Climate-induced conflict? The role of meteorological drought indicators for communal conflict prediction in North-Western Kenya

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Abstract

Recent Conflict Early Warning Systems have found little evidence of predictive power of drought indicators for conflict prediction. However, this may result from the context-specificity of the drought-conflict relationship, as stressed in the more recent climate-conflict literature.

The present thesis assesses the local role of meteorological drought indicators for communal conflict prediction in North-Western Kenya, as a region where the narrative of resource-scarcity driven conflicts exists.

A local-scale literature review on conflict dynamics followed by a fixed-effects logistic regression modelling approach stress the importance of the spatial dimension when analysing drought-conflict relationships. The role of cross-border transhumance in linking climate variability to conflict occurrence is stressed by the lower confidence intervals and more significant effects when moving the regression analysis from the spatial delimitation of administrative units to the agency level of ethnic groups.

Differences in between ethnic groups in the obtained patterns of conflict behaviour in response to drought or water abundance are explained by their migratory behaviour along with a differentiated account of their relative drought vulnerability.

The lack of any considerable role of drought in the subsequently built quasi-replication of the WPS Global Early Warning Tool, is therefore assigned to the mismatch of administrative units as the spatial unit of analysis in a pastoralist area, where herders frequently move their cattle to the other side of the border.

It is advocated for an ethnic-group centered approach to predicting conflict, which relaxes assumptions on spatial containment of conflict events. However, whether this alternative model specification leads to a greater role of drought indicators in conflict prediction and better overall predictions, needs to be assessed in future work.

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List of Abbreviations

ACLED	Armed Conflict Location & Event Data Project
ASALs	Arid and Semi-Arid Lands
CDS	Climate Data Store
CI	Confidence Interval
CEWARN	Conflict Early Warning and Response Mechanism
CEWS	Conflict Early Warning System
CRS	Coordinate Reference System
CWB	Climatic Water Balance
DEM	Digital Elevation Model
DI	Drought Indicator
ECMWF	European Centre for Medium-Range Weather Forecasts
EW	Early Warning
EA	Early Action
GLM	Generalized Linear Model
GDP	Gross Domestic Product
HDI	Human Development Index
KPRs	Kenya Police Reservists
LAPSSET	Lamu Port and Lamu-Southern Sudan-Ethiopia
LRM	Logistic Regression Model
LSTM	Long short-term memory
LTWPL	Lake Turkana Wind Power Limited
MDI	Mean Decrease in Impurity
ML	Machine Learning
OR	Odds Ratio
PET	potential evapotranspiration
PFI	Permutation Feature Importance
PWM	Probability Weighted Moment
RAST	Resource Abundance and Scarcity Theory
RF	Random Forest
RFE	Recursive Feature Elimination
SCAD	Social Conflict Analysis Database
SMOTE	Synthetic Minority Oversampling Technique
SMOTE-NC	Synthetic Minority Oversampling Technique for Nominal and Continuous
SRTM	Shuttle Radar Topography Mission
SPEI	Standardized Precipitation Evaporation Index
SPI	Standardized Precipitation Index
SpROC	Spearman's rank order correlation coefficient
UCDP	Uppsala Conflict Data Program
UCDP-GED	UCDP Georeferenced Event Dataset
UNDP	United Nations Development Programme
ViEWS	The Political Violence Early-Warning System

WPS Water, Peace and Security

1 Introduction

1.1 Societal relevance

Due to their long-lasting effects on lives and living standards, economy, natural habitats and societies, droughts are considered one of the most severe natural hazards, causing disproportionately many fatalities (Wirkus & Piereder, 2019). Relative to the pre-industrial period Intergovernmental Panel on Climate Change (IPCC, 2019) has reported an increase in the frequency and intensity of droughts in some regions of the world including large parts of Africa. And large areas of the world are projected to experience even more frequent and severe droughts due to climate change (United Nations Office for Disaster Risk Reduction (UNDRR) [UNDRR], 2021).

Drought is defined as a 'period of abnormally dry weather long enough to cause a serious hydrological imbalance' (American Meteorological Society, 2019). As such, a drought is always defined relative to the typical water availability in a region at the respective time of the year. Depending on the aspect of the hydrological cycle it is looked at, it is differentiated between (1) meteorological drought as a 'period with an abnormal precipitation deficit', (2) soil moisture drought or agricultural drought, which reflects the impact of precipitation shortages on crop production and ecosystem services, and (3) hydrological drought as periods of abnormally low surface and subsurface water storage (Intergovernmental Panel on Climate Change (IPCC) [IPCC], 2012).

As a creeping phenomenon of great spatio-temporal extent, it is challenging to characterize droughts and grasp and quantify the full extent of their impacts (UNDRR, 2021). Direct impacts on agricultural production as well as other economic sectors can trigger more widespread or spatially unrelated business and trade interruption, food insecurity, malnutrition and famine (Barnett & Adger, 2007; UNDRR, 2021). This in turn may lead to migration, social tensions and conflict (Carius et al., 2004; UNDRR, 2021). If detected early many of the impacts could be mitigated through active drought management. However, the cascading nature of drought impacts hampers the direct association to the underlying drought (UNDRR, 2021).

1.2 Scientific relevance

1.2.1 Drought-conflict Relationship

The Master Thesis engages within the scope of climate-conflict research which assesses the connection of climate variability or change including drought, on the one hand, and conflict, on the other hand.

In the context of climate-conflict research, conflict may take several forms. Quantitative studies often deal with a combination of multiple sub-groups of conflict because of their simultaneous presence in common conflict datasets or, they investigate a single one in detail. A distinction between different forms can be made along the following lines:

1. Violent vs. non-violent: Violent conflict is conflict between 'at least two parties using physical force to resolve competing claims or interests' (Frère & Wilen, 2015). Within quantitative analysis of the drought-conflict relationship it is often further restricted to conflict resulting in fatalities above a certain threshold as they rely on commonly available datasets (Buhaug & Theisen, 2012; Detges, 2016; Fjelde & von Uexkull, 2012; Hegre et al., 2016; Hoch et al., 2021; Slettebak, 2012; von Uexkull et al., 2016). Several publicly available datasets exist by now, which provide violent conflict records from news coverage. The UCDP dataset has traditionally focussed on civil war and has therefore established a threshold of 25 fatalities in a year to include a conflict between two actors into their database. Armed Conflict Location & Event Data Project (ACLED) (Raleigh, 2010) on the other hand does not apply any fatality threshold to their data. While the use of a threshold may come at the loss of conflict reports, it addresses the relatively higher importance of some conflict events to be accurately predicted than others (Kuzma et al., 2020). Further datasets, also including ACLED, as well as Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012) report on selected non-violent events such as peaceful demonstrations.

2. State-based, non-state conflict, one-sided violence: The distinction between conflict can also be made based on the actors involved, or also called the *dyad* as the pair of actors involved. State-based armed conflict is defined as violence between two organized actors with at least one being a government of a state, (2) non-state conflict is between actors which are not government of a state and in (3) one-sided violence a state government or a non-state organized group commits violence against unarmed civilians(Sundberg & Melander, 2013).

For the literature review no restriction to single forms of conflict is made. Rather, the full range of definitions within the climate-conflict literature is exploited and the definition is only gradually delimited to a definition of conflict used within the thesis (see Section 1.3.3).

The relationship between climate hazards, and droughts in particular, and conflict is widely discussed in literature but no consensus has been reached. While some case studies and larger studies suggest that drought contributes to conflict (Abel et al., 2019; Afifi et al., 2012; Cabot, 2017; Gleick, 2014; Hendrix & Glaser, 2007; Hendrix & Salehyan, 2012) other studies do not find evidence that conflict is triggered or aggravated by drought (Benjaminsen et al., 2009; Buhaug & Theisen, 2012; Hegre et al., 2016; Witmer et al., 2017). ASlettebak (2012) even shows evidence that, contrary to the common perception, the occurrence of natural disasters and droughts, in particular, decrease the risk for conflict. The author sees these results in line with sociological research on the risk for conflict after disasters where a decreasing importance of individual and cultural differences and an increased social cohesion may limit the potential for aggression. Furthermore, a government may have the potential to positively prove itself in the rehabilitation from such a disaster (Slettebak, 2012).

Part of the inconclusiveness within literature can be assigned to the varying research set-ups in terms of geographical and temporal resolution and choice of explanatory and output variables (Hoch et al., 2021). Furthermore, Detges (2016), Hegre et al. (2016), and Schleussner et al. (2016) assign the missing consensus to the fact that the impact of climate hazards on conflict are not solely determined by the meteorological condition but also by the vulnerability to natural disasters and are therefore context-specific. Variabilities in precipitation and temperature, as commonly used to define drought, cannot represent any influences of land cover, land use and topography on the actual drought experienced by the population (Meier et al., 2007). In addition, distinctions need to be made by people's dependence on drought-sensitive activities, such as livestock breeding and agriculture, and a society's adaptive capacity and resilience, which in turn is influenced by the government's capacity to support the people affected by drought, by economic opportunities and solidarity within and with vulnerable groups in the society (Hegre et al., 2016; UNDRR, 2021). The relationship between drought and conflict can therefore be considered highly context-specific.

The context-specificity of the drought-conflict relationship is backed by studies conducted by Fjelde and von Uexkull (2012), von Uexkull (2014) and von Uexkull et al. (2016) which show that there is a higher correlation between drought and conflict in contexts of politically marginalized groups and groups which are heavily dependent on (rain-fed) agriculture. Similarly, Schleussner et al. (2016) find a 23% coincidence of armed-conflict outbreak with climatic calamities in ethnically fractionalized countries. This leads them to the conclusion that, although not at the root of conflicts, the risk of conflict can be amplified by climate-related disasters in vulnerable settings. These are often the same countries and regions that are predicted to face a substantial increase in climate-related natural disasters due to climate change (Schleussner et al., 2016). Detges (2016) shows that drought is more likely to lead to conflict where key infrastructure is missing to cope with drought: civil conflict has a higher probability in cases of poorly developed road infrastructure, communal violence is more likely where improved water sources are missing.

The complexity of the drought-conflict relationship also reflects within the IPCC Sixth Assessment Report, where the impact of climate change on water resources is only seen as an indirect contributor to rising conflict risks with other factors considered to be more influential. However, also within the report, the varying impact of climate change on conflict depending on the region's vulnerability is stressed (IPCC, 2022).

1.2.2 Drought indicators in conflict prediction

The question of the drought-conflict relationship is also raised within the context of predictions of conflict risk as part of CEWS.

A CEWS is a system which integrates multiple conflict early warning practices in a standardized way to issue official warnings for political violence potential. It entails the processes of data collection and data analysis, quantitative and qualitative methods used for conflict forecasting. In addition, Early Warning (EW) mechanisms are considered to enable relevant decision-makers to discuss and take prevention, preparation and mitigation measures (Early Action (EA)) in time (Sweijs & Teer, 2022).

Different CEWSs engage with conflict forecasting at time horizons ranging from days to years and thereby address different dimensions of EA. Conflict prediction over shorter timer periods benefits from the presence of short-term predictions for more variable indicators for conflict probability. Longer time horizons can only include slow-moving and static drivers of conflict and therefore are often less accurate. However, they can indicate structural vulnerability especially when comparing different regions or countries. Therefore, they contribute to long-term conflict prevention (Sweijs & Teer, 2022).

Multiple efforts have been made to quantify conflict risk in CEWS. As part of The Political Violence Early-Warning System (ViEWS), three generations of models have been built which provide probabilistic assessments of conflict occurrence (VIEWS1 and VIEWS2) or fatality estimates (VIEWS3) for a certain country or grid cell one to 36 months into the future. Predictions are based on weighted predictions from multiple Machine Learning (ML) models, each taking one thematic feature set as input data. While not systematically considered in the original input data set of VIEWS1, climate hazards including drought and the related societal vulnerability constitute one of these feature sets in the newer models (Akbari et al., 2022; Hegre et al., 2019; Hegre et al., 2021).

Similarly, water-related variables have been included as predictors in the Global Early Warning Tool developed by the Water, Peace and Security (WPS) Partnership. The original model, the *Long-Term RF Model* provides probability assessments for conflict occurrence over the next twelve months for each *admin-1 level* unit, as the first subdivision of a country into administrative units, and at a monthly time scale (Kuzma et al., 2020). The model has been complemented with a second ML model structure predicting the number of conflict events for the next two months, referred to as the *Short-Term LSTM Model* (WPS Partnership, n.d.).

The present Master Thesis is related to the CEWS by the WPS Partnership and their effort to assess the impact of water-related variables on e.g. conflict. As part of the development of the *Long-Term RF Model* the value of water-related variables as predictors for conflict forecasts was investigated. Results showed that water variables, including meteorological drought forecasts, featured among the most relevant variables based on Recursive Feature Elimination (RFE). However, when removed in the final model, the model performance did not decrease significantly (Kuzma et al., 2020).

Based on the prior review of literature on the drought-conflict relationship, it is argued here that this is not a proof that drought is generally not important for conflict forecasting for multiple reasons:

1. The context-specificity of the drought-conflict relationship suggests that the impact of drought on conflict may be pronounced in some regions while not so important in other regions. Comparing overall performance of the model with or without water-related variables may not be representative for their importance in single regions.

2. The model is trained to predict the number of conflict events in a given month and district. However, within the training process no distinction is made between conflict onset (as conflict after a specified minimum time period of peace) and conflict incidence (conflict occurrence in general) (Kuzma et al., 2020). As also observed within the training of ViEWS by Uppsala University (Hegre et al., 2019), the model may therefore base much of its prediction on prior conflict history. However, these models do not perform well on emerging conflict. In fact, Kuzma et al. (2020) state, that when training the model on emerging conflict, only, the water-related variables including precipitation anomalies rank higher in RFE than for conflict incidence in general.

3. The model uses precipitation anomalies as predictors derived from the ECMWF Seasonal Forecast Data (Johnson et al., 2019). Such drought forecasts may degrade in quality with longer lead times, as the time between the present and the time for which the forecast is made.

4. Through the use of a meteorological DI, the impact of land management regimes and topography on the severity of droughts is not represented. Alternative measures of agricultural or hydrological DIs may be a better representation of on-the-ground drought conditions.

1.3 Research scope

While desirable to explore all four points mentioned above, the present thesis focusses on the first point. It assesses the local impact DIs can have on conflict prediction in a region, for which the narrative of resource scarcity driven conflicts exists, and how this effect is reflected in conflict predictions for the area. Through (1) the choice of the study area, (2) the definition of conflict and (3) the exploration of historical DIs rather than drought forecasts, the present thesis sets out to explore this local value of DIs in a *best-case scenario* where the impact of DIs on conflict is expected to be visible, if it exists.

Before delineating the research question and sub-questions, these three aspects shall therefore be described in detail.

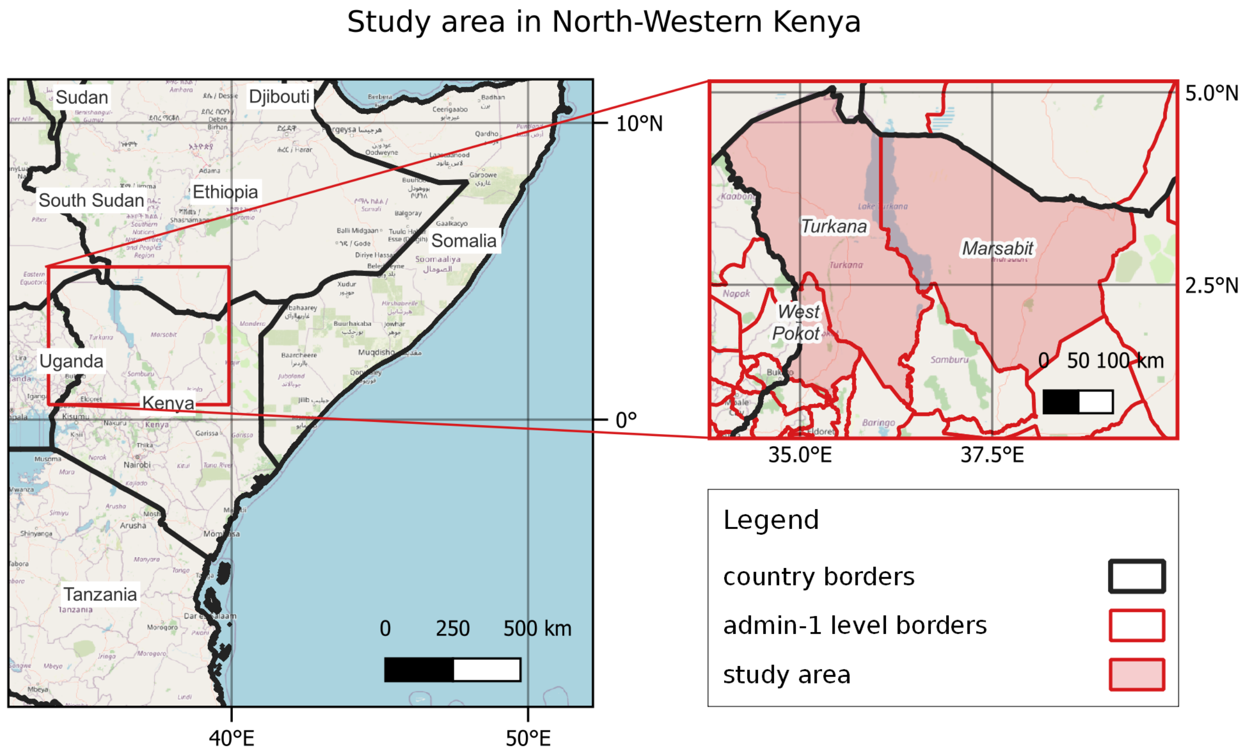


Figure 1.1.: Study area and its location within the wider context of the Horn of Africa (source of administrative unit borders: GADM (2018))

1.3.1 Study area

In order to assess the predictive value of DIs for conflict forecasting in such a *best-case scenario*, a study area was required where conditions exist which make a link between drought and conflict occurrence more likely. The following conditions, which have been identified before to make a conflict in response to drought more likely, were considered: dominance of drought-vulnerable activities such as pastoralism or (rain-fed) agriculture (UNDRR, 2021; von Uexkull, 2014), lack of critical infrastructure such as road networks and improved water sources (Detges, 2016), ethnic fractionalization (Schleussner et al., 2016) and political marginalization of certain groups. To establish a link between drought and conflict the study region needed to have a sufficiently large history of conflicts so that the contribution of DIs to conflict prediction can be evaluated.

Based on these criteria, the three counties West Pokot, Turkana and Marsabit in North-Western Kenya were chosen as the study area. A map of the three counties is displayed in Figure 1.1.

The three counties are located at the border to Uganda, Ethiopia and South Sudan in the Arid and Semi-Arid Lands (ASALs) of Kenya. In West Pokot, rainfall ranges widely between 1600 mm in the highlands in Southern West Pokot and 700mm in the lowlands (Huho, 2012). For Turkana annual rainfall is reported to range between 300 and 400 mm with minima in dry years reported as low as 50 mm (Omolo, 2011; Schilling et al., 2014). The district-wide average rainfall in Marsabit is reported to be 200 to 300 mm but again large spatial rainfall variations are observed with the Marsabit Mountain area receiving about 800 mm of rainfall per year (Witsenburg & Adano, 2009).

For all counties, rainfall follows a seasonal pattern with a period of long rains from Mid-March until June, a period of short rains from October or November until December and intermediate dry seasons (National Drought Management Authority [NDMA], 2022a, 2022b, 2022c). Annual precipitation totals and intra-annual and inter-annual rainfall variability are projected to increase, with more frequent erratic rainfall events and prolonged drought periods (Christensen et al., 2007; McSweeney, New, & Lizcano, 2010; McSweeney, New, Lizcano, & Lu, 2010). Water scarcity is amplified by the existence of only a few freshwater sources. Apart from smaller ephemeral rivers and the semi-permanent Turkwel and Kerio rivers, Lake Turkana represents the only permanent surface water source but it is suffering from high salt concentration (Schilling et al., 2015).

The dry climate can be seen as the underlying reason for pastoralism as the main subsistence strategy in the region (Johannes et al., 2015). Different ethnic groups living in the area, including the Turkana, Pokot, Borana, Gabra, Rendille, Samburu and Dassanetch, move their cattle in response to drought and may thereby come into closer proximity to each other (Ember et al., 2012; Ember et al., 2014).

