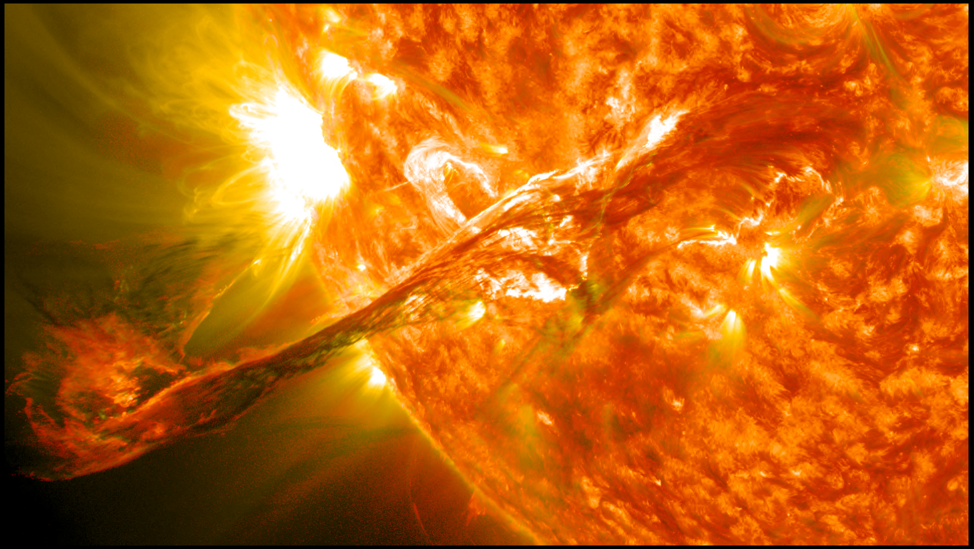
Machine Learning for Space Weather

Enrico Camporeale

Multiscale Dynamics



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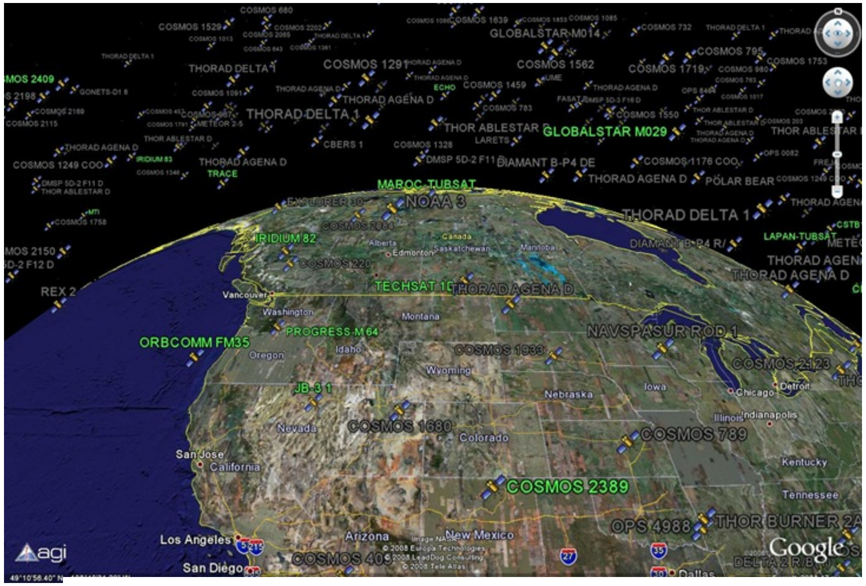
CWI
Centrum Wiskunde & Informatica

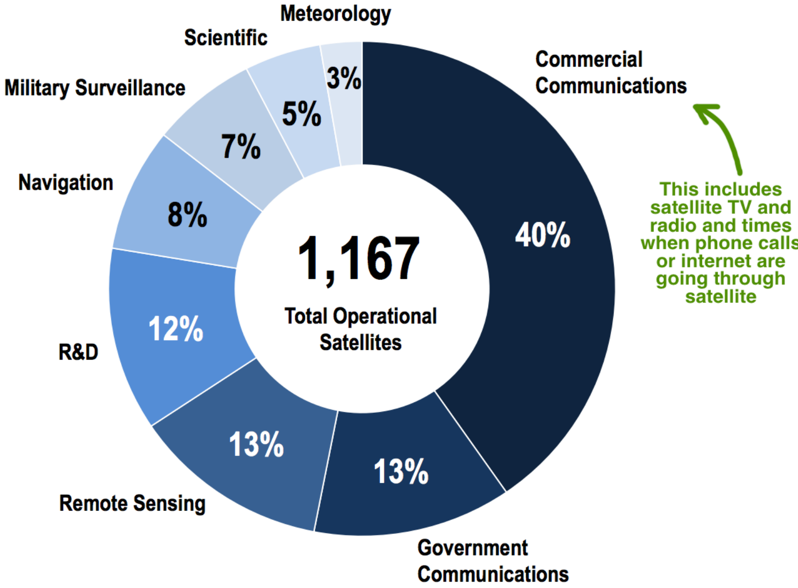
CWI Scientific Meeting
14th October 2016

Imagine a day...

...when satellites

stop working

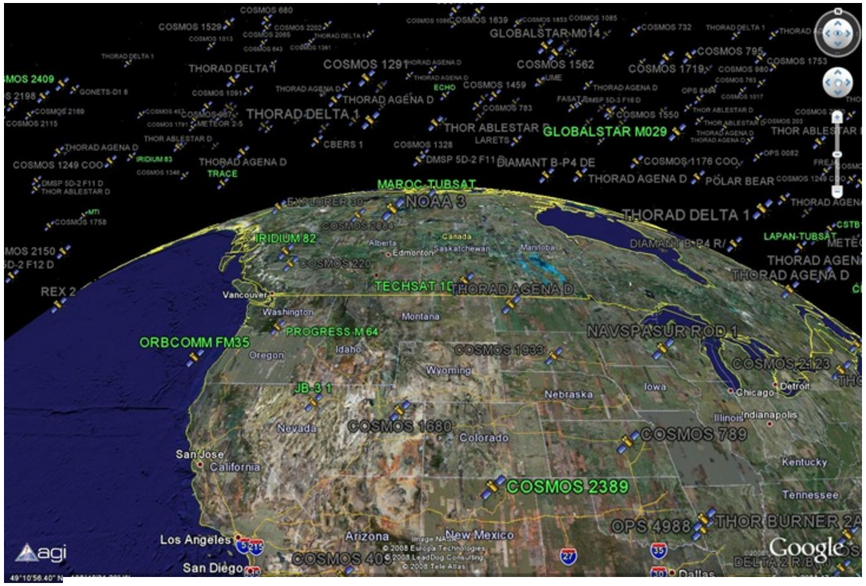


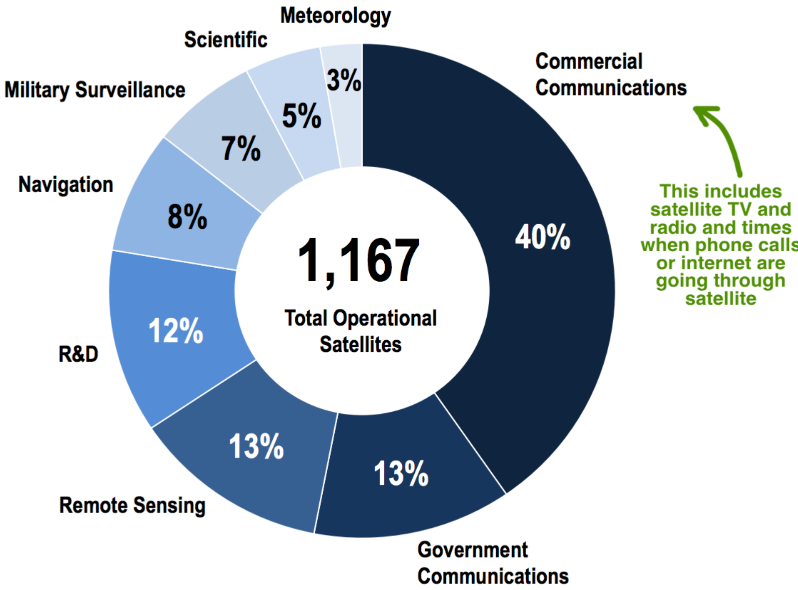


Imagine a day...

...when satellites stop working

- No telecommunications





Imagine a day...

