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Determining spatial variability of dry spells – a Markov based method, applied to the Makanya catchment, Tanzania

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Abstract

With a growing world population and a trend towards more resource intensive diets, pressure on land and water resources for food production will continue to increase in the coming decades. Large parts of the world rely on rainfed agriculture for their food security. In Africa, 90 % of the food production is from rainfed agriculture, generally with low yields and a high risk of crop failure. One of the main reasons for crop failure is the occurrence of dry spells during the growing season. Key indicators are the critical dry spell duration and the probability of dry spell occurrence.

In this paper a new Markov-based framework is presented to spatially map the probability of dry spell occurrence. The framework makes use of spatially varying Markov coefficients that are correlated to readily available spatial information such as elevation and distance to the sea. This map is then related to the critical dry spell duration, based on soil properties and crop water requirements, to assess the probability of crop failure.

The results show that in the Makanya catchment the probability of dry spell occurrence is highly variable in space, even over relatively short distances. In certain areas the probability of crop failure reaches levels, which makes rainfed agricultural practices unsustainable, even close to areas where currently rainfed agriculture is successfully practiced.

This method can be used to identify regions that are vulnerable to dry spells, and subsequently to develop strategies for supplementary irrigation or rainwater harvesting.

1 Introduction

Globally, increasing population causes increasing pressure on the available water resources, which represents a major challenge in water management (Falkenmark, 1998). In the case of sub-Saharan Africa, population is growing rapidly and a shift to a more resource intensive diet is expected (Savenije, 1999; WWAP, 2009),

requiring more use of the resources. These resources vary both spatially and temporally, alternating wet and dry years, and large variations between different locations (e.g. Mul et al., 2009). Climate change is expected to aggravate the situation. At the same time, average yields produced by rainfed agriculture have not increased, despite decades of investments in improving smallholder agricultural practices, yields still fluctuate around 1 ton ha^{-1} (Rockström et al., 2004). With increasing urbanisation, average food production per capita is declining (Love et al., 2006). In rural areas, demographic pressure and the limited availability of arable land, force people to move from areas where conditions are favourable to areas and ecosystems where conditions are less favourable or marginal (Enfors and Gordon, 2007).

In sub-Saharan Africa, rainfed agriculture is responsible for 90 % of the food production and 80 % of the population rely on it for a living (Rockström, 2000). However, rainfed agriculture has a high risk of crop failure with water as a main limiting factor (Savenije, 1998; Enfors et al., 2011; Makurira et al., 2011; Mutiro et al., 2006). The dependency on the irregular input of precipitation can cause a shortage of water commonly known as droughts or dry spells (Savenije, 1998; Rockström, 2003; Enfors and Gordon, 2007). The definition of a drought is differently used in meteorology, hydrology and agriculture (Rossi et al., 1992). Each discipline has its user-specific thresholds for declaring a drought (Mishra and Singh, 2010; Rockström, 2003; Rossi et al., 1992; Wilhite and Glantz, 2012). For a drought not only the amount of water in terms of volume is relevant, but also its availability at the time it is mostly needed. Especially for rainfed agriculture, the knowledge of water fluxes and the alteration of wet and dry periods is essential (Rockström, 2000, 2003).

Mathugama and Peiris (2011) showed that many authors in different countries analyzed long-term rainfall data related to dry spell characteristics with different techniques and varying data availability. Although sub-Saharan Africa has a long history of precipitation records, the spatial coverage of stations is coarse and data can be unreliable (De Groen and Savenije, 2006; Røhr and Killingtveit, 2003). Constrained by data availability, studies on precipitation usually give estimates on point scale processes (Barron

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et al., 2003; El-Seed, 1987; Sivakumar, 1991) which are sometimes generalized for a region (Enfors and Gordon, 2007; Ochola and Kerkides, 2003). Different studies tried to move beyond the point scale and give estimates of risk on water stress for a region (Deni et al., 2008; Yoo et al., 2012). For Tanzania, Tilya and Mhita (2007) analyzed the spatial and temporal frequency of wet and dry spells with 22 rain gauges spread over the country. This study shows the spatial structure of dry spells of Tanzania: Long wet spells in the north eastern highlands and long dry spells in the centre part of the country (Tilya and Mhita, 2007). At the same time, Mul et al. (2009) show that precipitation can be very localised and highly variable, this affects the reliability of interpolating precipitation estimates from long but coarse spatial resolution rain gauge data.

