FRIAS Research Focus October 2019 - October 2020:

Environmental Forecasting

1 Applicants

Prof. Dr. Carsten F. Dormann
Biometry and Environmental System Analysis, Faculty of Environment and Natural Resources
University of Freiburg; Tennenbacher Str. 4; 79106 Freiburg
carsten.dormann@biom.uni-freiburg.de; +49 (0)761 203-3750
http://www.biom.uni-freiburg.de/mitarbeiter/dormann

Prof. Dr. Kerstin Stahl
Environmental Hydrological Systems, Faculty of Environment and Natural Resources
University of Freiburg; Friedrichstraße 39; 79098 Freiburg
kerstin.stahl@hydrology.uni-freiburg.de; +49 (0)761 203-3532
https://www.hydro.uni-freiburg.de/staff/stahl/stahl-en?set_language=en

Prof. Dr. Stefan Baumgärtner
Environmental Economics & Resource Management, Faculty of Environment and Natural Resources
University of Freiburg; Tennenbacher Str. 4; 79106 Freiburg
stefan.baumgaertner@ere.uni-freiburg.de; +49 (0)761 203-3753
https://www.ere.uni-freiburg.de/team-en/stefan_baumgaertner?set_language=en

2 Name and summary of proposed Research Focus

Environmental Forecasting

Environmental models are the main tool through which our understanding of natural processes is transferred into practice in a human dominated world: weather forecasts, flood warnings, carbon balances of forests, landslides, recycling budgets are computed using environmental models along a range of complexity. Such environmental models comprise representations of the natural processes as well as human impacts, and include economic models, such as those simulating trade and environmental impacts at local to global scales.

Environmental disciplines have evolved strikingly divergent modelling cultures, of different scientific credibility. The aim of the proposed Research Focus at the FRIAS is to **understand modelling cultures** as reflecting distinct goals, **distil a best practice** from disciplinary experiences that makes environmental forecasts credible *across* environmental disciplines, and to **formulate a research agenda** for those areas where we can identify deficits without an existing solution. In addition to publications documenting the results of these activities, we want to write an **application for a DFG Research Training Group** to train a cohort of PhD researchers in a critical and cutting-edge approach to model development and application in the environmental sciences.

3 Exposé of the Research Topic

Environmental Forecasting, as we understand it here, faces the challenge of providing useful information to decision makers for complex, adaptive systems. Environmental systems, from natural lakes over managed forests to tightly interwoven socio-ecological systems, are exceedingly complicated. Their constituents, be it humans, biotic or abiotic factors, are dynamic, adapting and evolving, and interact in myriads of known and unknown ways. As a consequence, quantitative representations of environmental systems (henceforth called "environmental models") are dramatically simplified, even the most complex ones (such as multi-sectoral earth system models).

3.1 Modelling cultures

It is not obvious at all, **which system allows for how much abstraction**, or in other words, how many processes need to be at least represented in an environmental model to allow for useful application. Especially the uncritical use of model predictions, either ahead in time or to new environmental conditions (here collectively referred to as "forecasts" sensu Dietze, 2017), cause unease amongst their developers, as the **forecast horizon**[1] is often unknown.

Apart from the technical challenges both in measuring and in modelling, environmental models are used by very different parties and to very different ends (Fig. 1). In some parts of hydrology, for example, **models are an engineering tool** used to estimate flood hazard. Their main aim is to provide so called 'design-floods' for the construction of flood protection infrastructure.[2] In economics, in contrast, global trading models are to a large extent **tools to investigate strategies** of market participants. Their output is seen not as a realistic value, but a relative success e.g. of a development decision.