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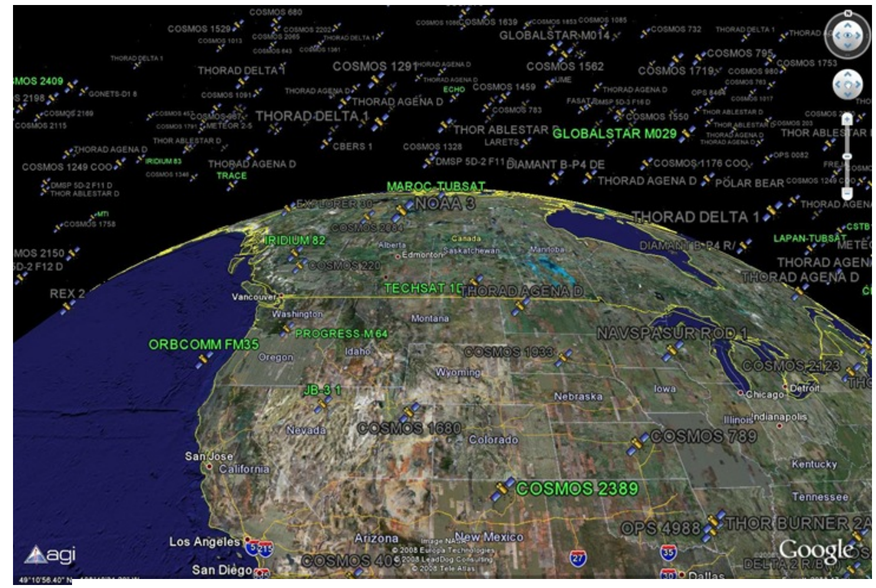
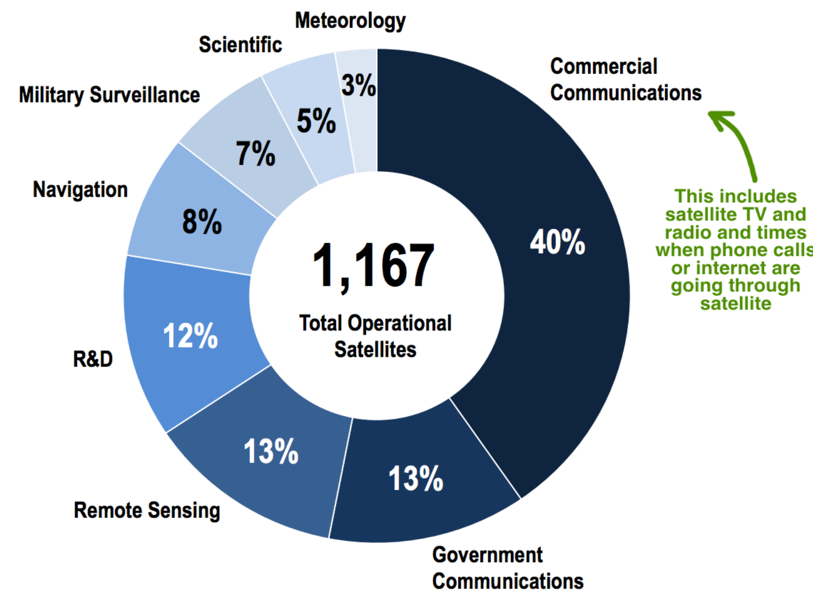
- No telecommunications
- Terrestrial and undersea lines overloaded





Imagine a day...

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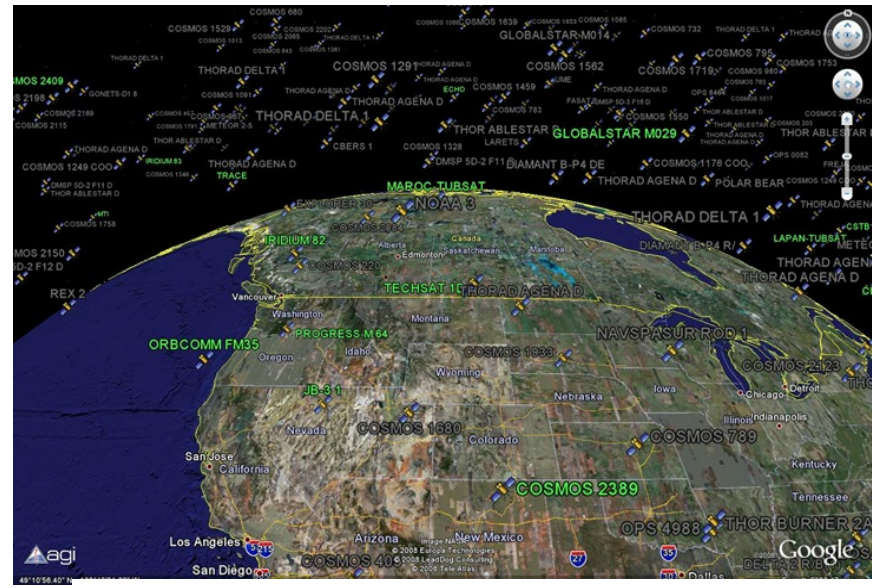
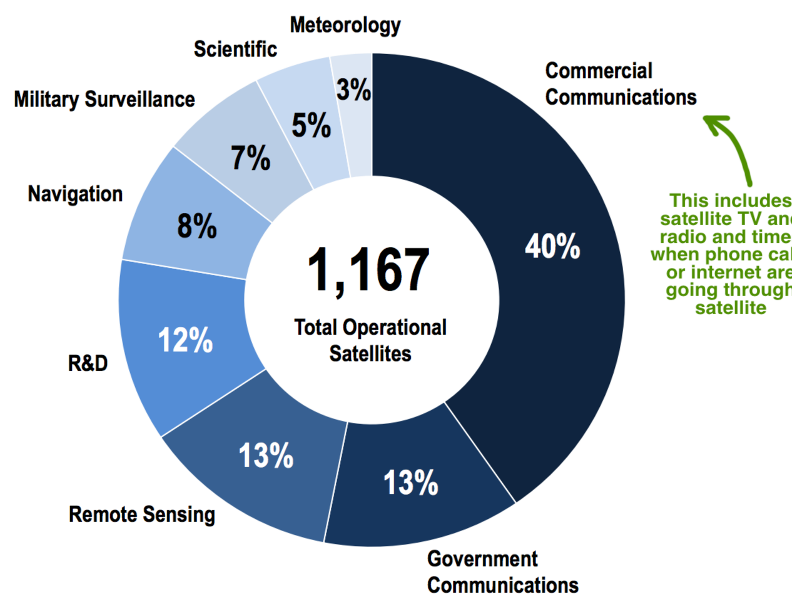
- No telecommunications
- Terrestrial and undersea lines overloaded
- No military surveillance
- No weather forecast





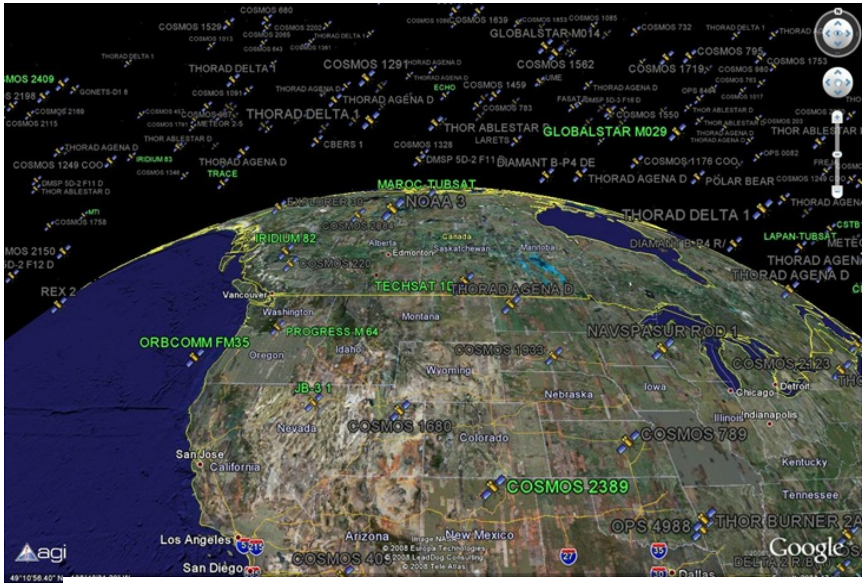
Imagine a day...

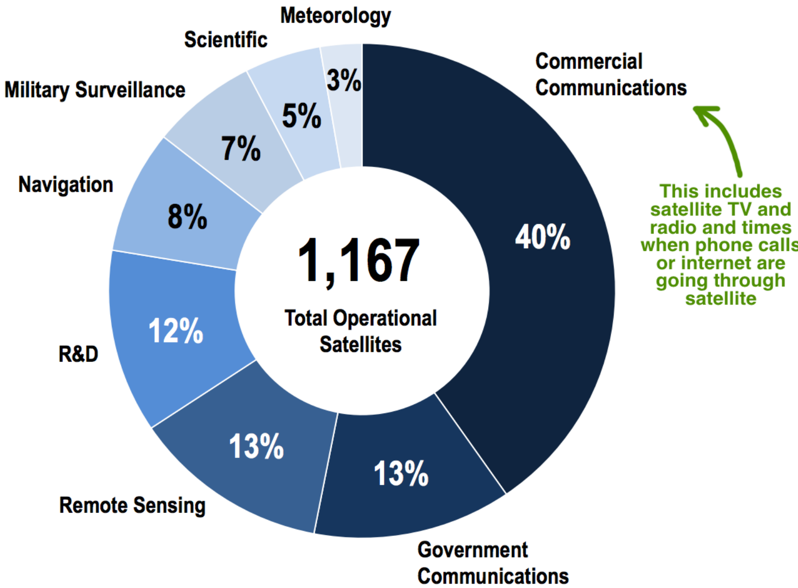
...when satellites

stop working

- No telecommunications
- Terrestrial and undersea lines overloaded
- No military surveillance
- No weather forecast

- **No GPS**





Imagine a day...