Competition over scarce water and land resources has been repeatedly mentioned in literature as an underlying reason of inter-ethnic conflict. In that context, livestock raiding has been historically considered an adaptation to the hostile environmental conditions of the region, serving as a way of redistributing resources (Hendrickson et al., 1998). However, the inflow of small arms into the region in recent years is considered to have turned livestock raiding into a more deadly type of conflict . Consequent rising insecurity in combination with the projected exacerbation of rainfall patterns have raised concerns about decreasing adaptive capacity of pastoralists in North-Western Kenya to drought (Gray et al., 2003).

The perception of pastoralism as a backward practice along with the insecurity in the area and the difficulties to tax mobile pastoralists have been named as reasons, why the region has historically been one of the most politically and economically marginalized areas of Kenya (Schilling et al., 2015; Schilling et al., 2016). Especially Turkana and Marsabit are among the counties of Kenya with the lowest Gross Domestic Product (GDP) and Human Development Index (HDI). Most of the governance funding has been historically directed towards the agricultural areas in the centre and the West of Kenya. Therefore, road infrastructure, health and education facilities are poorly developed. This, in turn, has further marginalized the region through a lack of job opportunities (Schilling et al., 2015).

Devolution of power in 2013 to the county level has resulted in increased political and economic interest in North-Western Kenya due to their important role as swing regions in elections and a windfall of public resources (Lind, 2018; Schilling et al., 2018). However, it remains to be seen whether this development will reduce structural marginalization (Mkutu & Mdee, 2020; Schilling et al., 2018).

1.3.2 Drought indicators

DIs quantify the departure from normal water availability in a specific location and time of the year. This definition allows for an intercomparison of regions in terms of the water deficit or water abundance they experience.

Within the present thesis, the analysis of the impact of DIs in the climate-conflict domain is restricted to (1) meteorological DIs and (2) the computation of DIs based on historical data rather than precipitation and evapotranspiration forecasts.

A Meteorological drought indicators vs. other drought indicators

In climate-conflict literature, mostly, meteorological DIs such as SPI and SPEI are used, as they can be directly derived from meteorological variables. For a given time period of the year in a specific location, the SPI describes deviations of precipitation totals from normal conditions (European Commission. IES - CRM Unit, 2013). The SPEI, additionally accounts for the impact of the atmospheric energy demand on the water balance. Instead of precipitation only, the difference between precipitation and potential evapotranspiration (PET), in the following referred to as Climatic Water Balance (CWB), is compared to the typical CWB in that specific location and at that time of the year.

Alternative DIs exist, which focus on other parts of the hydrological cycle, such as anomalies in the soil moisture content, groundwater level or water level in surface water bodies. As noted by Sutanto et al. (2020), such DIs may be of higher relevance for various impacted domains. While desirable to test alternative DIs, the present thesis still restricts itself to the analysis of meteorological DIs. The construction of a hydrological model to develop alternative DIs was found to be impractical because of the mismatch between the hydrological unit as the base unit of analysis while many other conflict predictor variables are only available at national and sub-national administrative levels (Görgen, 2021).

The restriction to meteorological DIs is considered satisfactory, as pastoralism is the main subsistence strategy within the study area, suggesting sensitivity of the residents' livelihood to changes in the meteorological water balance. In addition, through the use of different aggregation periods, it can be accounted for a propagation of the drought of a meteorological water deficit through the hydrological system (European Commission. IES - CRM Unit, 2013).

Aggregation periods refer to the time period over which precipitation or cwb is accumulated and compared to compute the meteorological DIs. Common aggregation periods used are 1, 3, 6, 12, 24 and 48 months. The aggregation period of a DI is usually indicated behind its name. Therefore, whenever referring to SPI-1, SPI-3, SPI-6, SPI-12, SPEI-1, SPEI-3, SPEI-6 and SPEI-12 in the following, the number suggests the time period in months which has been considered when computing how much precipitation or CWB deviate from normal conditions. For example, the SPI-6 for March 2007 indicates how the accumulated precipitation over the six months prior to March 2007 compares to the total precipitation values for the six months prior to each March of a year.

(Dai et al., 2020) finds coherence in several papers that a low SPI-1 is commonly associated to a meteorological drought while longer aggregation periods also suggest a soil moisture drought (SPI-3 and SPI-6) or a hydrological drought (SPI-12). Qualitatively, this is also confirmed by Lam et al. (2022)'s study on various drought impacts in Kenya, where predictive performance of meteorological DIs at long aggregation periods was comparable to those of alternative hydrological DIs.

B Historical drought indicators vs. drought forecasts

If droughts are contributing to conflict, CEWS would benefit from the inclusion of DIs in their quantitative and qualitative forecasting methods to improve EW and potentially to enrich EA by drought management options. If the time horizon of EW covers several months or even years, drought forecasts rather than DIs based on historical data are required to assess the risk of future droughts on conflict.

However, the assessment of the role of drought forecasts only, holds the risk of concluding that DIs do not play any role in predicting conflict while, truly, the missing predictive power is due to the low quality of drought forecasts. Within the present thesis the impact of historical DIs shall therefore be assessed. This serves as a benchmark against which to compare future analysis of the performance of drought forecasts in conflict prediction.

Here, historical DIs are DIs based on meteorological reanalysis data. Hence, estimates of meteorological variables have been developed with a model which assimilates to historical observations.

1.3.3 Conflict definition

As highlighted by the differentiated studies by Detges (2016) and Hendrix and Salehyan (2012), dynamics between rainfall deviations and conflict may vary by type of conflict. So far, it has mostly been looked at armed conflict in general (Hoch et al., 2021; Schleussner et al., 2016; Slettebak, 2012) and civil conflict, commonly defined as violent conflict between the government and at least one non-state party (Buhaug & Theisen, 2012; Hegre et al., 2016; Hendrix & Glaser, 2007; von Uexkull, 2014; von Uexkull et al., 2016). There is only a limited body of literature which only or at least explicitly considers non-state conflict or even restricts itself to the analysis of communal conflict (Detges, 2014, 2016; Fjelde & von Uexkull, 2012; Hendrix & Salehyan, 2012). This is despite many case reports finding a relationship between drought and communal conflict and some researchers supposing higher relevance of drought for non-state and communal conflict, in particular, than civil conflict (Buhaug & Theisen, 2012; Fjelde & von Uexkull, 2012; Raleigh, 2010).

Within the reviewed literature (Elfversson, 2019; Fjelde & von Uexkull, 2012; Nordkvelle et al., 2017; van Weezel, 2019), communal conflict is defined following its delimitation within the UCDP Non-State Conflict Dataset (Davies et al., 2022; Sundberg et al., 2012) as violent conflict between non-state groups 'along lines of communal identity' (Pettersson, 2022). As such, communal conflict events are restricted to those where lethal violence is used by non-state groups which are not formally organized like militas or rebels, but rather organize around the subjective and dynamic phenomenon of communal identity. Depending on space and time, communal identity can be, for example, of religious or ethnic nature, related to livelihood or settlement in a certain area (Elfversson & Brosché, 2012).

Several reasons have been defined within literature for a higher probability of a drought-conflict relationship in the case of non-state and communal conflict in particular.

1. The threshold to engage in conflict which challenges another non-state or communal group is lower than challenging the government due to the relative distance to other groups compared to the government as well as the higher costs and imbalanced power dynamics in state-based conflicts (Hendrix & Salehyan, 2012; Nordkvelle et al., 2017). It is the politically and economically marginalized groups which are most likely to suffer from drought and hence the groups with the lowest capacity to fight the government or highly organized rebel-groups or to organize themselves in long-standing rebel groups (Hendrix & Salehyan, 2012; Nordkvelle et al., 2017; Raleigh, 2010).
2. Other communal groups may be considered the more suitable target for demands on scarce resources, especially if the government has shown to be hesitant or incapable of redistributing resources (Hendrix & Salehyan, 2012).
3. In areas of minimal government presence, violence is a measure of self-governance to challenge established differences in access to scarce resources as a result of ethnic identity and political favourism (Raleigh, 2010).

Communal conflict differs from state-based conflict through its usually shorter time span: In contrast to state-based conflicts which usually last a couple of years to decades, communal conflict is characterized by single events of a couple of days of intense clashes. In addition, it has a lower degree of organisation and is more symmetrical. Less organisation and lower material strength result in usually lower destructive potential. However, as for example in Sudan, communal conflict can be a predecessor of civil war. This stresses the added value of detecting communal conflict potential early to prevent an increasing number of fatalities or transformation into other forms of violent conflict (Elfversson & Brosché, 2012).

1.3.4 Research question & sub-questions

Based on the above delimitations of the components of the research, the guiding research question is:

What role do meteorological drought indicators play in predicting communal conflict potential in North-Western Kenya?

The present Master Thesis can be seen as the first step towards a comprehensive evaluation of the contextual predictive value of drought forecasts in conflict prediction. Through evaluation of the predictive performance of meteorological DIs in a drought-vulnerable region, light shall be shed on the role that DIs could potentially play in the local prediction of conflict, if of acceptable quality, and what may hamper their performance.

To enable a critical assessment of the reasons why DIs may or may not contribute to conflict prediction in the study area, the research question is further split into three sub-questions.

1. What causal dynamics are found in literature for conflict in North-Western Kenya?
2. What statistical evidence does North-Western Kenya provide on the drought-conflict relationship?
3. What is the relative importance of DIs as predictors in a conflict prediction model?

The sub-questions shall illustrate that this Master Thesis mostly engages within quantitative modelling dimension of CEWS based on openly available data. It is stressed that the development and implementation of a CEWS is a complex procedure which involves input by experts from different fields as well as the inclusion of stakeholders in data collection, conflict risk assessment and incorporation of the EW within the policy cycle. In addition, it requires the active consideration of ethical and qualitative constraints of data collection approaches, as well as potential unintended consequences if malicious actors draw from the conflict risk predictions or if negative consequences of EA are overseen (Sweijs & Teer, 2022). It is considered beyond the scope of the research to include any considerations on data collection through field monitoring, qualitative assessment of conflict potential based on expert judgement or to engage in discussions on the delivery of the conflict EW product and potential EA measures. Even within the quantitative prediction component, the main aim of the model is not to produce improved predictions. In fact, it is likely that regional conflict models such as the model as part of Conflict Early Warning and Response Mechanism (CEWARN), which provides conflict risk assessments for the Greater Horn of Africa, can predict conflict more accurately and on a finer scale through data collected by countries which is not publicly made available (Goldsmith et al., 2020). Rather, the aim shall be to explore the relationship between DIs and conflict: the significance, magnitude and direction of the effect of DIs and their relative contribution to conflict predictions in the area.

Nonetheless, the first sub-question shall place the further quantitative drought-conflict analysis in the local context and shall raise awareness for the local specifics which shape conflict in North-Western Kenya. While focussing on the climate-conflict relationship, it is acknowledged that such conflicts are not happening in a vacuum. There is high consensus in climate-conflict literature that drought is, at best, a conflict contributor. One should therefore not loose sight of other important factors and acknowledge them in the research set-up and the discussion of any results obtained. In addition, a literature review may spark additional considerations on the necessary research set-up to retrieve a quantitative link between DIs and conflict occurrence if there is one.

The further sub-questions are concerned with delivering a comprehensive account of the importance of DIs for predicting conflict in the Lake Turkana region. A gradual shift from a simple statistical measures to map the impact of historical droughts on conflict (sub-question 2) to more advanced modelling techniques to assess the relative impact of droughts compared to other predictor variables (sub-question 3) enables to not only evaluate if drought forecasts can help in predicting conflict but also what may restrict their impact on prediction performance: (1) the lack of any drought-conflict relationship or (2) the little importance of drought as a conflict driver/contributor compared to other predictor variables.

1.4 Reading guide

In Chapter 2 the method to answer each of the sub-question is explained in detail along with the required data preprocessing steps. This is followed by the illustration and description of the results in Chapter 3 and their subsequent discussion and contextualization in Chapter 4 including limitations and recommendations for future research and application of CEWS. Main conclusions of the thesis are summarized in the final Chapter 5.

2 Method

As part of this chapter a detailed account of the method to answer each of the three sub-questions shall be given in Sections 2.1 to 2.3. In Section 2.4 the data retrieval and preprocessing steps for the quantitative analysis as part of Sub-question 2 and Sub-question 3 are described.

2.1 Sub-question 1: literature review on conflict dynamics in the study area

To shed light on the scientific research which has been done so far on the role of drought for conflict in the study area and to identify other conflict contributors, the literature on the causes of conflict in the study area was reviewed through a systematic literature review.

The process of literature research and literature selection was driven by the ambition of unbiased inclusion of all relevant causal contributors to inter-ethnic conflict in the study area. Therefore, a broad keyword search was conducted which retrieved any literature on the conflict dynamics in the study area, followed by the manual exclusion of sources based on transparent criteria of their relevance. Figure 2.1 visualizes the workflow of retrieving and filtering the literature.

An overview of the used keywords is provided in Figure 2.1 on the left. As the full scope of conflict dynamics in the study area was of relevance, the only conditions included were (1) the presence of the word *conflict* in the title or a word which can be considered synonymous in the regional context and (2) an areal description which overlapped with the study area or alternatively, the naming of one or several of the main ethnic groups (see Section 3.1.2) in the title, abstract or keywords. The keywords were combined in a logical expression which was used to search the *Core Collection of the Web of Science*.

Web of Science was chosen over other literature search engines due to its advanced abilities in restricting the occurrence of certain keywords to different parts of a piece of literature. By setting the requirement of the study area keyword to occur within the abstract it was made sure that studies which only used the study area as an example for their line of argumentation were largely removed. Although desirable for reducing the bias in the literature, a Google Scholar research with the same keywords resulted in a large number of sources which were not focusing on the study area within their research, and which would have needed to be manually excluded afterwards. The manual filtering of 972 sources from the keyword search on Google Scholar was beyond the scope of the literature review within the present research.

The keyword search resulted in a total of 177 sources which needed to be narrowed down based on the following criteria:

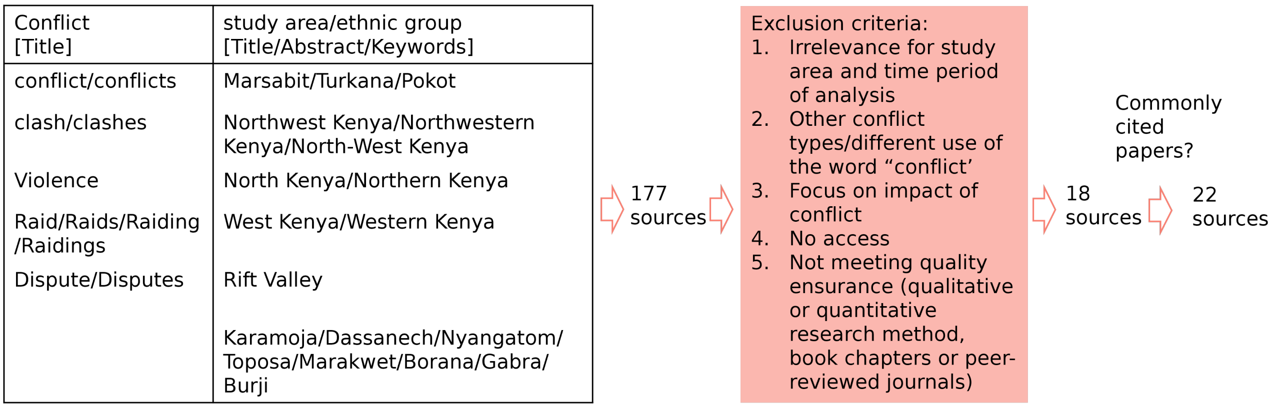


Figure 2.1.: Workflow of literature selection on regional conflict dynamics from *Web of Science Core Collection*. A broad keyword search (see table on the left-hand side) was conducted followed by the manual exclusion of sources based on a set of exclusion criteria (see red box)

1. The relevance of the findings for the study area and time of analysis: Only papers which at least partially overlapped with the study area, which were published after 2004 as the time period of analysis of the present thesis is set to 2004 to 2021. In addition papers should not adopt a historical perspective on former decades. Furthermore, papers where the study area only served as an example to answer a question on a more general note, were excluded, as these papers were not contributing to the available findings for the study area but rather reviewing existing literature.

2. The type of conflict analysed: The multidimensionality of the conflicts occurring within the area became evident from the 177 sources. As different causal dynamics are suspected to be at play for different types of conflict, only conflict along lines of ethnic identity was explored - in line with the dyads which have been found in the UCDP dataset for the study area. For the case of the full set of sources, this meant the exclusion of wildlife-human conflicts, domestic and inter-household conflicts, intra-ethnic conflicts as well as social conflicts which follow lines of different subsistence strategies rather than ethnic identity. Recently, further dimensions of conflict have emerged through the new presence oil and wind power companies in the study area and the sometimes forceful protest against their activities, as well as through the process of devolution which has lead to power struggles at the county level (Schilling et al., 2018; Schilling et al., 2016). However, all papers covering these community-company conflicts are also investigating the impact of these developments on existing ethnic conflict and were therefore kept as part of the set of sources to be reviewed (Mkutu & Mdee, 2020; Schilling et al., 2015; Schilling et al., 2018)

3. The focus on causes vs. impacts of conflict: Papers whose abstract suggests that they focus on the impacts of conflict (in the present subset mainly papers on HIV, child and psychological health) were excluded as the thesis is solely engaging within the realm of conflict prediction. This exclusion criterion is based on the assumption that the impacts described in these papers do not lead to enhanced or reduced conflict or, that if they do, these impacts also feature in other papers which are more focused on the causes of conflict.

4. Access to the papers: The access to papers (either directly via the university or via request from other libraries) was verified using the TU Delft library search function.

5. Quality: It has been refrained from the introduction of some threshold applied to the number of citations of a certain entry. This was suspected to bias the choice of papers towards older papers and towards certain perspectives on the relationship between conflict drivers or contributors and conflict. As a quality ensurance, only papers published in peer-reviewed journals and in edited books were included.

The resulting subset of literature consisted of 18 papers. To overcome the limits of the keywords used and of the *Web of Science Core Collection*, papers were compared in terms of common references which may be important but could not be found by the search strategy above. Four papers which were commonly cited by these papers (by at least four papers) and meet the inclusion criteria above were therefore added to the list of papers.

Both, an increase in conflict frequency and in conflict intensity, is likely to result in more conflict events being reported as part of the UCDP datasets. Therefore, literature was scanned for any causal relationships which suggest an increase or decrease in conflict risk as the combination of conflict probability and damage.

To derive causal relationships between a certain factor and conflict risk, all literature was scanned for direct or indirect causal explanation of conflict expressed as part of the one or multiple results chapters, the discussion and conclusion sections of a paper. This was an iterative process, as a factor may only be linked to an intermediate step in one paper. In this case the factor only gains its meaning for conflict through the link made between this intermediate factor and conflict in another paper. As, within the present thesis, the focus is on indicators which resulted in a trend of conflict frequency or intensity over the time period of study (2004-2021), factors, which historically have contributed to the present context of high interethnic rivalry, are not considered as part of the perceptual model.

Papers often provide evidence on a single relationship and a highly fragmented picture would be gained by only using the results obtained through the literature reviewed. Especially, papers, which statistically assess the impact of a factor on conflict, often explain the underlying causal dynamics based on secondary sources. Therefore, if a secondary source was used in a paper as part of the results to elaborate on a pathway to conflict rather than opposing that respective source, the causal relationships explained in that secondary source were considered to express the opinion of the author who used it. For the purpose of constructing a perceptual model of conflict dynamics in the study area, they were therefore considered as part of the author's argumentation.

A table of all causal relationships is provided in Appendix A.5 along with a quote to support the direction of the relationship. Where co-authored papers mention the same relationship twice and do not provide additional evidence, it is only considered once to counteract the bias in the representation of different opinions.

The following four questions therefore guided the retrieval of relevant relationships:

1. Does the stated relationship either directly or indirectly (also with regards to relationships found in other sources) contribute to an increase or decrease in conflict intensity or conflict frequency?
2. Does the stated relationship suggest a long-term or short-term increase or decrease in conflict risk over the course of the study time period (2004-2021)?
3. Can the stated relationship be considered the opinion of the author?
4. Has the stated relationship already been mentioned based on the same evidence in another paper where one or multiple of the same authors have been involved?

The direction of the relationship as well as potential uncertainty was determined based on the criteria displayed in Table 2.1. Multiple signs were assigned to a relationship when the author expressed differences in the effect of the factor e.g. in the short-term vs. the long-term or depending on the location.

