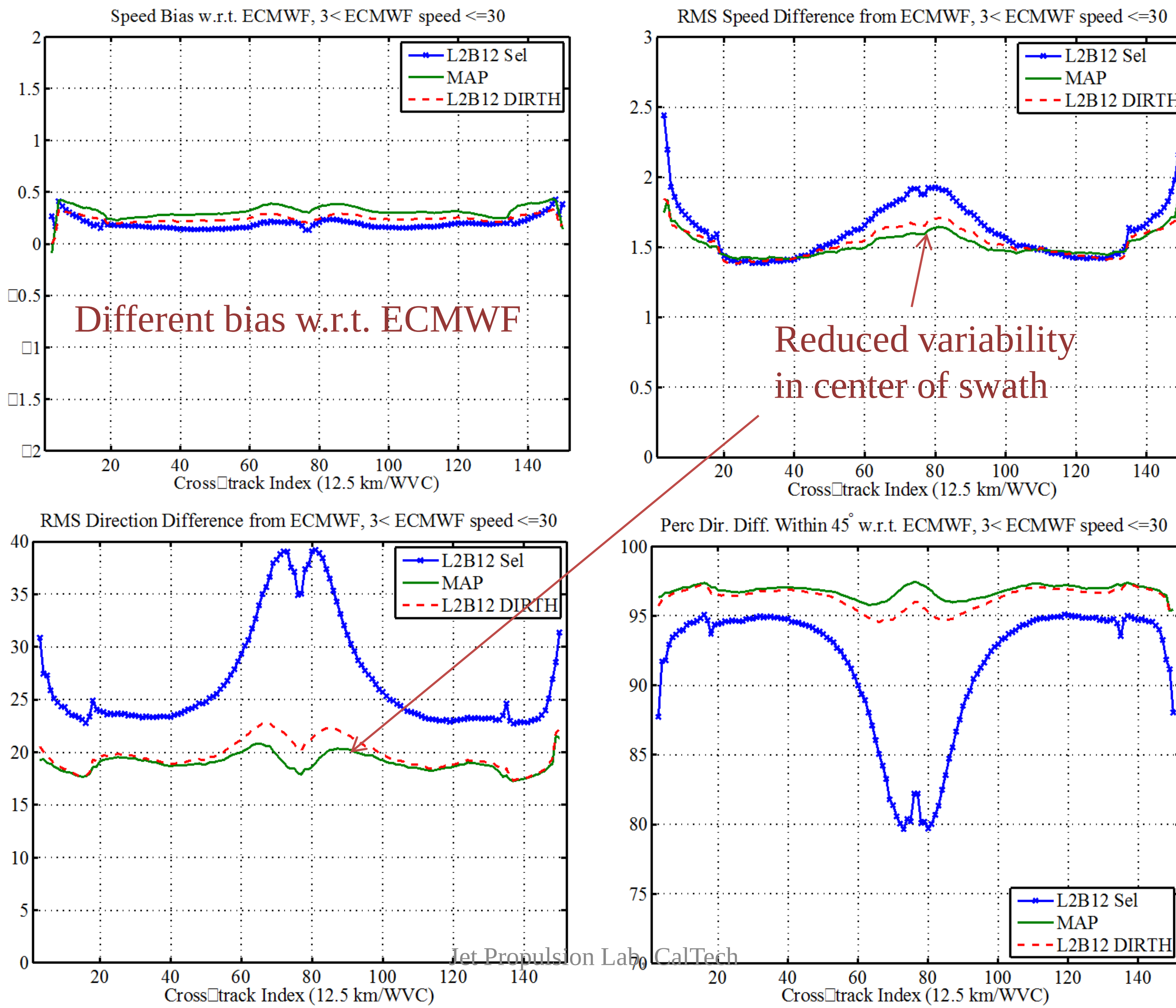




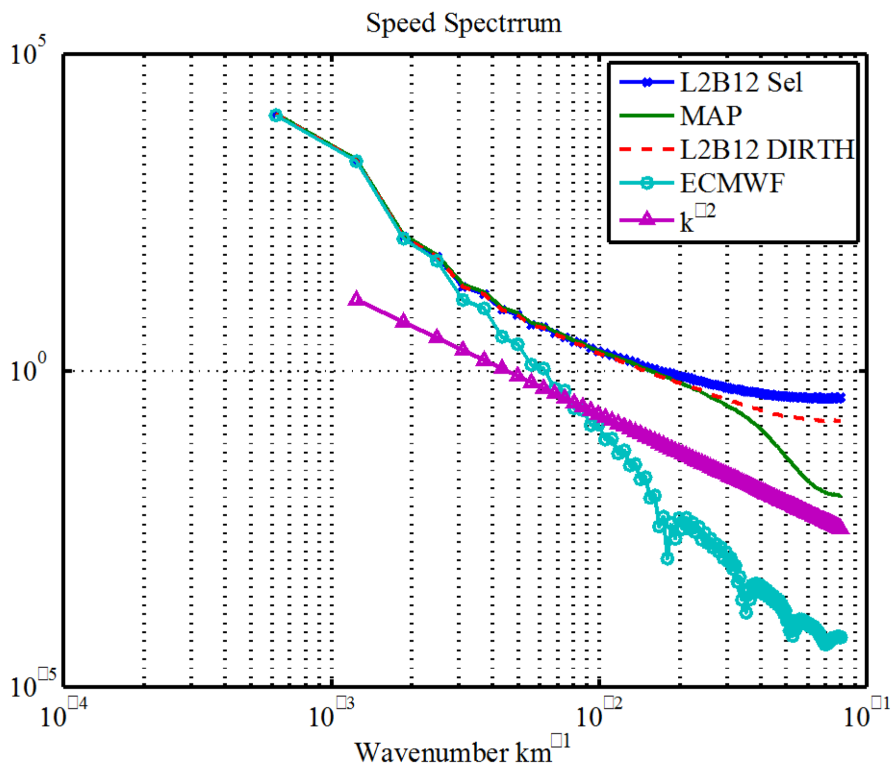


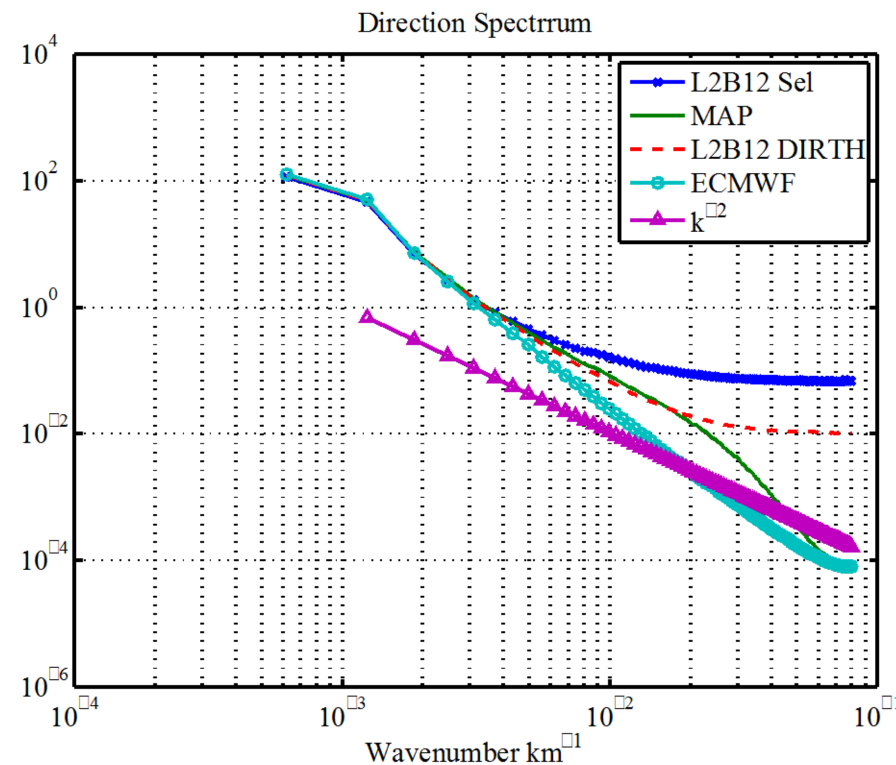
- 99 QSCAT Revs: 49663-49762
- MAP speed consistent with L2B12 DIRTH, but low speeds are biased slightly lower