No GPS

- Drilling, agriculture
- Aviation
- Railways

Imagine a day...

No GPS

GPS provides precise time stamps to:

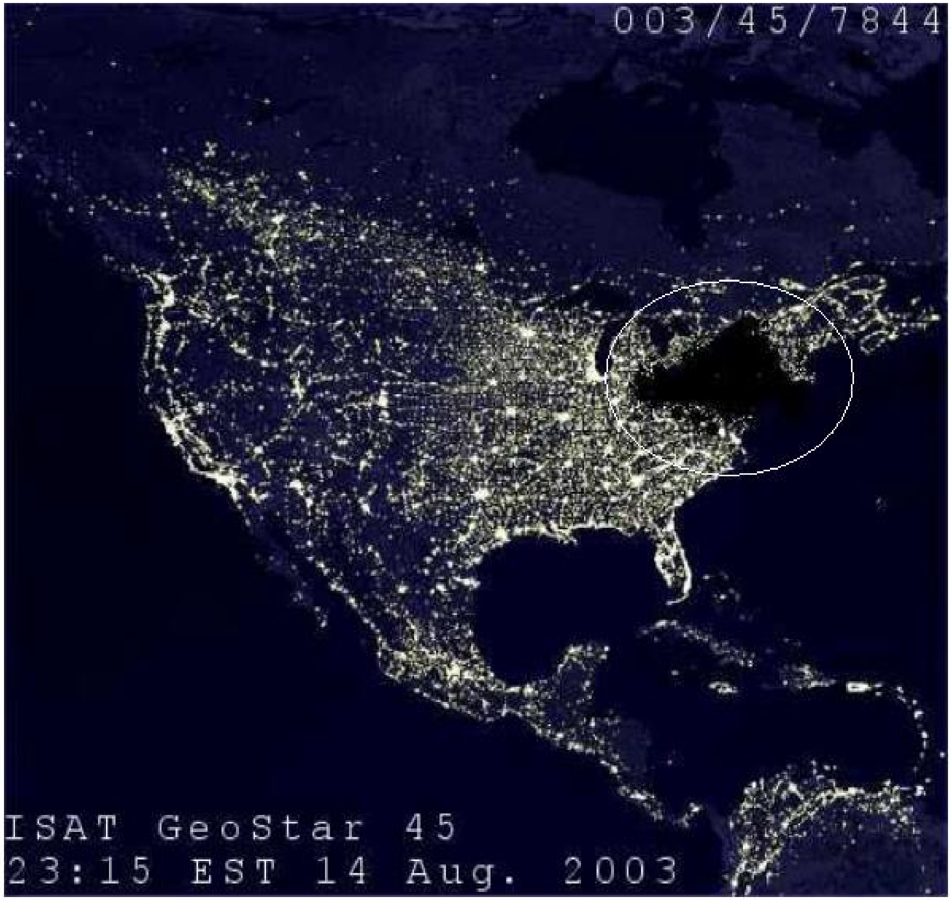
- Communications systems
- Electrical power grids
- Stock market

...and this is only the start

Imagine if...

- Several high-voltage transformers would be damaged, causing **widespread blackouts**, affecting:

- Transportation
- Water supply
- Communication
- Industry



...and finally...

Because military satellites are blinded the USA lost their ability of detecting long-range ballistic missiles

...and finally...

- Because military satellites are blinded the USA lost their ability of detecting long-range ballistic missiles
- President Trump decides to launch a pre-emptive nuclear strike on North Korea

What can possibly cause such a disaster?

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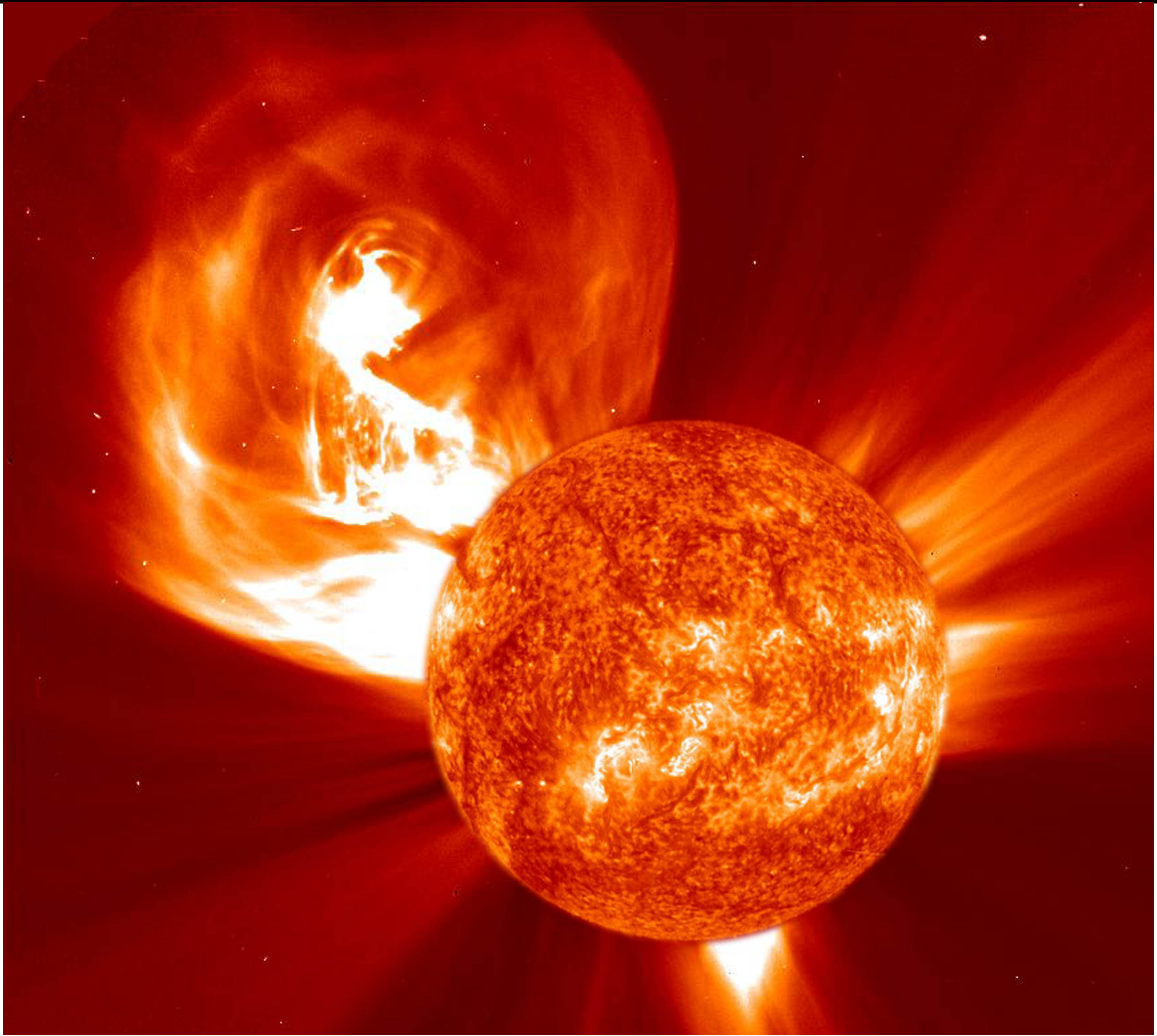
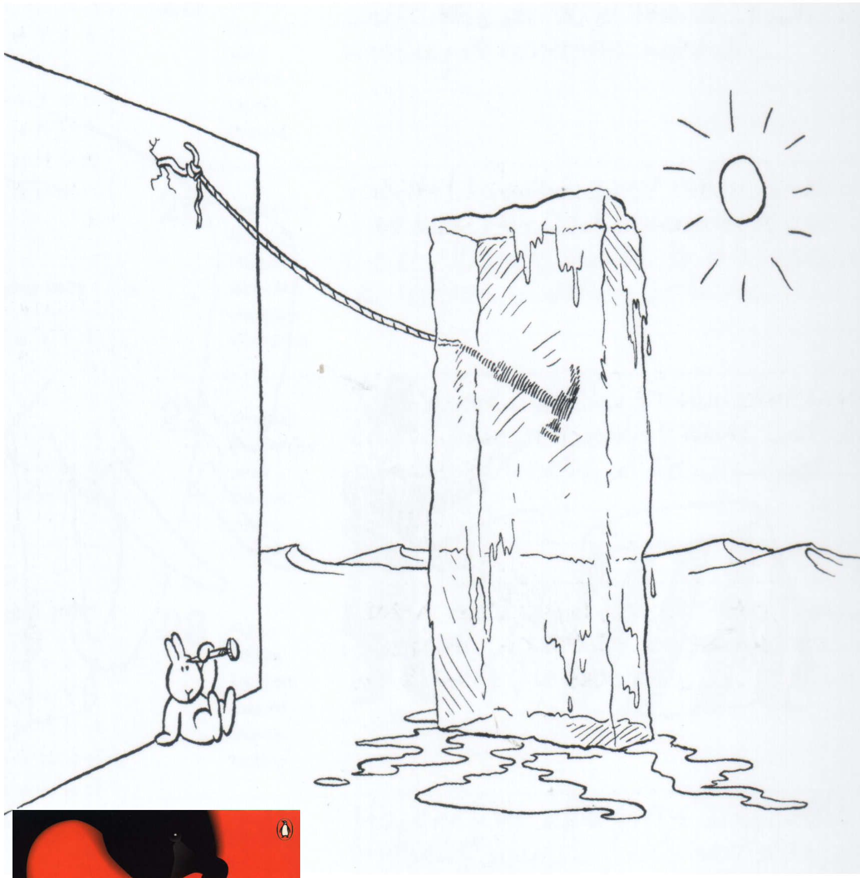
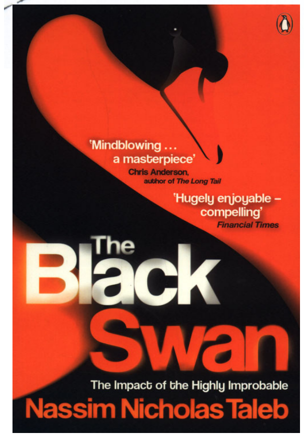