The obtained causal relationships were combined in a perceptual model of conflict dynamics in the study area. Differences in the authors' opinions are retained through assignment of multiple signs to a relationship thus enabling a discussion on the ambiguity of certain causal contributors.

Table 2.1.: Criteria for assigning one or multiple signs to the relationship between a factor and its impact

sign	explanation
+	A clear positive relationship between factor and impact is expressed
(+)	A limited positive relationship between factor and impact is expressed
()	The factor is said to have no negative or positive effect on the impact
(-)	A limited negative relationship between factor and impact is expressed
-	A clear negative relationship between factor and impact is expressed
?	Uncertainty is expressed with regards to the effect of the factor on the impact. This may be because the effect is lying in the future or because contradictory results have been found.

2.2 Sub-question 2: significance of drought-conflict relationship in North-Western Kenya

To investigate the magnitude and direction of the effect of different DIs on conflict in the study area, a fixed effects logistic regression model was set up, as commonly used in climate-conflict literature when investigating the impact of drought on conflict (Eklund et al., 2022; Hendrix & Salehyan, 2012; Theisen, 2012).

2.2.1 Spatio-temporal unit of analysis

In line with the WPS Global Early Warning Tool, the present thesis explores the role of DIs in conflict prediction at the *admin-1 level* for time horizons of one to seven months. This spatio-temporal restriction was applied for answering both, Sub-question 2 and Sub-question 3.

In a second step of Sub-question 2, the spatial restriction was relaxed and an agent-centered view was adopted, where regardless of the location, the occurrence of conflict was ascribed to the involved ethnic groups and the DI for their respective ethnic territories. For a detailed explanation it is referred to Section 2.2.5.

The time period analysed is restricted to 2004-2021 in the present and following modelling step, as conflict data uses other ethnic group identities before that point.

2.2.2 Independent variable

DIs were hence derived for the spatial delimitation of administrative units and ethnic group territories, respectively. As it was hypothesized that already small-scale phenomena of relative water abundance or drought may have an impact on conflict occurrence, gridded DIs were spatially aggregated using different spatial statistics (25th, 75th percentile, the median and the mean).

The study area is mostly used for pastoralism. Therefore, it is expected that already short-term drought phenomena may undermine the livelihood of communities in North-Western Kenya. At the same time prolonged droughts are likely to decrease water availability from the scarce surface water and groundwater sources in the region. In addition, prolonged drought may exhaust the adaptive capacity of pastoralists to climate extremes. To explore which DIs show the most significant impact, different aggregation times of 1, 3, 6, and 12 months were explored.

As found by Lam et al. (2022) in their drought impact investigation in several of Kenya's counties, most impacts occurred after the drought onset. Therefore, the impact of drought on conflict was additionally explored at various time lags of zero to seven months.

2.2.3 Dependent variable

As conflict variable, a binary variable of communal conflict occurrence in a certain month was used. The choice of this definition over other definitions such as the number of conflict events or the number of fatalities, is the high uncertainty associated to the later estimates.

Within conflict prediction literature, a further distinction was made between conflict onset and conflict incidence, where a conflict onset is often considered as such when the prior 12 months have not seen any conflict in the respective area (compare Ge et al. (2022) and Kuzma et al. (2020)). The direct application of this concept to communal conflict needs to be critically evaluated. As mentioned before, Elfversson and Brosché (2012) describe communal conflict as more disruptive singular events than for instance civil war.

This difference in conflict structure has led to the adoption of a binary classification into communal conflict and no communal conflict without further distinction between conflict onset and conflict incidence. This decision is backed by the analysis of the temporal conflict structure in Section 3.1.2. Conflict between a certain dyad rarely occurs in two subsequent months.

2.2.4 Fixed Effects Logistic Regression Model

To evaluate the impact of DIs on conflict without the consideration of other time-variable or spatially variable factors which contribute to conflict probability, a fixed effects logistic regression model was used.

A Logistic Regression Model

A LRM is a Generalized Linear Model (GLM) with a logit link function to transform linear predictor y to a probability p of occurrence of a certain event (Dunn & Smyth, 2018). For the binary output variable of conflict occurrence c, the probability that conflict occurs is therefore given by:

$$p = \Pr[c = 1] = \frac{exp(y)}{1 + exp(y)} \tag{2.1}$$

where y is a linear function. If the impact of the DI d on the binary conflict variable was investigated without taking any further variables, fixed effects or interactions (see C) into account, the linear part of the logistic regression equation would be as follows:

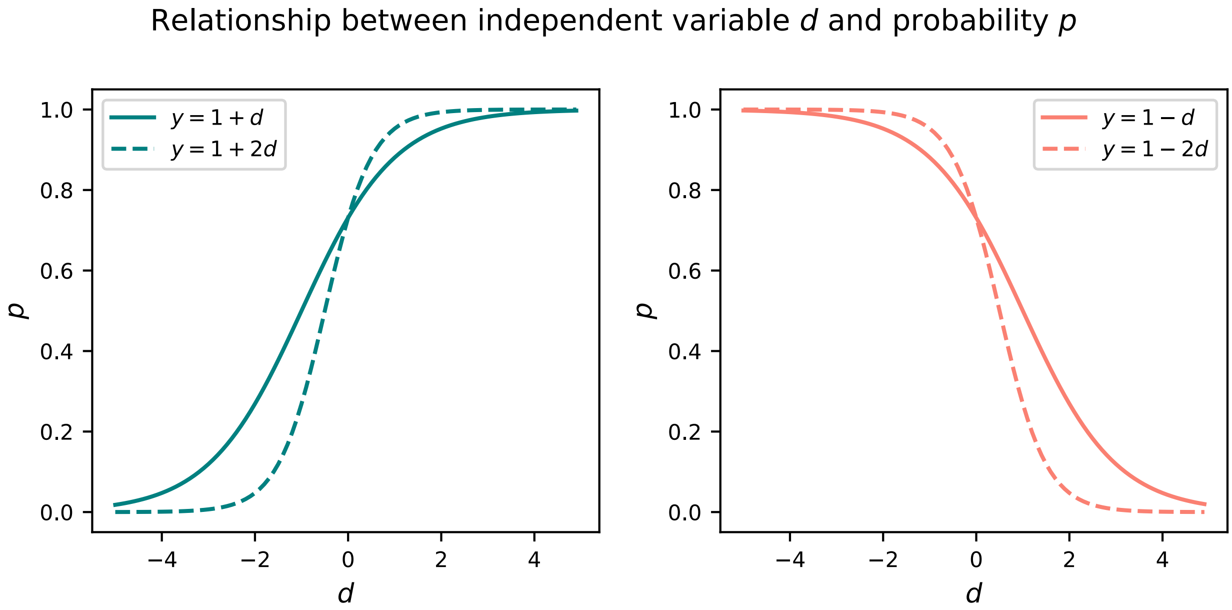


Figure 2.2.: Logistic regression function: Probability p as a function of independent variable d for different coefficients

$$y = \alpha_0 + \beta_1 * d \tag{2.2}$$

where α_0 is the intercept and β_1 is the coefficient of the DI. The resulting shape of the probability function in dependence of DI d is visualized in Figure 2.2 for two examplary negative and positive values of coefficient β_1. For SPI and SPEI a positive value for β_1 would suggest that less severe drought or more severe water abundance, respectively, would increase the risk of conflict. On the other hand, a negative coefficient would suggest that more severe drought or less water abundance increases the risk of conflict. A higher absolute value of the coefficients suggests a stronger impact of the DI, where a change in the DI is associated to a larger change in the probability of conflict.

B Odds

Due to the non-linear relationship between probability p and the linear predictor y, the quantitative interpretation of fitted coefficients is not straightforward. As can be seen in Figure 2.2, the effect of a unit increase or decrease in the independent variable on the probability depends on the starting value of the independent variable. To quantify the impact of an independent variable on the dependent variable, the concept of odds is introduced below.

If p describes the probability of occurrence of an event (e.g. conflict), then the odds of the event are the ratio of its probability of occurrence and the probability that the event does not occur (Dunn & Smyth, 2018).

$$\text{odds} = \frac{p}{1-p} \tag{2.3}$$

The logarithm of the odds or short, the log-odds correspond to the linear predictor y (Dunn & Smyth, 2018).

$$log(\text{odds}) = \alpha_0 + \beta_1 * d \tag{2.4}$$

$$\text{odds} = exp(\alpha_0)exp(\beta_1)^d \tag{2.5}$$

C Fixed effects and interactions

The observations of conflict, which were used to investigate the effect of DIs on conflict, cannot be treated as completely independent. Rather, they belong to the time series of three distinct counties or six ethnic groups respectively. Data which is pooled on a cross-section of e.g. multiple individuals, households, companies or administrative units and follows them "longitudinally" over several time periods, is called panel data (Baltagi, 2021).

In panel data it is commonly adjusted for time-invariant differences in the outcome in between cross-sectional units and variability over time which cannot be explained by the independent variable. A common way of accounting for omitted variables which explain these differences, is to use fixed effects.

For the case of the present analysis of the impact of DIs on conflict, it is likely that there are other unobserved covariates on the *admin-1 level* or level of the individual ethnic group. This can affect the probability of conflict. For example, some groups may be more inclined to engage in conflict because of long-standing feuds between them and other ethnic groups. Conflict may also be more likely in some counties because of higher marginalization and aridity in creating more incentive to engage in raiding.

In addition, there may be place-independent variability in conflict probability over time which is explained by omitted variables such as country-wide election periods. As the results obtained from the literature review have shown, accounting for these influences is crucial, as climate variability is only one in a complex system of conflict contributors (see Section 4.1). In addition, conflict reporting is likely to have increased over time resulting in an increase of records in media-reporting-based conflict datasets.

To account for covariates at admin-1 level or ethnic group level but also over time, fixed effects were included. As temporal fixed effects, 2-year dummies have been chosen over a 1-year dummies, as 1-year dummies may confound the impacts of DIs with aggregation times of 12 months. In addition, there has been no conflict in the study area in 2016. A dummy variable, for which little to no variability in the output variable is observed, can lead to inflated coefficients and standard errors and cause perfect or quasi-perfect separation of the results (Clark et al., 2023).

Apart from 2-year dummies, seasonal dummies are considered crucial to account for differences in conflict probability in between the dry season and the rainy season, as suggested by the prior literature review. A table of the months which are assigned to the rainy season or dry season per administrative unit and ethnic group territory is provided in Appendix B.

For administrative unit a and 2-year period i and season s, the linear part $y_{a,i}$ of the model is therefore extended by three additional intercepts $\alpha_{adm,a}$, $\alpha_{2y,i}$ and $\alpha_{seas,s}$.

$$y_{a,i} = \alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s} + \beta_1 * d \tag{2.6}$$

While fixed effects, can capture inter-individual or inter-temporal differences between the probability of the outcome, they do not account for the differences in the effect of the independent variable of interest (here: drought) e.g. in between administrative units. As the literature review for the study area suggests such potentially diverging *responses* to drought per administrative unit or even ethnic group, the definition of interaction terms is necessary.

For the case of an interaction between a dummy variable for the administrative unit and the continuous independent variable of the DI d, the linear part of the logistic regression for administrative unit a is further extended to:

$$y_{a,i} = \alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s} + \beta_1 * d + \beta_{adm,a} * d \tag{2.7}$$

where $\beta_{adm,a}$ is a coefficient which is specific to the administrative unit a.

Consequently the odds for equation 2.7 are given by:

$$\text{odds} = exp(\alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s})exp(\beta_1 + \beta_{adm,a})^d \tag{2.8}$$

D Odds Ratio

To evaluate the impact of a change in DI on the odds of conflict, the concept of the odds ratio OR is introduced, which describes how many times greater the odds are in the case of a one unit increase or decrease in the DI. For the present analysis, the odds ratio used for positive DIs is calculated for a unit increase in DI:

$$\text{OR}_{\Delta d=1} = \frac{exp(\alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s})exp(\beta_1 + \beta_{adm,a})^{d+1}}{exp(\alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s})exp(\beta_1 + \beta_{adm,a})^d} = exp(\beta_1 + \beta_{adm,a}) \tag{2.9}$$

For negative DIs it is defined per unit decrease in DI:

$$\text{OR}_{\Delta d=-1} = \frac{exp(\alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s})exp(\beta_1 + \beta_{adm,a})^{d-1}}{exp(\alpha_0 + \alpha_{adm,a} + \alpha_{2y,i} + \alpha_{seas,s})exp(\beta_1 + \beta_{adm,a})^d} = \frac{1}{exp(\beta_1 + \beta_{adm,a})} \tag{2.10}$$

Through the above definition, OR > 1 suggests an increase in odds in the direction of the extremes (drought and water abundance respectively). OR < 1 suggests a decrease in odds in the direction of the extremes.

E Clustering of standard errors

As independence of observations is not ensured for cross-sectional data, standard errors may be underestimated when correlated within administrative units (Cameron & Miller, 2015). Therefore, it is common practice in econometric analysis to cluster standard errors. As the present data only consists of a low number of clusters G ($G = 3$ for the administrative units and $G = 6$ for the ethnic group analysis), the cluster-adjusted variance-covariance matrix is derived using the approach by Bell and McCaffrey (2002) as recommended by Cameron and Miller (2015). In addition, the degrees of freedom are adjusted to $G - 1$ (Cameron & Miller, 2015).

To compute the significance of coefficients and odds ratios the Wald t-test statistic was used with $G - 1$ degrees of freedom. The Wald t-test rejects the hypothesis that the estimated coefficient $\hat{\beta}$ is different from a value β_0 based on the following statistic.

$$W = \frac{\hat{\beta} - \beta_0}{\hat{se}(\hat{\beta})} \tag{2.11}$$

where $\hat{se}(\hat{\beta})$ is the estimated standard error of $\hat{\beta}$(Cameron & Miller, 2015).

As the alternative hypothesis tested was that the coefficient is significantly different from zero, the test statistic reduced to:

$$W = \frac{\hat{\beta}}{\hat{se}(\hat{\beta})} \tag{2.12}$$

$\hat{se}(\hat{\beta})$ can be retrieved from the adjusted variance-covariance matrix (Cameron & Miller, 2015):

$$\hat{se}(\hat{\beta}) = \sqrt{\hat{var}(\hat{\beta})} \tag{2.13}$$

For the combined coefficient $\hat{\beta}_1 + \hat{\beta}_{adm,a}$, as required to estimate the significance of the odds ratio for administrative unit a, the estimated variance is given by:

$$\hat{var}(\hat{\beta}_1 + \hat{\beta}_{adm,a}) = \hat{var}(\hat{\beta}_1) + \hat{var}(\hat{\beta}_{adm,a}) + 2 * \hat{cov}(\hat{\beta}_1, \hat{\beta}_{adm,a}) \tag{2.14}$$

where $\hat{cov}(\hat{\beta}_1, \hat{\beta}_{adm,a})$ is the estimated covariance of the two coefficients (Pollard, 2014).

2.2.5 Model specifications

Originally, the primary objective of this stage of the thesis was to determine which DIs, defined by their aggregation time and the lag applied as well as the spatial statistics, are most influential within an administrative unit, to then use these DIs in the predictive model, developed as part of Sub-question 3. However, findings during the prior stage of the literature review suggest potentially different responses in different parts of the study area and among different ethnic groups. In addition, cross-border migration was repeatedly mentioned in the literature as a way to secure access to scarce resources (see Chapter 4.1. Therefore, four different model structures were investigated to allow for a more profound understanding of the underlying climate-conflict dynamics in the study area:

1. **Model 1**: Model at *admin1-level* of the effect of DIs on conflict occurrence within the same county with fixed effects for the county, 2-year-intervals and the season. The obtained coefficients and changes in odds inform about the impact of drought or water abundance on conflict within the same county where magnitude and direction of the impact are considered independent of the county.
2. **Model 2**: Model at admin1-level of the effect of DIs on conflict occurrence within the same county with fixed effects for the county, 2-year-intervals and the season and an interaction component between the county and DI. The effects found within this model suggest an effect of drought or water abundance on conflict for a specific county. Effects found may differ in magnitude and direction.
3. **Model 3**: Model at the level of ethnic groups where the effect of DIs within the ethnic homeland is mapped to any conflict between the ethnic group and any other ethnic group with fixed effects for the ethnic group, 2-year-intervals and the season. The obtained coefficients and changes in odds inform about the impact of drought or water abundance on conflict involving the ethnic group where magnitude and direction of the impact are considered independent of the ethnic group in question.
4. **Model 4**: Model at the level of ethnic groups where the effect of DIs within the ethnic homeland is mapped to any conflict between the ethnic group and any other ethnic group with fixed effects for the ethnic group, 2-year-intervals and the season. The effects found within this model suggest an effect of drought or water abundance on conflict involving a specific ethnic group. Effects found may differ in magnitude and direction per ethnic group.

A non-linear relationship between the DIs and conflict has been found in prior literature, where both, positive and negative anomalies in SPI increased the risk of communal conflict (Nordkvelle et al., 2017). Similarly, the literature review on the drought-conflict relationship suggested that it may be both or only one of the extremes that affects the conflict behaviour of different ethnic groups (see Chapter 4.1). Therefore, the impact of positive and negative DIs on conflict was investigated in separate logistic regression models. In combination with the different aggregation times (n=1, 3, 6, 12 months) and different lags (i =0, 1, 2, 3, 4, 5, 6, 7 months) as well as the different spatial statistics for the DI (25th, 75th, Mean, Median), this resulted in a total of 1024 model set-ups.

While it was originally considered to also include the 10th and 90th spatial percentile of DIs to assess, whether widespread to very local drought or water abundance phenomena have a higher explanatory power for conflict occurrence, the separate consideration of negative and positive DIs resulted in inflated coefficient estimates as there was no to little variance in the 10th percentile variable for positive DIs and the 90th percentile variable for negative DIs.

2.3 Sub-question 3: Predictive performance of drought indicators in a conflict model

As stressed by Ward et al. (2010) significance of the relationship between a predictor variable and conflict does not necessarily imply a large increase in predictive performance when evaluating models on unseen data. Therefore, the predictive performance needs to be evaluated through comparison of a full conflict model with DI included relative to a baseline model without that indicator.

The limited transferrability of the causal relationships established by regression models to unseen data has resulted in a shift in conflict research from understanding the relationships between supposed conflict drivers and conflict to a more prediction-centered approach with ML approaches being commonly employed in public CEWS (Hegre et al., 2019; Kuzma et al., 2020). While ML models limit the insight into the causal relationships they may be able to unravel more complex relationships between predictor variables, including drought, on conflict. Thereby, they also enable the detection of underlying causal relationships independent of human preconception (Hoch et al., 2021). The missing consensus on conflict drivers and their causal relationships in conflict research highlights the potential of ML in that field (Kuzma et al., 2020). Comparisons to regression models have repeatedly found that ML algorithms such as gradient boosting, Long short-term memory (LSTM) and RF provide better conflict predictions at varying time scales than traditional logistic regression models (Colaresi & Mahmood, 2017; Görgen, 2021; Musumba et al., 2021).

As the interest as part of the thesis was the value of DIs within conflict prediction rather than exploring the detailed causal relationships, it was decided to also use a ML model approach as part of the thesis.

The activities entailed within this step of the thesis have therefore been (1) the choice and construction of a ML model, (2) the preparation of independent and dependent variables, (3) the improvement of the model structure to prevent overfitting, (4) the evaluation of the final model on a separate set of data and the consequent assessment of the role of the different independent variables, including the DIs.

2.3.1 A Machine Learning model for conflict prediction

In conflict research several different ML model types have been tried to predict conflict (Colaresi & Mahmood, 2017; Ge et al., 2022; Görgen, 2021; Hegre et al., 2019; Hoch et al., 2021; Kuzma et al., 2020; Musumba et al., 2021; Perry, 2013). However, tree classifiers and RF classifiers, in particular, feature dominantly within the literature reviewed (Colaresi & Mahmood, 2017; Ge et al., 2022; Hegre et al., 2019; Hoch et al., 2021; Kuzma et al., 2020; Perry, 2013).