Analysis: Metrics w.r.t. ECMWF



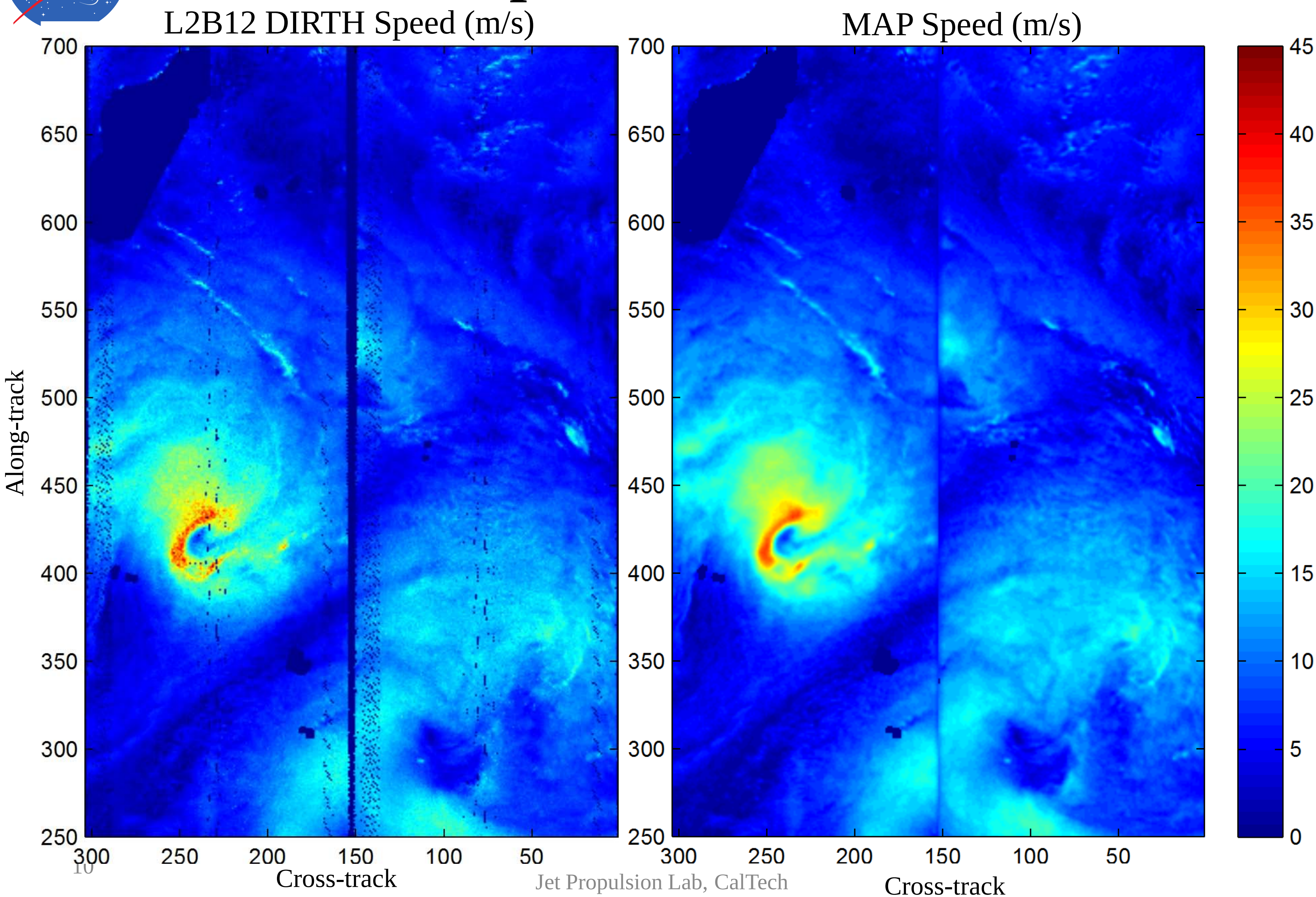
Analysis: Speed and Direction Spectra





- Average speed resolution ~ 25-33 km
- Average direction resolution ~ 50km

Examples:Tiled Revs



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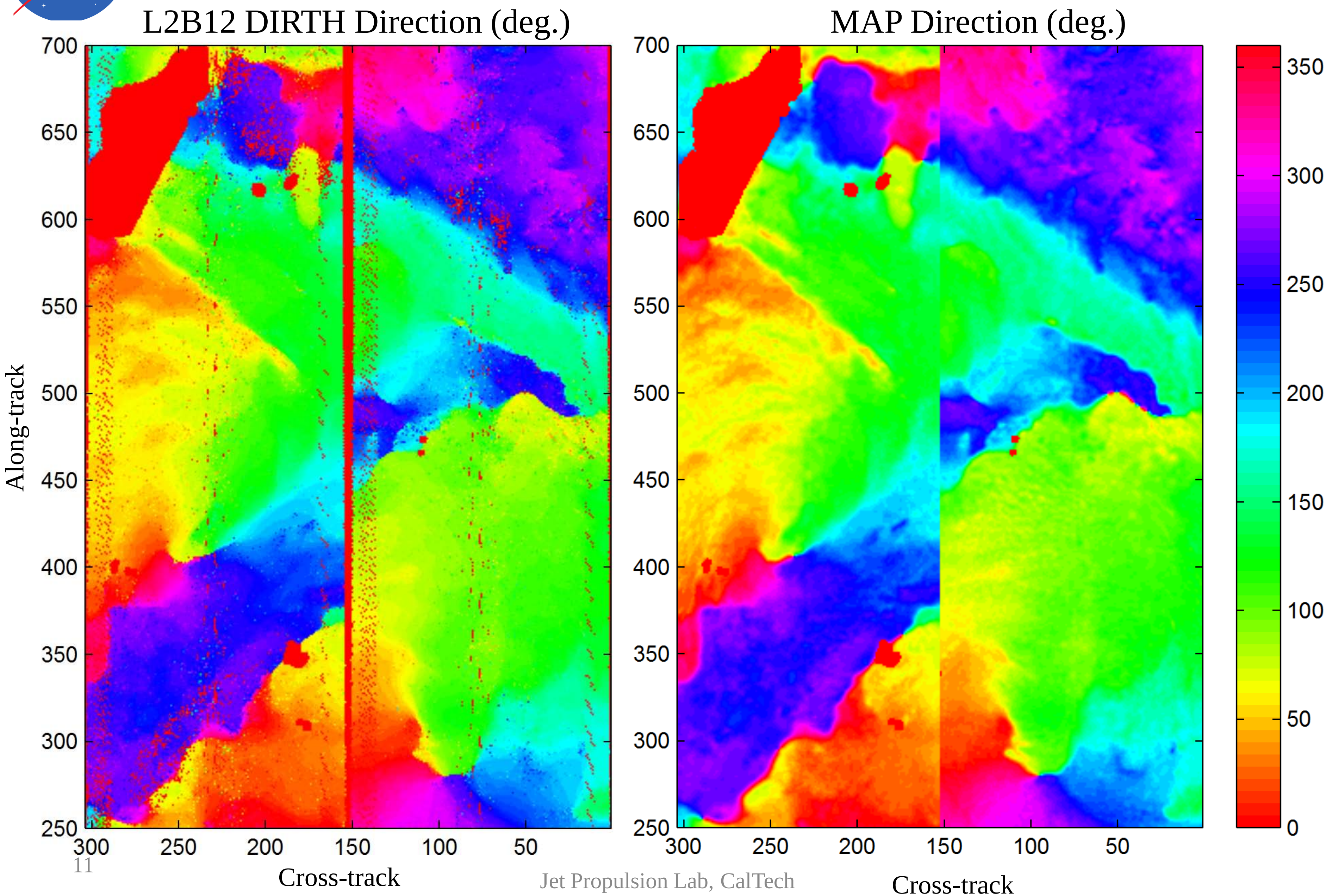
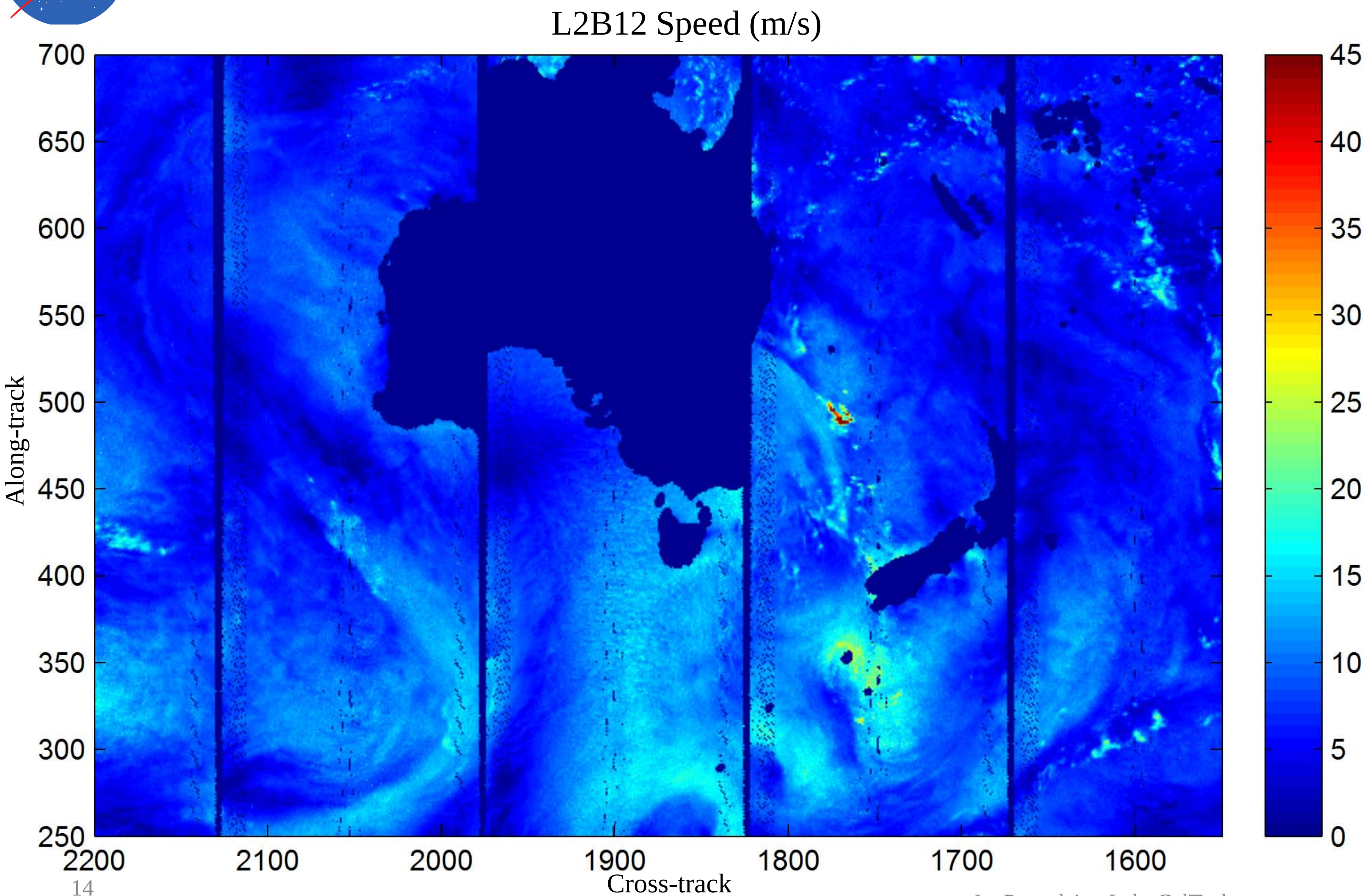