A disaster waiting to happen

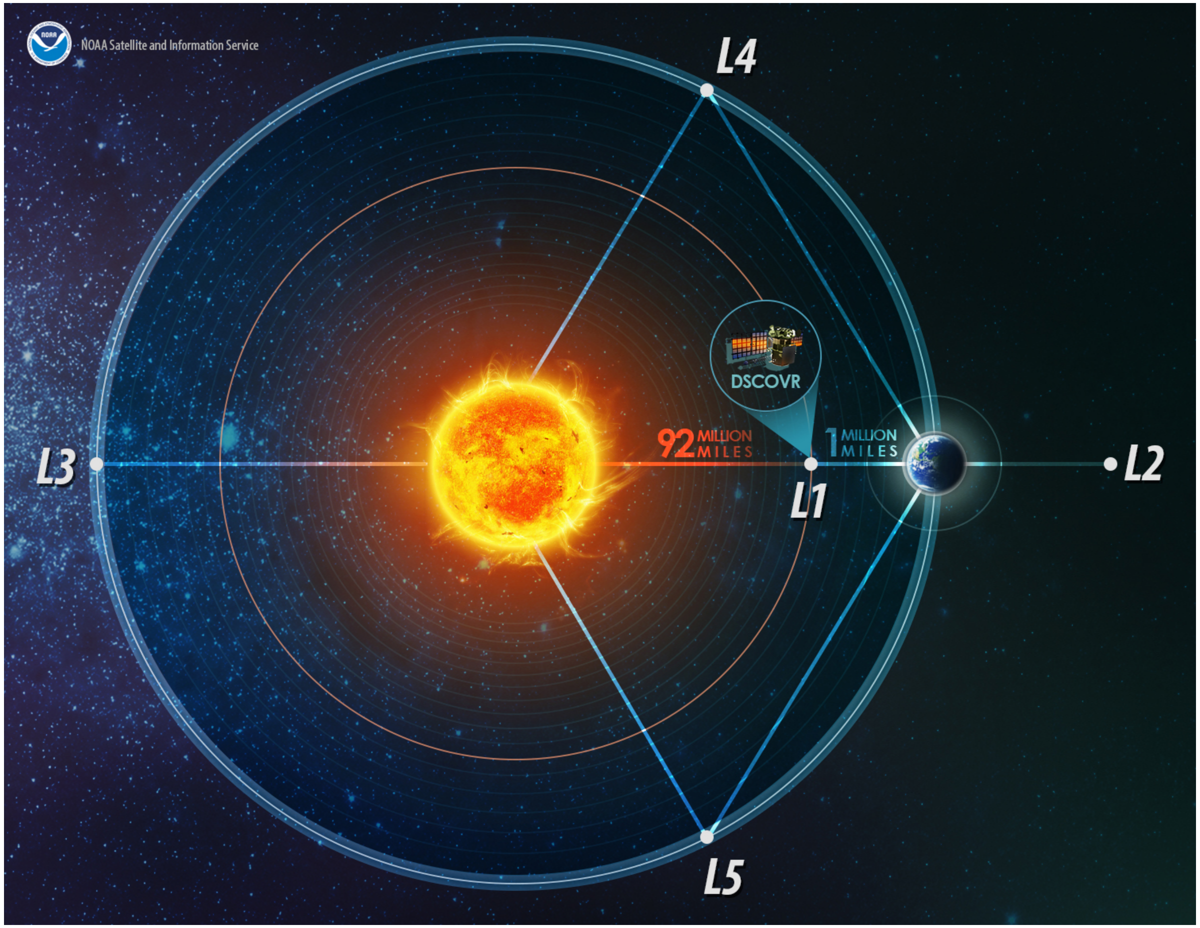
- The adverse impact of space weather is estimated to cost **$200–$400 million** per year;
- losses to satellite companies range from thousands of dollars for temporary data outages up to **$200 million** to replace a satellite;
- economists also estimate that timely warnings of geomagnetic storms to the electric power industry would save approximately **$150 million** per year;
- a 1% gain in continuity and availability of GPS would be worth **$180 million** per year.
- **a “big one” would cause $2.6 trillion damage**





From
The book of bunny suicides

Space Weather predictions



The 1st Lagrangian point is our privileged Sun observatory from which we gather:

– remote images

– in situ data

L1 data are then complemented with ground-based and low altitude satellites data

Our project (CWI / INRIA)

Machine Learning for Space Weather

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Coupling physics-based simulations with Artificial Intelligence

Goal

In this project we aim at enhancing the current state-of-the-art simulations for Space Weather, by using prior knowledge gathered from historical satellite data. Several Machine Learning techniques will be used for data-mining, classification, and regression. The long-term objective of the project is the creation of a portfolio of data-enhanced reduced models, along with automated rules for model selection. Depending on the real-time conditions observed by satellites, the resulting 'grey-box' model should choose the relative importance between physical and empirical estimations.

CWI/INRIA consortium

This project has started as funded by a CWI/INRIA collaboration. However, several other parties have joined in this activity, either as external collaborators, or more actively involved. Visit the team page for a list of all the people involved.

CWI Centrum Wiskunde & Informatica

Inria INVENTEURS DU MONDE NUMÉRIQUE

CWI is the Dutch National Center for Mathematics and Computer Science. INRIA is the French Institute for Research in Computer Science and Automation.

