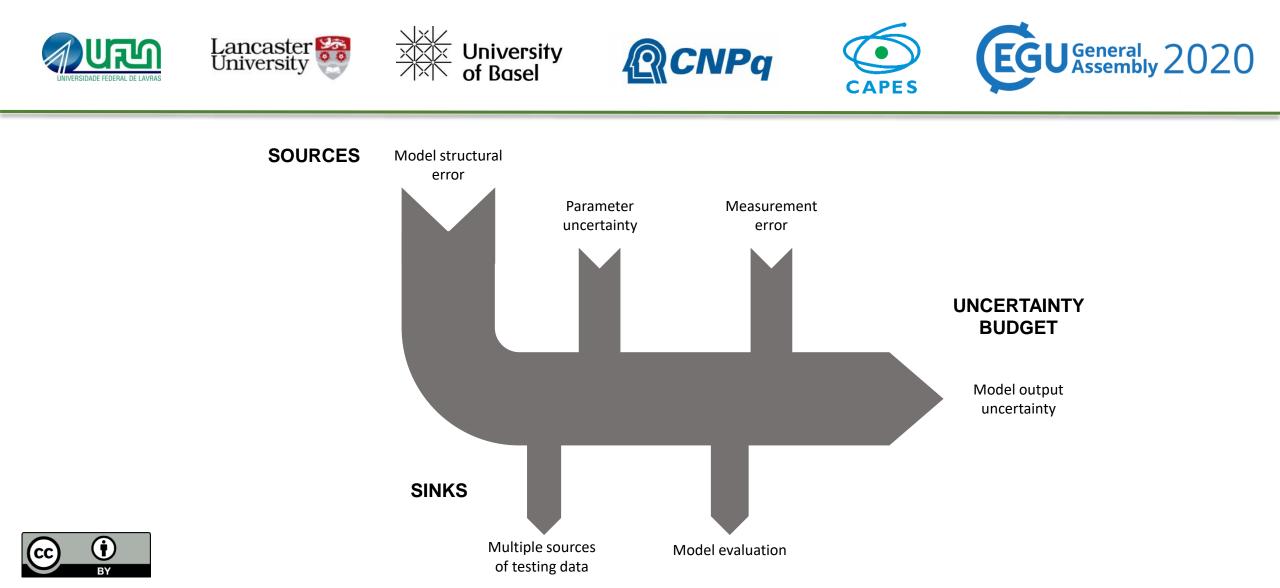
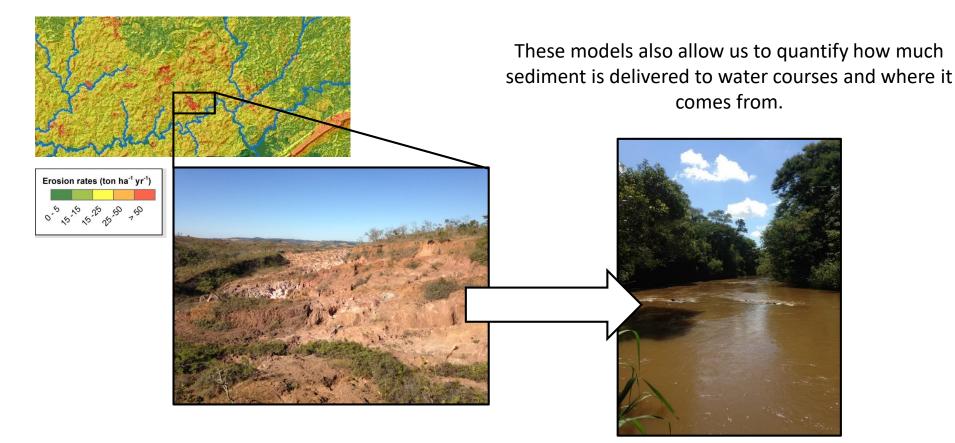
Pedro V. G. Batista, J. Patrick Laceby, Jessica Davies, Teotônio S. Carvalho, Diego Tassinari, Marx L. N. Silva, Nilton Curi, John N. Quinton