Conclusion

- MAP estimation with priors that incorporate spatial structure
  - Outperforms DIRTH in all metrics except speed bias w.r.t. ECMWF
  - Automatically filters (attenuates) signal components that are expected to be noisy
  - Only parameters to tune (given a prior) are Kp_m, WVC posting, and numeric gradient search parameters (i.e., step size, max iterations, and initialization)
- This methodology may be applied to improve several special applications
  - Special priors for hurricanes, fronts, or other storm features
  - Wind and rain estimation with rain priors
  - Coastal and ice-edge applications (can handle sigma0 from mixed surfaces)

Backup Slides

Examples:Tiled Revs



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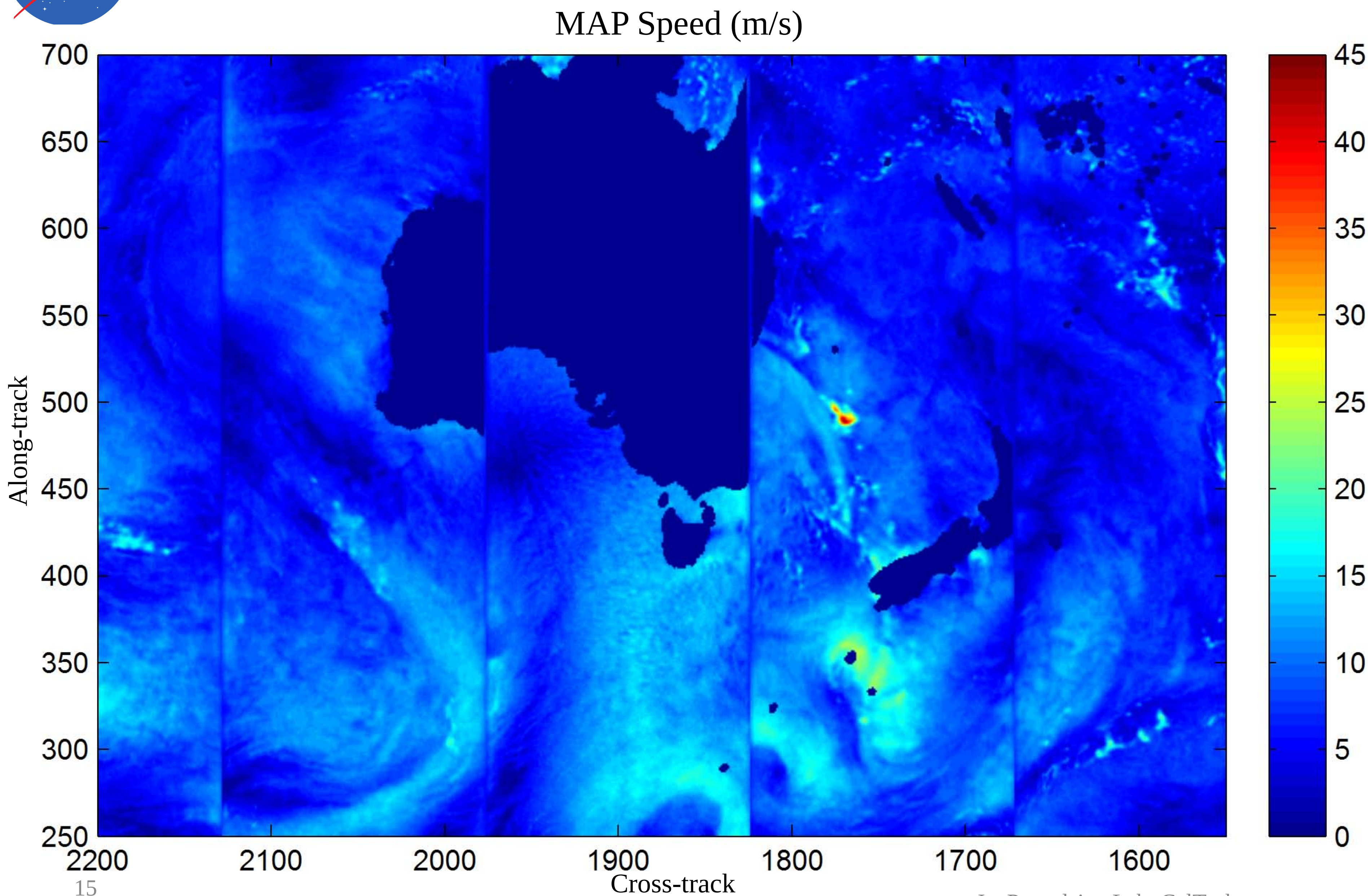

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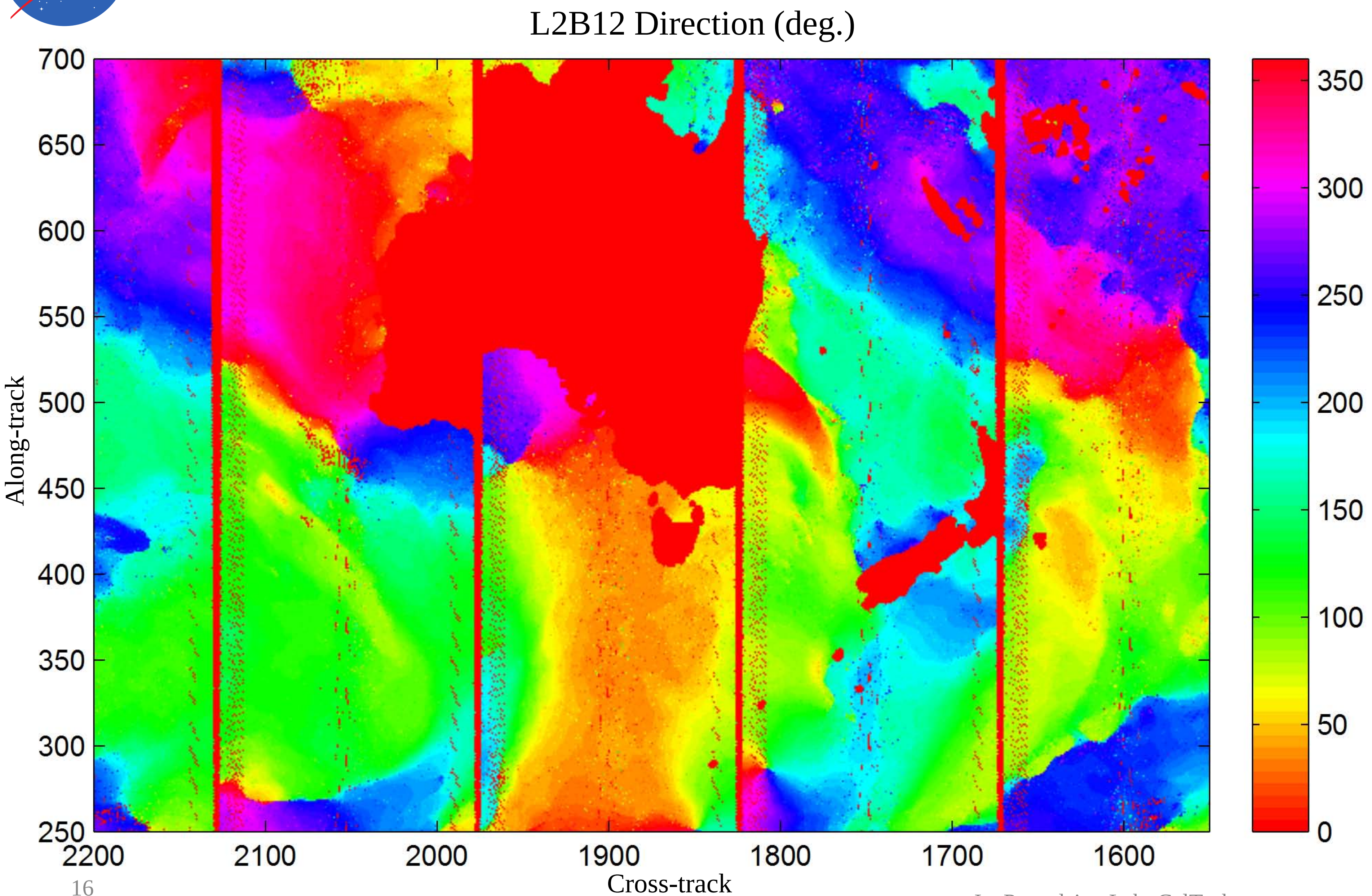