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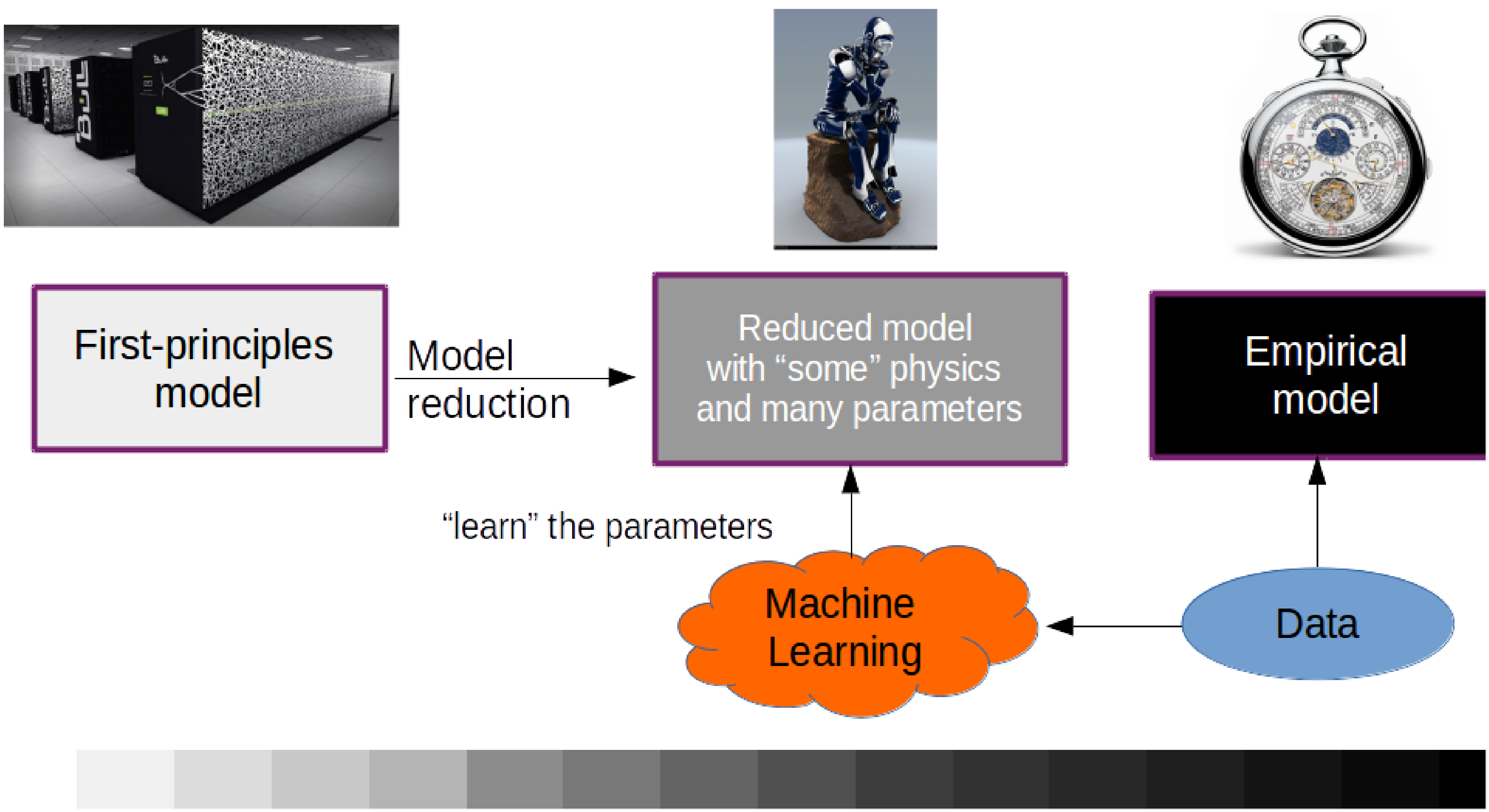
The gray-box paradigm



A quick overview

- Information theory
  - Wing, S., Johnson, J. R., Camporeale, E., & Reeves, G. D. (2016). Information theoretical approach to discovering solar wind drivers of the outer radiation belt. *J. Geophys. Res.*
- Uncertainty Quantification
  - Camporeale, E. , Shprits, Y., Chandorkar, M., Drozdov, A., Wing, S. (2016) On the propagation of uncertainties in radiation belt simulations, *Space Weather*
  - Camporeale, E. , A. Agnihotri, C. Rutjes (2016) Adaptive selection of sampling points for uncertainty quantification, *J. Sci. Comp.*, under review.
- Machine Learning
  - Chandorkar, M., Camporeale, E., Wing, S. (2016) Gaussian Processes Autoregressive Models for Forecasting the Disturbance Storm Time Index, *J. Space Weather Space Clim.*, under review

Information theory

Question: which quantity in the solar wind drives the changes in electron flux in the radiation belt?

Entropy: $H(x) = -\sum_{\aleph_1} p(\hat{x}) \log p(\hat{x}); \quad H(y) = -\sum_{\aleph_2} p(\hat{y}) \log p(\hat{y})$

Joint Entropy: $H(x, y) = -\sum_{\aleph_1 \aleph_2} p(\hat{x}, \hat{y}) \log p(\hat{x}, \hat{y})$

Mutual information (not directional)

$$\mathrm{MI}(x, y) = H(x) + H(y) - H(x, y)$$

Conditional mutual information

$$\mathrm{CMI}(x, y \mid z) = \sum_{\aleph_1 \aleph_2 \aleph_3} p(\hat{x}, \hat{y}, \hat{z}) \log \frac{p(\hat{x}, \hat{y} \mid \hat{z})}{p(\hat{x} \mid \hat{z})\, p(\hat{y} \mid \hat{z})} = H(x, z) + H(y, z) - H(x, y, z) - H(z)$$

Information theory

Conditional mutual information

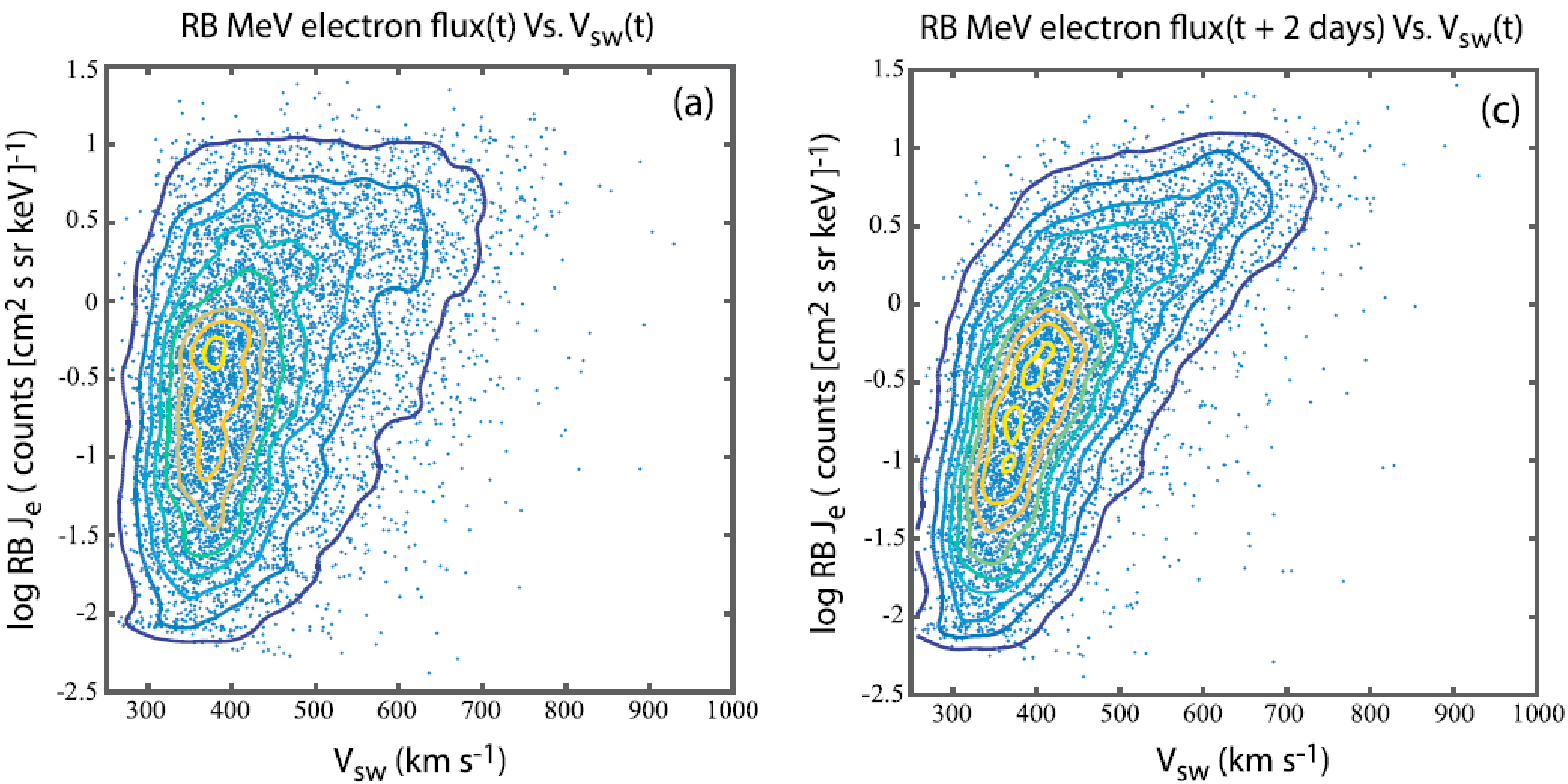
$$\mathrm{CMI}(x,\ y \mid z) = \sum_{\aleph_1 \aleph_2 \aleph_3} p(\hat{x}, \hat{y},\ \hat{z}) \log \frac{p(\hat{x}, \hat{y} \mid \hat{z})}{p(\hat{x} \mid \hat{z})\, p(\hat{y} \mid \hat{z})} = H(x,z) + H(y,z) - H(x,y,z) - H(z)$$

Transfer entropy

$$\mathrm{TE}_{x\to y}(\tau) = \mathrm{CMI}(y(t+\tau), x(t) | yp(t))$$

where $yp(t) = [y(t),\ y(t-\Delta), \ldots, y(t-k\Delta)]$. The transfer entropy can be considered as a conditional mutual information that detects how much average information is contained in an input, x, about the next state of a system, y, that is not contained in the past history, yp, of the system [*Prokopenko et al.*, 2013].