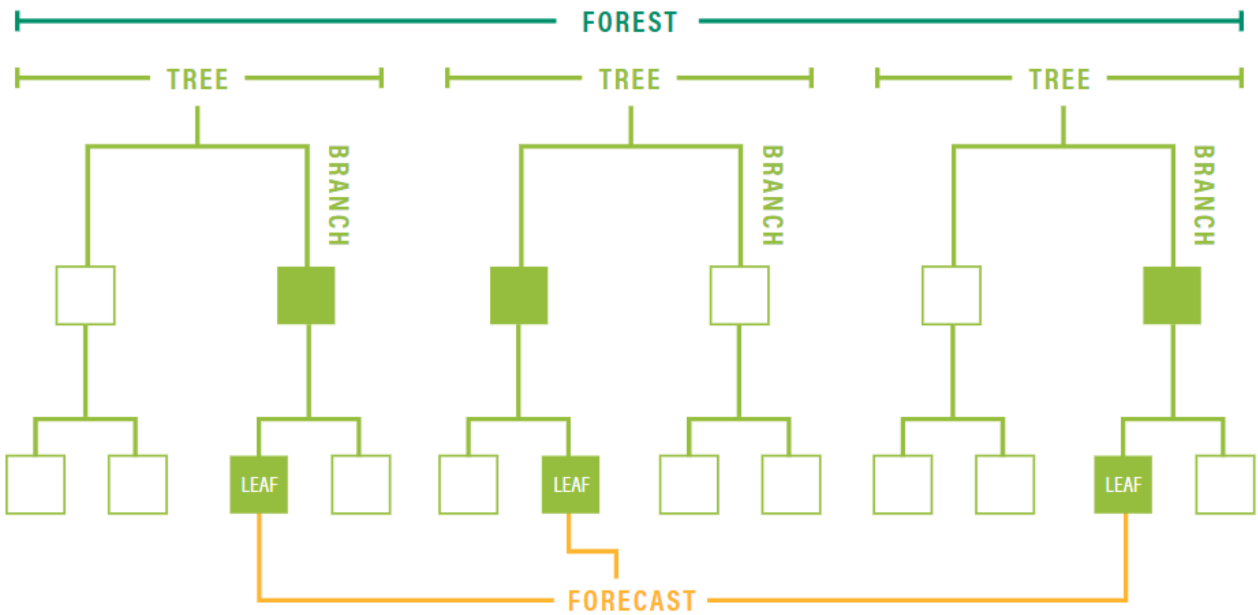


Figure 2.3.: Schematic visualization of a Random Forest model (Source: Kuzma et al. (2020))

RFs are an aggregation of multiple individual decision trees. Figure 2.3 illustrates the set-up of Random Forests. Within each tree the data is progressively split, where each split corresponds to a variable and its value which most meaningfully splits the data based on the Gini index. Each tree obtains a sub-sample of the training data and the predictor variables. It attempts to find the sequence of input variables and their threshold values which best split the data into the different target classes (Perry, 2013). The classification of an observation as *no conflict* or *conflict* is then obtained for each tree based on the number training samples of each class in the end node the observation is assigned to ("sklearn.ensemble.RandomForestClassifier", n.d.). It is then aggregated to a final decision of the RF model on the class of the observation(Perry, 2013). The predicted class is the one with the higher mean probability estimate across all trees ("sklearn.ensemble.RandomForestClassifier", n.d.).

Reasons for the choice of RF over other algorithms range from their ability to deal with a large number of structurally different predictor variables without prior preprocessing and with large quantities of observations (Kuzma et al., 2020; Perry, 2013), the relative transparency of how the model arrives at a decision compared to other ML algorithms, through investigation of the single trees within the RF model (Kuzma et al., 2020) and the good performance of the algorithm in prior research within the conflict prediction domain (Hegre et al., 2019). Its wide use within conflict prediction field, which makes the thesis comparable to other efforts including ViEWS and the WPS CEWS (Hegre et al., 2019; Kuzma et al., 2020), as well as the little need for prior feature engineering, have also encouraged the adoption of an RF modelling structure for the thesis.

2.3.2 Adjusted study area

For the RF model the study area was expanded to cover administrative units in Ethiopia, Kenya, South Sudan (also as former part of Sudan), Uganda and Somalia where communal conflict has occurred between 2004 and 2021. Thereby, the dataset increased in size from 648 observations to a total of 12,700 observations.

2.3.3 Model data

The choice of variables was based on the set-up of the WPS Global Early Warning Tool models. A quasi-replication of the model was performed at the regional scale, where only drought and conflict variables were replaced with the variables used within the present thesis.

A Predictor variables

Table 2.2 gives an overview of all independent variables considered to build the RF model within the present thesis and the temporal lag applied. Variables are lagged because of the conflict prediction context in which up-to-date information may not always be available at the time of prediction. In addition, for DIs it has shown in the results of Sub-question 2 (see Section 3.3 that climate conditions still significantly affect the conflict response up to several months later. Apart from DIs and spatially and temporally lagged conflict variables, other variables which have been relevant in the WPS Global Early Warning Tool are considered as part of the set of input variables.

These variables, based on the United Nations Development Programme (UNDP) human security framework, include demographic variables on local population density (*local population density*), count (*local population count* and ratio of population living in a rural vs. urban environment (*rural to urban ratio*, gender ratios in certain age groups (*ratio of males in age-group 25-64, ratio of males in age-group 65+* as well as the total the percentage of males which are 65 or older (*percentage of males who are 65+*). In addition, economic variables on GDP(*GDP per capita, PPP*), the contribution of agriculture to the GDP (*agriculture value added to GDP (%)* and the value of rainfed agriculture (*value of rainfed crop*) are considered. Finally, water-related variables on access to sanitation (*sanitation access*), intra-annual and interannual variability in available water supply (*seasonal variability, interannual variability*) and the risk associated to flooding in terms of the percentage of people affected (*riverine flood risk*) (Kuzma et al., 2020).

The variables have mostly been obtained from the DataCube, which holds all relevant input and output data. Therefore, little preprocessing was necessary. However, a few variables could not be obtained for the right temporal scale and in their filled version. The retrieval of the corresponding original data products from their respective sources could solve the temporal issue. However, the required filling of null values in two of the variables (*GDP per capita, PPP* and *agriculture value added to GDP (%)*) for Somalia and South Sudan, following the complex procedure described by Kuzma et al. (2020), was beyond the scope of this activity within the thesis. A restriction of the study area to the subset of countries with complete time series for the variables *NY.GDP.PCAP.PP.KD* and *NV.AGR.TOTL.ZS* was prone to overfitting of the model. Therefore, instead, the two variables were removed from the analysis.

The choice of DIs was based on the findings of significant relationships in the prior analysis at *admin1-level* as part of Sub-question 2 (see Section 3.3. It was assumed that these relationships were most likely to also picture in a predictive model at *admin-1 level.*

SPEI-1 and SPEI-6 at lags of zero months were included, as a decrease in positive SPEI for these two aggregation periods has been globally found to significantly reduce the conflict odds. The same effect has been found for SPEI-3 at lags of zero to two months and SPI-3 at a lag of two months. To reduce the risk of multicollinearity, only one of these variables is used. SPI-3 has been chosen because of the additional significance found for a decrease in negative SPI-3 at a lag of two months.

These DIs, which globally show a significant one-directional pattern in the effect on the odds of conflict, were complemented by three variables for which opposing patterns were found in between Turkana and West Pokot county: SPI-1, SPI-6 and SPI-12 at a lag of seven, four and two months respectively.

Table 2.2.: Overview of variables considered as part of the RF model

Variable name long	Variable name	Temporal frequency	Temporal lag [months]
WPS Global Early Warning Tool			
local population density	locdensity_y	yearly	0
local population count	loccount_y	yearly	0
GDP per capita, PPP*	NY.GDP.PCAP.PP.KD	yearly	24
agriculture value added to GDP (%)*	NV.AGR.TOTL.ZS	yearly	24
ratio of males in age-group 25-64	sex_ratio_25-64	yearly	0
ratio of males in age-group 65+	sex_ratio_65+	yearly	0
percentage of males who are 65+ **	male_pct_65+	yearly	0
santitation access	sanitationaccess	yearly	48
riverine flood risk	rfr_s	static	-
seasonal variability	sev_s	static	-
interannual variability	iav_s	static	-
rural to urban ratio	rurratio_s	static	-
value of rainfed crop	spam_V_agg_r_sum_s	static	-
DIs			
Median SPI-1	Median_SPI-1_lag7	monthly	7
Median SPEI-1	Median_SPEI-1_lag0	monthly	0
Median SPEI-3	Median_SPI-3_lag2	monthly	2
Median SPEI-6	Median_SPEI-6_lag0	monthly	0
Median SPI-6**	Median_SPI-6_lag4	monthly	4
Median SPI-12**	Median_SPI-12_lag2	monthly	2
Conflict variables			
time since last communal conflict	dt_conflict	monthly	0
spatially lagged communal conflict	spat_com_t-1	monthly	1
spatially lagged other conflict	spat_oc_t-1	monthly	1

*variables which have not been used in the final model because of missing values for some of the countries; **variables which have not been used because of multicollinearity among variables

Within the WPS Global Early Warning Tool, further variables on the conflict history have been included. However, as the model was based on ACLED conflict data, which employs a different distinction between conflict types, the variables are replaced by variables based on the UCDP conflict data prepared as part of the thesis. Conflict input features are supposed to account for the lagged effect of past conflict and potential spillover effects from adjacent administrative units on communal conflict. Following Fjelde and von Uexkull (2012), it is distinguished between three variables: (1) the time since the last communal conflict in months, (2) the occurrence of communal conflict in one of the adjacent administrative units and (3) the occurrence of other conflict types in one of the adjacent administrative units.

B Multicollinearity

Multicollinearity among independent variables describes the phenomenon when independent variables can be linearly predicted from other predictor variables within the set of input features. While this was not suspected to affect the performance of the model, multicollinearity can confound the importance of an individual variable for the predictive performance. As the main purpose of this stage was the impact assessment of DIs, among highly correlated features, only one is chosen.

To assess multicollinearity, Spearman's rank order correlation coefficient (SpROC) was computed. The resulting correlation matrix is displayed in Appendix C. With values higher than 0.7, the SpROC is high among three feature pairs. Hence, three variables are removed, as indicated by ** in Table 2.2. The removal of these variables did not decrease RF model performance.

C Dependent variable

As independent variable, WPS uses a binary variable which classifies each month based on the criterion whether there have been at least 10 fatalities recorded in ACLED data within the next year. Instead, here, the same monthly binary conflict variable was used, as throughout the prior steps.

Within the resulting dataset, approximately 4% of the observations are months when conflict was reported for the respective admin-1 unit. Unbalanced datasets can corrupt model performance, especially where capturing the minority class is of interest. When training the RF model on the unbalanced dataset, it is likely that the model will resort to never predicting conflict. The dataset can be balanced by undersampling, through removal of non-conflict records until the number of *no conflict* and *conflict* records is roughly the same. However, in the present case this would drastically reduce the size of an already small dataset. Instead, Synthetic Minority Oversampling Technique (SMOTE) was used, as a method of artificially oversampling conflict records (Chawla et al., 2011).

D SMOTE

Through SMOTE synthetic training data of the minority class was created by randomly sampling features along the line segments between sample A and its k nearest neighbouring samples in the feature space (Chawla et al., 2011). Synthetic Minority Oversampling Technique for Nominal and Continuous (SMOTE-NC) can additionally account for categorical variables which are present in the dataset (here: *spatially lagged communal conflict* and *spatially lagged other conflict*). The algorithm assigns the value to categorical features which is most present among the k nearest neighbours (The imbalanced-learn developers, n.d.).

The *imblearn* algorithm *SMOTENC*, in its default set-up with $k = 5$, has been applied to the training data during hyperparameter tuning and when training the final model (Lemaître et al., 2017). Validation and testing subsets are not oversampled to assess the model's performance to provide good predictions on imbalanced datasets.

E Training, validation and testing subsets

It is commonly distinguished between a training and a testing subset of the data to make sure that the model also performs well on data which it has not seen yet during training. Therefore, a part of the data (e.g. 1/3) is held out and only used to evaluate model performance in the end.

In addition, Colaresi and Mahmood (2017) recommend to also hold out a part of the data during the step of hyperparameter tuning, to avoid a model structure which is prone to overfitting. This can be done by splitting the training data set again into a subset which is fed into the model during the model tuning phase and another static subset, called validation data, which is used to evaluate the performance and inform the model structure. Alternatively, k-fold cross-validation can be performed, where k iterations are performed with always 1/k of the training data being held out, while the model is fit on the remainder. Overall model performance is then obtained through averaging performance obtained over the k iterations.

Table 2.3 illustrates the split of the data performed as part of each phase. This will be elaborated on in the following sections.

2.3.4 Hyperparameter tuning

In contrast to parameters which were determined as part of the training process to map input data to the output data, hyperparameters in ML are the parameters that control the learning process itself. For the case of an RF model, examples of hyperparameters are the number of trees, the number of splits allowed per tree, the minimum number of training samples before a split is conducted or the minimum number of training samples in a leaf. Determination of these hyperparameters can improve the performance of the model while simultaneously delimiting the risk of overfitting.

Hyperparameter tuning was performed by manually or automatically trying different hyperparameter combinations on a training dataset and evaluating the performance on a validation dataset. For the present case of a relatively small dataset, stratified 10-fold cross validation was performed. 10% of the data is held out which contains about the same fraction of *conflict* months as the entire dataset. The other 90% are used to build the trees. This process was repeated 10 times. The performance was then obtained by averaging the predictive performance of the model over the 10 held out validation datasets.

Three different motivations are underlying the hyperparameter tuning process within the present thesis:

1. Model performance shall be improved with respect to the measure of recall, as the percentage of conflict months which are detected (see B for a detailed explanation). As the algorithm for Random Forest Classifiers aims to decrease overall node impurity, default settings of hyperparameters favour a reduction in overall accuracy, resulting in a very low recall.
2. The risk of overfitting shall be reduced. Therefore, the number of trees to grow, the depth of the trees and the number of features to try at each split, were restricted.
3. Feature importance shall be assessed. If too few trees and splits are performed and the number of features is small, actual feature importance risks to be concealed by coincidental choice of features.

Grid search has been used to determine a suitable combination of number of trees and maximum depth of the trees and the number of features randomly sampled per split. The validation performance was assessed for a number of trees of 20, 30, 50 and 100 trees and a maximum tree depth of 2, 3, 5, or 10 levels. The restriction of the maximum number of features per split to decide on the best threshold to increase purity of the nodes, was set to values of 2, 3, 5 and 7 features. These hyperparameter ranges were considered to counteract overfitting through a low number of relatively small trees. At the same time, setting the minimum limits for the hyperparameter ranges ensures that each feature is being considered within the model. With the present minimum limits, the probability that a feature has never been drawn from the set of features is approximately 0.3%.

The best hyperparameters were determined based on the averaged recall over the ten validation datasets of the stratified 10-fold cross-validation. The final model consists of 20 trees with a maximum depth of two levels. A maximum of three features was used at each node to decide on the best split.

2.3.5 Model evaluation

A Final model training & testing

After the model had been determined in terms of hyperparameters, the final model was trained again and its performance was tested on another held-out dataset to evaluate how well the model generalizes to unseen data. A temporal split has been used where hyperparameter tuning and the subsequent retraining of the dataset has been performed on data for the time from 2004 to 2015. Data for the time period from 2016 to 2021 has been used to evaluate the final model performance.

B Performance metrics

Evaluation of model performance in classification tasks is based on the number of correctly and incorrectly predicted observations. As priority within the present case is the correct prediction of *conflict* months, it is distinguished between *True Positives* (TP) as *conflict* months which are correctly predicted as such and *True Negatives* (TN) as *no conflict* months which have been correctly predicted. In addition, *False Negatives*(FN) are *conflict* months which have been incorrectly predicted to have no conflict. And *False Positives* (FP) are conflict months which have been incorrectly classified as *conflict* months. This terminology is illustrated in Figure 2.4

	no conflict predicted	conflict predicted
no conflict observed	*True Negative*	*False Positive*
conflict observed	*False Negative*	*True Positive*

Figure 2.4.: Confusion matrix for conflict prediction (adapted from Kuzma et al. (2020))

For a classification task, overall *accuracy* as the overall percentage of correct classification, is a widely used measure. However, it is not suitable for a highly imbalanced dataset like conflict data, where often conflict observations only make up a few percent of all observations (Kuzma et al., 2020; Musumba et al., 2021). The model may just resort to never predicting conflict and thereby still achieve a high accuracy. While SMOTE is expected to counteract this model behaviour, there are the alternative metrics of recall and precision available, which measure the ability of the model to classify a positive observation (here: *conflict*) as positive or to not mistake a negative observation (here: *no conflict*) as positive, respectively.

Recall describes the percentage of *conflict* observations which have been classified as *conflict*.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2.15}$$

Precision describes the percentage of true *conflict* observations within all observations which have been classified as *conflict*.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2.16}$$

As a higher recall comes at the cost of a lower precision, additional measures such as the F1 or F2 score, the area under the recall-precision curve or under the receiver operator curve Colaresi and Mahmood (2017), Kuzma et al. (2020), and Musumba et al. (2021). In coherence with Kuzma et al. (2020), and as a score, which can be easily calculated and compared across literature, the F2 score is used here.

The F2 score is the weighted harmonic mean of the precision and recall. The 2 indicates that recall is weighted to have twice as much influence as precision (Kuzma et al., 2020).

$$\text{F2} = (1 + 2^2)\frac{\text{Precision} * \text{Recall}}{(2^2 * \text{Precision}) + \text{Recall}} \tag{2.17}$$

C Feature importance

To evaluate the importance of DIs in conflict prediction, the Permutation Feature Importance (PFI) was computed. PFI assesses the importance of a variable through randomly shuffling the values of that variable. Thereby, the relationship between this input variable and the output breaks down and it can be evaluated how this affects the performance metric of interest. The PFI is defined as the decrease in the score of the metric of interest when shuffling the variable. Thus a positive PFI suggests that the variable has improved the prediction while a negative PFI shows that the model is better without that variable. The process was repeated m times to obtain the average PFI and its standard deviation (Breiman, 2001; scikit-learn developers, n.d.).

PFI has been chosen over the alternative feature importance based on Mean Decrease in Impurity (MDI) because it can be computed on the held out testing set. Thereby it assesses which variables improve the predictive power most in a generalized setting. Variables which have a high PFI on the training dataset, but do not improve model prediction, when the model was tested on the held-out data, can contribute to overfitting (scikit-learn developers, n.d.).

2.4 Data preprocessing

2.4.1 Administrative units

To delimit administrative units the GADM 3.6 dataset was used. GADM maps administrative areas at global scale for all levels of division. Data has been downloaded from the project website for each of the countries within the wider study area (GADM, 2018). GADM 3.6 has been chosen over the more recent version 4.0 because it has been the base for data retrieval and assignment to the admin-1 level as part of the WPS Global Early Warning Tool (Kuzma et al., 2020). As the conflict prediction model within Sub-question 3 is partially replicating the structure of the WPS Global Early Warning Tool, GADM 3.6 was used for consistency in the delimitation of borders.

Table 2.3.: Overview of time periods for training, validation and testing subsets

Time period	**Training dataset 2004 - 2015**	**10-th fold for validation**	**Testing dataset 2016 - 2021**
Model set-up	Fitting model (SMOTE-oversampled data)	Evaluating model performance	
Final performance evaluation	Fitting model (SMOTE-oversampled data)		Evaluating model performance
Model comparison			Comparing model performance

2.4.2 Ethnic territories

In addition to administrative units, ethnic group territories are used to investigate whether conflict occurrence for a certain ethnic group can be explained by a change in the DI within its "homeland". The definition of an ethnic territory is meant to be indicative only. As prior literature for the study area suggests, ethnic territories are difficult to assign due to fluctuating communal borders, territories often not being inhabited by one single ethnic group and the dynamic definition of ethnic identity (Detges, 2014; Ember et al., 2014).

Different definitions of ethnic identity are a key challenge which prohibit the use of the GeoEPR dataset on powerful ethnic groups and their respective territories (Vogt et al., 2015) . Within this dataset the key ethnic actors of Turkana and Pokot which form the dyad with the most conflict events within the study area (see 3.1.2), were merged within one larger ethnic territory. Following Detges (2014)'s and Fjelde and von Uexkull (2012)'s approach, ethnic group territories are therefore instead identified through the georeferencing of other ethnic group maps which identify separate territories for the ethnic groups of interest (CEWARN, 2016a, 2016b, 2016c; Ember et al., 2014; ICPAC, 2017; Marc L. Felix, 2001; Onditi, 2022).

Figure 2.5 shows the derived ethnic territories for different groups, where striped areas indicate difficulties in assigning areas to one single ethnic group. These difficulties arise from different sources assigning these territories to different ethnic groups.

