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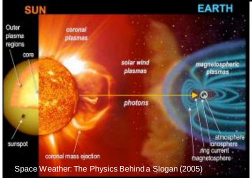
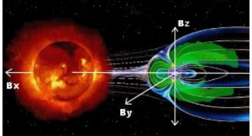


Space Weather: The Physics Behind a Slogan (2005)



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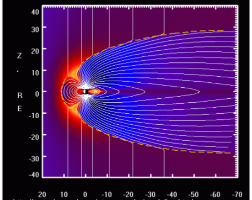

http://geo.phys.spbu.ru/~tsyganenko/modeling.html

Characterisation of Near-Earth Magnetic Field Data for Space Weather Monitoring

Statistical modelling of the near-Earth magnetic field with in-situ measurements

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November 17, 2014

Introduction

Space weather refers to electromagnetic disturbances in the near-Earth environment.

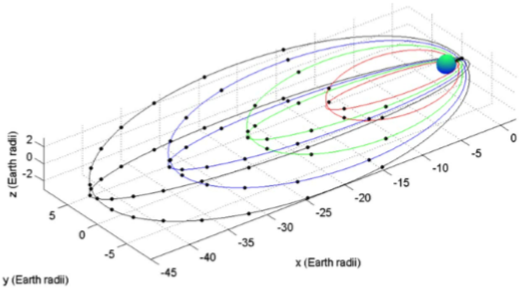
Space weather monitoring and early storm detection can be used to mitigate risk in sensitive technological systems.

Main Objectives

- To build spatio-temporal statistical models for
  - characterising the magnetic field variation
  - comparing storm and non-storm behaviour
  - detecting change points related to storm events
- To design a CubeSat constellation for sampling the near-Earth magnetic field

Question

What are the best strategies for space weather monitoring with a network of small satellites?

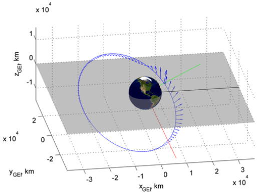


J. P. Eastwood, CENTINEL: A CubeSat space weather constellation

A sensor network will be able to provide reliable estimates of near-Earth magnetic field and detect and predict storm events.

The basic network design challenge:

to develop new statistical methods which recognise the change in spatio-temporal sampling around an orbit



First Steps:

- sample hourly magnetic field data $\boldsymbol{B}_{(X,Y,Z)}$ at CLUSTER satellite position $\boldsymbol{r}_{(X,Y,Z)}$
- regress hourly $\boldsymbol{B}_{(X,Y,Z)}$ on its time-dependent potential covariates:

$$\underbrace{B_{(X,Y,Z)_t}}_{\text{satellite observation}} = \underbrace{B_{I(X,Y,Z)_t} + B_{E(X,Y,Z)_t}}_{\text{model simulations}} + \underbrace{r_{(X,Y,Z)_t}}_{\text{position}} + \underbrace{Dst_t + Kp_t}_{\text{geomagnetic indices}} + \underbrace{\delta_t}_{\text{discrepancy term}} \qquad (\star)$$

$\mathbf{B_I}$ - internal field simulated from IGRFmodel; $\mathbf{B_E}$ - external field simulated from Tsyganenko model T96

- capture the autocorrelation structure in δ_t with a time series model $\delta_t = c + \sum_{i=1}^{p} \phi_i \delta_{t-i} + \epsilon_t$

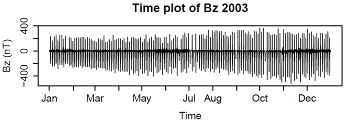
the error term ϵ_t is assumed to be normally and independently distributed

- check model assumptions and investigate the presence of non-stationarity in ϵ_t

Exploratory Analysis

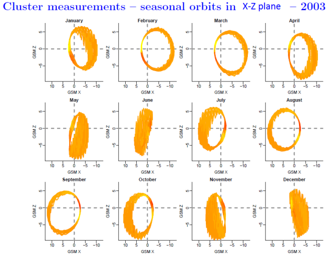
hourly $\boldsymbol{B_Z}$ values for 2003:

Z component of the magnetic field responses to reconnection process in storms

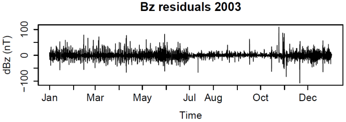


Data coverage: the satellite orbit sweeps

through the space allowing for a **360°** scan of the space each year.



After removing the covariate effects of $\boldsymbol{B_Z}$ as in (✦), the residual plot suggests:

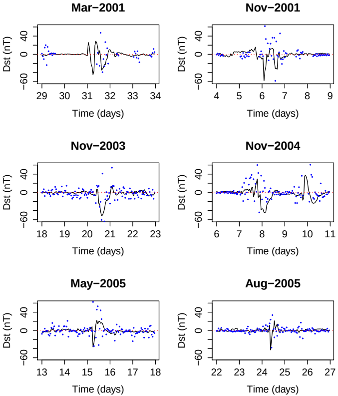


- non-stationary variability

in the error term ϵ_t.

> **non-stationarity**
>
> How does the presence of non-stationarity in residuals relate to storm occurrance?

We performed similar analysis for $\boldsymbol{B_Z}$ from 2001 to 2005. Selected storm periods:



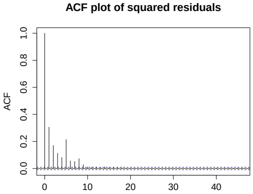
- black line - Dst index
- dashed red line - zero line
- blue dot - $\boldsymbol{B_Z}$ residual

Progress

So far we fitted statistical models to gain knowledge of temporal variation in magnetic field data.

Conclusion

- There is temporal variation (non-stationary volatility) not captured in the $\boldsymbol{B_Z}$ model residuals.
- The preliminary result shows that the changes in variability of $\boldsymbol{B_Z}$ model residuals accompany storm occurrences.



The autocorrelation function of squared $\boldsymbol{B_Z}$ residuals suggests the existence of temporal dependencies in the variance.

The Future

- Extending statistical modelling to examine the variation of magnetic field data in time and space
- Recognising the change in magnetic field data volatility as a function of storm condition and quantitatively characterising the storm and non-storm behaviour using
  - GARCH models for modeling the variance
  - moving standard deviation for change point detection
- Using the statistical properties of magnetic field data to design a theoretical network, sampling the near-Earth magnetic field

Acknowledgement This PhD project is funded by a Sensor University Scholarship, University of Glasgow. Qingying Shu has received travel support from School of Mathematics and Statistics, University of Glasgow.