LATE REQUEST FOR A SPECIAL PROJECT 2022–2024

MEMBER STATE: Germany

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Project Title: **AG**ricultural Decision-Tailored (Sub)S**E**aso**N**al **D**rought Forec**A**sting for **S**ub-**S**aharan **A**frica (AGENDA-SSA)

If this is a continuation of an existing project, please state the computer project account assigned previously.	**SP** ___________________	
Starting year: (A project can have a duration of up to 3 years, agreed at the beginning of the project.)	2022	
Would you accept support for 1 year only, if necessary?	YES X	NO ☐

Computer resources required for 2022-2024: (To make changes to an existing project please submit an amended version of the original form.)		**2022**	**2023**	**2024**
High Performance Computing Facility	(SBU)	2,000,000	1,000,000	1,000,000
Accumulated data storage (total archive volume)[2]	(GB)	2,000	2,000	2,000

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[1] The Principal Investigator will act as contact person for this Special Project and, in particular, will be asked to register the project, provide annual progress reports of the project's activities, etc.

[2] These figures refer to data archived in ECFS and MARS. If e.g. you archive x GB in year one and y GB in year two and don't delete anything you need to request x + y GB for the second project year etc.

Extended abstract

Short Abstract

Agricultural productivity and food security in sub-Saharan Africa (SSA) heavily depend on uncertain rainfall. The exposure to climate risk characterizes the livelihood of the majority of the region's population: high rainfall variability impedes the farmers' efforts to intensify agricultural production and negatively affects the level of food security. The overall goal of this Special Project (SP) is to contribute to improving agricultural management strategies with sufficient lead time by optimizing water usage for agriculture. To achieve this goal, two different approaches are pursued: i) Development of improved regionally adapted and optimized seasonal drought forecast products that integrate technical and climatic limitations and farmers' needs, ii) assessment of optimized (intra-)seasonal agricultural management rules by coupling the improved seasonal forecasts with process-based and more simplified mechanistic agricultural sectoral models. This will be achieved by analyzing the skill of the raw- as well as the bias corrected and the dynamically downscaled ECMWF SEAS5 data. For the downscaling (WP3 of this SP), it is applied for 4 Mio. SBUs and 2 TB of permanent storage at the Atos HPC.

Background

In the past, the whole Sub-Saharan Africa (SSA) experienced a long history of rainfall fluctuations of varying lengths and intensities (Nicholson; 2001). Such fluctuations often culminated in crop failures, food insecurity, famines, and mass migration together with negative economic growth. This demonstrates that existing food systems are not robust enough in responding adequately to recurrent droughts. Subsistence farmers in Sub-Saharan Africa (SSA) are highly vulnerable to natural disasters and high climate variability as they grow their crops under rainfed conditions. For the future it is expected that the inadequacy of mitigating droughts and floods will even worsen due to population growth, land degradation, and changing climate. As climate variability is expected to increase further, it will probably create major problems for food production in SSA. Therefore, the vulnerability of agriculture to climate variability must be reduced in the long run through improved technologies in combination with a more informed choice of management practices. Information about the management options to take is needed with a certain lead time (see Table 1).

Table 1: Various agricultural management decisions and typical decision frequencies, modified according to Stone and Meinke (2005). The research concept aims at improving the management decisions on the intraseasonal and seasonal scale (bold font).

Agricultural Management Decision	Typical Frequency (years)
Planting Date	Intraseasonal ($>$ 0.2)
Harvesting Date	Intraseasonal ($>$ 0.2)
Fertilizer/Pesticide Use	Intraseasonal (0.2 – 0.5)
Supplementary Irrigation	Intraseasonal (0.2 – 0.5)
Crop Type	Seasonal (0.5 – 1)
Crop Sequence	Interannual (0.5 – 2.0)
Crop Rotation	Annual/Biannual (1 – 2)
Crop- and Agricultural Industry	Decadal to interdecadal (10 – 20)
Landuse and Climate Change Adaptation	Multidecadal ($>$ 20)