As noted by Detges (2014) more accurate data on territories would be preferable, but small inaccuracies are considered to not affect the analysis of the drought-conflict relationship in a significant way. This is also the case for the present study, where the high correlation in DIs among administrative units already suggests that the exact position of borders is of minor importance. In addition, through the use of various spatial statistics beyond the mean, the impact of the inclusion or exclusion of individual grid cells is considered to be minor.

For the following analysis the wider extent of ethnic territories were used for each ethnic group.

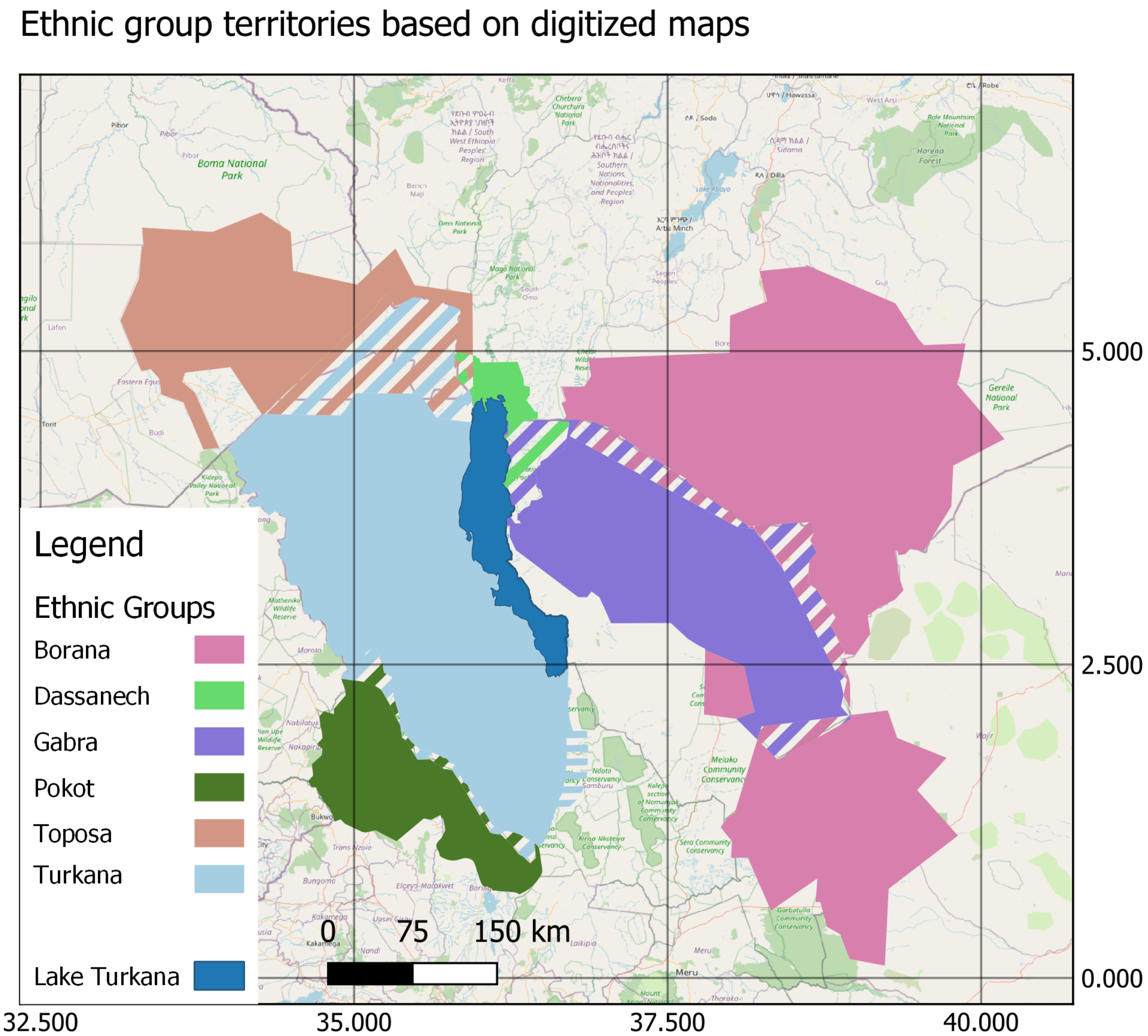


Figure 2.5.: Ethnic group territories for ethnic groups which are part of the dominant dyads in the study area. Based on digitized maps from different sources ((CEWARN, 2016a, 2016b, 2016c; Ember et al., 2014; ICPAC, 2017; Marc L. Felix, 2001; Onditi, 2022)). Striped areas indicate conflicting assignments by the different sources

Table 2.4.: Overview of ERA5 variables, temporal aggregation method and unit transformation applied

variable	variable name long	aggregation	original unit	destination unit
T	air temperature	minimum & maximum	K	°C
R_{sns}	surface net longwave radiation	sum	J/m^2	MJ/m^2
R_{snl}	surface net shortwave radiation	sum	J/m^2	MJ/m^2
u_{10}	10m windspeed u-component	mean	m/s	m/s
v_{10}	10m windspeed v-component	mean	m/s	m/s
T_{dew}	2m dewpoint temperature	minimum & maximum	K	°C
p_{msl}	mean sea level pressure	mean	m	m
P	total precipitation	sum*	mm	mm

*Some hourly precipitation values are slightly below zero as a result of closing the energy balance. These values are set to zero before temporally aggregating the data to daily.

2.4.3 Drought indicators

A Datasets

ERA5

ERA5 (Hersbach et al., 2020) by ECMWF provides reanalysis data (HRES) at hourly time steps for various atmospheric, ocean and land variables. Variables are obtained through running an atmospheric model coupled to a land surface and an ocean model. It can be differentiated between atmospheric variables obtainable at different pressure and potential temperature levels, and surface or single-level data including precipitation, top of atmosphere radiation as well as 2m temperature and soil temperature data provided by the land-surface model (ECMWF, 2022). The native resolution of HRES data is 31km or 0.28125 degrees. However, data available through the C3S Climate Data Store (CDS) is already interpolated to a regular latitude longitude resolution of 0.25 degrees. In the horizontal, data is referenced relative to the WGS ellipse (ECMWF, 2022).

The single products used have been downloaded from the C3S CDS using the CDS API at an hourly resolution and in netcdf format. All data was clipped to a common extent covering the wider study area to reduce the computation power required for any further steps. Hourly data was then aggregated to daily resolution and the units were changed to the required units for any further data pre-processing. An overview of the retrieved data products from ERA5 as well as the aggregation and unit transformation applied are summarized in Table 2.4.

Surface elevation data

Surface elevation data was required as part of the PET calculation. It was downloaded from Shuttle Radar Topography Mission (SRTM) at the native resolution of 1 arc second (CRS: WGS84) using the *SRTM downloader* as part of QGIS version 3.26.3. The different tiles were merged using *GDAL build virtual raster* and then transformed into a *.tif* file. To obtain data at the same resolution as ERA5 data of 0.25 degrees, the *GDAL Warp* tool was used within QGIS, where the target resolution was set to 0.25 degrees and the origin and target Coordinate Reference System (CRS) to *EPSG: 4326 - WGS 84*.

Table 2.5.: Classification of SPI values from extreme dry to extreme wet and associated probability and return period

SPI Value Range	Probability of Event [%]	Return period [years]	Class
[2,)	2.3	50	Extreme wet
(1.5, 2]	4.4	20	Severe wet
(1, 1.5]	9.2	10	Moderate wet
(-1, 1]	68.2	3	Near normal
(-1.5, -1]	9.2	10	Moderate dry
(-2, -1.5]	4.4	20	Severe dry
(,-2)	2.3	50	Extreme dry

B SPI

To derive the SPI-1, SPI-3, SPI-6, SPI-12, daily precipitation data was accumulated to monthly, 3 months, 6 months and 12 months. As proposed by Mckee et al. (1993) a gamma distribution is used to characterize long-term distribution of the probability of certain precipitation amounts for the given time periods and a specific location and month of the year. The World Meteorological Organization (WMO) and Global Water Partnership (GWP) (WMO and GWP, 2016) recommends the use of at least thirty years to fit the the distribution. Therefore, the time period from 1993 to 2022 is used to have a sufficiently long and recent time period which can accomodate changes due to climate change. For each location (longitude and latitude) and month of the year (January to December) the accumulated precipitation values was extracted for all years of the reference period and the gamma distributions was fitted to the non-zero records.

Based on the fitted gamma distribution, the cumulative probability was then calculated for the accumulated precipitation of each month and aggregation period. As only non-zero values were used to fit the gamma distribution it was adjusted to the presence of zero precipitation values through the following formula.

$$cdf_{all} = p_{zero} + (1 - p_{zero}) * cdf_{nonzero}) \tag{2.18}$$

where p_{zero} is the probability or relative frequency of zero-values within the respective location-month subset of the data (European Commission. IES - CRM Unit, 2013).

The SPI can be derived through transformation of the cumulative probabilities to the corresponding normal distribution. It therefore takes up values centered around 0, where if the SPI drops below -1 this is understood as rainfall deficits of increasing severity and if it rises above 1 this means increasingly severe rainfall abundance (European Commission, 2020). A more detailed classification is provided in Table 2.5. In addition, it includes the probability and return period of a drought event (World Meteorological Organization [WMO], 2012; WMO & GWP, 2016).

C SPEI

The SPEI can be calculated in a similar way through fitting a distribution to the difference D between precipitation P and reference evapotranspiration ET_0.

$$D = P - ET_0 \tag{2.19}$$

The SPEI was first introduced by Vicente-Serrano et al. (2010). Since then, several renewals have been proposed in terms of how reference evapotranspiration is calculated and which distribution is used to fit the data.

$$\mathrm{ET_o} = \frac{0.408\Delta(R_n - G) + 900/T_{mean}\gamma w_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{2.20}$$

Δ	slope of the vapour pressure curve [kPa °C^{-1}]
R_n	net radiation [MJ m^{-2} day^{-1}]
G	soil heat flux [MJ m^{-2} day^{-1}]
T_{mean}	daily mean air temperature [°C]
γ	psychrometric constant [kPa °C^{-1}]
w_2	wind speed at 2m height [m s^{-1}]
e_s	saturation vapour pressure [kPa]
e_a	actual vapour pressure [kPa]

Reference evapotranspiration - FAO Penman-Monteith Equation

While originally the Thorntwaite equation was used to calculate reference evapotranspiration, Beguería et al. (2014) suggest to use the Penman-Monteith equation instead, where extensive data on radiation, temperature, relative humidity and wind speed is available. The simplified FAO 56 Penman-Monteith (Allen et al., 1998) equation is used as part of the thesis which defines the reference evapotranspiration $\mathrm{ET_o}$ [mm day^{-1}] for a grass reference crop with a surface resistance of 70 $\frac{\mathrm{s}}{\mathrm{m}}$, a crop height of 0.12 m and an albedo of 0.23. The formula to calculate $\mathrm{ET_o}$ is given by:

The calculation of each of the components of the formula is described in Appendix D

Log-logistic Distribution

To determine the SPEI, the difference between precipitation P and reference evapotranspiration is calculated to then fit a distribution for each month of the year and grid cell. Vicente-Serrano et al. (2010) suggest a log-logistic distribution. The three-parameter log-logistic probability distribution function for variable x is given by:

$$F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma}\right)^{\beta}\right]^{-1} \tag{2.21}$$

where α, β and γ represent the scale, shape and origin parameters (Beguería et al., 2014).

The distribution is fitted using the concept of unbiased Probability Weighted Moments (PWMs) as suggested by Beguería et al. (2014) in an update of the SPEI calculation.

The unbiased PWM w_s of order s is given by the formula:

$$w_s = \frac{1}{N}\sum_{i=1}^{N} \frac{\binom{N-i}{s} x_i}{\binom{N-1}{s}} \tag{2.22}$$

where N is the number of data points to fit the distribution to (Beguería et al., 2014; Hosking, 1986).

The PWMs are then used to calculate the scale, shape and origin parameters following Singh et al. (1993) and Vicente-Serrano et al. (2010):

$$\beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2} \tag{2.23}$$

$$\alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma(1+1/\beta)\Gamma(1-1/\beta)} \tag{2.24}$$

$$\gamma = w_0 - \alpha\Gamma\left(1+\frac{1}{\beta}\right)\Gamma\left(1-\frac{1}{\beta}\right) \tag{2.25}$$

where $\Gamma(x)$ is the gamma distribution.

Like for the SPI, the SPEI represents the standardized version of $F(D)$. Vicente-Serrano et al. (2010) suggest the use of an approximation of this standardization. Based on the probability of exceedance P of D_i as the difference between precipitation and reference evapotranspiration for month i

$$P = 1 - F(x = D_i) \tag{2.26}$$

W is defined as

$$W = \begin{cases} \sqrt{-2\ln(P)} & P \leq 0.5, \\ \sqrt{-2\ln(1-P)} & P > 0.5 \end{cases} \tag{2.27}$$

The SPEI for D_i can consequently be calculated as

$$\mathrm{SPEI}(D_i) = W - \frac{C_0 + C_1 Q + C_2 W^2}{1 + d_1 W + D_2 W^2 + d_3 W^3} \tag{2.28}$$

where $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

Although, it is suggested by Vicente-Serrano et al. (2010) and Beguería et al. (2014) that this method should result in no values below the origin of the distribution and a smooth fit, the present dataset does contain outliers SPEI below -5 and null values. As outliers are few and DIs are spatially aggregated over the administrative unit, outliers are not considered to affect the following analysis. As null values were obtained for meteorological water balances below the origin of the fitted log-logistic distribution, they were filled with a very low probability of 10^{-10}.

D Spatial aggregation

To answer Sub-question 2 and Sub-question 3, DIs were required as input products at a monthly time scale and at admin-1 level, as well as at ethnic territory level for the additional agent-based analysis of the effect of DIs on conflict.

Gridded SPI and SPEI data was clipped to the extent of GADM 3.6. administrative units and ethnic group boundaries using the *rioxarray.clip* functionality in Python. The spatial statistics of mean, median, 25th and 75th percentile were then calculated across the grid cells assigned to one administrative unit or ethnic territory.

2.4.4 Binary conflict variable

A Conflict data

There are several different conflict datasets available with different focal points in terms of specific categories of conflict included and their representation within the dataset. The present thesis relies on the UCDP dataset family for its long history of conflict data and the easy isolation of communal conflict through combination of the UCDP-GED dataset with the UCDP Non-state conflict dataset. In addition, it allows for the analysis of different actors. The separate analysis of different ethnic groups and their response to drought has been found to be crucial for a differentiated analysis of the drought-conflict relationship in the study area (see Chapter 4.1).

UCDP-GED

UCDP-GED (Davies et al., 2022; Sundberg & Melander, 2013) and the prior country-year UCDP dataset are the most commonly used datasets within the climate-conflict literature reviewed (Buhaug & Theisen, 2012; Detges, 2016; Fjelde & von Uexkull, 2012; Hegre et al., 2016; Hendrix & Glaser, 2007; Hendrix & Salehyan, 2012; Hoch et al., 2021; Slettebak, 2012; von Uexkull, 2014; von Uexkull et al., 2016). With an initial focus on Africa and later spreading to other regions of the world, data from 1989 to 2021 can be retrieved ("UCDP - Uppsala Conflict Data Program", n.d.). UCDP-GED represents a disaggregated, spatially and temporally referenced dataset of *armed conflict* events. Event information is obtained from media reporting. Any event is included which can be associated to a certain dyad with the only condition that the dyad must have had at least one year of intense clashes with a minimum of 25 deaths during that year. Other years where the threshold is not passed for the same dyad are also included (Högbladh, 2022).

It is distinguished between the three different types of fatal organized violence which have been defined beforehand based on the actors involved: state-based, non-state conflict and one-sided violence. The distinction highlights the need of all actors to be organized and clearly identifiable (Sundberg & Melander, 2013).

Apart from information on the conflict type, the UCDP-GED dataset contains the spatial and temporal reference as well as precision of a certain event, the assignment to actors and to a certain potentially already ongoing wider conflict, the number or estimated range of total fatalities, fatalities per side and fatalities among civilians, information on the source(s) from which the event has been retrieved as well as data quality indicators (Högbladh, 2022).

UCDP Non-state Conflict

In the Non-state Conflict Dataset, non-state conflicts are further distinguished between (1) conflicts by formally organised groups including rebel groups with an official name as well as military groups or informally organised groups, where it is further distinguished between (2) impermanent groups which support a political candidate or party or (3) groups with a common identification along lines of ethnicity, religion, clans, tribes or nationalities. The latter is defined as *communal conflict* (Davies et al., 2022; Sundberg et al., 2012). Within the dataset, the location is only provided in terms of the country. Therefore, it can only be used as additional support to decide on the level of organization of different actors (Pettersson, 2022).

Matching the dyad information of the UCDP-GED dataset with the organizational information of the non-state dataset allows for the isolation of communal conflict records from UCDP-GED.

B Spatio-temporal assignment of conflict data to the unit of analysis

Admin-1 level month

Based on the spatial coordinates and the date or date range provided as part of each record within the UCDP-GED dataset, conflict events can be assigned to a month and administrative unit. However, the complexity of this processing step lies in the varying spatial and temporal precision of events within UCDP-GED and the dynamics of administrative units in Kenya.

The uncertainty associated to spatial and temporal specifications in UCDP-GED is expressed through spatial and temporal precision codes. Spatial precision codes used within the UCDP-GED dataset have the following meaning:

- 1 - exact location known and coded
- 2 - location known within a 25km radius

- 3 - admin-2 level known
- 4 - admin-1 level known
- 5 - location not known as a point or an administrative delimitation but a linear feature or fuzzy polygon
- 6 - country is known
- 7 - event in international waters or airspace

In addition, the temporal precision is given through the following classes:

- 1 - exact date is known
- 2 - 2-6 day range within which the event occurred is known
- 3 - the week of the event is known
- 4 - an 8 - 30 day range or the month of the event is known
- 5 - only a day range longer than one month is known

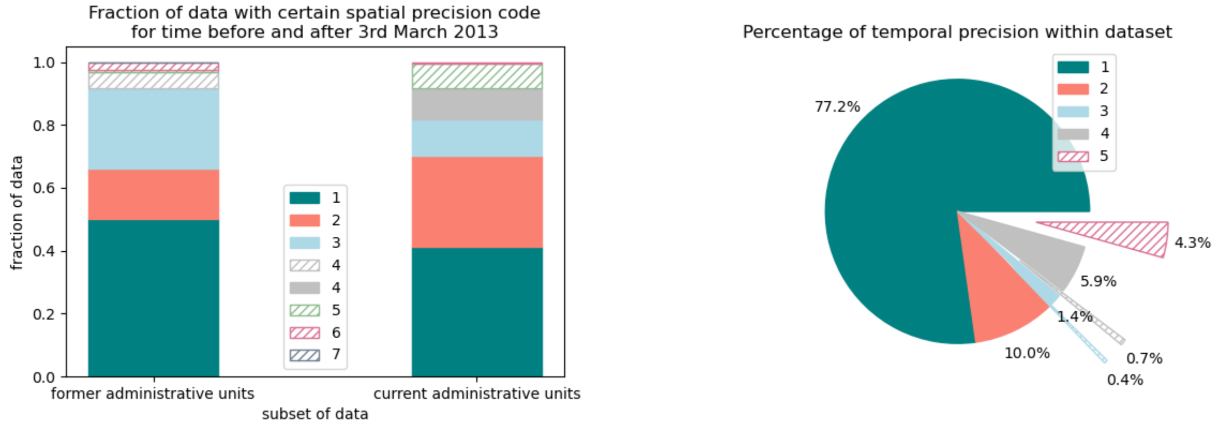
These precision codes suggest that a conflict event with a spatial precision code or a temporal precision code of higher than 4 cannot be clearly assigned to the spatio-temporal unit of analysis of the present thesis. These conflict events are removed.

The complexity of removal was increased through the dynamics of administrative units in Kenya. While formerly organized into eight provinces at the admin-1 level which were further subdivided into a variable number of districts, the country is now split into 46 counties + Nairobi as the admin-1 level since the general elections on 3rd March 2013.

The mapping of conflict events to the administrative units within UCDP-GED is "time-aware" (Högbladh, 2022, p.20). This means that the reported administrative units are always those which have been in place at the time of reporting. Hence, a conflict event in Kenya which could be clearly assigned to a former admin-1 unit, may not be clearly assignable to a current admin-1 unit defined in GADM version 3.6.. The issue can be solved through requiring a higher precision for conflict events in Kenya before 3rd March 2013. All former admin-2 units where conflict events occurred can be clearly mapped to one single current admin-1level.