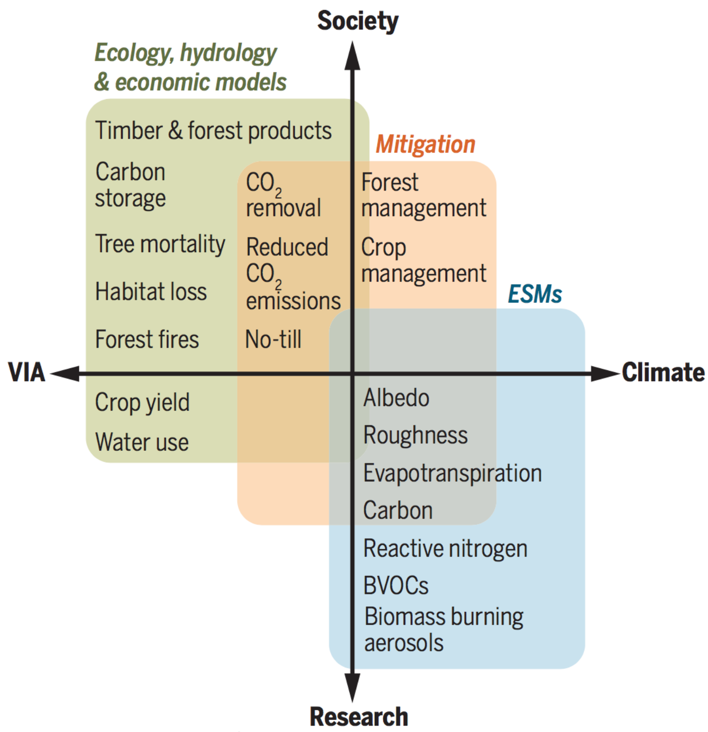


Figure 1: Various environmental processes, and their position on a gradient of societal-to-academic relevance (top to bottom) and the climate-impact gradient (from climate research on the right, to vulnerability, impact and adaptation (VIA) assessment on the left). ESM refers to Earth System Models, which are the most physical description of our world. (From Bonan & Doney, 2018)

[1] The "forecast horizon" (Petchey *et al.*, 2015) delimits where the model prediction becomes untrustworthy because the uncertainty exceeds the trend.

[2] This latter step foregoes a need for 'proper' uncertainty quantification, which from experience is known to be less than the safety margin.

Table 1: The extremes of a gradient of goals for environmental models (prediction or synthesis), and the consequences for technical and philosophical modelling characteristics. Compiled from various sources (Ojima *et al.*, 1991; Clark & Gelfand, 2006; Easterbrook & Johns, 2009; Schmolke *et al.*, 2010; Getz *et al.*, 2018).

Model characteristic	**Prediction** (applied, engineering)	**Synthesis** (academic, understanding, explanation)
metaphor	autonomous driving	standard model in physics
quality criterion	societal relevance	scientifically reproducible
process realism	irrelevant ("stupid")	comprehensive ("monster")
process type	stochastic	deterministic
process uncertainty	model averaging, uncertainty quantification	model comparison
scale selection	scale specific	multi-scale
state variable representation	state-variable specific	multiple state variables
complexity challenge	how much detail is required?	runtime: fitting, sensitivity analysis
data	for training	– (forward modelling)
parameters	case specific	universal
parameter interpretation	"effective" parameters	true parameters
time	future oriented	time neutral

Across and within environmental disciplines, models range from strategic, 'what-if' models, over detailed process-models aiming to capture a specific compartment of a larger system, to authoritative balance-and-quantify models (Table 1). This **complexity gradient** is defined by the level of detail included, but all models here are built on (assumed) system understanding.

Independent of model type one can evaluate models on their predictive performance alone. In the extremes, we can think of a weather forecasting model, which is very detailed and physics-strong, and an autonomous driving system for cars, which is process-free and trained on (lots of) real-world data: both predict fine, albeit for very different reasons. Correct predictions make for credible models, but how to evaluate forecasts into the future? Are there good proxies for forecasting success, or are there other correlates of a credible environmental forecast?

Within each discipline, both the complexity gradient and the skill gradient are intensively discussed (e.g. Moody, 1995; Brooks & Tobias, 1996; **?**; **?**; **?**; **?**), but with extremely little reflection of why they differ *among* disciplines. The few interdisciplinary reviews and guideline papers (Wikle & Hooten, 2010; Committee on Mathematical Foundations of Verification, Validation, and Uncertainty Quantification *et al.*, 2012) neither do justice to the specific uses of environmental forecasts, the epistemology of the field, nor the technical details.

We propose to review forecasting cultures in this Research Focus, in an attempt to understand and better justify methodological decisions in environmental modelling. Key motivations for modelling, and hence for differences in modelling cultures, will include *model purpose* (explanation or forecasting), *target audience* (decision maker, peers, public), *economic impact* (academic, engineering, policy), *community size* (large field, niche group), *education* (physicist, computer scientist, environmental scientist) and perceived *societal importance* (relevance/legitimacy/credibility).

3.2 Best practice for credible environmental forecasts

Scientists have to select among a range of potential models for their specific question and application. Rarely does the question lead to an obvious choice for an approach, and for forecasts to be maximally credible beyond the cultural tradition, the modelling process itself should be reflected upon. Two strategies lead to increasing the *scientific* trust in a modelling approach and hence its subsequent forecasts:[3]

1. Validation of model predictions with unused data, preferably from sites, times and systems different to the ones used to develop and fine-tune the model.

2. Quantification of uncertainty of model forecasts, through propagation of errors from inputs, boundary conditions, parameters and scenarios into model predictions, so as to reveal sources of bias and variance.