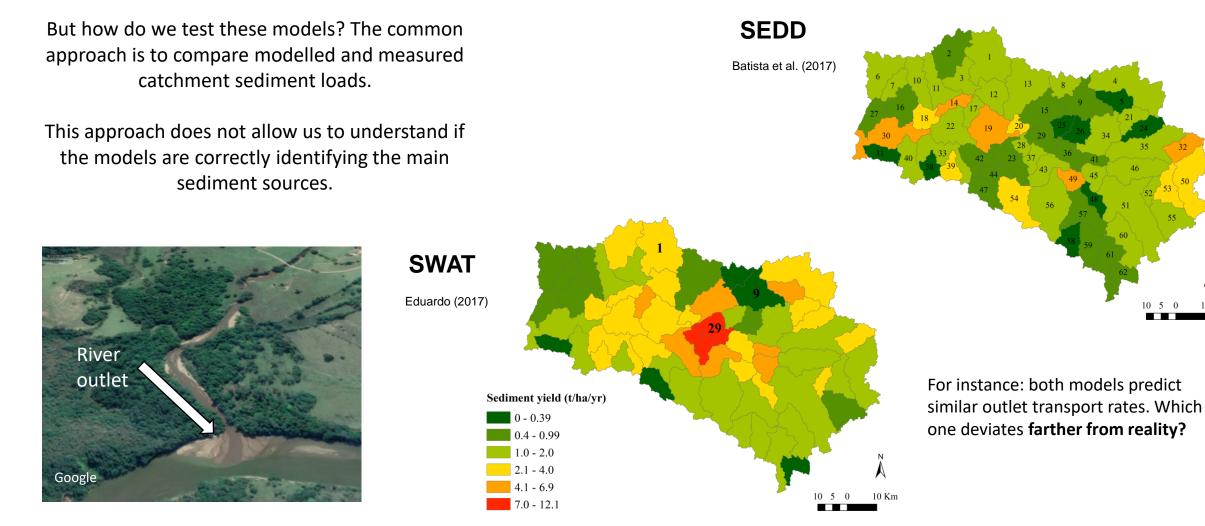
Spatially distributed soil erosion and sediment delivery models can inform us about where, when, and with which magnitude erosion occurs.





5 0

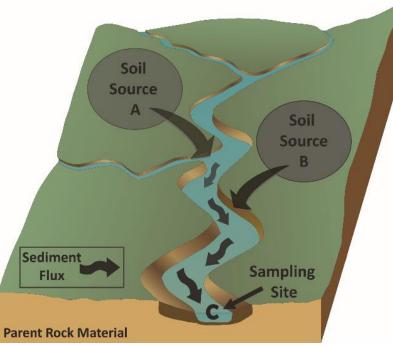
10 Km





Sediment fingerprinting provides quantitative apportionments of sediment sources.

A comparison between soil erosion/sediment delivery models and fingerprinting source apportionments may be used to evaluate the capability of the models to identify the main sources in a catchment.



Source: Patrick Laceby (personal communication)

However, testing soil erosion models requires representing the uncertainties associated to:

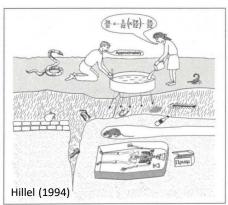
The system representation:





Reality x Model

Parameter estimation:



Observational testing data:

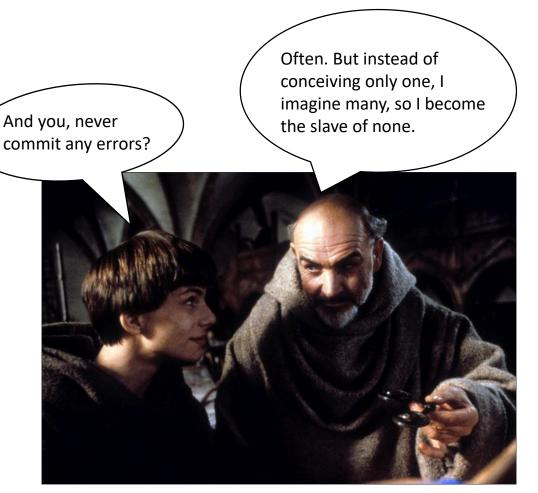




The Generalised Likelihood Uncertainty Estimation (GLUE) (Beven & Binley, 1992) provides a framework for testing models, or model realizations, as hypotheses.