Consequently, the following criteria for the inclusion of events are set up:

1. For events in Kenya earlier than 3rd March 2013 the event must be clearly assignable to an admin-2 level. Therefore, the event must have a spatial precision code $<= 3$. For events after or on 3rd March 2013 or in the other countries used as part of the RF model, the event must be clearly assignable to an admin-1 level. Therefore, the precision code must be $<= 4$.
2. Events must be clearly assignable to one month and cannot exceed a monthly day range. Therefore a temporal precision code $<= 4$ is required.
3. In addition, also events with a higher temporal precision can overlap two months. These events also need to be excluded.



(a) Spatial precision codes

(b) Temporal precision codes

Figure 2.6.: Percentage of conflict events in Kenya (2004 - 2021) with a certain spatial or temporal precision code and fraction of data excluded

For Kenya, the percentages of the respective spatial and temporal precision codes as well as the fraction of data removed based on the spatial and temporal exclusion criteria are displayed in Figures 2.6a and 2.6b. Figure 2.6a shows that the different thresholds applied to the spatial precision code prior and after 3rd March 2013 do not lead to a higher percentage of data removed within the prior temporal subset. Rather, for both time periods about 8% of the data is removed. Based on the temporal precision criteria, all the data with a precision code of 5 and some data with a precision code of 4 or 3 is removed (compare to Figure 2.6b), with about 5% of the data being removed in total, based on the temporal precision exclusion criteria. Combining all criteria, the Kenyan conflict event dataset for the time period from 2004 to 2021 is reduced by about 13%.

The remaining conflict events were clipped to the respective admin-1 unit based on the administrative borders from GADM version 3.6. A map of the resulting subset of conflict events in North-Western Kenya is provided in Figure 2.7.. Conflict events within an admin-1 unit were summarized per month and the conflict variable received the value 1 for a month and spatial unit if at least one communal conflict event has happened within that spatio-temporal unit and otherwise it received the value zero.

Ethnic group

For the LRMs 3 and 4 conflict events were assigned to a certain ethnic group based on the information on the dyad provided as part of each conflict record in UCDP-GED.

As UCDP-GED only includes conflict event records which can be clearly assigned to one dyad, the restriction of included conflict records based on spatial precision codes, can be relaxed. Therefore, only conflict events which could not be clearly assigned to one month were removed.

All remaining conflict records were then assigned to the ethnic groups which form part of the dyad reported. Dyad information provided in UCDP-GED did not allow for a further distinction between the agressor and the victim. Ethnic group territories and the conflict events per dyad are diplayed in Figure 2.8.

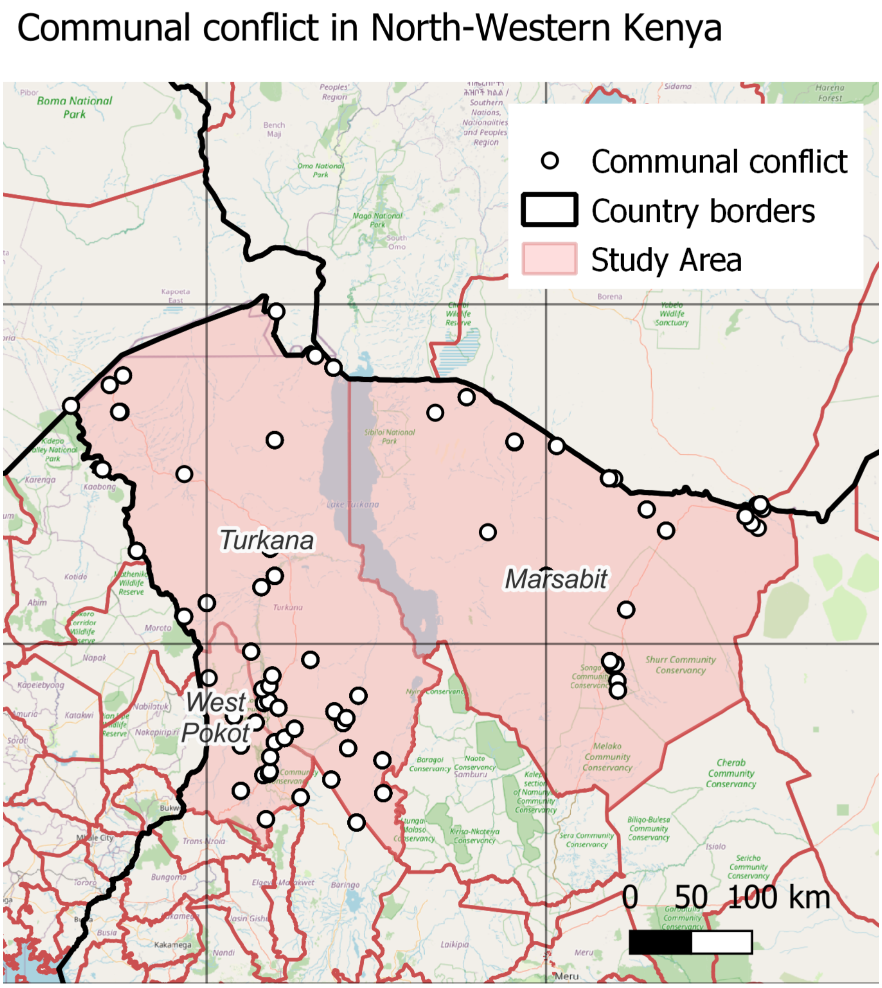


Figure 2.7.: Communal conflict events in North-Western Kenya for time period 2004-2021 with satisfactory precision

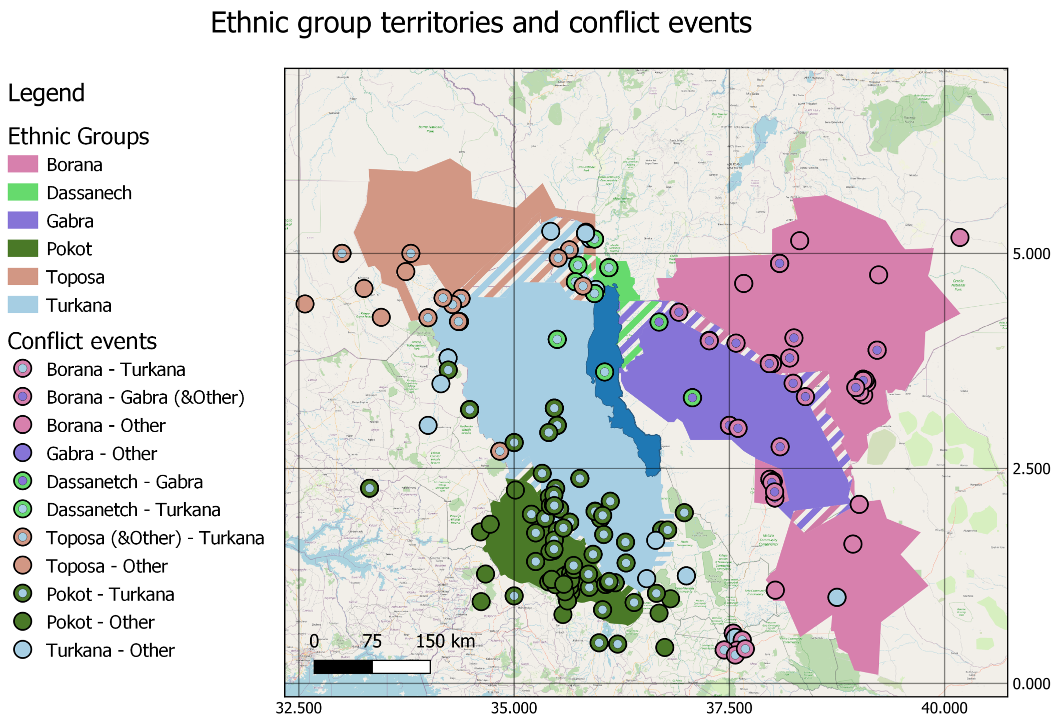


Figure 2.8.: Territories for ethnic groups of interest and conflict events of satisfactory temporal precision associated to each of the ethnic groups

2.4.5 Further input features of the Random Forest model

Most of the input features for the RF model have been obtained in their prepared version at admin-1 level and monthly timescale from the DataCube created as part of the WPS project. For the preprocessing of the variables *local population density, local population count, riverine flood risk, rural to urban ratio, value of rainfed crop, seasonal variability* and *interannual variability* it is therefore referred to the description of data processing steps provided in the Appendix A.4 of Kuzma et al. (2020).

In the following, the preprocessing steps for the other input variables are described. This includes input variables which could not be obtained for the right time period from the DataCube and the conflict input variables which have replaced the conflict input variables of the WPS Global Early Warning Tool.

A Demographic variables

The variables *ratio of males in age-group 25-64, ratio of males in age-group 65+*, and *percentage of males who are 65+* have been obtained from the United Nations, Department of Economic and Social Affairs, Population Division (UN DESA Population Division, 2022) datasets *Sex Ratio by Select Age Groups* and *Population Percentage by Select Age Groups - Male.* Variables are pulled from the columns in the *Estimate* tab which correspond to the age groups required.

Following Kuzma et al. (2020), yearly country-level data was assigned to all admin-1 units of that country and to all months of that year.

B Sanitation access

Data on sanitation access has been retrieved from the WHO/UNICEF Joint Monitoring Programme for Water Supply, Sanitation and Hygiene (World Health Organization & United Nation's Children's Fund [WHO][& UNICEF], 2021a, 2021b) Country files for Uganda, Kenya, South Sudan, Somalia and Ethiopia have been downloaded.

The variable *sanitation access* has been based on the estimates of *at least basic (improved and not shared)* sanitation for each of these countries. Like for the demographic variables, yearly country-level data is to all corresponding admin-1 units and months.

C Conflict variables

Based on the binary communal conflict variable as well as a corresponding variable for all other types of conflict three additional input variables have been generated.

The variable *time since last communal conflict* describes the number of months which have passed since the last communal conflict event in the same admin-1 unit. As for some units, communal conflict occurrence is scarce all communal conflict events from the start of data recording as part of the UCDP-GED dataset, in 1989, were used. Where for the time range of 2004 to 2021 still null values were found, these were filled with the maximum time lag found within the remainder of the data. For the purpose of an RF model which splits the data according to thresholds, this tagging of months with null values as months which are following a long peaceful period was considered sufficient.

The variables *spatially lagged communal conflict (t-1)* and *spatially lagged other conflict (t-1)* were obtained using the SQL functionality of QGIS on admin-1 units in Ethiopia, Kenya, South Sudan, Somalia and Uganda as well as the neighbouring countries Central African Republic, Democratic Republic of Congo, Djibouti, Eritrea, Rwanda, Sudan and Tanzania.

Binary variables were constructed, which, for each admin-1 unit indicate whether there has been any communal conflict or other conflict in one of the adjacent admin-1 units in the prior month.

3 Results

In the following, the results obtained as part of the thesis are presented. These entail a description of the crucial characteristics of drought and conflict data in Section 3.1 followed by the results for each of the three sub-questions: In Section 3.2 the perceptual model of conflict dynamics in the study area is described, followed by an analysis of the results of the logistic regression model on the effect that DIs have on conflict in the study area in Section 3.3. The final section, Section 3.4 is dedicated to the third research question on the role of meteorological DIs in the regional conflict prediction model.

For an in-depth discussion of the results and their meaning for answering each of these sub-questions it is referred to Chapter 4.

3.1 Analysis of drought indicators and conflict data

3.1.1 Drought indicators

Figure 3.1 visualizes the SPEI over time for different aggregation periods in the example of Turkana County. Only the spatial median of the SPEIs is displayed as this has been the primary metric reported in the following sections (compare to Section 3.3).

The y axis illustrates that the spatial median of the SPEI approximately ranges between -2 and 2. Negative values represent a negative anomaly in CWB, Positive values represent a positive anomaly in CWB. Time periods which are colour-coded in red, therefore, represent periods with drier than normal conditions. Time periods which are colour-coded in dark turquoise, represent periods with wetter than normal conditions.

Compared to longer-term aggregation periods, the SPEI-1 shows higher fluctuation where months of relative water abundance are directly followed anomalously dry months. Nonetheless, a relationship between the different aggregation periods is detectable, where multiple 1-month negative peaks can result in longer periods of negative values for SPEIs of longer aggregation periods.

When zooming in on these patterns for the time period of 2016 to 2017 (see Figure 3.2, a slight lag is detectable between the onset of a short-term dry period and the corresponding longer-term periods of negative SPEI. This delay of the signal is visible for many intervals within the time series and for both positive and negative anomalies.

3.1.2 Conflict data

Figure 3.3 and 3.4 display the yearly count of conflict events and the number of conflict months within a year (based on the monthly binary conflict variable) from 2004 to 2021 for each of the three counties. The figures show that the highest number of conflict events and conflict months has occurred in 2014. Other peaks for both, the number of conflict events and the number of conflict months, are visible in 2008, 2010 and 2013.

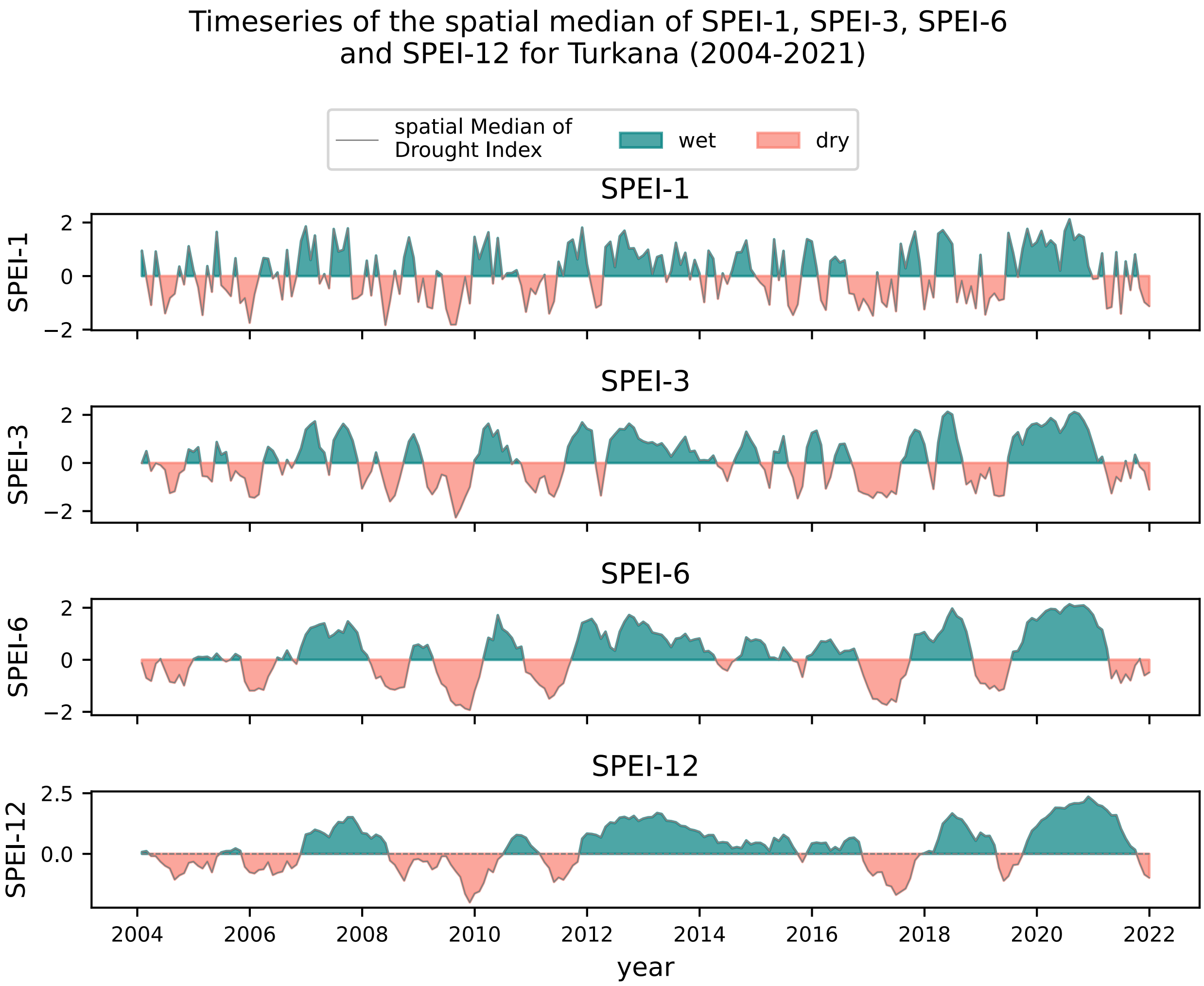


Figure 3.1.: Time series of the spatial median of gridded SPEI-1, SPEI-3, SPEI-6, SPEI-12 in Turkana County (2004-2021)

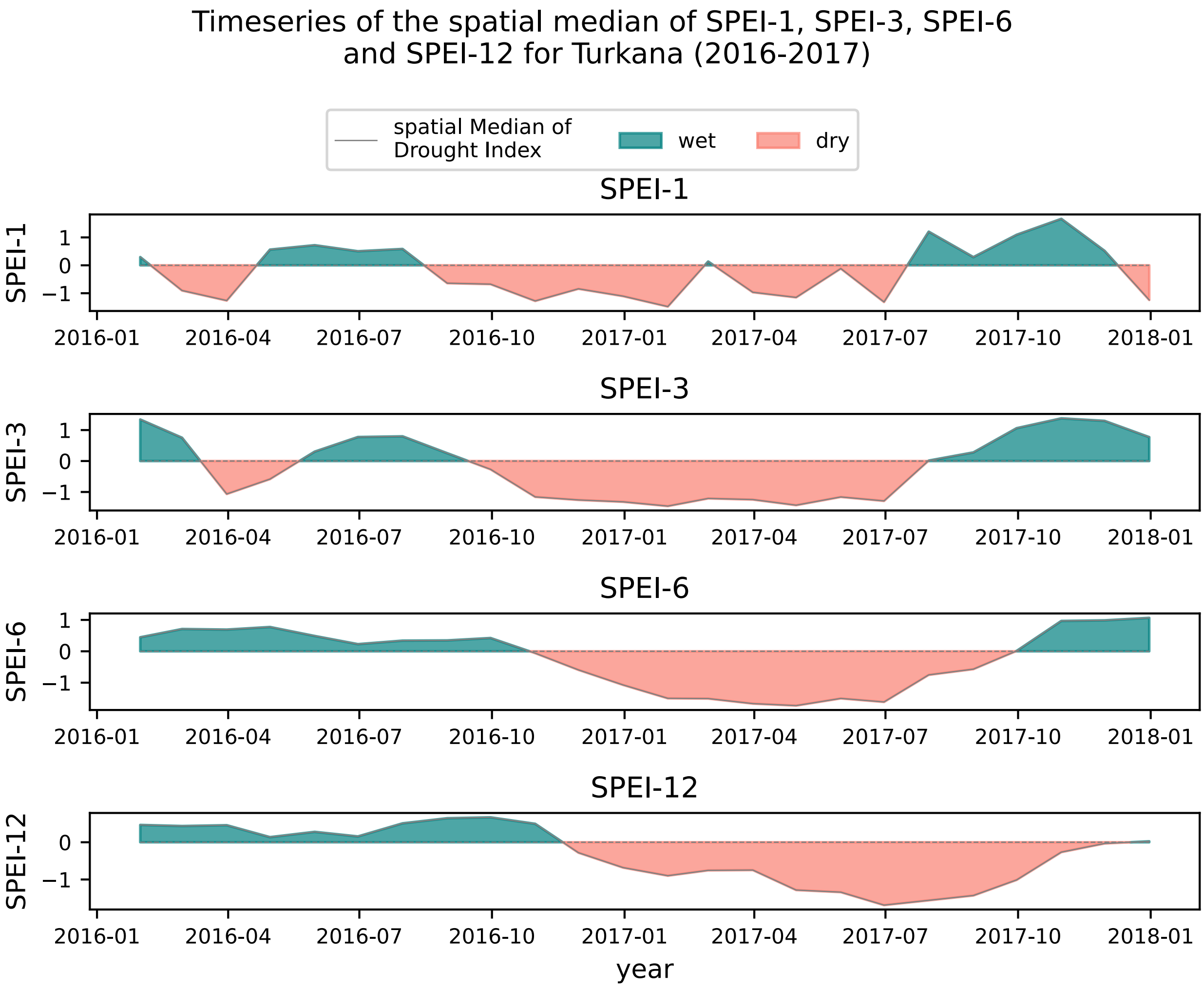


Figure 3.2.: Subset of the time series of the spatial median of gridded SPEI-1, SPEI-3, SPEI-6, SPEI-12 in Turkana County (2016-2017)