Both points have their own challenges. Validation is standard procedure in, for example, meteorological modelling, where new data become available on a daily basis, enabling the forecasters to validate yesterday's (or last week's) predictions. That is not the case for climate modellers and their predictions for 2050 or later. Instead, they often use "hindcasting" (prediction to the past)as validation strategy (e.g. Katragkou *et al.*, 2015), although the future may be driven by processes quite different to those of the past.

Uncertainty propagation is, in principle, open to any modelling approach, either through analytical approaches, Monte-Carlo-like simulations, or bootstrapping (Dietze, 2017). Analytical approaches are (typically) no option for stochastic systems. Some model's computational runtime is prohibitive of numerical methods (e.g. some earth system models running for months for a single simulation), but even here uncertainty analysis is clearly appreciated (e.g. Murphy *et al.*, 2011).

There is a range of challenges that model developers need to address (Table 1). For each of them, the decision process should, ideally, be transparent and guided by what is best for the intended goals. In environmental modelling there is a tendency for a run-away process of increasing detail, simply because we know that a process occurs in nature (although we typically do not know whether it will be relevant for what we want to forecast).

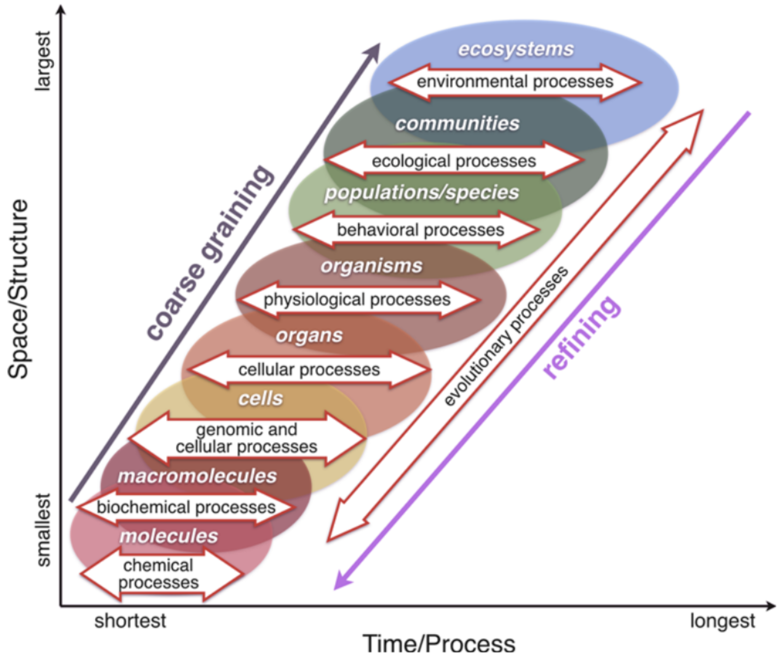
Science, just like any other human activity, is error-prone. The Scientific Method emerged as a long-term strategy of self-correction (Ford, 2000), but how can we achieve *short-term* correctness? One approach is **model comparisons** (Huber *et al.*, 2014), i.e. generating forecasts from different models that try to represent the same state variables (e.g. different climate models, or different forest growth models). Without open-source code, open data and disinterested scientists, such model comparisons cannot be epistemologically valuable: How can we judge models, if each uses different input and scenario data? How can one learn from a 'better' model, if one cannot inspect how it works? Again, modelling cultures may facilitate or obstruct scientific progress and better forecasting.

3.2.1 Strategies to improve environmental forecasts

From an ongoing collaboration within the group of modellers (see section 4.4 below), we preliminarily identified several important elements that differ substantially between disciplines, e.g. consideration of uncertainty and error propagation, identification of a model's forecasting domain, use of observations for model parameterisation, interpretation of model parameters, degree of model comparisons and model code exchange, open-source availability, or attitudes towards necessary level of detail. We cannot here go into detail in all of those, but expound in the following two sections on two exemplary issues: identification of required complexity, and model parameterisation using observed data. These

[3] Very different reasons may persuade *laypeople* to put their faith into predictions from a models: the quality of the presentation; the reputation of the developer; the confirmation of own expectations; the simplicity of the message, and so forth.

Figure 2: Spatial and temporal scales of environmental processes, overlapping and with many examples reaching beyond this apparent hierarchy (e.g. microbial DMSP-production affecting weather processes) (From Getz *et al.*, 2018)



two examples shall provide a brief and necessarily superficial illustration how potential steps in a framework for any environmental model could be discussed.