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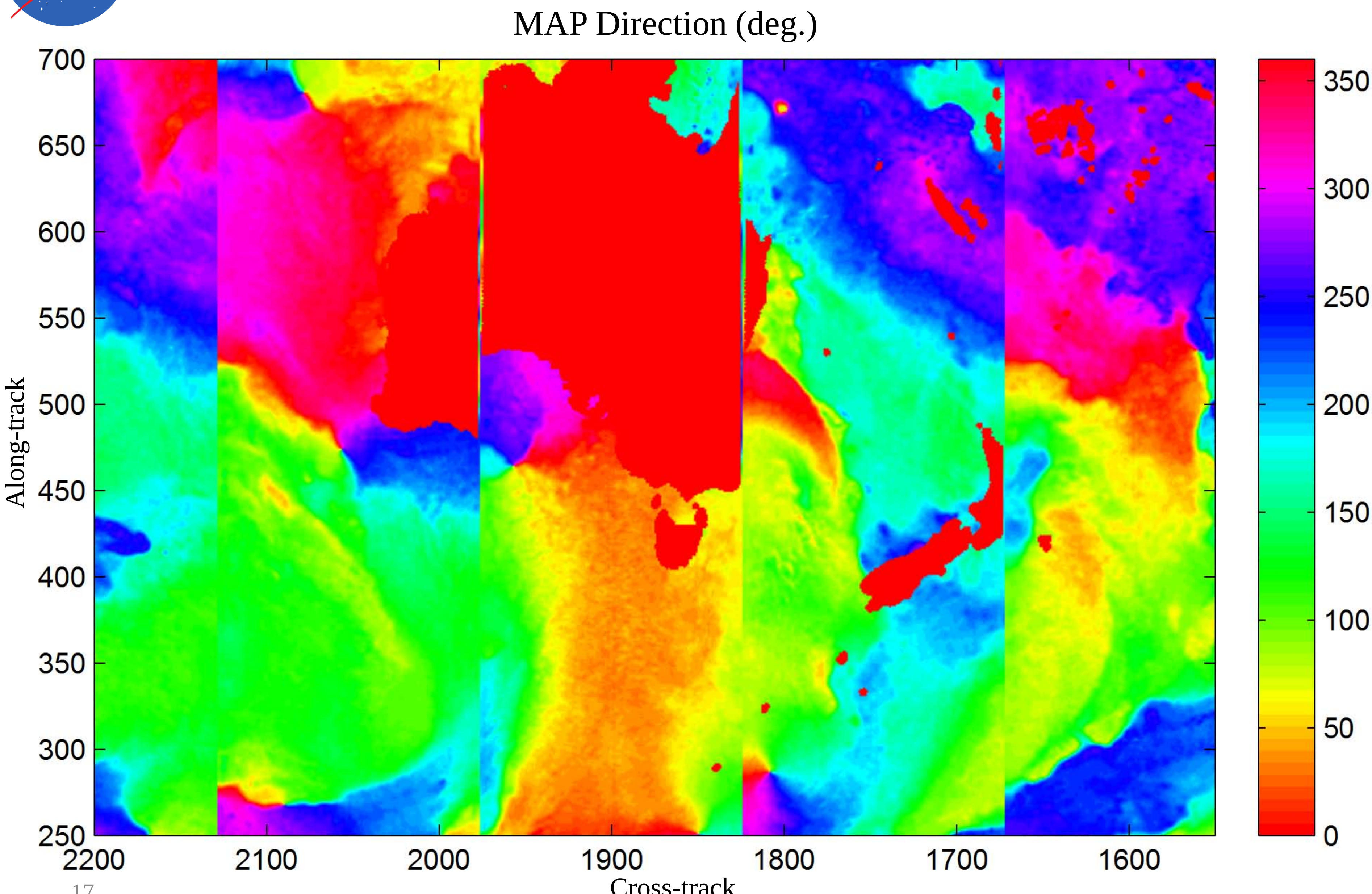

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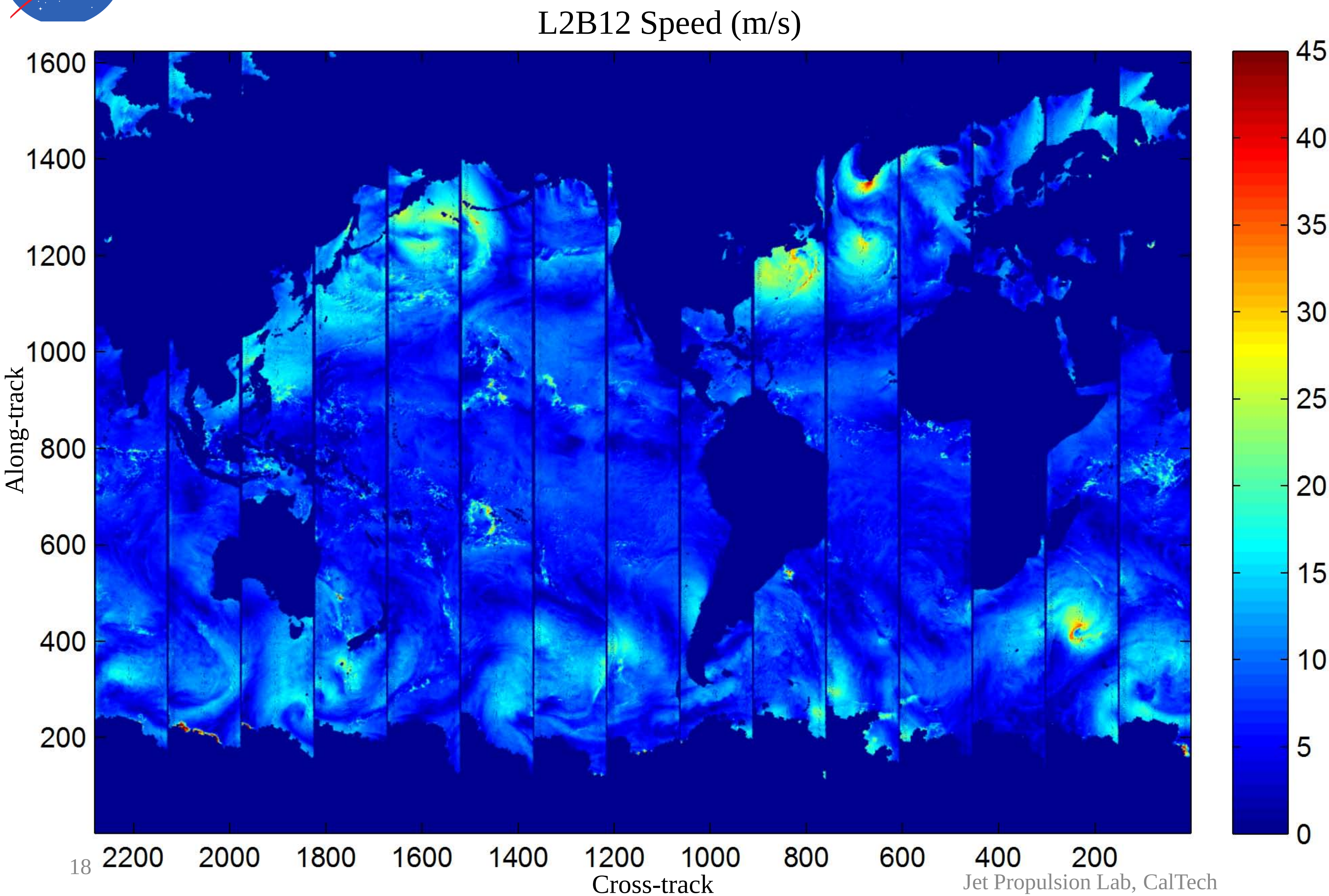

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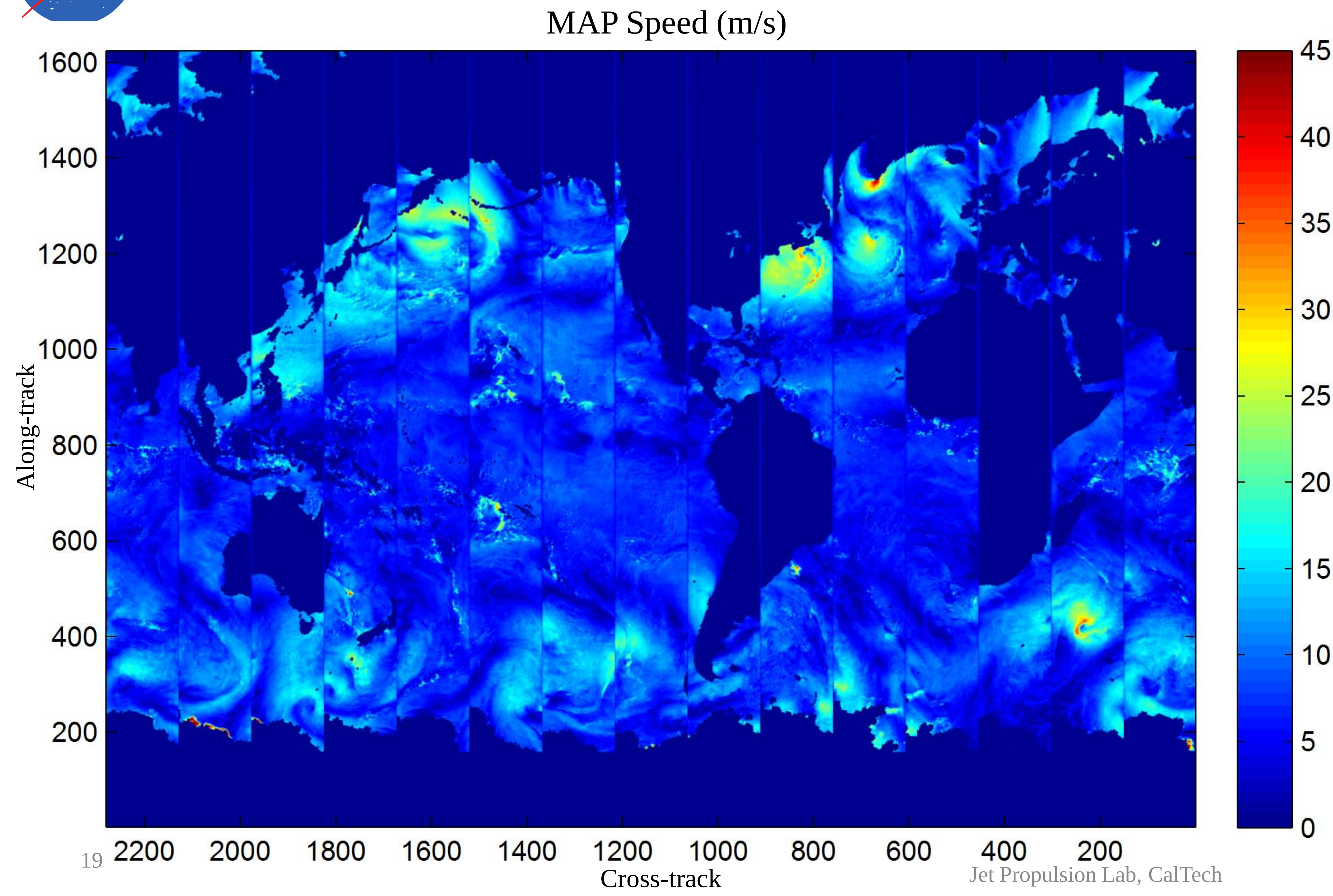
Examples:Tiled Revs