The basis of **GLUE** can be summarized in a few decision steps (Beven, 2009):

- I. Decide on a rejection criteria for nonbehavioral realizations (non-acceptable reproductions of the observational data).
- II. Decide on which parameters are uncertain.
- III. Decide on a prior distribution to characterize the uncertainty of the chosen parameters.
- IV. Decide on a simulation method for generating model realizations.



The Name of the Rose, Umberto Eco

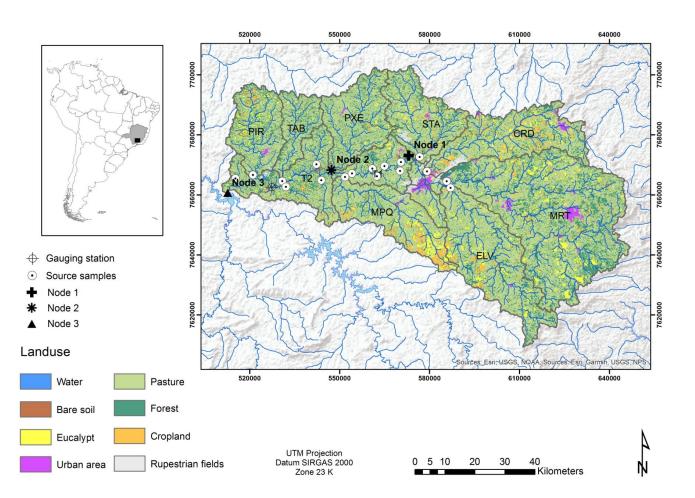


Objectives:

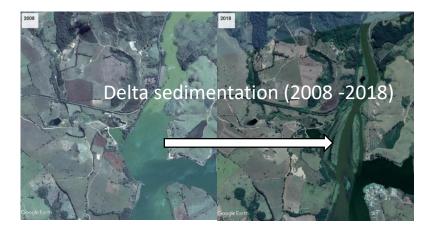
- To develop an approach to the evaluation of spatially-distributed soil erosion/sediment delivery models that incorporates sediment fingerprinting source apportionments while representing the uncertainties in models and observational forcing/testing data.
- More specifically:
 - To apply the RUSLE-based Sediment Delivery Distributed (SEDD) (Ferro & Porto, 2000) model within the GLUE methodology at a large catchment in Southeast Brazil.
 - To define limits of acceptability of model error based on the uncertainty of sediment load measurements.
 - To evaluate behavioral simulations against tributary-based fingerprinting source apportionments.



Mortes River catchment:



- ~6600 km²
- Humid subtropical with dry winters and warm summers (Cwb)
- ~1500 mm yr⁻¹
- Acrisols (48%) and Cambisols (35%) are the main soil classes
- Land use:
 - Pasture: 66 %
 - Forest: 22 %
 - Cropland: 5 %
 - Eucalypt: 5 %





Outlet sediment loads – forcing data:

• Sediment concentration and water discharge measurements (2008 – 2012)

Sediment rating curve:

- Log-transformed data
- Ordinary least squares
- Posterior simulations of model coefficients: propagation of regression uncertainty into long-term sediment load estimates (analogous to SEDD outputs).







Sediment fingerprinting – testing data:

Hierarchical tributary sampling design:

- 20 composite samples of lag deposits per tributary
- Sink nodes sampled during the dry and rainy season

Lab work:

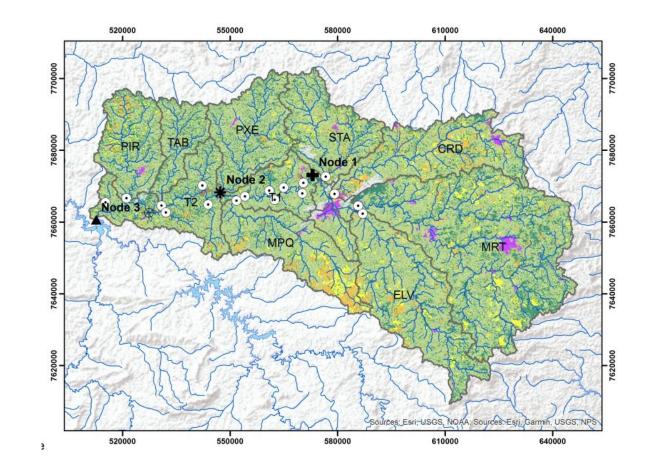
- Sieving < 0.2 mm
- Sediment geochemistry: ICP OES