Solar wind velocity vs RB flux



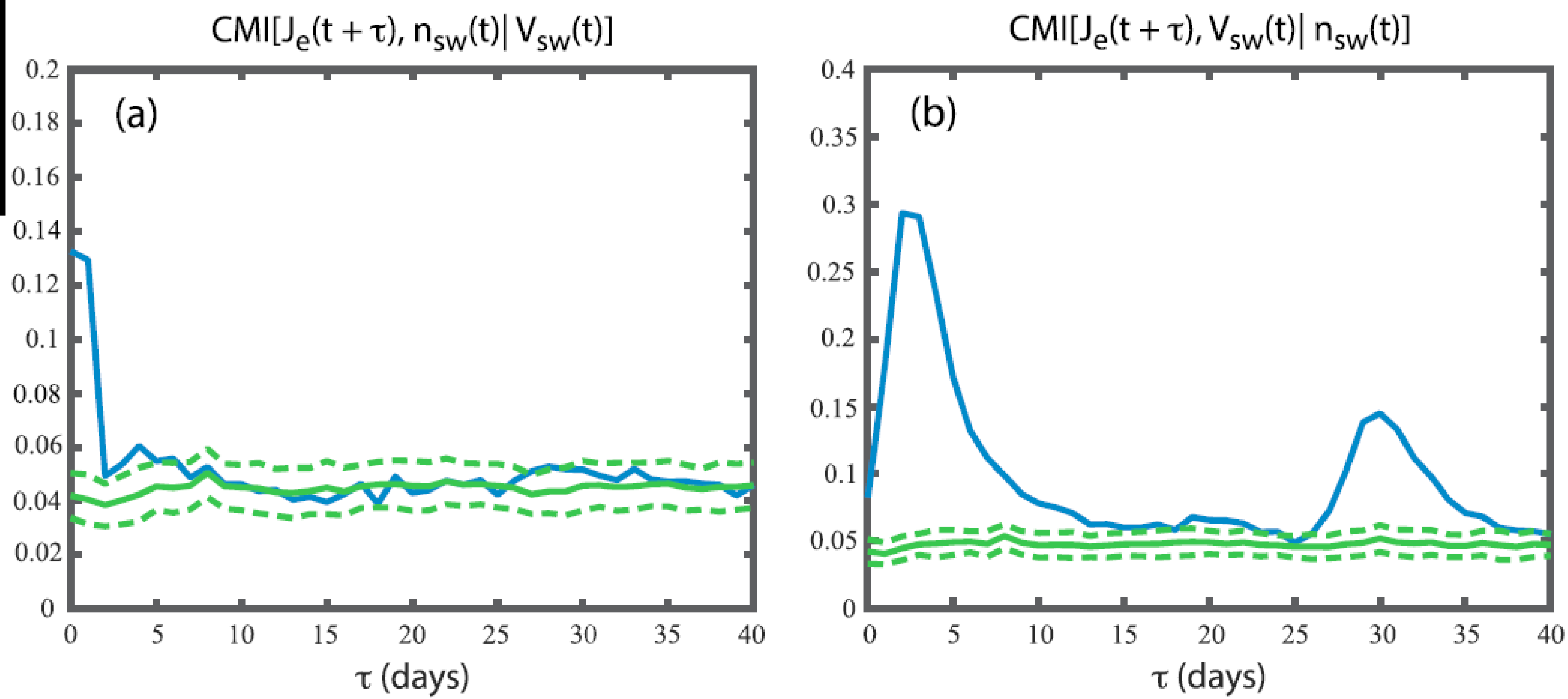
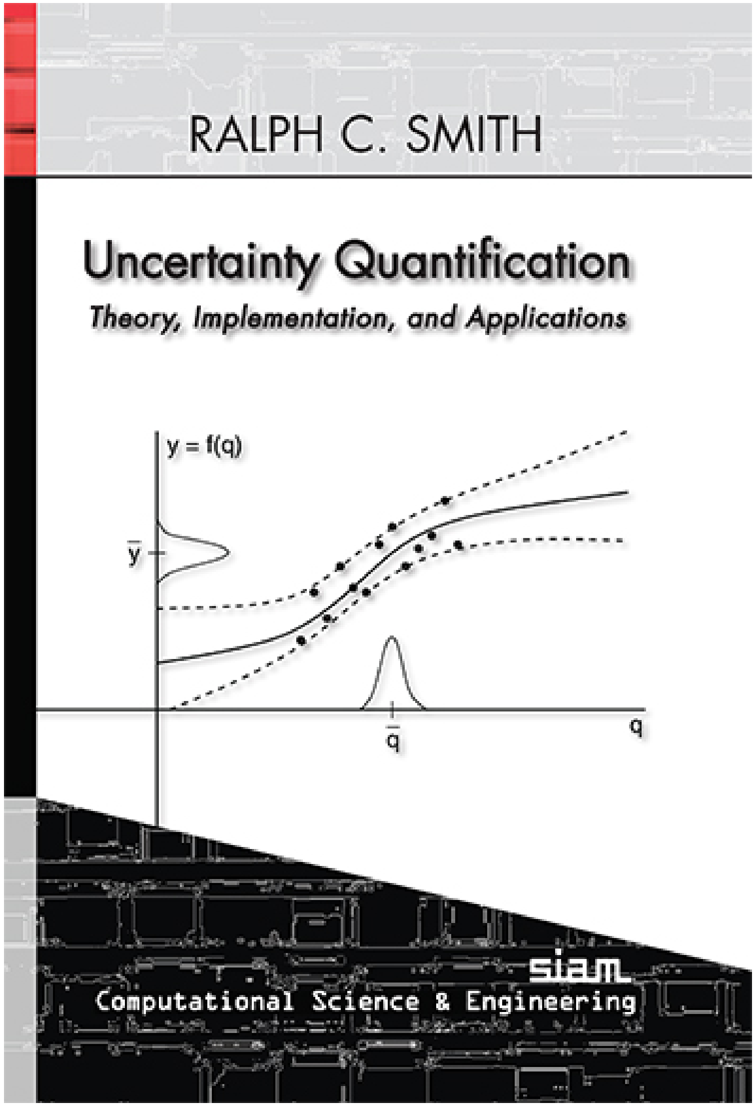


Table 1. Ranking of the Importance of the Solar Wind Parameters Based on Information Transfer to Geosynchronous MeV Electron Flux (J_e) at $\tau_{\max}$, Where $\tau_{\max}$ is the Lag Time When the Information Transfer Peaks[a]

Rank	Solar Wind Parameters	Peak Information Transfer ($it_{\max}$)	Signal-to-Noise Ratio at $\tau_{\max}$	Significance at τ_{max} (σ)	τ_{max} (days)	Prediction Horizon (days)
1	V_{sw}	0.25	6.6	94	2	10[b]
2	IMF $\|\mathbf{B}\|$	0.12	3.9	48	0	2
3	P_{dyn}	0.092	3.4	35	0	2
3	n_{sw}	0.091	3.2	34	0	2
4	σ(IMF B)	0.075	3.9	48	0	2
5	IMF $B_z < 0$	0.064	2.7	26	0	2
6	E_{sw}	0.056	2.9	22	1	5
7	IMF B_y	0.052	2.3	20	0	2
8	IMF $B_z > 0$	0.048	3.1	22	0	2
9	IMF B_x	0.044	2.2	19	0	2

Uncertainty Quantification



Probably, the most used methods are *non-intrusive*, which means that a **black-box computational model** is used repeatedly, for different inputs. The main question is:

What input parameters do you choose? (sampling problem)

- Monte Carlo
- Quasi – Monte Carlo
- Stochastic Collocation
-
- etc.