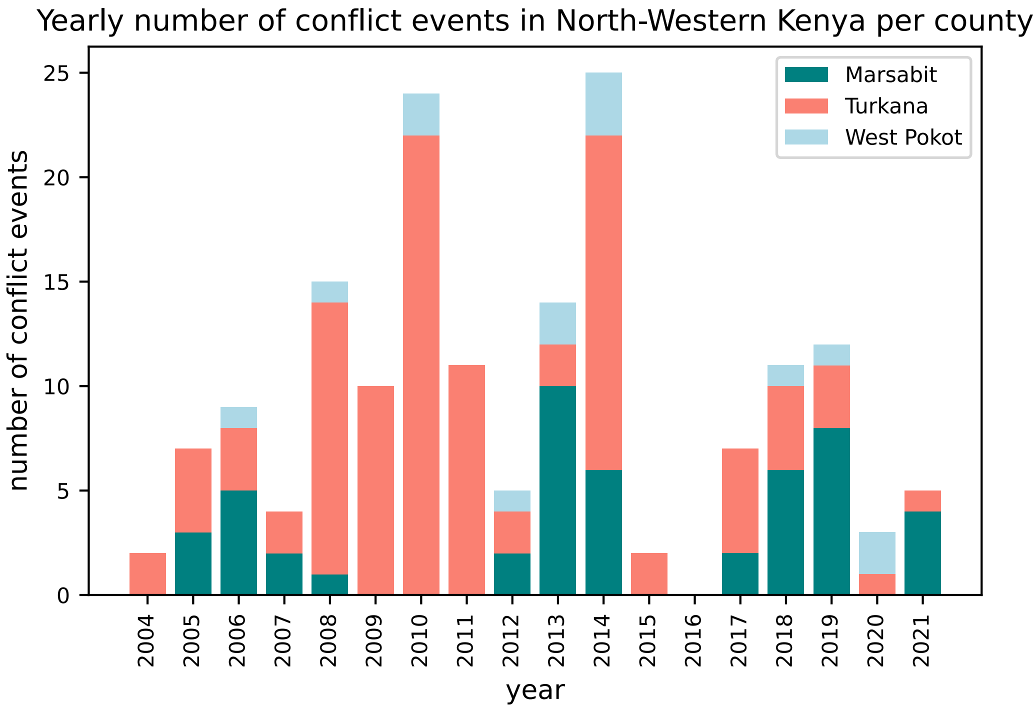


Figure 3.3.: Yearly number of conflict events in Marsabit, Turkana and West Pokot from 2004 to 2021 (based on data from UCDP-GED)

The counts vary per county. While most of the conflicts in Marsabit are observed in the years 2006, 2013, 2014, 2018, 2019 and 2021, peaks in the number of conflict months and conflict events for Turkana are visible in 2008, 2010 and 2014. For West Pokot yearly conflict levels are generally low, with a maximum of three conflict events spread over two months in 2014.

The total number of conflict months and conflict events for each county are displayed in Table 3.1. Turkana experiences about twice as many conflict events as Marsabit and about seven times as many conflict events as West Pokot. In Turkana, 58 months out of the 216 months time period (2004 - 2021) are violent. This corresponds to 27 % of the months. For Marsabit 13% of all months between 2004 and 2021 are recorded to be violent and for West Pokot 5.6% of all months.

Table 3.1.: Number of conflict events and conflict months for Marsabit, Turkana and West Pokot (2004-2021) (based on data from UCDP-GED)

	Marsabit	**Turkana**	**West Pokot**
number of events	49	103	14
number of conflict months	28	58	12

Conflict in Marsabit, Turkana and West Pokot can be assigned to several dyads. The binary conflict variable per dyad is displayed in Figure 3.5. For each month of the time period from 2004 to 2021 it is indicated whether two ethnic groups engage in conflict with each other. The value 1 on the y-axis suggests *conflict* while the value 0 stands for *no conflict* It can be seen that the frequency of conflict varies per dyad. While some ethnic groups regularly attack or are attacked by a certain other ethnic group, for other pairs of ethnic groups violent exchange is only sporadic. The dyads which most frequently engage in conflict are (1) Pokot-Turkana, (2) Dassanetch-Turkana, (3)Toposa-Turkana, (4) Borana-Gabra.

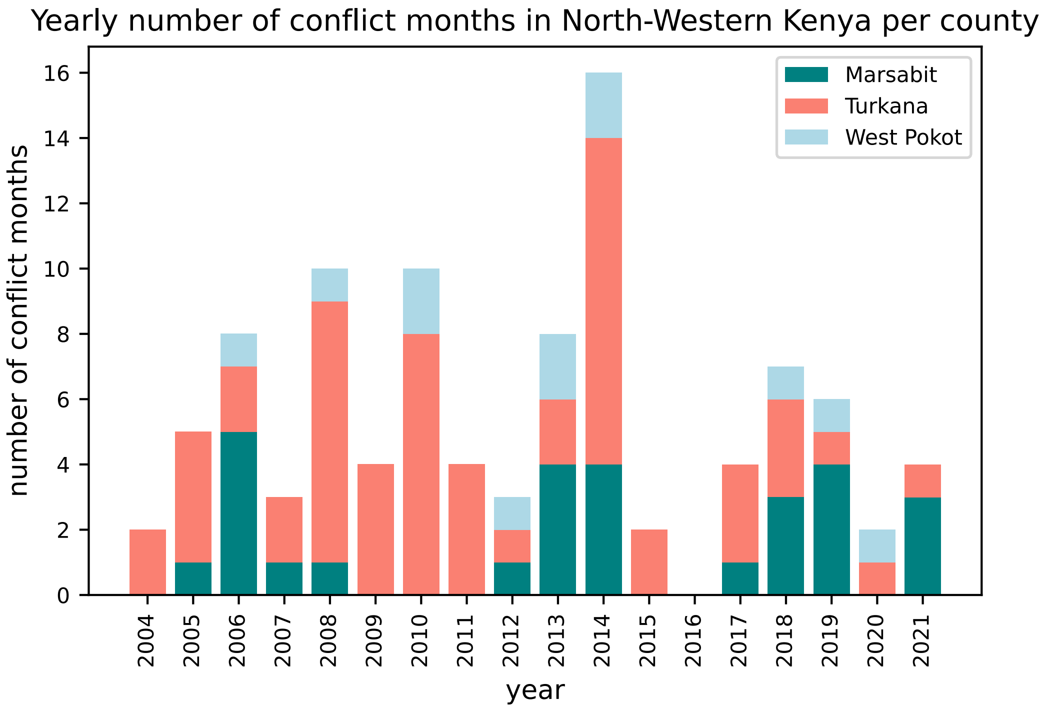


Figure 3.4.: Yearly number of conflict months (as a month when at least one conflict occurred) in Marsabit, Turkana and West Pokot from 2004 to 2021 (based on data from UCDP-GED)

Table 3.2.: Number of conflict events and conflict months for Turkana, Pokot, Borana, Gabra, Dassanetch and Toposa (2004-2021) (based on data from UCDP-GED)

	Turkana	Pokot	Borana	Gabra	Dassanetch	Toposa
number of events	196	148	92	51	40	24
number of conflict months	95	78	49	35	24	15

Within the timeseries of the binary conflict variable for each of these dyads, times of more frequent and less frequent conflict are visible. However, even in times of high conflict frequency, the occurrence of two or three consecutive conflict months is rare. Most often conflict months are preceded and followed by peaceful months, according to UCDP-GED records.

In Table 3.2 the number of conflict events and conflict months per ethnic group is displayed. The total number of conflict events and conflict months varies largely across the ethnic groups. While Turkana engage in conflict in 44% of the months between 2004 and 2021, conflict months for Toposa only account for 7% of all months.

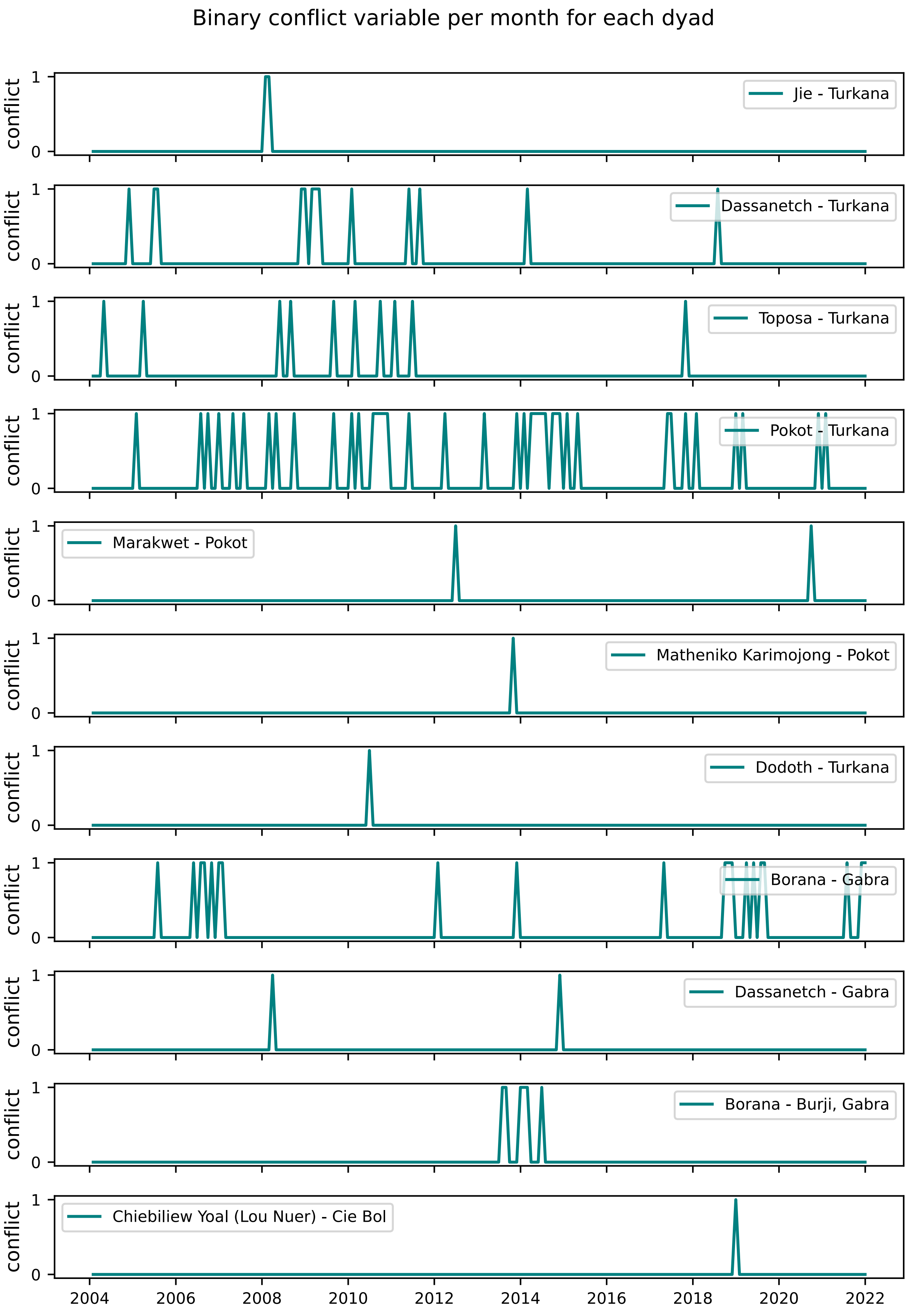


Figure 3.5.: Binary monthly conflict variable per dyad for conflicts in Marsabit, Turkana and West Pokot from 2004 to 2021. The y-axis indicates whether conflict has occurred in a certain month (1) or whether there has been no conflict in that particular month (0) (based on data from UCDP-GED)

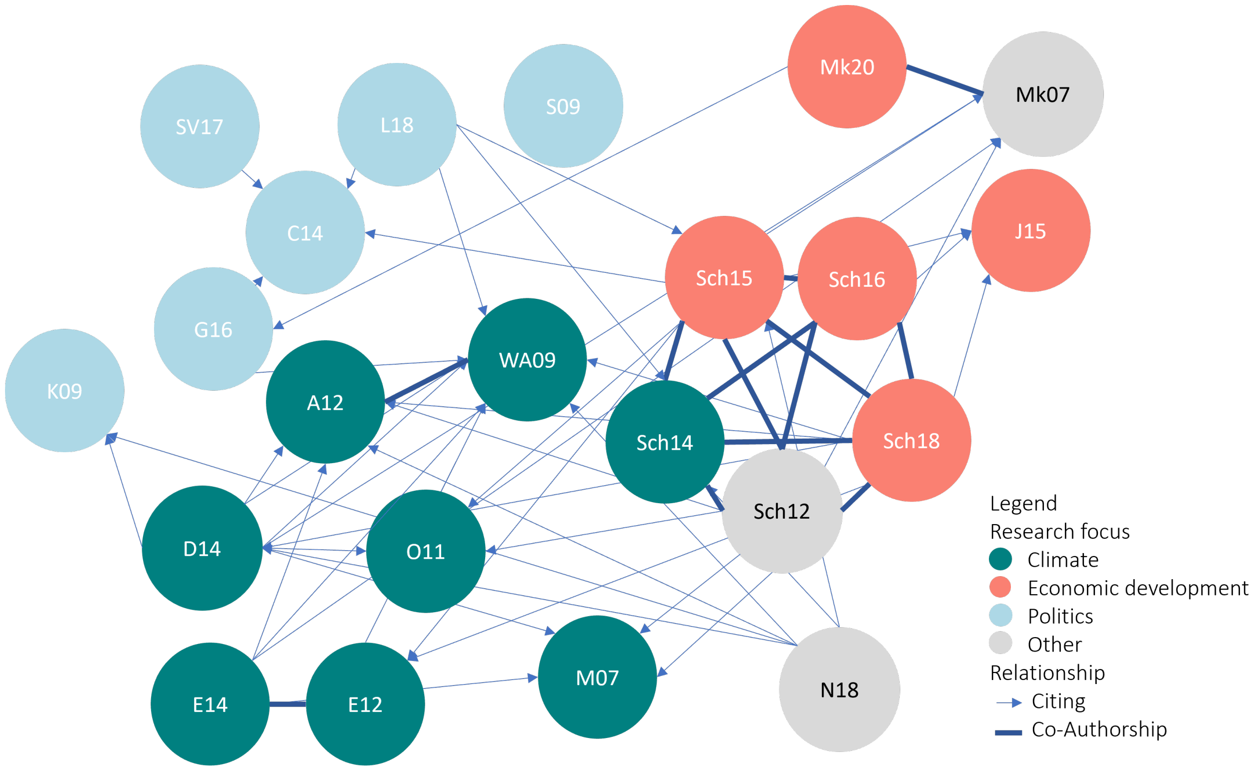


Figure 3.6.: Network of referencing and co-authorship within literature for conflict dynamics in the study-area (A12: Adano et al. (2012); C14: Carrier and Kochore (2014); D14: Detges (2014); E12: Ember et al. (2012); E14: Ember et al. (2014); G16: Galaty (2016); J15: Johannes et al. (2015); Kanyinga (2009); L18: Lind (2018); M07: Meier et al. (2007); Mk07: Mkutu (2007); Mk20: Mkutu and Mdee (2020); N18: Noonan and Kevlihan (2018); O11: Omolo (2011); Sch12: Schilling et al. (2012); Sch14: Schilling et al. (2014); Sch15: Schilling et al. (2015); Sch16: Schilling et al. (2016); Sch18: Schilling et al. (2018); S09: Smith (2009); SV17: Scott-Villiers (2017); WA09: Witsenburg and Adano (2009)

3.2 Literature review of conflict ddynamics in the study area

3.2.1 Overview of reviewed literature

An overview of the literature which has been used to infer the causal dynamics of conflict for the study area is provided in Figure 3.6 in a network format linked by their citation of each other and co-authorship among the papers.

While all related to causal factors of ethnic conflict in parts of the study area or a wider area, which at least partly overlaps with the study area, the exact scope of the pieces of literature differs in terms of (1) the research focus within the realm of conflict analysis, (2) the research set-up, as well as (3) the exact spatial extent and the ethnic groups they cover.

A Research focus

Within literature several dominant fields of analysis can be identified, which explore a specific conflict contributor in more detail. The literature can largely be grouped into three groups based on the dominant fields of analysis (as colour-coded in Figure 3.6):

1. Climate: literature investigating the impact of climate variability, climate change or of related environmental variables (vegetation cover, pasture, water) on conflict

2. Politics: literature assessing how especially changes in national-scale politics through elections, the failing of governments or the establishment of national or administrative borders has influenced inter-ethnic violence
3. Economic development: literature on the impact of recent economic development projects such as the exploration and exploitation of oil and wind resources as well as the construction of dams on inter-ethnic conflict

Furthermore, there are several papers which cannot be clearly assigned to any of these three research fields. Mkutu (2007) investigates the impact of the proliferation of arms and commercialization of pastoralism in the region. Although, it is the only paper focussing on this topic, the related trend in conflict intensity is mentioned by many authors. It also builds on the heritage of many papers which have discussed the topic before but have not been included due to the restriction to literature published after 2004 (Gray et al., 2003; Hendrickson et al., 1998). Noonan and Kevlihan (2018) and Schilling et al. (2012) investigate the individual motives for conflict between Turkana and Pokot, in general and for the specific case of the siege of Loregon, as a phase of very violent clashes between Pokot and Turkana.

The focus of research differs over time. During the beginning to mid of the last decade, the impact of climate and seasonal variability and climate change has been discussed intensely. More recent literature largely focusses on the devolution of power in Kenya as part of the new Kenyan constitution adopted in 2010 and recent economic development projects. In the aftermath of the 2008 and 2013 election, an intense debate on the causal dynamics underlying political violence can be observed.

B Field-work vs. empirical analysis

Like in the wider context of conflict research (Ide et al., 2014), the subset of literature considered contains descriptive studies, field-work as well as empirical research approaches. Descriptive studies are mostly related to the nation-wide analysis of causes of ethnic conflict surrounding elections. The field-work approaches consist of focus group discussions and individual interviews (Schilling et al., 2018) as well as social surveys. On the other hand, empirical studies employ a top-down approach of retrieving the quantitative effect of a certain causal factor on conflict in the study area.

However, much of the literature reviewed also complements top-down empirical approaches with the use of interviews, to understand underlying dynamics, or vice versa, the additional use of descriptive statistics of conflict data to back individual statements during interviews.

C Spatial extent

The studies rarely investigate the causal conflict dynamics of interest for the entire study area of the present thesis. Figure 3.7 illustrates the number of sources per research focus category for each of the three counties. In addition, there are two sources on the 2008 general elections which investigate the dynamics of political violence during the 2008 general elections for the entire country (Kanyinga, 2009; Smith, 2009).