Element selection:

• Forward step-wise LDA

Un-mixing modelling:

• Monte Carlo simulation sampling from Multivariate-Normal distributions



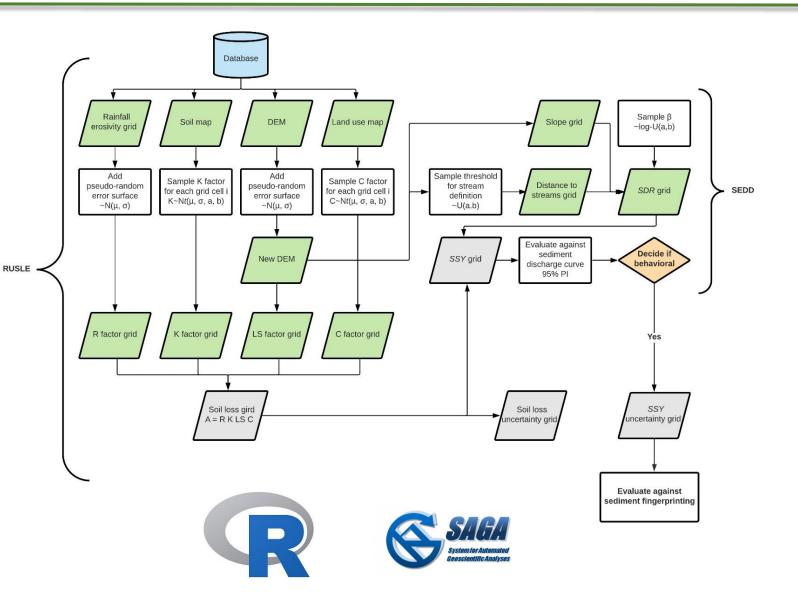


Soil erosion and sediment delivery modelling

RUSLE-based Sediment Delivery Distributed model (SEDD):

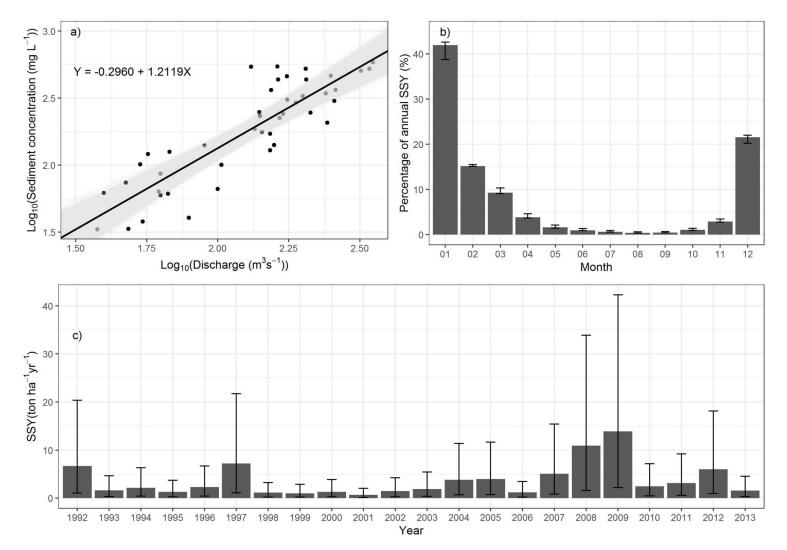
 $SSY_i = \exp\left(-\beta \frac{l_i}{s_i}\right) * (R K LS C P)$

- Model realizations generated by a Monte Carlo simulation (1000 iterations)
- Rejection criterion: 95% PI of curveestimated sediment loads (forcing data)
- Evaluation data: sediment fingerprinting source apportionments
- One-way sensitivity analysis: RUSLE factors



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Results – Sediment-rating curve