In addition to the meteorological input dynamics, site specific characteristics, such as soil properties affect crop yields, as they determine water availability in the root zone (Enfors and Gordon, 2007). Crop water stress depends on the water holding capacity of soil, water demand and antecedent wetness conditions (Barron et al., 2003). In rainfed agriculture, soil water storage can buffer for dry spells. If the water availability in the soil cannot buffer for the difference between supply and demand, the development of plants will be hampered and in worst case the plants will wither. This will happen if a dry spell lasts longer than the available soil moisture can supply. We defined this period as the critical dry spell.

2 Methodology

2.1 Study area

The study area is a tributary in the Pangani basin ($43\,600\,\text{km}^2$), the Makanya catchment ($\pm320\,\text{km}^2$), which is located in the South Pare Mountains (see Fig. 1). The area experiences a bimodal rainfall pattern (Griffiths, 1972; Rohr and Killingtveit, 2003), consisting of a short rainy season called *Vuli* (October–December), followed by a longer rainy season called *Masika* (March–May) (Tilya and Mhita, 2007). Rainfall in the catchment

varies with altitude, the higher areas receive on average ±800 mm yr^{-1} compared to the lower regions with ±550 mm yr^{-1} (Mul et al., 2008).

In this area, the majority of the people are traditional small scale farmers whose livelihoods depend on rainfed agriculture and supplementary irrigation (Makurira et al., 2007; Mul et al., 2011). Like other sub-Saharan regions, population growth leads to land pressure and an expansion of agricultural land into other types of ecosystems (Rockström et al., 2004; Enfors and Gordon, 2007). The dominant migration is from the higher elevation, with abundant water, where land is becoming scarce to more water scarce regions in the valley. For most of the years, supplementary irrigation is required to obtain reasonable yields (Mul, 2009), the actual need for supplementary irrigation is related to the occurrence of dry spells at that particular location, and the water holding capacity of the soils (Enfors and Gordon, 2007).

As Mul et al. (2009) show, rainfall is highly variable in this area, farmers migrating to less favourable areas face two-fold challenges, the rainfall distribution (in terms of dry spell occurrences) and soil characteristics in the new location. Therefore we need to improve the knowledge on spatial and temporal rainfall characteristics in combination with site and crop characteristics. In this study we present a Markov-based framework which maps and regionalises the probability of dry spells.

2.2 Markov-based framework for critical dry spell analysis

The following Markov-based framework (see Fig. 2) has been applied to assess the spatial probability of occurrence of a critical dry spell in the Makanya catchment for which a short, but high spatial resolution data set on rainfall exists. However to be able to assess the probability of dry spell occurrences, long time series are required. In the Pangani basin, there are a number of stations, which have up to 90 yr of daily rainfall data. The Markov chain properties for these stations were determined and then regionalised using a multiple linear regression correlation model using elevation and distance to the sea. Using these spatially determined properties and the interpolated seasonal

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rainfall map for the Makanya catchment, maps are created showing the duration of a dry spell for a particular probability of occurrence (20, 50 and 80 %). At three locations, the probability of dry spells was compared to the critical dry spell length, based on soil properties and potential evaporation. In order to assess the probability of a critical dry spell occurring at these locations, the dry spell length was drawn as a function of the probability.

2.3 Spatially distributed Markov chain properties

Dry spells are defined as a number of consecutive days without rainfall (for this study the threshold was set at 0.1 mm day^{-1}), and consecutive days with rainfall are called wet spells. The interchange between wet and dry days can be stochastically described by Markov chains (Gabriel and Neumann, 1962). This study adopted first order two state Markov chains to describe wet and dry spells where the probability of a wet or dry day only depends on whether the previous day was a wet or dry day. This method was already successfully adopted in the region by several authors (De Groen and Savenije, 2006; Biamah et al., 2005; Barron et al., 2003; De Groen, 2002; Madamombe, 1994; Sharma, 1996). In Markov chains, the transition probability is defined as the ratio of the number of transitions from one state to another to the total number of transitions (see Eq. 1). In this way, the probability that a dry day is followed by a wet day can be written as Eq. (2), and the probability of a wet day after a wet day as Eq. (3).