Identifying required level of complexity through comparison with machine learning Environmental systems have no single process scale (Fig. 2). It is hence a priori unclear, which processes to include in a process model, and which to ignore. Apart from comparing process models that only differ in the inclusion of one process (as is typically done during model stepwise model refinement), one can juxtapose process models with mechanism-free, phenomenological machine-learning models to gauge the level of achievable predictive power this specific state variable can attain.

Phenomenological models benefit from an enormous improvement in flexible modelling strategies (often summarised as 'machine learning'), which can represent non-linearities and interdependencies in the data (Hastie *et al.*, 2009; Jordan & Mitchell, 2015). At the same time, only the data at hand enter this machinery, soon making forecasts extrapolations beyond the data, and hence extremely vulnerable to fundamental mismatches with unobserved data.

Process models, representing 'universal' mechanisms, should be more robust under such extrapolation. However, if mechanisms change, or if mechanisms that may be relevant under different circumstances are not part of the current model, the extrapolation problem is just the same. For example, while the vegetation model PreLES is able to represent current growth and carbon dynamics in boreal forests nicely and across several sites (Peltoniemi *et al.*, 2015; Minunno *et al.*, 2016), it does not allow for a changing CO_2-concentration, biasing forecasts to a carbon-rich atmosphere (Medlyn *et al.*, 2011).

Machine-learning models can be used as a comparison to process models. They show how much the data tell, compared to how much the model structure as defined by the processes constraints the model forecasts. We argue that **regions of discrepancy between correlative and process model predictions indicate where the knowledge about mechanisms has the largest effect**, and should hence be a focus of future research.

Formal statistical calibration with observed data Environmental models of any description have parameters. A common but fundamentally erroneous perception is that such "physical" (or chemical or biological) parameters can be measured in the field or lab, and that hence a model has few "free" parameters not measurable in such a way, and only those need to be calibrated. In fact, all **models are likely to be biased abstractions**, or in other words, structurally wrong. As a consequence, when such a "wrong" model is fitted to data, the optimised estimates for the measurable parameters are typically different from the lab measurements; they become "effective parameters" (Blöschl & Sivapalan, 1995; Samaniego *et al.*, 2017). Indeed, the misfit between lab-parameter values and fitted parameter values is an indication of an incomplete or functionally incorrect model structure and hence can guide model improvements.

Current approaches to model parameterisation thus have a formal statistical framework, which embraces both lab-valued parameters (as *prior* distribution, or knowledge not pertaining to the data: Jaynes, 2003), as well as data to drive parameterisation, yielding the *posterior* distribution of parameter estimates. Any misspecification in the model will make the data "distort" the priors, exhibiting a mismatch of posteriors relative to our lab-based priors.

Our ability to predict the state of our system, as described by the model is represented by the posterior: the wider, the more uncertainty in our prediction. In fact, because the posterior of all parameters is a multidimensional distribution, it contains the uncertainty introduced through all modelling steps so far (data uncertainty, parameter uncertainty, and, if multiple models are used, model strutural uncertainty). Any model prediction using the posterior distribution automatically yields uncertainty estimates, e.g. in the form of a 95% credible interval. So, for a range of environmental models to be applied to a specific question, possibly models ranging from rules-of-thumb to rather sophisticated mechanistic models, the same formal approach can be used to parameterise them, and to compare the uncertainty in their predictions. We hypothesise that in the majority of cases **a sweet spot of balancing explained variance in the data and yielding low variance predictions will be far from either end of model complexities** (following the logic of the "bias-variance trade-off": Hastie *et al.*, 2009).

Additional, and complementary, approaches to assessing the predictive quality of a model are *benchmarking*, which compares the performance on a common problem (typically a common data set), as well as *hindcasting*, which compares model predictions to past data, not used for calibrating the model. Predictions to *independent validation data*, however, are the Gold Standard for assessing model predictive performance. It is a contentious issue, whether it is wiser to use all data for best calibration, or retain some fully independent data to realistically quantify predictive model error (Hastie *et al.*, 2009). *Block cross-validation* (i.e. repeatedly withholding data from fitting and using it as test data) is a compromise between these positions, and the current standard in environmental statistics (Roberts *et al.*, 2017).

4 Work Programme

The working programme has two complementary parts: **causes of disciplinary modelling cultures** and **towards best practice in environmental forecasting**.

4.1 Tier 1: Causes of displinary forecasting cultures

In a two-pronged approach we will try to understand why different disciplines practice forecasting in such very different ways. To do so, we will analyse the arguments put forward in forecasting studies from the disciplines represented in the research focus and beyond (i.e. at least in hydrology, meteorology, forest growth modelling, macro-economic modelling).