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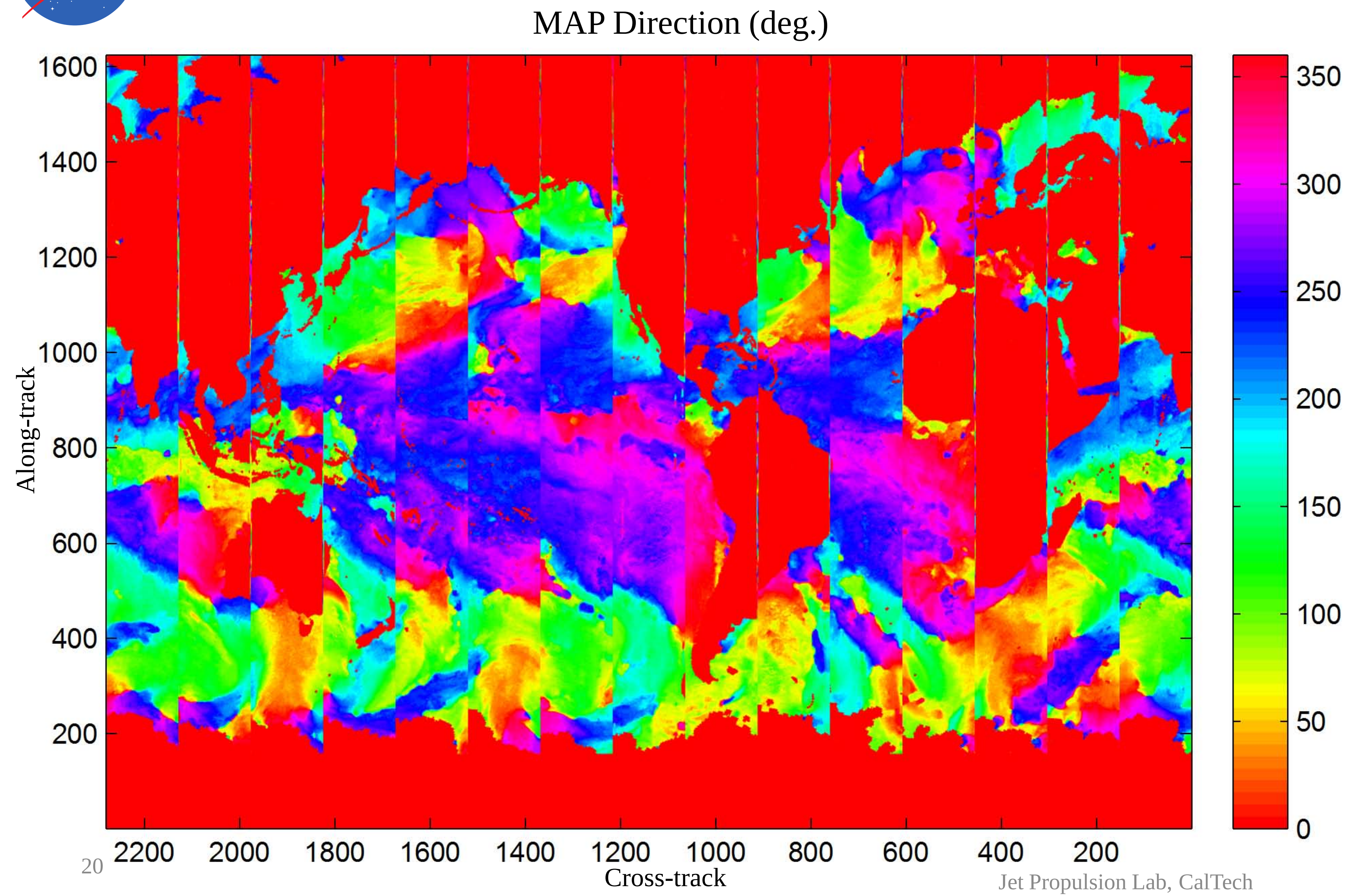