$$p_{xy} = \frac{\sum t_{xy}}{\sum t_x} \tag{1}$$

$$p_{01} = \frac{\sum t_{01}}{\sum t_0} \tag{2}$$

$$p_{11} = \frac{\sum t_{11}}{\sum t_1} \tag{3}$$

De Groen (2002) showed that individual monthly transition probabilities p_{01} and p_{11} can be expressed as a power function of the monthly rainfall (see Eqs. 4 and 5).

$$p_{01} = a_{01} P^{b_{01}} \tag{4}$$

$$p_{11} = a_{11} P^{b_{11}} \tag{5}$$

Comparing different locations in Zimbabwe, De Groen and Savenije (2006) show that the power functions coefficients a and b can be regionalised to describe the Markov probabilities for different rain gauges distributed in space. This spatial correlation can be used to determine the spatial distribution of the probability of dry spell occurrence. To do so, the coefficients a_{01} and a_{11} were fixed at the average value of all stations (see Eqs. 6 and 7):

$$p_{01} = \bar{a}_{01} P^{b_{01}} \tag{6}$$

$$p_{11} = \bar{a}_{11} P^{b_{11}} \tag{7}$$

Subsequently we allowed the exponent, **b**, to vary in space. We applied a simple formula, whereby the Markov coefficient (**b**) is a function of altitude (**H**) and distance to sea (**D**):

$$\boldsymbol{b} = \alpha + \beta H + \epsilon D \tag{8}$$

where α, β and ϵ are the regression coefficients. The values for α, β and ϵ, are derived by performing a multiple linear regression using spatial information on altitude and distance to the sea. In combination with an interpolated seasonal rainfall map, using Ordinary Co-Kriging, the spatially distributed transition probabilities p_{01} and p_{11} for ungauged locations can be obtained (see Fig. 2).

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2.4   Probability of dry spell duration

For rainfed farming, the critical factor determining crop failure is the maximum dry spell duration that can be expected during a growing season. De Groen (2002) developed an expression for the maximum dry spell length with a probability of occurrence F. This yields for a certain point, with transition probabilities p_{01} and p_{11} and for a given probability of non-exceedance F, the maximum dry spell length $n_{\text{dry,max}}$:

$$n_{\text{dry,max}}(F) = \frac{\ln\left(\frac{\ln(F)}{-n_{\text{ls}}\left(\frac{p_{01}}{p_{11}-p_{01}}\right)(1-p_{11})}\right)}{\ln(1-p_{01})} \qquad (9)$$

With the interpolated transition probabilities p_{01} and p_{11}, the dry spell length for ungauged locations can be derived. The result is a spatial map with dry spell length of a given probability of occurrence for ungauged locations.

2.5   Critical dry spell

The critical dry spell length is the time period that the ecosystem can bridge. It is the ratio between the available soil moisture and the transpiration rate of the vegetation (see Eq. 10). If the transpiration demand is larger than the available soil moisture the development of the plant will be hampered or, in the worst case, the plant will wilt. The critical dry spell length (n_{cr}) can thus be calculated at every point in space as the ratio of the available soil moisture (θ) to the potential evaporation (E_{p}).

$$n_{\text{cr}} = \frac{\theta}{E_{\text{p}}} \qquad (10)$$

Due to data limitations of spatially distributed soil moisture and evaporation measurements in the Makanya catchment, the critical dry spell length has been calculated for

only three locations. Location 1 and 2 were selected in the lower middle part of the catchment with coarse erosion sediments, while location 3 was selected for higher altitudes with clayey soils (see Fig. 1 for locations). Soil moisture measurements in the catchment indicated that the maximum soil moisture content varies between 8 and 12 % (Makurira et al., 2010). To estimate the available soil moisture stock it is assumed that maize, the staple crop grown in the area, has a root depth of approximately 500 mm. With the assumption that at the beginning of the rainy seasons this stock has been replenished, the available soil moisture for the crop is around 10 % (50 mm). Data collected from a Class A-pan in locations 2 (Valley) and 3 (Mountain) was used to determine the potential evaporation (Fig. 4).The critical dry spell length is then combined with the probability of a dry spell occurring, providing essential information on the vulnerability of an area.