Additionally we shall organise a workshop, inviting active environmental modellers to address the question of *How to achieve credibility of environmental forecasts?* This question will inevitably lead to discussions on the purposes, and evaluation of appropriateness, of models in the separate fields, and which current practices ensure a positive uptake of the model and its forecasts in that discipline.

Finally, we shall endeavour to understand the demand-side of environmental forecasting: what do decision makers want and expect from models? While the modelling literature is replete with statements of what *modellers think* decision makers want, far less information is available on what decision makers themselves expect. Typically larger projects with a clear management goal (flood management, forest harvesting, recycling logistics) also provide such a decision perspective, which we shall analyse qualitatively.

4.2 Tier 2: Towards best practice in environmental forecasting

Back-to-back with the exploration of causes we shall develop a fine-grained best-practice framework for environmental forecasting, taking into account the different goals of models, current practice and cutting-edge modelling possibilities (see Section 3.2.1). From many discussions in our group we are confident that the applied-fundamental-dichotomy is far less relevant than is often claimed. Indeed, environmental models face very similar challenges, which can be addressed in a common conceptual modelling framework. Elements of such a framework are, among others, uncertainty quantification, comparisons among models, fit to data, comparison with machine-learning approaches, an open-source culture and strategies to identify relevant processes and scales.

4.3 Environmental systems and the models considered here

Across the team behind this application (see below), our expertise covers a wide range of environmental topics. Among the applicants, we can cover models of biodiversity facets, primary productivity, hydrological process, catchment management, and economic models. The model types range from simple deterministic differential equations in strategic models, over simple deterministic models either parameterised on data or on literature, to complex stochastic models with a large number of parameters, few of which can actually be fitted from data (due to runtime constraints).

Generally we plan activities to be open to the inclusion of a range of different model types, to a wide range of disciplines and across disciplinary borders. At any time, interested modellers may join with their expertise and models, given matching goals. One specific type of model that we will try to embrace are cross-sectoral models, e.g. a natural process, coupled with an economic evaluation and a governance model (see, e.g., Rogelj *et al.*, 2013). The sub-models have necessarily to be relatively simple to still be able to analytically or numerically evaluate its behaviour (e.g. through Monte Carlo simulations).

Our primary focus however will be on models that each of the applicants is familiar with, so as to immediately being able to implement a set of case studies, spanning a range of forecasting questions (error propagation into forecast uncertainty, comparison with machine-learning models, trade-offs in model complexity, parameterisation on data, etc.). We will make use of two project that we are involved with. One of them, PROFOUND,[4] has been at the forefront of such development for a range of forest growth models[5] and aims at comparing forest growth models for a set of reference sites. We can thus build on a standardised set of environmental data, some open-source forest growth models that can immediately be run, and a statistical framework to parameterise the models on these data. Since we use two of these forest growth models already in teaching at MSc-level (BasFor and Preles), this case study shall also guide the second anticipated case study's set-up.

The second case study focusses on analysing and forecasting drought in different catchments across Europe. It will use models from ongoing work within the DRIeR project[6] and ASG-Rhine-Future.[7] Model types include highly parameterized conceptual hydrological models, numerical groundwater models as well as correlative impact and risk models. Previous efforts have focused on parameter uncertainty and ongoing modelling focuses on scenario predictions. The developed models will provide excellent test beds for the elaboration on best-practices for parameterization, validation, as well as uncertainty analysis, quantification and communication.

4.4 Team

The three applicants cover three important, complementary facets of environmental modelling and forecasting: *Carsten Dormann* covers **ecological systems**, including the geographic distribution of species, population dynamics and aspects of forest growth and marine ecology. Additionally, he has a strong interest in the statistical toolbox of model analysis (both sensitivity/uncertainty analysis and inverse (Bayesian) parameterisation, topics he also teaches in the Master Profile "Environmental Modelling & GIS", which he coordinates).

Kerstin Stahl covers **hydrological and water resources system** modelling, including experience with multi-model ensemble analysis. Her interests in the focus area are the challenges of model-coupling and the use of diagnostic indices, e.g. with the aim of reducing uncertainty in climate change attribution.

Stefan Baumgärtner contributes expertise on **economics and ecological-economic modelling**, in particular on linking normative decision objectives and descriptive models, and on how to conceptualize and analyse different types of uncertainty. He is an internationally renowned senior researcher, and through his network in the ecological-economics community will bring excellent international contacts to FRIAS.

The applicants are members of an informal group of process modellers at the Faculty of Environment & Natural Resources, which comprises more disciplines, and more highly experienced scientists, which will contribute to this FRIAS Research Focus:

Prof. Dr Andreas Christen (Environmental Meteorology) measures and describes **urban energy and carbon fluxes**, complemented by & PD Dr Dirk Schindler from the same chair, who models **meso-scale wind effects**.