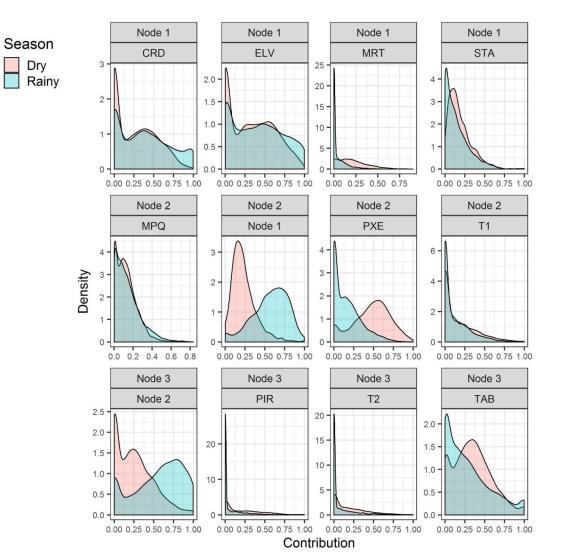


Long-term average area specific sediment yield (**SSY**):

- 95% PI = 0.47 11.95 ton ha⁻¹ yr⁻¹
- Mean = 3.45 ton ha⁻¹ yr⁻¹
- Median = 2.52 ton ha⁻¹ yr⁻¹

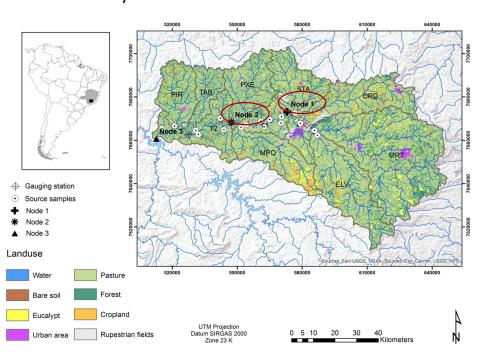
> 90 % of sediment transport during the rainy season





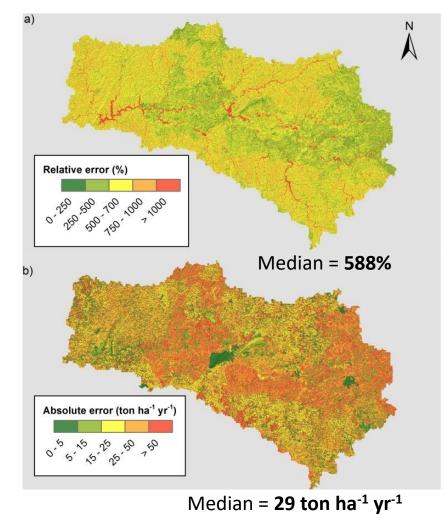
Results – Sediment fingerprinting source apportionments

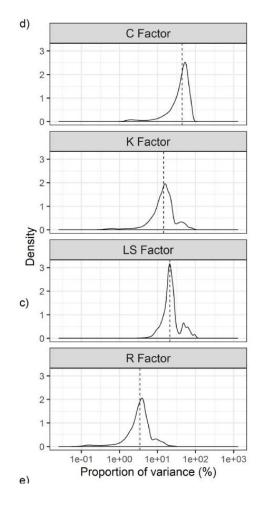
Increased contributions from **Nodes 1 and 2** during the rainy season (median ~ 60%) in comparison to the dry season (median ~ 20%). As expected, the catchment is more connected during the rainy season, and upstream tributaries have higher relative contributions. During base-flow, sediments are mainly derived from proximal tributaries (e.g. PXE and TAB).