3 Results

3.1 Markov properties

The Markov properties were determined using the eight available rain gauges in the Pangani basin (Fig. 1), the transition probabilities (p_{01} and p_{11}) for each of these stations were calculated for the three individual month of the Masika season (March, April and May) and for the season as a whole using Eqs. (2) and (3) (Table 1). Single seasonal transition probability values scatter around a median value of a rainfall class (De Groen, 2006). To demonstrate the stability of the power function, individual transition probabilities were clustered in at least 6 rainfall classes with their median transition probabilities (Fig. 3). The transition probabilities expressed on a monthly basis show better correlation (see Table 1), however for the further analysis we will focus on the seasonal Markov properties, as we intend to demonstrate the framework related to the agricultural production, which is a function of seasonal precipitation. Figure 3 and

Table 1, show the variability of the coefficients a and b of the power function of the transitional probabilities calculated using Eqs. (4)–(7).

The results of the multiple linear regression model, using the eight rainfall stations in the Pangani basin, are presented in Table 2. These coefficients are subsequently used in the Makanya catchment to obtain the spatially variable Markov coefficients b_{01} and b_{11}. To obtain the spatial transition probabilities p_{01} and p_{11}, the daily rainfall set in the Makanya catchment (16 stations) was regionalised to produce rainfall maps. The Masika seasons used (2006) was considered a "wet" season with above average precipitation amounts. To compensate for this, the rainfall amounts were scaled to an average of the rainfall season. The scaling factor is derived by dividing the seasonal rainfall value of the Masika season in 2006 by the long term average amounts for the rain gauge located in Same (1940–2007) resulting in a factor of 0.55 [–]. All rain gauge data of the Makanya catchment for Masika season 2006 were scaled by this factor. This new "synthetic" rainfall data has been used for Ordinary Co-Kriging to make a rainfall map for further analysis (see Table 3 for Kriging results and Fig. 4a for the map). The combination of the fixed coefficients, $\bar{a}_{01}$ and $\bar{a}_{11}$, the spatially distributed coefficients, b_{01} and b_{11}, with the seasonal rainfall map, making use of the power functions of Eqs. (6) and (7), provides the spatially distributed transition probabilities map of p_{01} and p_{11}.

3.2 Dry spell maps

Three different dry spell maps (Figs. 4b–d), were compiled using the interpolated rainfall map of the Makanya catchment (Fig. 4a). These three graphs show the probability of non exceedance of dry spells of 80 %, 50 % and 20 % (based on Eq. 9). A high spatial variability of precipitation and dry spells is visible within the Makanya catchment. In the higher parts of the catchment, rainfall amounts are higher and the probability of long dry spells is lower. This information is combined with the information on critical dry spells length for the three locations, which ranges between 8 and 17 days depending on the soil type and potential evaporation (see Table 4 and Fig. 5).

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The probability of occurrence of a critical dry spell for the three sites ranges between 5 % for the higher areas and 90 % for the lower areas (see Fig. 5). Not only is this a result of the higher probability of dry spells, this also is due to the lower soil moisture holding capacities in the lower areas.

5   The results indicate that not only are the areas in the valley affected by the higher probability of occurrence of dry spells, this area is also more easily affected by dry spells due to the soil properties and higher potential evaporation.

4   Discussion and conclusion

The presented Markov-based framework clearly shows the high spatial variability of
10 dry spell occurrences. Previous research focussed on evaluating point data, which is often very coarse. In many areas, the required information is insufficient to assess the spatial vulnerability of local agriculture to dry spell occurrences. The results presented are based on parameters determined using the Masika season as a whole. As we show in Sect. 3.1, the transition probabilities using monthly values show a better correlation,
15 But since farmers require seasonal rather than monthly information we focussed on the Masika season. We applied the same approach to the Vuli season, but the results were not as good as for the Masika season. In particular the MLR model performed worse due to the fact that the main wind direction during the Vuli season is north and rainfall is therefore not related to the distance to the sea (which is located east of the
20 catchment). As a result, an alternative MLR model may have to be developed for the Vuli season. The framework, however, requires substantial amount of short term data to be able to spatially distribute the Markov chain properties. In addition, the use of an above average season of Masika in 2006 and its dry spell map underestimate the situation for certain years. Still the dry spell map clearly demonstrates the regional
25 behaviour and underlines the need for spatially distributed dry spell analysis.

In applying this approach we have used Class A Pan evaporation as a proxy for potential evaporation, which may not be fully correct. However, the framework is

independent of the method used to determine the potential evaporation or the available soil moisture. The essence is that both the meteorologically expected dry spell length and the critical dry spell length vary in space and that the matching of these two quantities provides an indication of areas where farmers have difficulty achieving a reliable yield.