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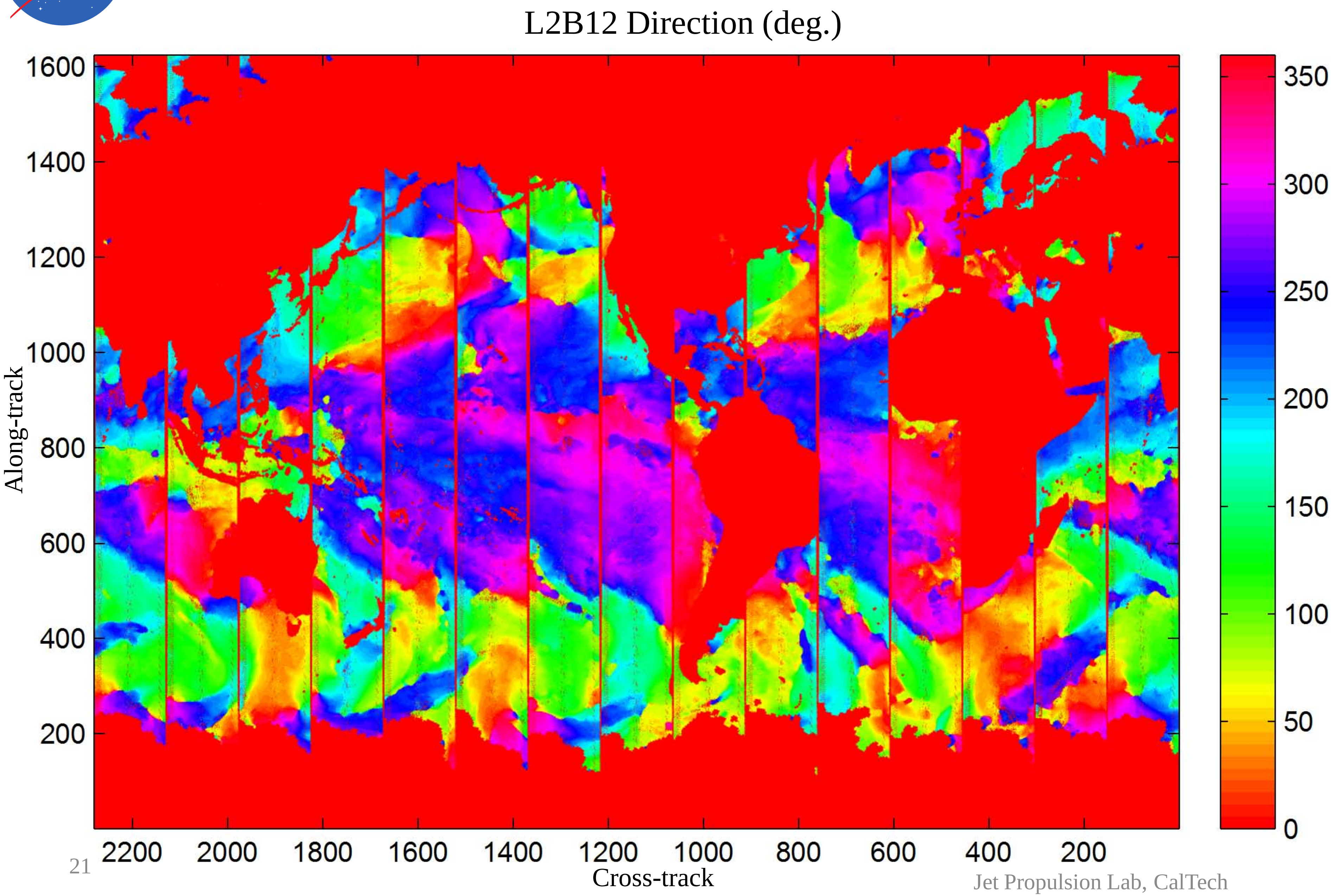
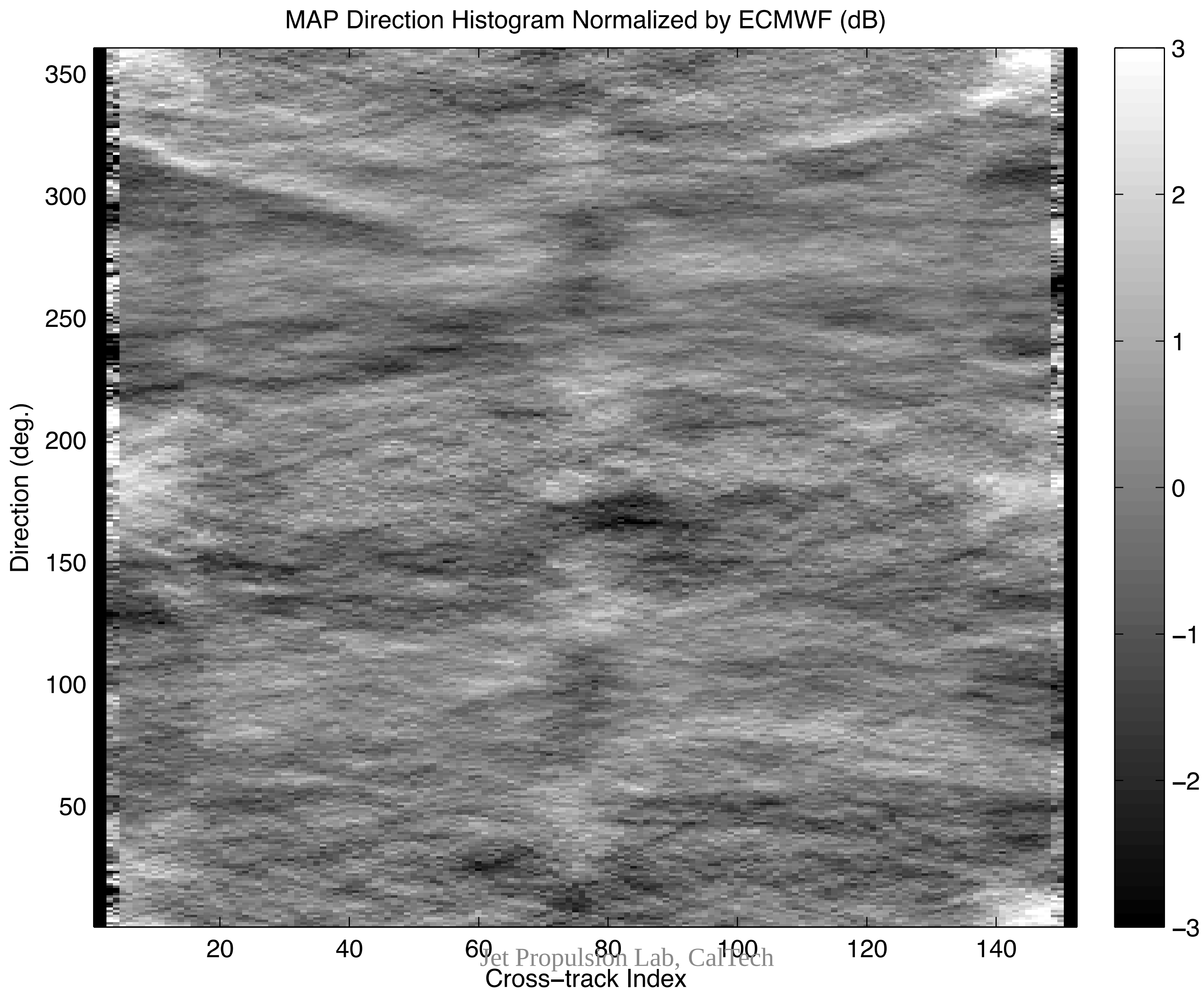
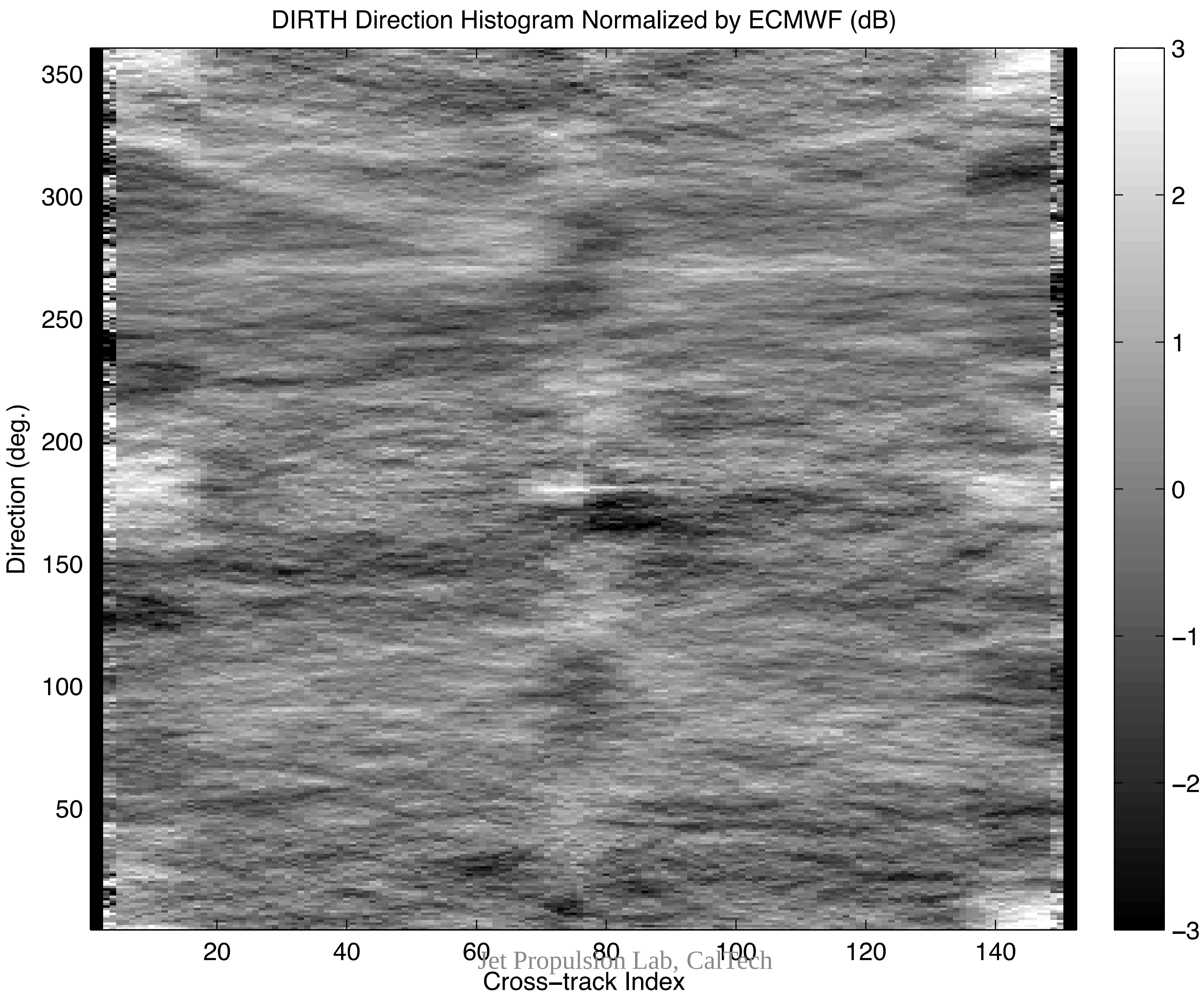