Prof. Dr Marc Hanewinkel (Forest Economics & Forest Planing) and Dr Rasoul Yousefpour use forest growth models in combination with economic models to understand and predict **forest use**

[4] EU-COST-action, `http://cost-profound.eu/site`

[5] `https://github.com/COST-FP1304-PROFOUND/ProfoundProducts/tree/master/Models`, see also Augustynczik *et al.* (2017); Bagnara *et al.* (2018)

[6] `http://www.drier.uni-freiburg.de`; funded by Water Research Network of Baden-Württemberg

[7] `http://ihf-projektplattform.uni-freiburg.de/asgrhein`; funded by the International Commission for the Hydrology of the Rhine Basin (CHR)

and wood production.

JunProf. Dr Andreas Hartmann (Hydrological Modelling & Water Resources) and his DFG-Emmy-Noether-group model surface and subsurface **water fluxes of karst systems** from local to global scale.

Prof. Dr Stefan Hergarten (Geophysics) investigates geological mass fluxes, such as **landslides**.

JunProf. Dr Stefan Pauliuk (Industrial Ecology) uses economic models to describe local and global **fluxes of materials** such as steel or aluminium, and compute their environmental footprint.

PD Dr Helmer Schack-Kirchner (Soil Ecology) specialises in the description of soil physics, including modelling of **erosion** and **soil organic matter**.

Prof. Dr Markus Weiler (Hydrology) specializes in the use of experimental data to inform and develop credible models from soil column to the small catchment scale. He also works closely with practitioners on **flood hazard modelling** and improved urban hydrology models.

4.5 Organisation of Research Focus

Our basic work model for this Research Focus is an open biweekly meeting of this group, to which we will invite, from the start, other researchers interested in the topic.

The applicants will be responsible for jointly driving the two-tiered approach. In addition to the open meetings, we are planning to spend a large part of our time on demonstrating the feasibility of our approach, which will then lead to the application for a DFG-Research Training Group towards the end of the FRIAS Research Focus.

Since we shall start with the focus on "Forecasting Cultures", the organisation of the workshop and the publication of its results will form an initial main activity.

Simultaneously, we will gently fade in the technical second tier "Towards a Best Practice in (Environmental) Forecasting". This will initially comprise (a) organising data and models for public access and (b) setting up a computing framework for fitting the models. At this point, we shall host an university-wide, one-day workshop to introduce our set-up and strategy to the wider community (i.e. the team as listed under 4.4 as well as the ALU-interests of section 5). At present, we anticipate that this technical workshop will have three elements:

1. Challenges of environmental forecasting with process models.
2. Statistical parameterisation of process models.
3. Model emulation and reference models using machine-learning (see section 3.2.1).

Each of them will be an interface to other researchers at the FRIAS, ALU and beyond. Our internal activities will then seek to link all three up in a few case studies.

4.6 Time table

Start-up phase We want to hold the **workshop** *Credibility of environmental forecasts* early on in this Research Focus, ideally even just before the winter term starts (e.g. early October 2019). This will allow more interested scholars to participate before their teaching phase. As a consequence, we will invite participants already in spring 2019, ask for specific points they want to suggest covering, and preparing some talks ourselves to illustrate important questions for the workshop.

Main phase The main phase will start with the winter term 2019, following the workshop. Our plan is to develop the contributions from the workshop into a **"Forecasting cultures" review**. Also, this workshop will help us detailing the steps of the demonstration case studies, which shall collate the best elements across all environmental forecasting cultures. Right from the beginning, data, source code, technical papers and tutorials will be posted on a project web page, for both internal and external access, facilitating communication with visiting colleagues.

We anticipate to welcome **colleagues for a research stay or shorter visit** along the two tiers outlined above: Refining the aspects of cultures in environmental forecasting; and providing suggestions and guidance on implementing best practice.

Alongside these activities we **develop a research application** for the German Research Foundation (DFG) that will heavily build on both activities. We need the review of cultures to make the point that interdisciplinary reflection on forecasting practice can deliver a clearer understanding of which approach may be useful for which goal. And we need to demonstrate an avenue, if not a fixed framework, for moulding specific environmental models and their forecasts onto. Thus, both Research Fokus tiers contribute complementarily also to our long-term aim of teaching critical forecasting to a new generation of environmental scientists.

The summer term 2020 will start the phase of presenting our work on environmental forecasting to the wider academic community through a **FRIAS research colloquium**. In addition to presentations by the internal and external fellows, we shall also strategically invite colleagues that can contribute controversial and complementary perspectives on our Research Focus' topic.