This paper demonstrates a framework for assessing the spatial distribution of critical dry spells in a data scarce environment. The results show that within a 5 km radius, the probability of the occurrence of a critical dry spell ranges between 5 and 90 %. This is both related to soil conditions and potential evaporation which result in a range of the critical dry spell length between 8–17 days. In addition, in the valley with lower rainfall amounts, the probability of dry spells is also higher. This combination, low soil water content, high potential evaporation and long dry spell occurrences in the valley contribute to the high vulnerability of this area (90 %) to droughts. At the same time, in these areas access to surface water to supplement the shortage in rainfall is limited. In contrast, at location 3 in the mountains, dry spell occurrences are not frequent, soil properties are good and potential evaporation is low. In addition, surface water is plentiful and can supplement rainfall.

Using the spatial information on dry spell occurrence in water management provides opportunities to develop new water management strategies by: (1) indicating potentially water scarce regions, (2) developing techniques to improve soil characteristics or decrease non-productive evaporation fluxes, (3) increasing storage to bridge dry spells or decrease the vulnerability to dry spells.

This study sets the first step to use available rainfall data to reveal spatial and temporal patterns of dry spell occurrence. The next step would consist of developing spatially distributed soil and potential evaporation maps and to combine these with dry spell maps for the entire region, resulting in a spatially distributed critical dry spell map.

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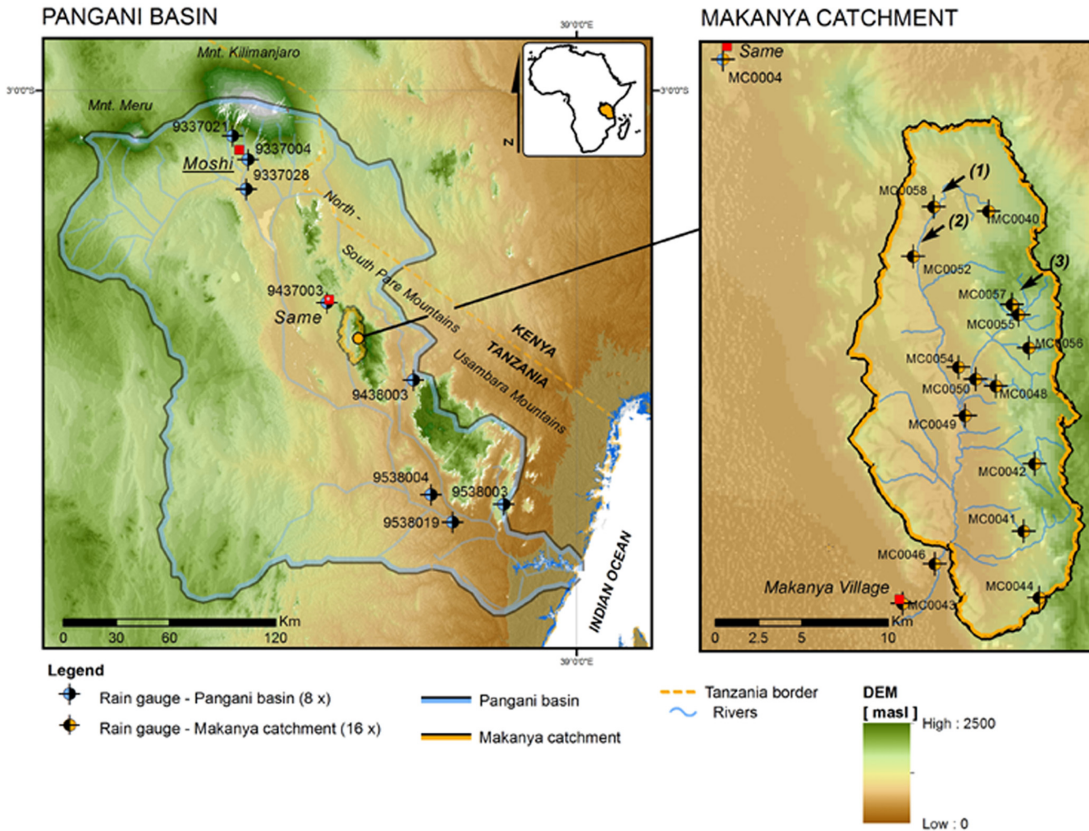|◀ | ▶|

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Table 1. Markov properties for both transition probabilities p_{01} and p_{11} for the eight rain gauges of the Pangani basin for Masika season, on monthly and seasonal basis.