Research into local climate perceptions and knowledge showed that farmers in SSA are keenly aware of the growing variability of weather and climate (West et al.; 2008) and open to receiving scientific climate forecasts as they believe that their own traditional predictions have become less reliable due to increasing climate variability. Figure 1 shows the inherently high intra-annual rainfall variability of the past four decades in a typical region, i.e., the Mwea irrigation scheme in the Tana river basin in Kenya. This high intra-annual variability underpins the need to optimally capitalize the time window for cropping and the need for reliable (sub)seasonal forecasts. The planting date plays a crucial role in this context (e.g., Laux et al.; 2008, 2009,2010 & Waongo et al., 2013). Planting too early might lead to total crop failure in case no significant rain falls in the following days, whereas planting too late is reducing the vegetation period and thus crop yield as well. Farmers, in general, are willing to change their management actions, primarily the time of planting and the selection of cultivars (Patt et al.; 2005) as well as the cropped area (Phillips et al.; 2001).

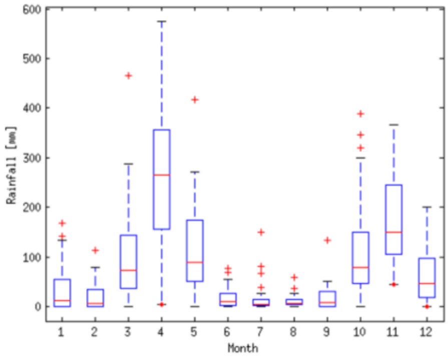

Figure 1: Intraannual rainfall variability at the Mwea irrigation scheme, Tana river basin, Kenya (1970-2010). The boxes represent the mean 50% of the distribution, while the whiskers illustrate 1.5 x the interquantile range. Outliers are shown as red crosses.

Seasonal meteorological forecasts are routinely produced by World Meteorological Organization (WMO) Global Producing Centers, such as the National Center for Atmospheric Research (NCAR), the European Centre for Medium-Range Weather Forecasts (ECMWF), and other international climate centres, such as the International Research Institute for Climate and Society (IRI). They are potentially useful to improve drought forecasts. Regional Climate Outlook Forums (RCOF) were initiated in southern, eastern and western Africa in 1997/98.

Supported by the previously mentioned climate forecast centres, RCOFs bring together national meteorological services (NMS) and various users to develop and distribute a consensus forecast of rainfall (and sometimes other variables) for the coming season. These national forecasts are constructed based on primarily statistical regression-based methods (Hansen et al.; 2011). Both regional and global seasonal forecast products, however, do not provide adequate information to directly support farmers in their decision on an intra-seasonal time scale. For Burkina Faso, for instance, research indicates that the existing scientific regional seasonal climate forecasts currently produced at the PRESAO and disseminated by the *Direction Générale de la Météorologie* are of limited usability (Ingram et al.; 2002). Their limitations center on the variables forecasted, temporal and spatial scales, lead time, and skill of products are found to be heavily biased (Hopson and Webster; 2010; Webster et al.; 2010) and provide information about seasonal rainfall amount only expressed as tercile probabilities compared to the long-term mean values, i.e., below normal, normal, and above normal. In all agroecological zones of Burkina Faso, however, farmers stressed the importance of duration and distribution of rainfall over time and space rather than the seasonal amount (Roncolli et al.; 2003). Intra-seasonal or sub-seasonal rainfall characteristics, such as timing, frequency, and intensity of precipitation, and drought conditions are difficult to forecast (Barnston et al., 2010).

Skill is found for ECMWF seasonal forecasts over the Greater Horn of Africa (GHA) using ECMWF's System 4 and 5 (SEAS5), particularly for the OND season at long leads (Dutra et al; 2013, Mwangi et al.; 2014, MacLeod; 2018). Therefore, it is decided to apply the latest product (SEAS5) for this Special Project.