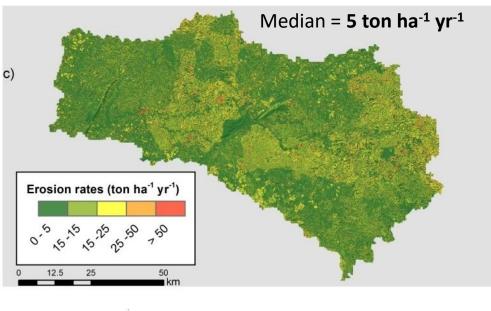


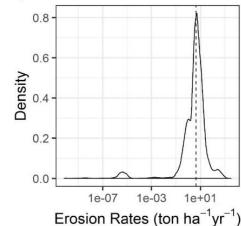


Results – RUSLE uncertainty and sensitivity analysis



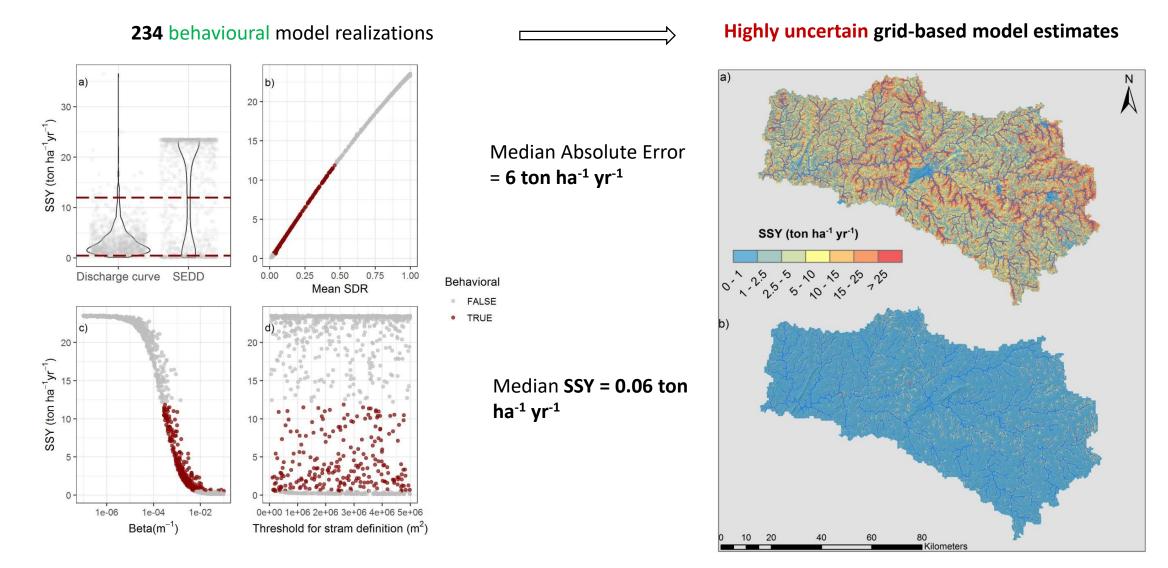








Results – SEDD model

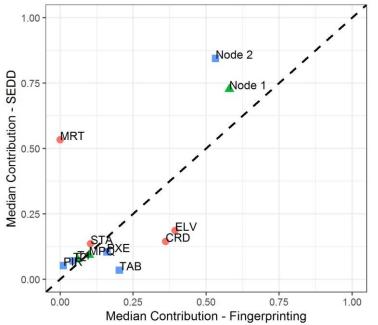


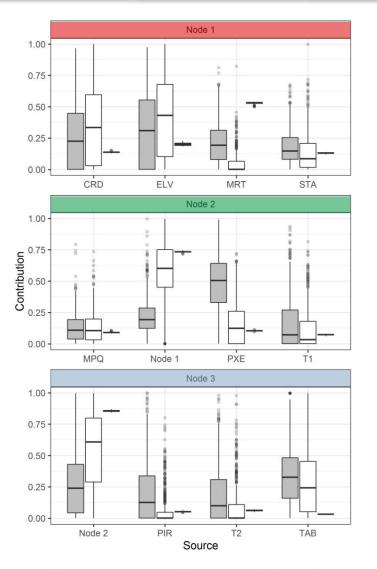


Results – evaluation against sediment fingerprinting source apportionments

SEDD results are far less uncertain when lumped into **relative sub-catchment contributions**.

Fingerprinting and SEDD source apportionments for Node 1 are contrasting. For nodes 2 and 3, most behavioural SEDD realizations are within the inter-quartile range of the fingerprinting apportionments (rainy season), and both results show a similar pattern.







Conclusions:

- We have demonstrated how sediment fingerprinting source apportionments can be used to evaluate soil erosion and sediment delivery models, while representing the uncertainty in both models and observational data.
- From a falsificationist perspective, the SEDD model could not be rejected, as multiple model realizations produced acceptable system representations. However, this was largely facilitated by the uncertainty in the forcing data and the model sensitivity to the empirical parameter β.
- Although grid-based SEDD results were highly uncertain, the evaluation against fingerprinting apportionments indicate the model might be useful for identifying main sediment sources at sub-catchment scale.
- Uncertainty in the RUSLE factors contributed significantly model variance. Uncertainty analysis should become a **standard procedure** for RUSLE model applications.
- We need better data in order to reject models, or model realizations, as hypotheses. This will require honest representations of the uncertainty in models and the observational data.



Thank you!

pedro.batista@unibas.ch