Type	trans.prop.	Parameter	Rain gauge							
			9337004	9337021	9337028	9437003	9438003	9538003	9538004	9538019
Monthly:	p_{01}	$a_{var\ a}$	0.03	0.05	0.03	0.05	0.07	0.04	0.03	0.02
		$b_{var\ a}$	0.46	0.41	0.43	0.38	0.33	0.42	0.42	0.56
		R^2	0.86	0.86	0.90	0.91	0.65	0.80	0.85	0.87
		$\bar{a}_{fixed}$	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
		$b_{fixed\ a}$	0.42	0.44	0.39	0.41	0.43	0.44	0.39	0.39
		R^2	0.86	0.86	0.90	0.91	0.64	0.80	0.84	0.87
	p_{11}	$a_{var\ a}$	0.16	0.15	0.38	0.37	0.12	0.10	0.11	0.06
		$b_{var\ a}$	0.26	0.28	0.05	0.07	0.34	0.36	0.31	0.43
		R^2	0.89	0.59	0.72	−0.04	0.89	0.92	0.95	0.93
		$\bar{a}_{fixed}$	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
		$b_{fixed\ a}$	0.24	0.25	0.22	0.24	0.25	0.26	0.23	0.21
		R^2	0.89	0.57	0.63	−0.07	0.90	0.91	0.94	0.85
Seasonal:	p_{01}	$a_{var\ a}$	0.03	0.24	0.02	0.03	0.05	0.09	0.02	0.01
		$b_{var\ a}$	0.35	0.06	0.40	0.37	0.32	0.23	0.42	0.49
		R^2	0.91	−0.14	0.96	0.77	0.63	0.73	0.89	0.87
		$\bar{a}_{fixed}$	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
		$b_{var\ a}$	0.26	0.26	0.23	0.24	0.28	0.29	0.25	0.26
		R^2	0.91	−0.14	0.97	0.77	0.63	0.73	0.89	0.87
	p_{11}	$a_{var\ a}$	0.16	0.29	0.10	0.07	0.08	0.35	0.10	0.16
		$b_{var\ a}$	0.22	0.15	0.28	0.37	0.35	0.12	0.29	0.22
		R^2	0.80	0.85	0.97	0.82	0.94	0.76	0.90	0.67
		$\bar{a}_{fixed}$	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
		$b_{var\ a}$	0.23	0.25	0.21	0.23	0.24	0.25	0.22	0.21
		R^2	0.80	0.85	0.97	0.82	0.94	0.76	0.90	0.67

Table 2. Coefficients and statistics of the seasonal derived Multiple Linear Regression Model of the Pangani basin.

	coef.		coef. value	95 % confidence intervals		R_2 statistic	F statistic
Seasonal	b_{01}	α	2.48×10^{-1}	1.66×10^{-1}	3.29×10^{-1}	0.41	1.41
Parameter:		β	5.11×10^{-5}	-7.47×10^{-5}	1.77×10^{-4}		
		ε	-1.43×10^{-4}	-3.88×10^{-4}	1.03×10^{-4}		
	b_{11}	α	2.07×10^{-1}	1.61×10^{-1}	2.53×10^{-1}	0.54	2.37
		β	5.15×10^{-5}	-1.93×10^{-5}	1.22×10^{-4}		
		ε	-7.99×10^{-5}	-2.18×10^{-4}	5.82×10^{-5}		

Table 3. Ordinary Co-Kriging model and cross validation results for Masika season.