FINAL PHASE Starting in early summer 2020, we will enter a phase of consolidating what we have achieved: manuscripts will be posted at the day of submission also on the arXiv or equivalent pre-print servers; we will select the most relevant publications into a reader for people entering this research field as novices. We shall finalise the documentation and tutorials to go with the online material.

4.7 Anticipated output

Based on a workshop on *Credibility of environmental forecasts*, we shall produce a **review paper of the current state of practice across environmental disciplines**, which highlights opportunities for learning and improving practices.

We aim to outline a detailed **framework for model forecasting** as a guide for maximising credibility of environmental forecasts. We shall use two case studies (one on Alpine forest growth and one on drought hydrology) to demonstrate the applicability of this framework, and shall provide model, data, documentation and all relevant code as a starting point for a recursive, stepwise improvement and further detailing of this framework.

Another key goal is to use the Research Focus at the FRIAS to develop a **DFG-proposal for a Graduate School on Environmental Forecasting**, training the next generation of competent and critical environmental modellers. While the technical side will probably dominate this application, it is important to understand when environmental forecasting is usefully employed, and where it suffers from curable deficits. Thus, Tier 1 of our work programme (Causes of disciplinary forecasting cultures) is instrumental in being able to outline a way forward.

The work in the Research Focus will be made visible and inviting by a transparent and open-access **web-platform with resources** that allow others to reproduce, improve and contribute to our work (such as a "living" (github-based) online document/resource of the interdisciplinary framework of modelling with links, examples, code, data; a reader containing the most important literature for novices).

5 Importance of Research Focus for the ALU

"Environment and Sustainability" is one of eight "profile fields" of the University of Freiburg.[8] The basis of an environmentally sustainable future is the operationalisation of our understanding of environmental systems, as well as a quantification of our uncertainty about the many things we do not know. Environmental modelling is the prime activity of environmental scientists, both applied and academic, to make our knowledge available to decision making as well as to rigorous experimental testing. As such, the proposed research focus "Environmental Forecasting" is pivotal for making environmental models credible across disciplines. Even if any given field accepts its own standards, in an interdisciplinary science such as environmental research, a common acceptance of methods *across* disciplines is required. Our proposed research focus explicit aims to provide the framework for such an interdisciplinary acceptance, and will lead to an application to train a next generation of critical, open-minded and interdisciplinary cohort of environmental modellers with an explicit and strong routing in both data and application.

The interdisciplinary Faculty of Environment & Natural Resources is already devoted to research in sustainability, but there are many other centres, institutes, departments and individual chairs that we welcome to join in our proposed Research Focus at the FRIAS.

References

Augustynczik, A.L., Hartig, F., Minunno, F., Kahle, H.P., Diaconu, D., Hanewinkel, M. & Yousefpour, R. (2017) Productivity of fagus sylvatica under climate change – a Bayesian analysis of risk and uncertainty using the model 3-PG. *Forest Ecology and Management*, **401**, 192–206.

Bagnara, M., Gonzalez, R.S., Reifenberg, S., Steinkamp, J., Hickler, T., Werner, C., Dormann, C.F. & Hartig, F. (2018) Rlpj: an R package facilitating sensitivity analysis, calibration and forward simulations with the LPJ-GUESS dynamic vegetation model. *Environmental Modelling and Software*, **in revision**.

Blöschl, G. & Sivapalan, M. (1995) Scale issues in hydrological modelling: A review. *Hydrological Processes*, **9**, 251–290.

Bonan, G.B. & Doney, S.C. (2018) Climate, ecosystems, and planetary futures: The challenge to predict life in earth system models. *Science*, **359**, eaam8328.

Brooks, R. & Tobias, A. (1996) Choosing the best model: Level of detail, complexity, and model performance. *Mathematical and Computer Modelling*, **24**, 1–14.

Clark, J.S. & Gelfand, A.E. (2006) A future for models and data in environmental science. *Trends in Ecology and Evolution*, **21**, 375–80.

Committee on Mathematical Foundations of Verification, Validation, and Uncertainty Quantification, Board on Mathematical Sciences and Their Applications & Division on Engineering and Physical Sciences (National Research Council) (2012) *Assessing the Reliability of Complex Models*. The National Academic Press, Washington D.C.

Dietze, M.C. (2017) *Ecological Forecasting*. Princeton University Press, Princeton, N.J.

Easterbrook, S.M. & Johns, T.C. (2009) Engineering the software for understanding climate change. *Computing in Science & Engineering*, **11**, 64–74.