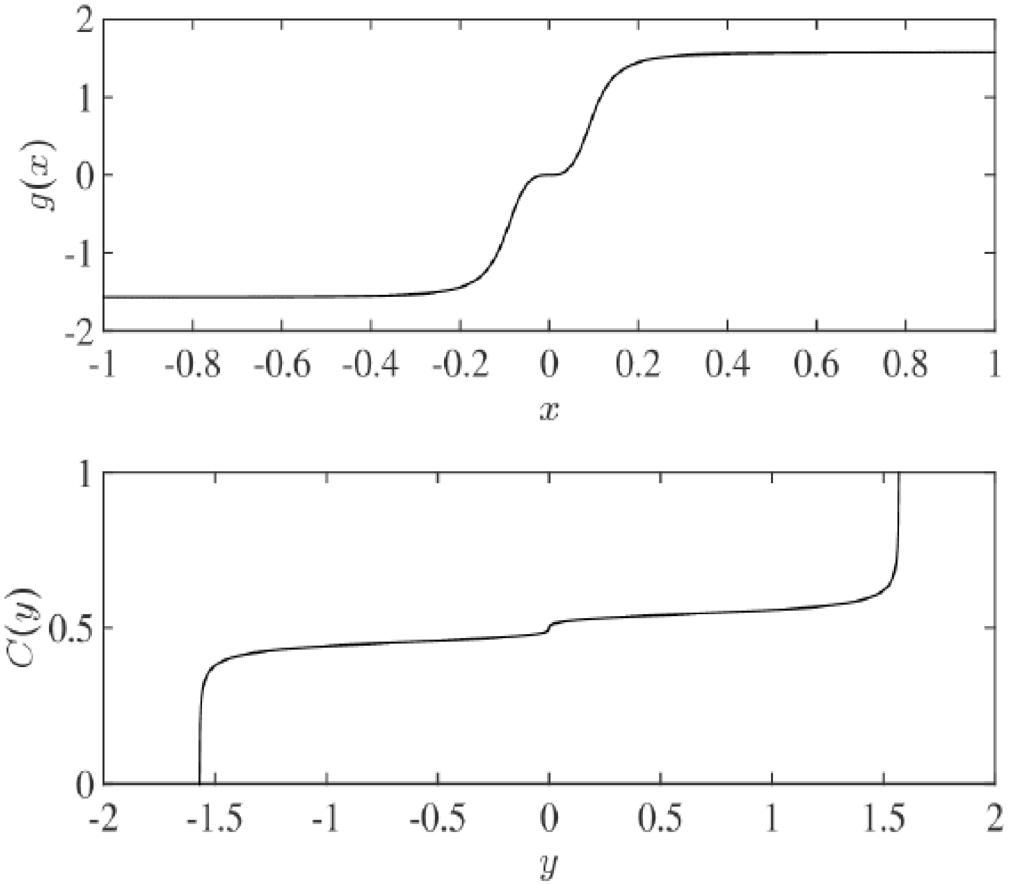
A simple adaptive method for sampling

Interpolant: radial basis function (mesh free)

Simple consideration:

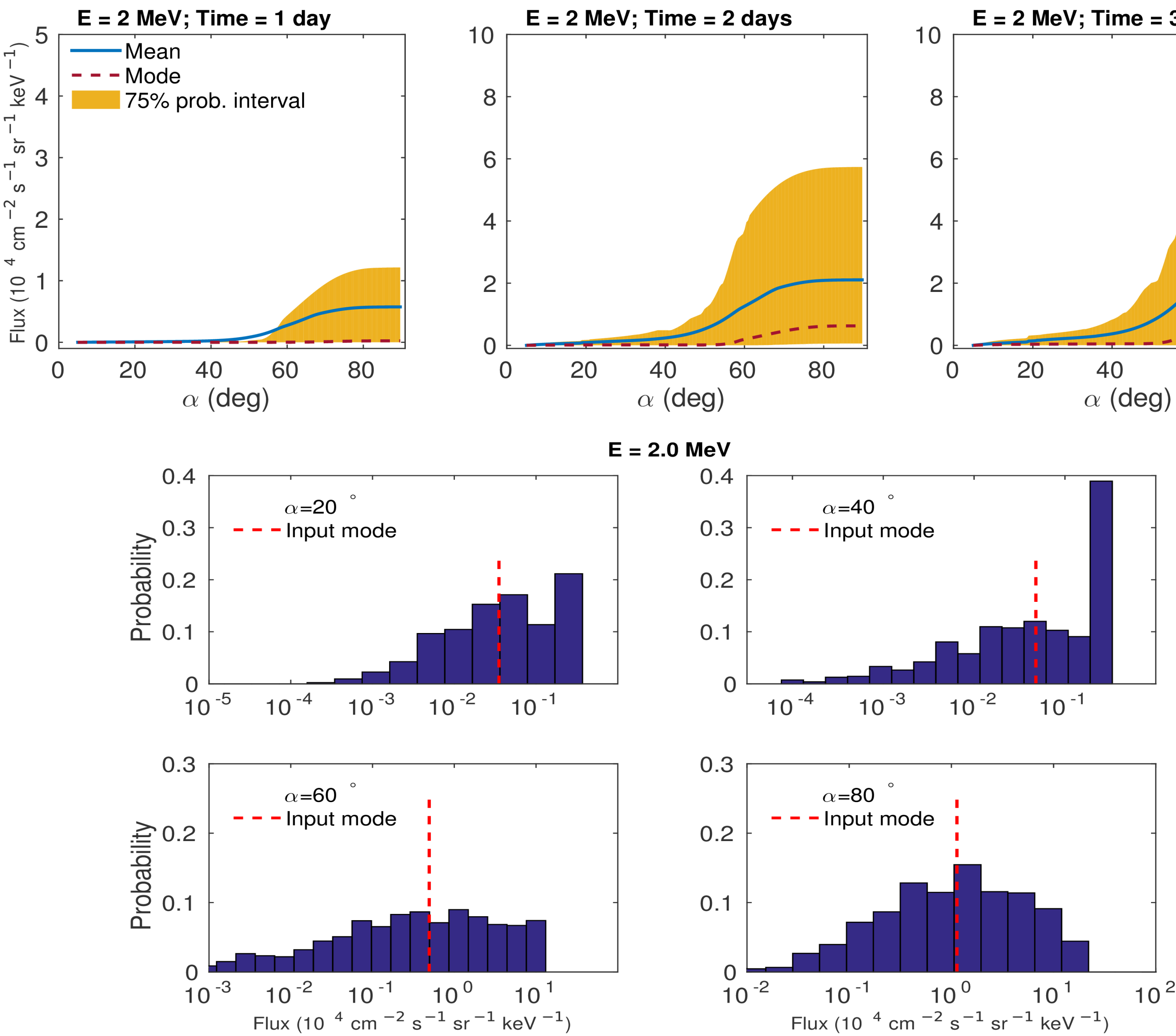
Large and small derivative of mapping function determine “flat” and “steep” regions in the cumulative distribution function.

This is “more or less” all you need to determine your sampling points!



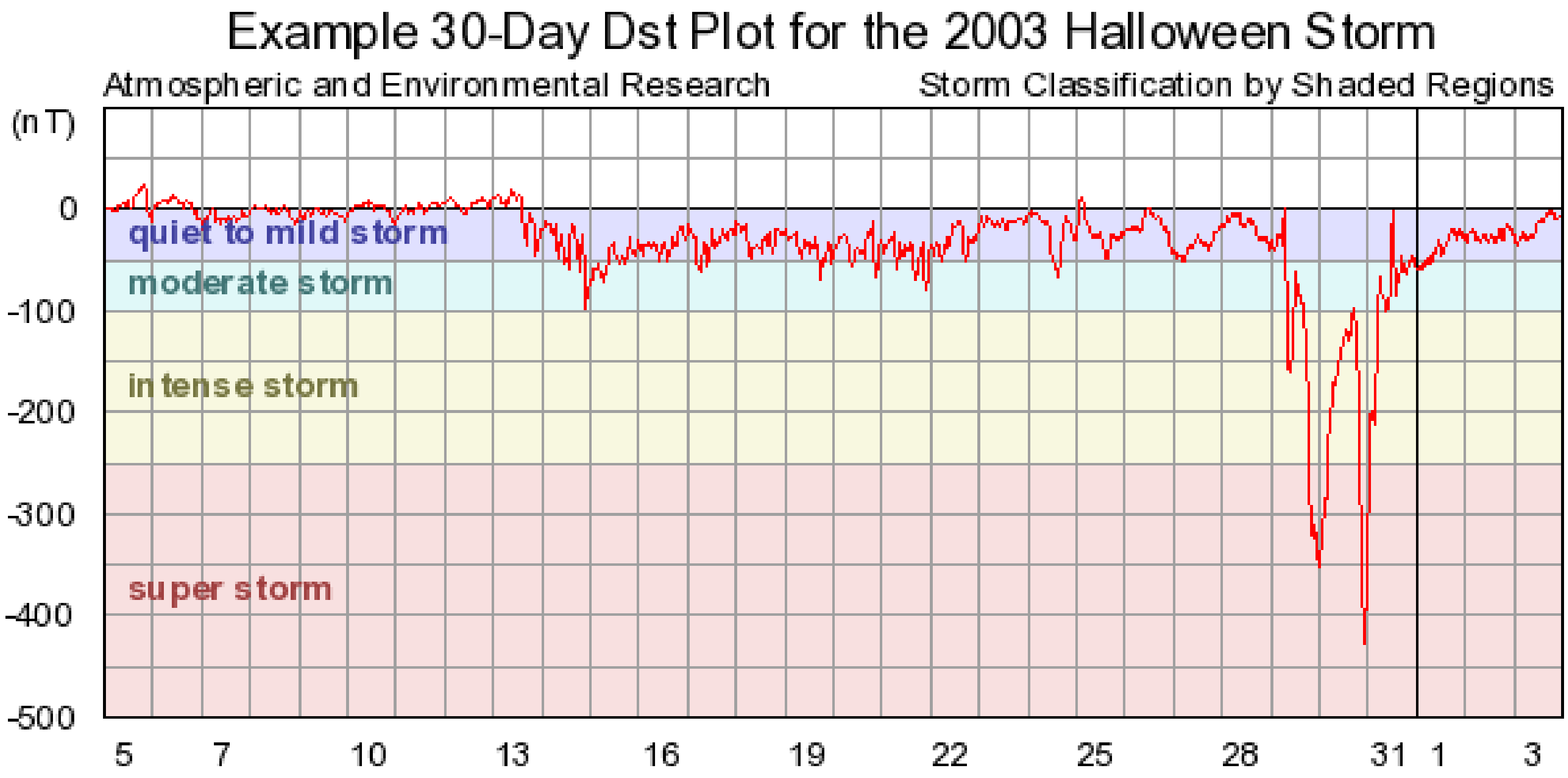
$g(x) = \arctan(10^3 x^3)$. *Top panel:* $g(x)$; *bottom panel: cdf* $C(y)$.