Interpolation type	Model	ME	RMSE	ASE	MSE	RMSSE
OCK	Exponential	−5.22	59.46	57.68	−0.07	1.03

Table 4. Values of critical dry spell length n_{cr} for the three locations indicated in Fig. 4.

location	θ available [%]	D rootdepth [mm]	θ available to crop [mm]	E_p [mm d^{-1}]	n_{cr} [d]
1	8	500	40	4.9	8.2
2	10	500	50	4.9	10.2
3	12	500	60	3.5	17.1

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Fig. 1. The Pangani basin with the locations of the 8 rain gauges with daily rainfall data (1940–1989) (left map). The Makanya catchment with the locations of the 16 rain gauges with daily rainfall data (2005–2006) (right map). The numbers (1), (2) and (3) indicate the location for which the critical dry spell length was calculated.
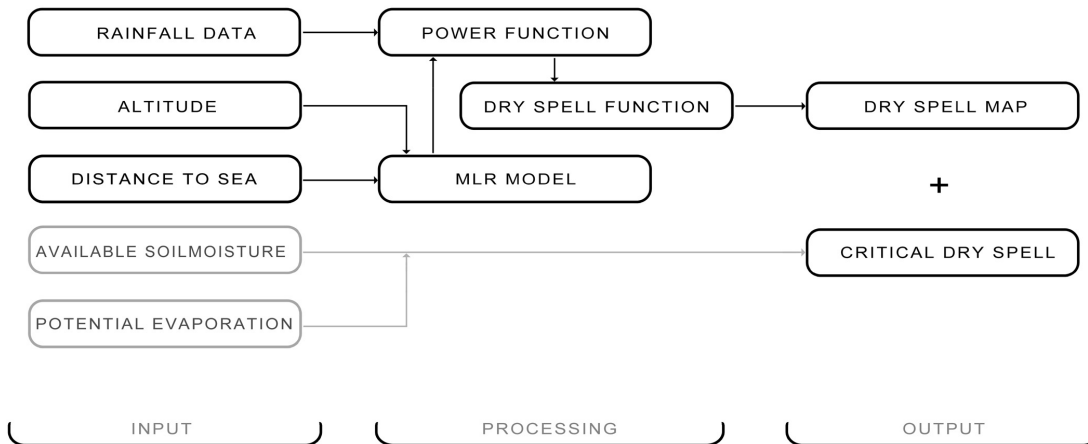
Fig. 2. Markov-based Framework for critical dry spell analysis.
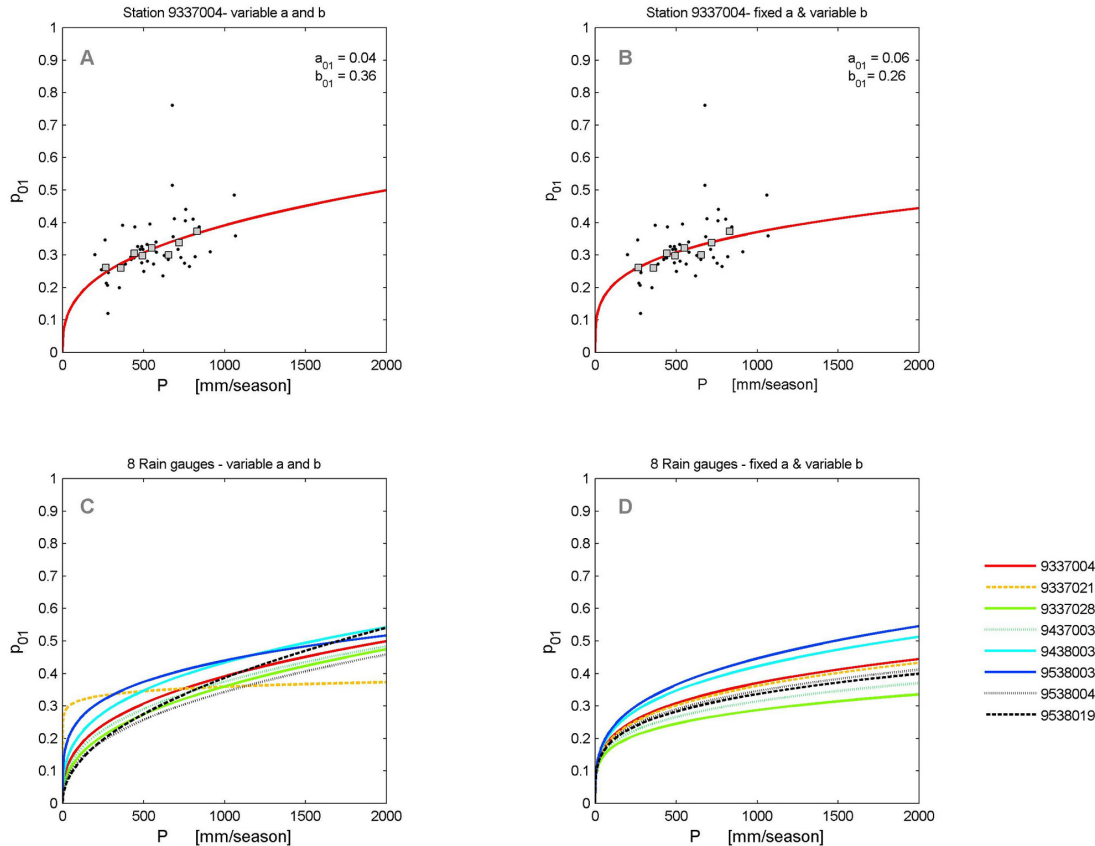
Fig. 3. Transition probabilities p_{01} vs. precipitation in Masika season. Scatter plot of one rain gauge 9337004 with **(A)** variable a and b, **(B)** fixed a and variable b. Dots represent individual seasons and squares represent the median value per rainfall class. Plot of all eight rain gauges of the Pangani basin with **(C)** variable a and b, **(D)** fixed a and variable b. R^2 are listed in Table 1.