Outline of Research Plan

Based on the research needs that were identified for SSA in the past, the research concept will be outlined below. An interdisciplinary approach, consisting of climate modeling, agricultural modeling, and agricultural decision support for efficient and sustainable use of water is to be pursued. The goal of this approach is to develop scientifically sound intra-seasonal and seasonal agricultural management strategies for decision support and sufficient lead time by optimizing the usage of water for agriculture. Beyond the 3-year planning period, the research activities can be expanded by specific improvement of single components, such as the implementation of pests and diseases in agricultural modeling or the impacts of high ozone concentrations or the exposure to high-temperature stress during critical crop development stages and its effects on crop health. The proposal considers biophysical processes only, but socio-economic drivers, such as global and regional market prices, also trigger a range of inseparable responses in yield, including abrupt changes (e.g., policy interventions), smooth trends (e.g., technical innovation). Moreover, this project has great potential to be linked with Malaria forecasts, reservoir management, or with livestock management in SSA. The research plan is subdivided into the following four work packages (WPs):

WP1: Skill and Predictability of Agrometeorological Variables Derived from Observations and Global Seasonal Forecasts

Retrospective and real-time global seasonal forecasts by the global seasonal forecasting system of ECMWF (SEAS5) will be analyzed. A comprehensive assessment of their forecast performances will be made using different verification techniques to determine the skill of ensemble and probability forecasts, such as the ranked probability skill score (Wilks; 2006). This will be done for three-month precipitation amount and monthly mean temperature, and for different spatiotemporal scales and lead times. The forecasts will be compared to monthly gridded observations, such as CRU (Harris et al.; 2012) and evaluated for both, the retrospective and the real-time forecasts with a special focus on droughts. Recently, Portele et al. (2021) demonstrated the economic-value of using seasonal forecasts in water reservoir management. Beyond the analysis of standard variables obtained by the global seasonal forecasts, integrated drought indices, such as the Standardized Precipitation Index (SPI) (McKee et al.; 1993; Guttman; 1999), the Effective Drought Index (EDI) (Byun and Wilhite; 1999) and other agricultural drought indices, including meteorological variables critical for the plant-available water computed from daily time scales, will be analyzed. These indices will be computed based on the daily observations and the retrospective seasonal forecasts of SEAS5. This analysis will serve as a baseline for the following WPs.

WP2: Statistical Bias Correction of Global Seasonal Forecast Products and Determination of Conditional Forecast Skills

After assessing and evaluating the predictability of agrometeorological parameters and the skill of these parameters within operational global seasonal forecasts, these forecasts will be post-processed as a means of producing enhanced predictors for regional and local climate variability. Different state-of-the-art bias correction techniques will be applied. Simple techniques, such as quantile mapping, in which the observed cumulative distribution function (CDF) of precipitation is mapped onto the numerically generated CDF, will be compared with more sophisticated approaches, such as copulas (Laux et al.; 2011) or multivariate methods as already tested for the SSA region (e.g., Adeyeri et al; 2020, Dieng et al.; 2022). Applying those bias correction techniques to the SEAS5, daily temperature, precipitation forecasts (as well as other relevant variables for agricultural impact models) will be adjusted for SSA. After identifying crucial agrometeorological variables, oceanic, atmospheric, and land surface conditions that potentially enhance the predictability of these variables are analyzed systematically, e.g., sea surface temperature in the Guinean Sea as a precursor of the regional start of the wet season in the Volta basin (Laux et al.; 2009). Indices for potential precursor parameters are identified and used for conditioning of the forecast products. Dynamically evolving conditioned skill maps are developed for identifying regions with enhanced predictability as a function of the state of the observed system both at the time of initialization and during the evolution of the growing season. This analysis will provide important additional information on when (i.e., for what initial states) the skill of the forecasts is expected to be high and when it becomes negligible (Branstator and Teng; 2012).