Ford, E.D. (2000) *Scientific Method for Ecological Research*. Cambridge University Press, Cambridge, UK.

Getz, W.M., Marshall, C.R., Carlson, C.J., Giuggioli, L., Ryan, S.J., Romañach, S.S., Boettiger, C., Chamberlain, S.D., Larsen, L., D'Odorico, P. & et al. (2018) Making ecological models adequate. *Ecology Letters*, **21**, 153–166.

Hastie, T., Tibshirani, R.J. & Friedman, J.H. (2009) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer, Berlin, 2nd edition.

Huber, V., Schellnhuber, H.J., Arnell, N.W., Frieler, K., Friend, A.D., Gerten, D., Haddeland, I., Kabat, P.,

[8] `http://www.uni-freiburg.de/forschung-en/research-profile`

Lotze-Campen, H., Lucht, W., Parry, M., Piontek, F., Rosenzweig, C., Schewe, J. & Warszawski, L. (2014) Climate impact research: beyond patchwork. *Earth System Dynamics*, **5**, 399–408.

Jaynes, E.T. (2003) *Probability Theory: The Logic of Science*. Cambridge University Press, Cambridge, U.K.

Jordan, M.I. & Mitchell, T.M. (2015) Machine learning: Trends, perspectives, and prospects. *Science*, **349**, 255–260.

Katragkou, E., García-Díez, M., Vautard, R., Sobolowski, S., Zanis, P., Alexandri, G., Cardoso, R.M., Colette, A., Fernandez, J., Gobiet, A. & et al. (2015) Regional climate hindcast simulations within euro-cordex: evaluation of a wrf multi-physics ensemble. *Geoscientific Model Development*, **8**, 603–618.

Medlyn, B.E., Duursma, R.A. & Zeppel, M.J.B. (2011) Forest productivity under climate change: a checklist for evaluating model studies: Checklist for evaluating model studies. *Wiley Interdisciplinary Reviews: Climate Change*, **2**, 332–355.

Minunno, F., Peltoniemi, M., Launiainen, S., Aurela, M., Lindroth, A., Lohila, A., Mammarella, I., Minkkinen, K. & Mäkelä, A. (2016) Calibration and validation of a semi-empirical flux ecosystem model for coniferous forests in the boreal region. *Ecological Modelling*, **341**, 37–52.

Moody, J. (1995) Economic forecasting: challenges and neural network solutions. *CSETech*, **266**, 8.

Murphy, J.M., Sexton, D.M.H., Barnett, D.N., Jones, G.S., Webb, M.J., Collins, M. & Stainforth, D.A. (2011) Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, **430**, 768–772.

Ojima, D.S., Kittel, T.G., Rosswall, T. & Walker, B.H. (1991) Critical issues for understanding global change effects on terrestrial ecosystems. *Ecological Applications*, **1**, 316–325.

Peltoniemi, M., Markkanen, T. & Härkönen, S. (2015) Consistent estimates of gross primary production of finnish forests - comparison of estimates of two process models. *Boreal Environment Research*, **20**, 196–212.

Petchey, O.L., Pontarp, M., Massie, T.M., Kéfi, S., Ozgul, A., Weilenmann, M., Palamara, G.M., Altermatt, F., Matthews, B., Levine, J.M. & et al. (2015) The ecological forecast horizon, and examples of its uses and determinants. *Ecology Letters*, **18**, 597–611.

Roberts, D.R., Bahn, V., Ciuti, S., Boyce, M.S., Elith, J., Guillera-Arroita, G., Hauenstein, S., Lahoz-Monfort, J.J., Schröder, B., Thuiller, W., Warton, D.I., Wintle, B.A., Hartig, F. & Dormann, C.F. (2017) Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, **40**, 913–929.

Rogelj, J., McCollum, D.L., Reisinger, A., Meinshausen, M. & Riahi, K. (2013) Probabilistic cost estimates for climate change mitigation. *Nature*, **493**, 79–83.

Samaniego, L., Kumar, R., Thober, S., Rakovec, O., Zink, M., Wanders, N., Eisner, S., Müller Schmied, H., Sutanudjaja, E.H., Warrach-Sagi, K. & Attinger, S. (2017) Toward seamless hydrologic predictions across spatial scales. *Hydrology and Earth System Sciences*, **21**, 4323–4346.

Schmolke, A., Thorbek, P., DeAngelis, D.L. & Grimm, V. (2010) Ecological models supporting environmental decision making: a strategy for the future. *Trends in Ecology and Evolution*, **25**, 479–86.

Wikle, C.K. & Hooten, M.B. (2010) A general science-based framework for dynamical spatio-temporal models. *TEST*, **19**, 417–451.