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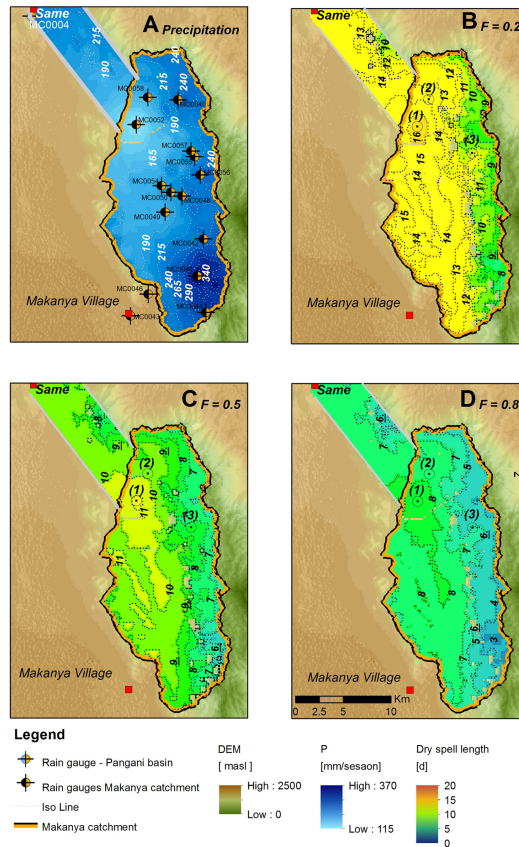
Fig. 4. Ordinary Co-Kriging derived synthetic rainfall map for rain season Masika. **(B–D)** Dry spell maps, showing the length of the occurrence of dry spell for a probability of non-exceedance F = 0.8, 0.5 and 0.2. Numbers in brackets indicate locations for which the critical dry spell was calculated.

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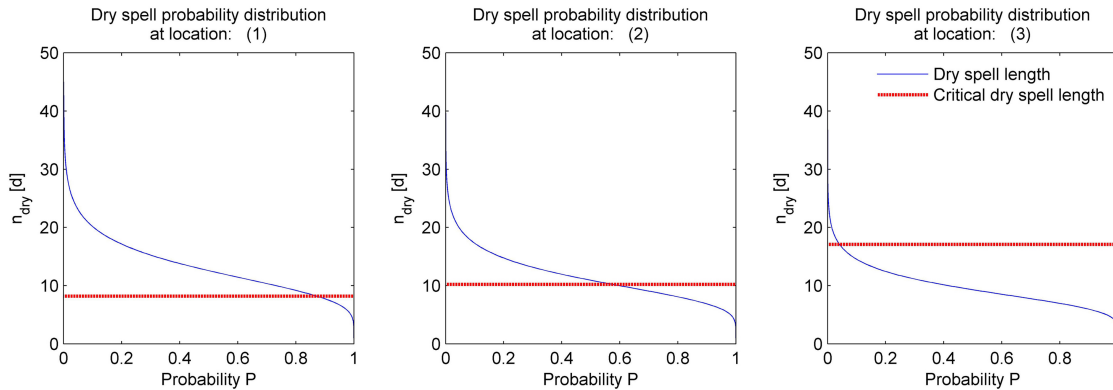
Fig. 5. Dry spell probability distribution for the three locations indicated in Fig. 4.