WP3: Regional Seasonal Forecasts Using Dynamic Downscaling Techniques and Novel Statistical Techniques for Predicting Agrometeorological Variables and Drought Indices

In WP3, SEAS5 seasonal forecasts will be dynamically downscaled using a nested-approach in Weather and Research Forecasting (WRF). For two selected years, a relatively wet and a dry year, the retroforecasts (1 member only, lead time 0) will downscaled to provide highly resolved seasonal forecasts for the forthcoming rainy season. This will be done using a target resolution of 9 km based on a given geographical setup and a set of physical parameterization schemes (Laux et al., 2021a). Based on the results of Laux et al. (2021a) and Siegmund et al. (2013), the Cumulus (Cu) parameterization plays the most crucial role for the variability of the obtained simulation results in SSA, in particular for the simulated precipitation patterns. Therefore, at least 3 more Cu schemes will be tested. Moreover, it is tested for selected member(s) whether there is an additional improvement by applying convection-permitting simulations (i.e., without using Cumulus parameterization). The performance of WRF is assessed by comparing e.g. drought indices (see WP1) with the performance of the raw SEAS5 data

(WP1) as well as the bias-corrected SEAS5 data (WP2). The added-value of the increased resolution by the dynamical downscaling is assessed. Since SEAS5 are probabilistic forecasts, the variability of the simulations will be quantified using the perturbed initial condition (PIC) members of the SEAS5 retroforecast (see Figure 2). It will be checked whether or not the ensemble can be restricted to a smaller ensemble size to save computational resources. Another important aspect is the impact of the lead time on the performance of the WRF simulations (Figure 2). For this reason, simulations using different lead times will be analyzed in WP3.

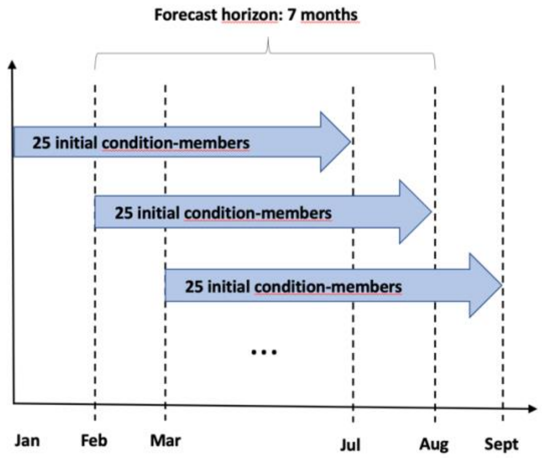

Figure 2: ECMWF-SEAS5 retroforecast product. The product is a coupled ocean-atmospheric model, which is initialized on the 1st of every month for a forecast horizon of 7 months. The ensemble consists of 25 to allow an assessment of the uncertainties due to perturbed initial conditions.

The following Specific Tasks are performed for WP3:

WP3.1 Horizontal resolution & Cu parameterization runs (first year):

A set of WRF downscaling experiments for SSA using two different spatial resolutions (9 km, 3 km) for a wet and a dry year in order to derive the added-value of the improved resolution; the 9 km-runs are driven by Cu schemes, which haven't been tested yet for the SSA region. This will lead to the decision if covection-permitting resolutions shall be performed or if coarser resolutions are sufficient. Due to the computational expenses of convection-permitting simulations, this is a crucial first step. Note that the demands of CPUh for the year 2 and 3 depend on the results of WP3.1.

WP3.2: PIC runs (second year):

Based on the most promising setup found in WP3.1, the 25 perturbed initial condition (PIC) members of the retroforecast period for the two selected years (i.e., the rainy season of a dry and a wet year) are dynamically downscaled. The variability of the PIC ensemble is analyzed. It will be analyzed if the ensemble spread can be reduced (compared to the raw SEAS5 data) and if the PIC ensemble can be restricted to fewer members (e.g., considering a randomly selected ensemble of 5 members).

WP3.3: WRF lead time runs (third year):

Based on WP3.1 & 3.2, the rainy season is simulated by applying different lead times, ranging from lead time 0 (no lead time) to 4 (4 months lead time). This will be done separately for the wet and the dry year, since the predictability might differ significantly for dry and wet years, respectively.