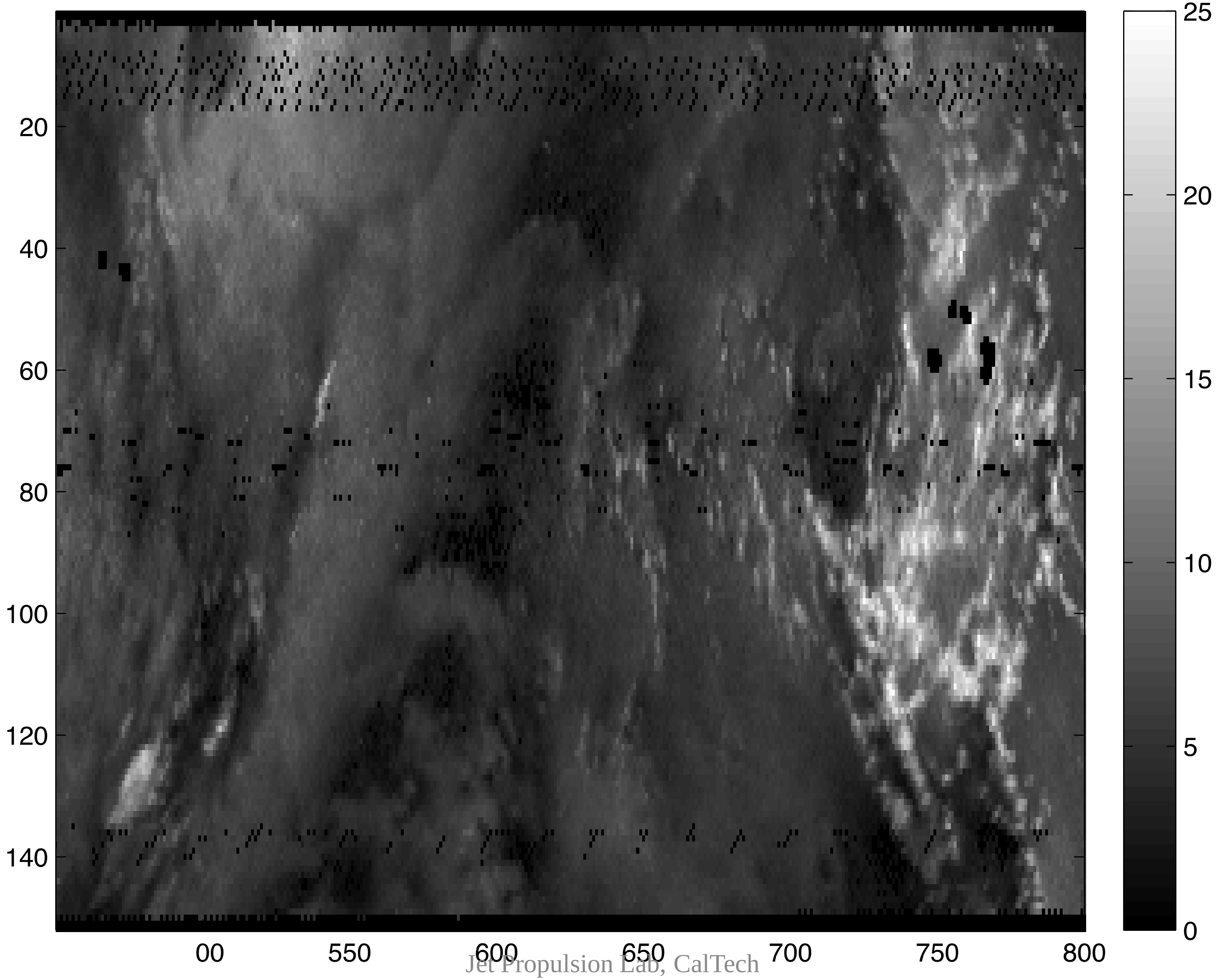
MAP Direction Histogram



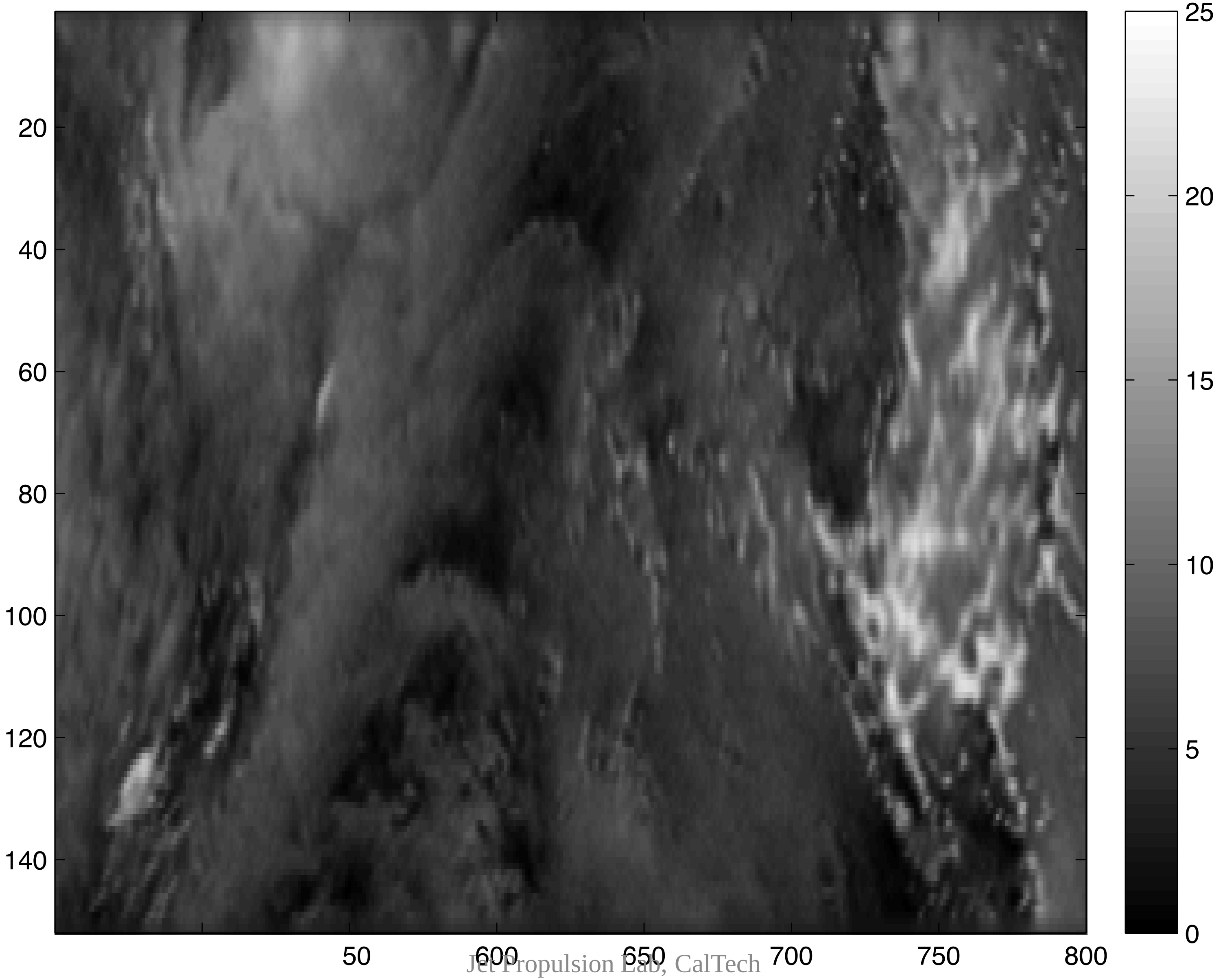
L2B12 DIRTH Direction Histogram



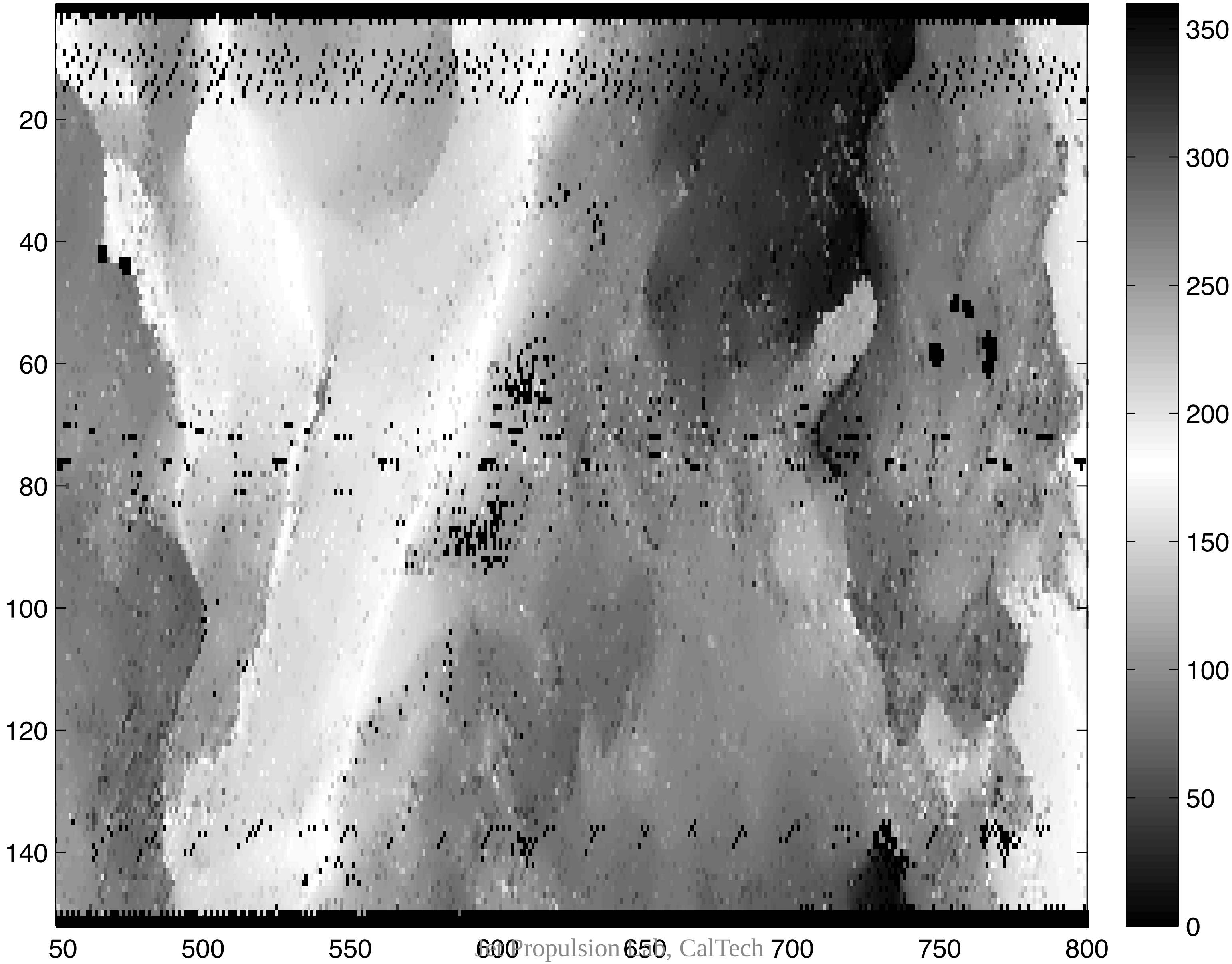
L2B12 DIRTH Speed



12.5km MAP Speed



L2B12 DIRTH Direction



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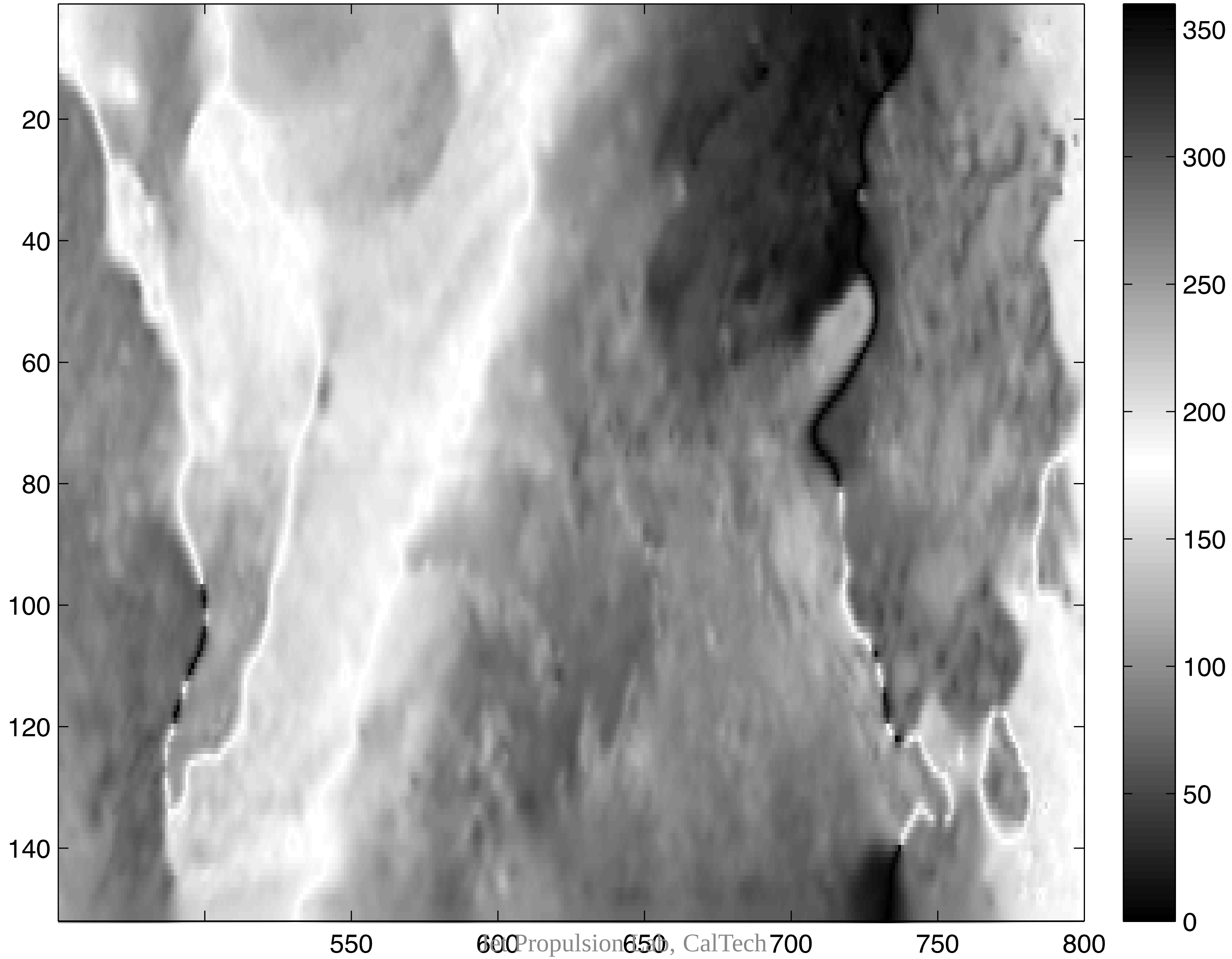
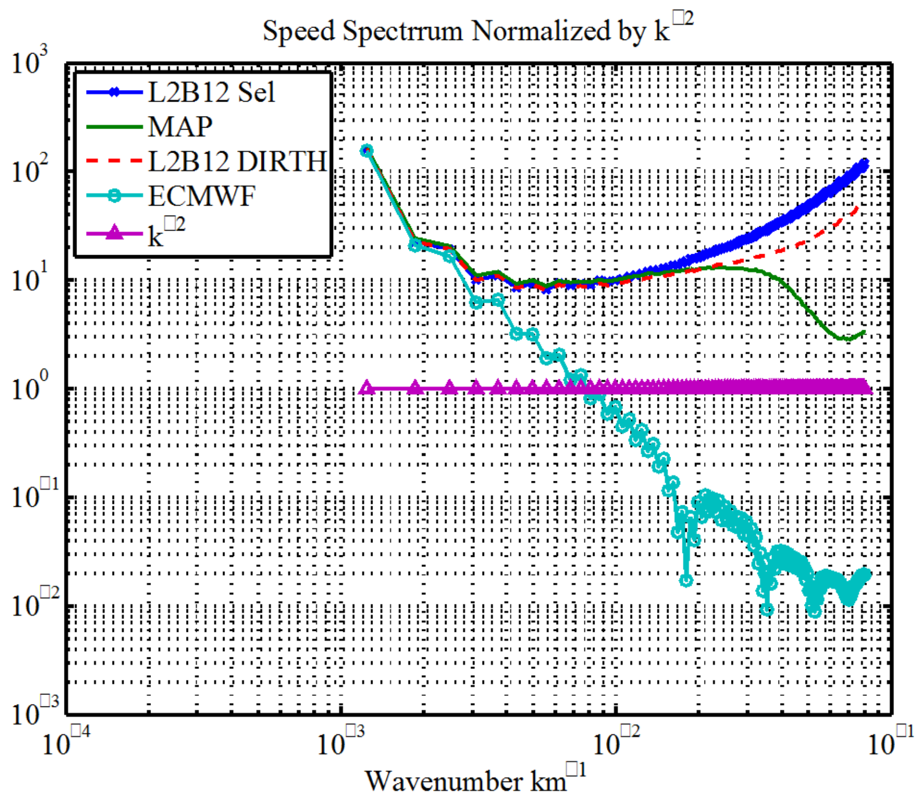
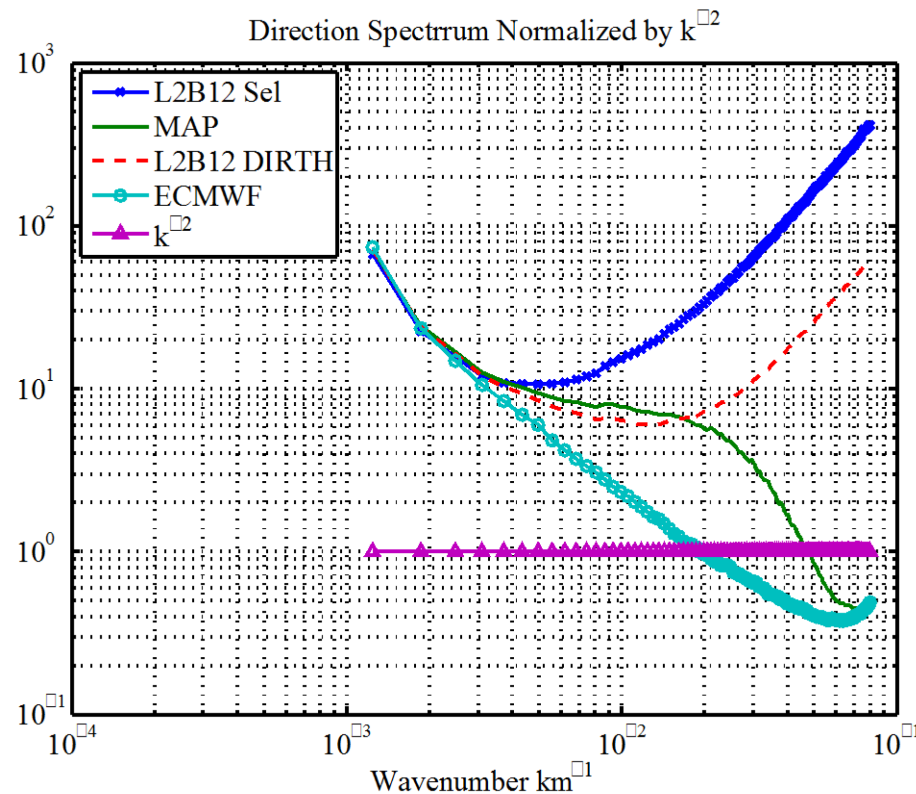


Analysis: Speed and Direction Spectra Normalized by k^{-2}





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MAP Estimation Implementation

- Maximize log of posterior (gradient search)

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$$\frac{\partial}{\partial U_i(x)} \log f(\vec{\sigma}_m^0|\vec{U}(x)) = \sum_n -K_n A_n(x) \frac{\partial \mathrm{gmf}_n(\vec{U}(x))}{\partial U_i(x)}$$

$$K_n = \left[\frac{(\sigma_n^0 - T_n(\vec{U}(x))) - (\alpha_n T_n(\vec{U}(x)) + \beta_n/2)}{R_{n,n}} + \frac{(\sigma_n^0 - T_n(\vec{U}(x)))^2(\alpha_n T_n(\vec{U}(x)) + \beta_n/2)}{R_{n,n}^2} \right]$$

$$T_n(\vec{U}(x)) = \sum_x A_n(x) \mathrm{gmf}_n(\vec{U}(x))$$