UQ on radiation belt simulations



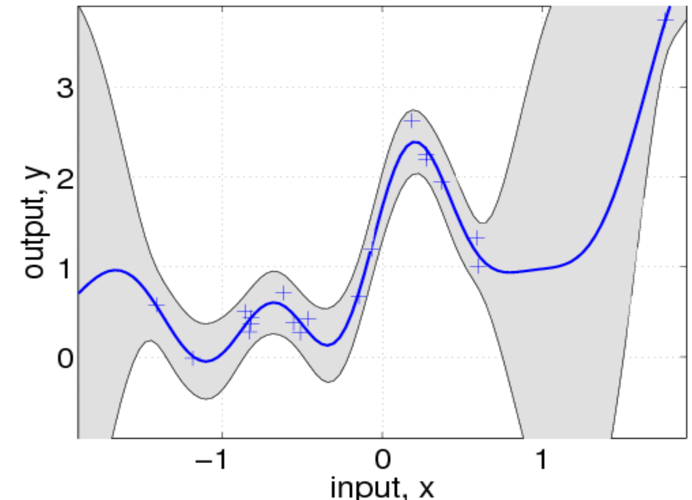
Gaussian Processes for forecasting the DST index

The DST index is a proxy for the geomagnetic activity



Gaussian Processes in a nutshell

We want to infer the values of an unknown function *f*. We assume that the conditional distribution of *f* with respect to input data is normally distributed.



$$\mathbf{f} = \begin{pmatrix} f(\mathbf{x}_1) \\ f(\mathbf{x}_2) \\ \vdots \\ f(\mathbf{x}_N) \end{pmatrix}$$

$$\mathbf{f}|\mathbf{x}_1, \cdots, \mathbf{x}_N \sim \mathcal{N}(\mu, \mathbf{\Lambda})$$

$$p(\mathbf{f} \mid \mathbf{x}_1, \cdots, \mathbf{x}_N) = \frac{1}{(2\pi)^{n/2} det(\mathbf{\Lambda})^{1/2}} exp\left(-\frac{1}{2}(\mathbf{f} - \mu)^T \mathbf{\Lambda}^{-1}(\mathbf{f} - \mu)\right)$$

$$\mu_i = \mathbb{E}[f(\mathbf{x}_i)] := m(\mathbf{x}_i)$$

$$\Lambda_{ij} = \mathbb{E}[(f(\mathbf{x}_i) - \mu_i)(f(\mathbf{x}_j) - \mu_j)] := K(\mathbf{x}_i, \mathbf{x}_j)$$

We need to specify the covariance matrix (kernel)

Gaussian Processes in a nutshell

The conditional distribution on new test points can be computed analytically (because we are dealing with Gaussian)

$$\mathbf{f}_*|\mathbf{X}, \mathbf{y}, \mathbf{X}_* \sim \mathcal{N}(\bar{\mathbf{f}}_*, \Sigma_*),$$

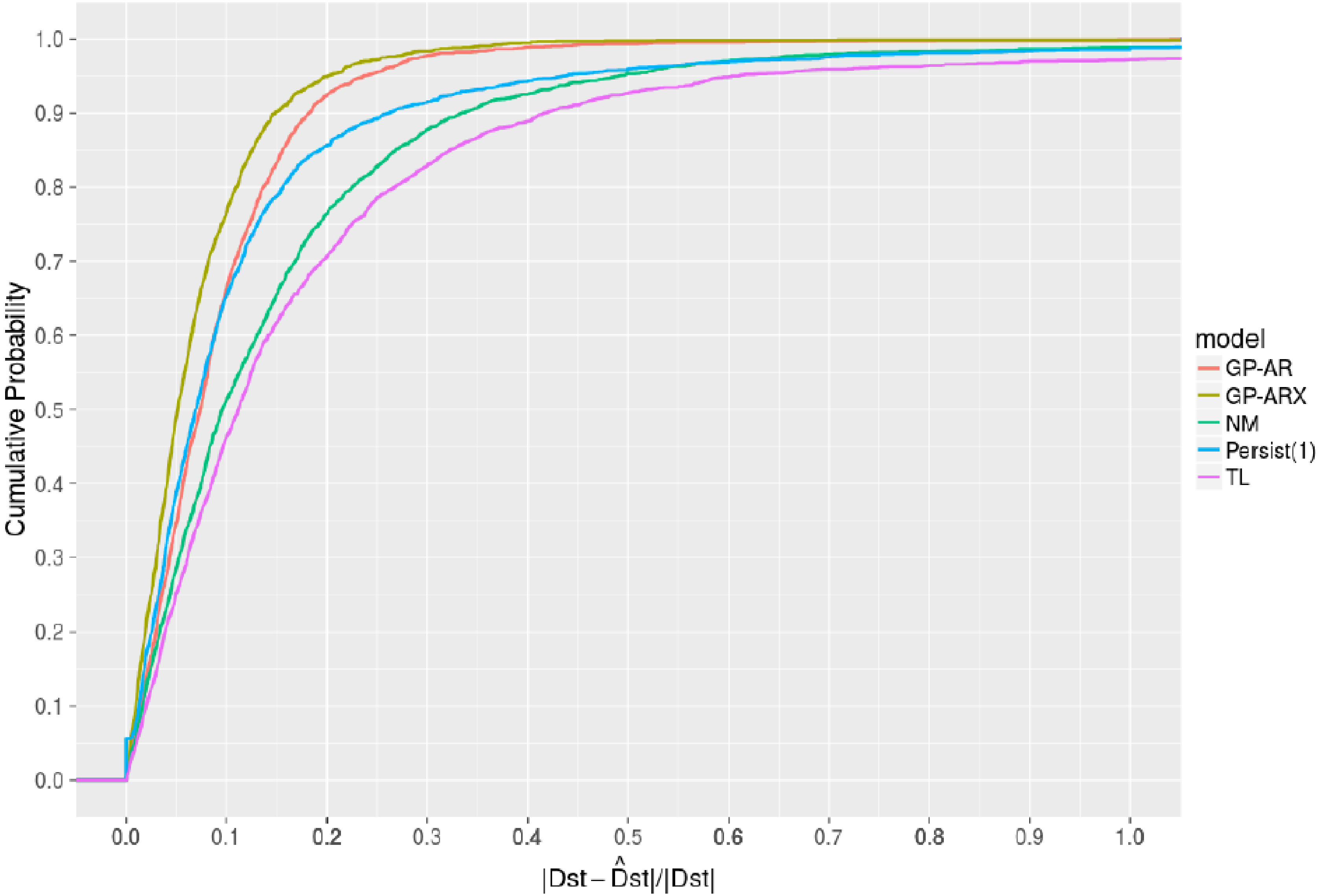
where

$$\bar{\mathbf{f}}_* = \mathbf{K}_*^T[\mathbf{K} + \sigma^2\mathbf{I}]^{-1}\mathbf{y}$$

$$\Sigma_* = \mathbf{K}_{**} - \mathbf{K}_*^T\left(\mathbf{K} + \sigma^2\mathbf{I}\right)^{-1}\mathbf{K}_*$$

GP models do not make point predictions but output predictive (normal) distributions

CWI GP-ARX is the best model on the market!



Future challenges

- Bayesian parameter estimation (inverse problem) to feed physics-based models
- Classification and regression of solar wind and magnetospheric conditions based on solar images

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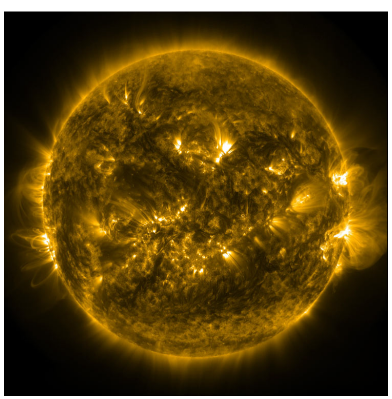
Dog!



CWI

80% chance of a geomagnetic storm!