WP4: Optimized Agricultural Management Rules to Facilitate Improved Planting Dates and Other Intraseasonal and Seasonal Decisions with Lead Time

The determination of the onset of the rainy season is the most urgent issue for farmers in the Volta basin (Ingram et al.; 2002; Laux et al.; 2009) and Kenya (Camberlin and Diop; 2003; Camberlin et al.; 2009). In WP4, planting schedules are optimized for meteorological information obtained from the seasonal predictions. After reviewing approaches to estimating the planting dates for SSA, the rainfall-based approach as developed and tested for the Volta basin (Laux et al.; 2008, 2009; Waongo et al.; 2013) and

Cameroon (Laux et al.; 2010) will be further improved and applied to SEAS5 data for the first time. Planting rules will be converted into mathematical expressions using fuzzy logic and optimized for different crops, crop varieties, and locations by coupling the new approaches with process-based crop models (e.g., CropSyst, GLAM) or more simple mechanistic models such as Crop Suitability (Laux et al., 2021b). The coupling explicitly aims at optimizing planting dates (or other management decisions), but intrinsically also accounts for growing conditions throughout all crop development stages, because the modeled yield is an integrator function of many explanatory variables, such as radiation, temperature, precipitation, and soil. The crop models act as surrogate laboratories, and once they are calibrated and validated for SSA, they can be driven by seasonal climate forecasts and different management decisions. Besides planting rules, rules for supplementary irrigation and fertilization will be derived to support decisions as to where, when, and what to plant for the forecasted upcoming or ongoing season. Collaborations with agricultural research institute in SSA exist, which are interested in collaborating and sharing research findings of field experimentations needed for the calibration of crop models.

Justification of Computer Resources Requested

It is applied for **4 Mio. SBUs at the Atos HPC** to conduct the works suggested in WP3. Since more trial-and-error simulations (resolution impact and Cu scheme impact) are necessary during the first year, it is applied for 2 Mio. SBUs, whereas for year 2 and 3 only 1 Mio. SBUs are estimated. However, the number of SBUs depends on the results obtained after the first year, thus a modification might be necessary to successfully conduct the simulations thereafter (see Specific Tasks of WP3). Calculations and simulations for the other WPs (such as the impact models) do not need HPC and will be performed at the linux cluster at KIT/IMK-IFU in Garmisch-Partenkirchen.

Before applying WRF, the SEAS5 data will be retrieved from the MARS archive. Access to MARS is given to the PI (userid: de4l). Several preprocessing steps (ungrib, metgrid, real, all of them part of the WRF preprocessing tools WPS) are necessary to get the input files ready to run WRF. Both, WPS preprocessing steps and WRF simulations require HPC resources and will be done on the Atos HPC system.

Therefore, a test account is required to perform performance tests (scalability). Code performance analyses such as speedup depending on the number of nodes will be performed at the beginning of this special project. This will finally allow for a more accurate estimation of the required CPUh. The PI holds experience on different HPC systems (e.g., at ForHLR2 in Karlsruhe, SuperMUC in Munich, and at Cray XE6 in Stuttgart). **Approximately 2 TB of permanent storage** are required to perform WRF simulations simultaneously and to preprocess the input data in WP3.

Technical Characteristics of the Code

The Regional Climate Model to be used to downscale global-scale seasonal climate forecasts is in this special project is the *Weather Research and Forecasting/Advanced Research* (WRF) model (Skamarock et al.; 2005). WRF is a mesoscale numerical weather prediction system and climate model. It is the community regional atmo- spheric model developed primarily at the *National Center for Atmospheric Research* (NCAR) and other US weather-related institutions with contributions from a worldwide user community. WRF is used in a very wide range of applications from idealized large eddy simulation case studies to operational weather forecasts of national weather services as well as long regional climate change runs, just to name a few. Updates are annually with a major release in spring and a bug-fix release in autumn, the current release is v4.2 WRF is to be used with the ARW solver: The equation set for ARW is fully compressible, Eulerian and non-hydrostatic with a run-time hydrostatic option. It is conservative for scalar variables. The model uses terrain following, hydrostatic-pressure vertical coordinate with the top of the model being a constant pressure surface. The horizontal grid is the Arakawa-C grid. The time integration scheme in the model uses the third-order Runge-Kutta scheme, and the spatial discretization employs 2nd to 6th order schemes. The model supports both idealized and real-data applications with various lateral boundary condition options. The model also supports one-way, two-way and moving nest options. It runs on single processor-, shared- and distributed-memory computers. In this case, it is compiled to be used on a distributed-memory machine.

References

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