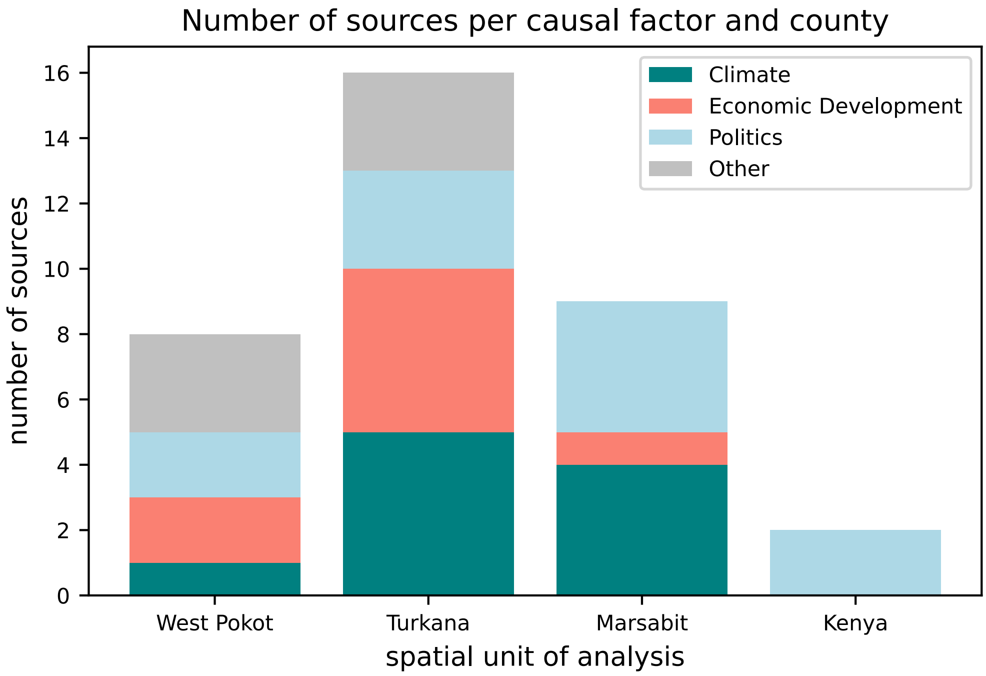


Figure 3.7.: Number of sources for every county and Kenya in general and their research focus

In between the three counties there are differences in the general coverage of each county within the literature. More sources investigate the conflict dynamics for Turkana than for West Pokot and Marsabit. In addition, the center of gravity of research varies per research focus with much of the climate-conflict debate centered in Turkana (Ember et al., 2012; Omolo, 2011; Schilling et al., 2014) and Marsabit (Adano et al., 2012; Ember et al., 2014; Witsenburg & Adano, 2009). Research on economic development is strongly focussing on the recent oil findings and related projects in Turkana (Johannes et al., 2015; Mkutu & Mdee, 2020; Schilling et al., 2015; Schilling et al., 2018; Schilling et al., 2016). Marsabit, on the other hand, is the most discussed county with regards to devolution and related political violence as part of the 2013 election (Carrier & Kochore, 2014; Lind, 2018; Scott-Villiers, 2017). In-depth accounts of motives of ethnic groups to engage in conflict are mostly investigated for the case of the Pokot and Turkana with interviews taking place at the border of their respective ethnic territories (Noonan & Kevlihan, 2018; Schilling et al., 2012).

3.2.2 Conflict motives & risk Factors

Throughout the majority of the literature reviewed, larger-scale conflict contributors are linked to the agency of ethnic groups members through their motives to engage in conflict. Therefore, the perceptual model has been initialized from the level of motives identified as part of the research. Figure 3.8 displays the different motives and the number of mentions of each of these motives.

Some of the motives are related to direct material gains from raiding livestock. For example, livestock raiding may be used to restock livestock (Detges, 2014; Ember et al., 2012; Schilling et al., 2014; Witsenburg & Adano, 2009), counteract food insecurity or poverty (Omolo, 2011; Schilling et al., 2012), for personal wealth (Schilling et al., 2012) or to pay dowry (Omolo, 2011; Schilling et al., 2012).

However, most dominantly, livestock raiding and related conflict is associated to strategic considerations of gaining access to land and water resources or to enforce ones territorial claim to land (Carrier & Kochore, 2014; Detges, 2014; Ember et al., 2012; Galaty, 2016; Johannes et al., 2015; Kanyinga, 2009; Lind, 2018; Meier et al., 2007; Mkutu & Mdee, 2020; Noonan & Kevlihan, 2018; Omolo, 2011; Schilling et al., 2018; Schilling et al., 2012; Scott-Villiers, 2017; Smith, 2009; Witsenburg & Adano, 2009). Access to land and water resources is repeatedly mentioned as a response to resource scarcity (Detges, 2014; Ember et al., 2012; Omolo, 2011; Schilling et al., 2014) or in anticipation of future resource scarcity (Detges, 2014).

Territorial rights as a motive to engage in conflict are linked by several researchers to the long-term grievances over land governance during and after the colonial era (Kanyinga, 2009; Smith, 2009). While formerly, land was often shared by several ethnic groups, the colonial era land attribution and redistribution along ethnic lines and the maintenance of this status quo after independence, has led to an increased ethnic awareness and proprietary feelings towards land (Galaty, 2016; Smith, 2009).

Closely tied to the question of territorial rights is the motive to engage in conflict to secure political patronage (Carrier & Kochore, 2014; Galaty, 2016; Lind, 2018; Scott-Villiers, 2017). As Kanyinga (2009) state, these two struggles should even be considered in combination where a change in territorial land distribution is destined to change power relations and, vice versa, political power may be used to secure territorial rights in the favour of one's own ethnic group.

Further motives which have been mentioned repeatedly are rituals, like age-set ceremonies, which are considered to have turned livestock raiding in the area into an accepted cultural practice (Ember et al., 2014; Omolo, 2011; Witsenburg & Adano, 2009). In addition, retaliatory raiding is repeatedly mentioned (Lind, 2018; Noonan & Kevlihan, 2018; Schilling et al., 2012; Witsenburg & Adano, 2009). Retaliation leads to vicious circles of violence where cooperation is becoming increasingly difficult to achieve (Noonan & Kevlihan, 2018; Schilling et al., 2012).

Especially in recent years the increased job opportunities related to oil and wind power development in the region as well as dam projects have also intensified inter-ethnic competition over jobs. These tensions are considered to raise the risk of inter-ethnic conflicts (Noonan & Kevlihan, 2018; Schilling et al., 2018).

The mentioned motives, which suggest an active partaking of ethnic group members in an increase or decrease of conflict risk, are supplemented by risk factors which passively expose the inhabitants of North-Western Kenya to a greater risk of inter-ethnic conflict. Through transhumance to areas with richer resources, patoralists may be more vulnerable to attacks by other ethnic groups (Ember et al., 2012; Omolo, 2011). In addition, proliferation of small arms in the area is commonly considered to increase the number of fatalities in raids (Carrier & Kochore, 2014; Johannes et al., 2015; Omolo, 2011; Schilling et al., 2014).

Many of the motives and risk factors identified above can be causally linked to larger-scale variability or trends in climate-related variables, politics or economic development. In addition, several conflict mitigation and climate adaptation efforts have been mentioned in literature which counteract or amplify conflict risk.

The derived perceptual model of conflict dynamics in North-Western Kenya is displayed in Figure 3.9. The model is strucutred based on the diffeent categories of causal factors. Motives are indicated in diamond-shaped boxes. In the following, the relationship shall be described in detail per category of causal factors.

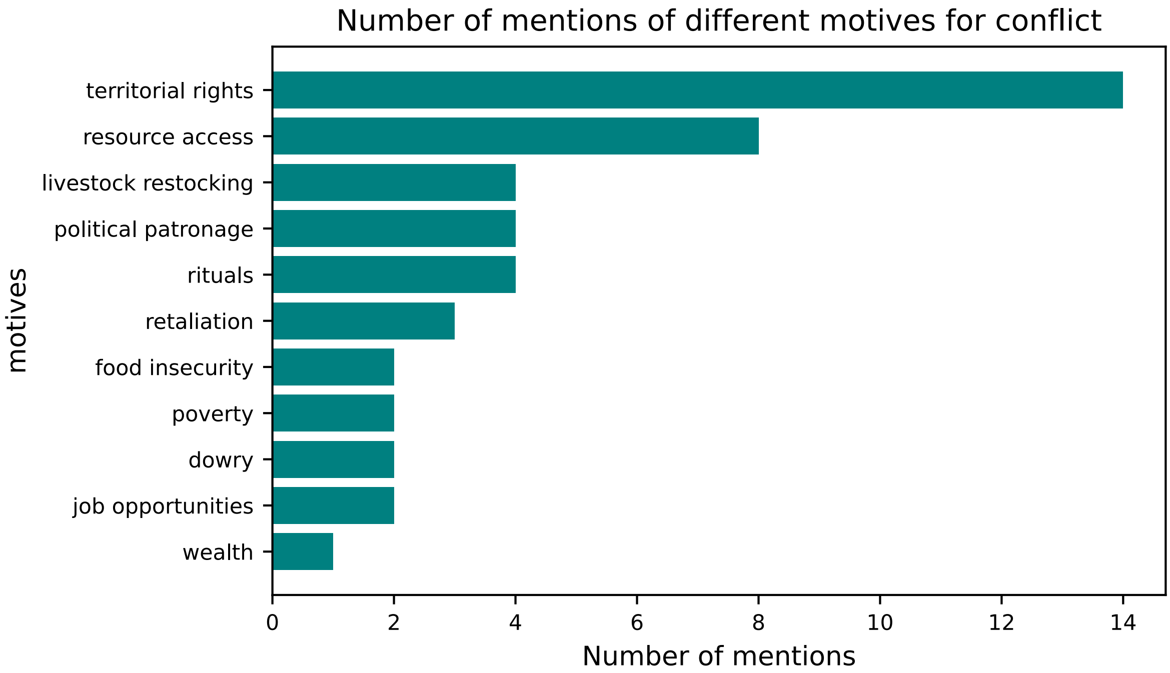


Figure 3.8.: Number of mentions of different motives for conflict in literature on conflict dynamics in North-Western Kenya

3.2.3 The climate-conflict pathway

Despite the claim that droughts may lead to more conflict in the region, the regional scientific literature is similarly divided on that topic as large-N studies. It can be roughly divided into two camps. While findings by Ember et al. (2012) and Omolo (2011) suggest an increase in conflict in times of drought and the dry season, Adano et al. (2012) and Witsenburg and Adano (2009) speak of an exacerbation of conflict in times of more rainfall, being it the wet season or years with more rain.

The former literature builds on the resource scarcity theory. This pathway is illustrated in Figure 3.10. During droughts and dry seasons, when resources are scarce, tension surrounding the remaining resources is considered to increase. Pastoralists migrate to areas which are further from their base-camps to be able to feed and water their livestock. In these remaining areas, they come into direct contact with other pastoralist groups, putting them at greater risk of being attacked, but also providing motivation to acquire arms and attack to secure access to the limited resources or to restock their herds by raiding livestock (Ember et al., 2012; Mkutu, 2007). In addition, the loss of livestock during these periods puts pastoralists at risk of hunger and poverty providing further incentive for herders to engage in livestock raids (Omolo, 2011). Feedback loops from conflict are considered to exacerbate grievances through further reduction in livestock (Noonan & Kevlihan, 2018; Schilling et al., 2012). In addition, the feeling of insecurity may lead to the complete abandonment of some pastures while other pastures are overused (Noonan & Kevlihan, 2018; Omolo, 2011; Schilling et al., 2012). Therefore, conflict puts additional pressure on already scarce resources. The resource scarcity pathway is backed by empirical analysis by Ember et al. (2012) on seasonal and inter-annual variability in livestock-raiding related deaths in Turkana. They found that the average number of deaths associated to livestock raids was higher in the dry months and the months before the rain season. Below normal precipitation for a certain month or year or month of the year were equally associated to higher mean monthly or yearly deaths (Ember et al., 2012).

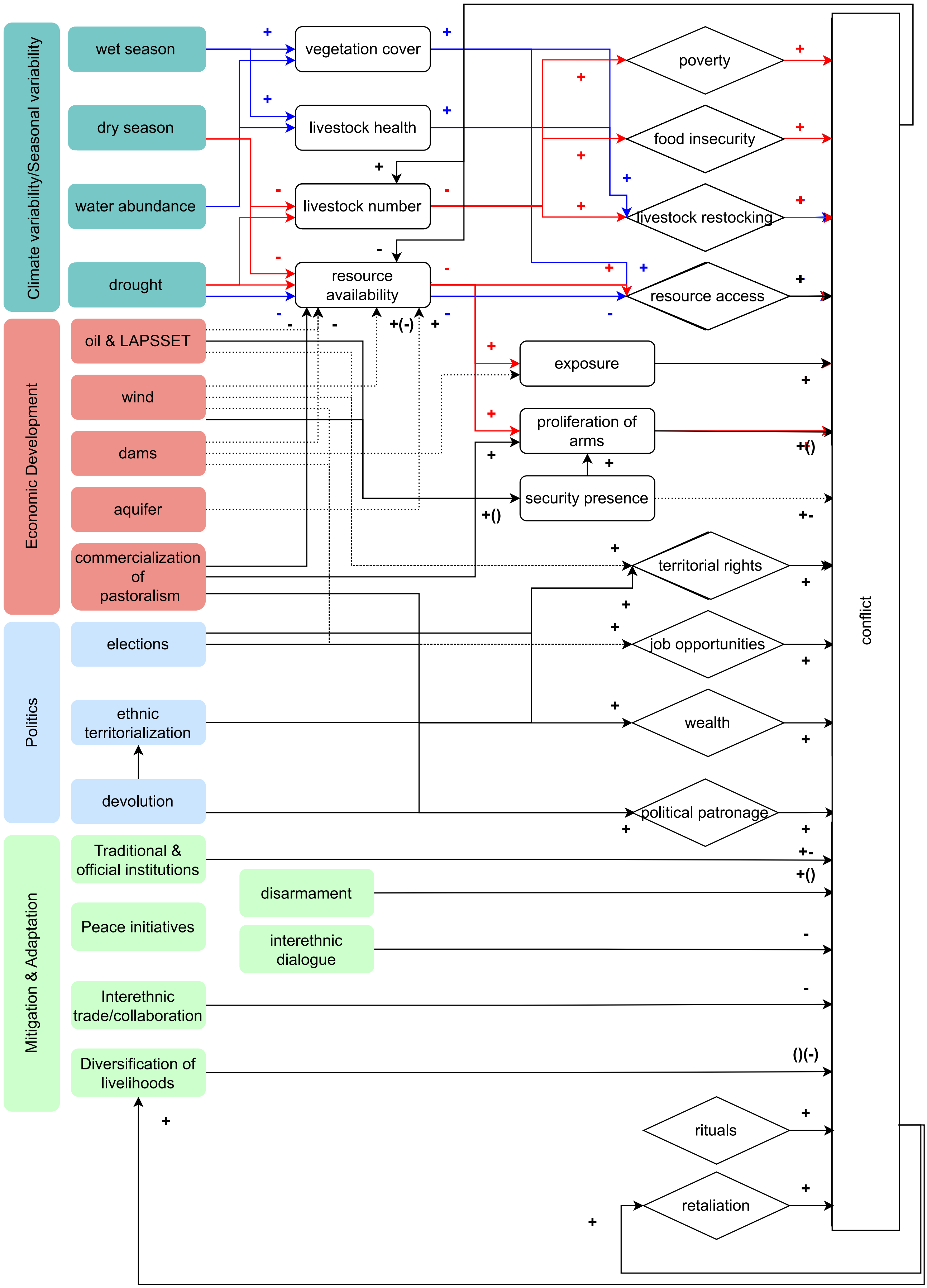


Figure 3.9.: Perceptual model of causal dynamics of ethnic conflict based on literature for North-Western Kenya

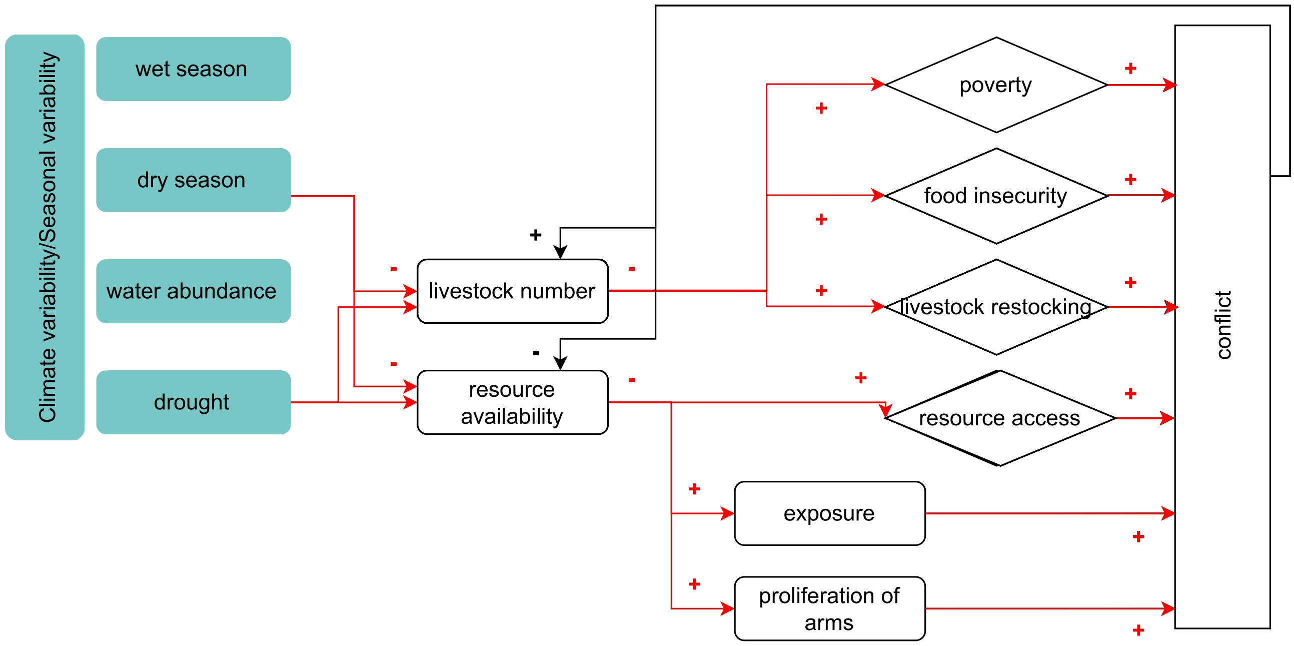


Figure 3.10.: Climate-Conflict Pathway I: scarcity-driven conflict

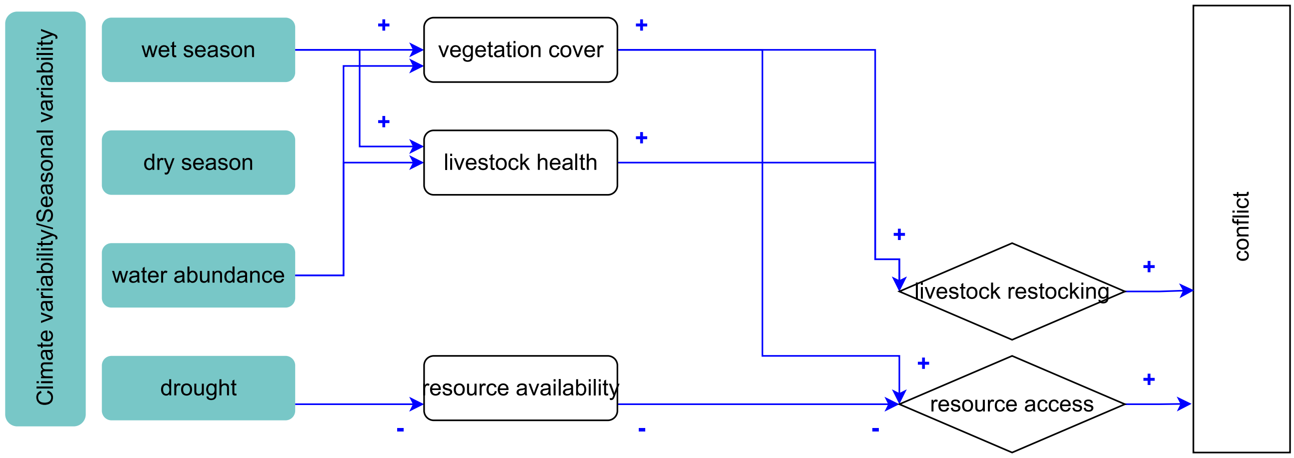


Figure 3.11.: Climate-Conflict Pathway II: strategically planned conflict

These results are opposite to prior research by Witsenburg and Adano (2009) for Marsabit. In their work, higher mean numbers of deaths were found for wet years and wet months. For the alternative measure on the number of conflict events, no clear pattern was found. The pathways used to explain these results are illustrated in Figure 3.11. Adano et al. (2012) and Witsenburg and Adano (2009) reason their findings on the increase in fatalities during wet conditions with strategic considerations of pastoralists. In rainy seasons pastoralists may be more inclined to engage in violent raids because livestock is in better health and resources are more readily available which makes it easier to go on long tracks. In addition, vegetation is fuller, giving more opportunities to hide. On the other hand, resource scarcity associated to drought is suspected to make ethnic groups more inclined to solve their tensions peacefully and to cooperate to ensure shared access to the remaining resources (Witsenburg & Adano, 2009). Therefore in these times, resource access as a motive for conflict is considered to be lower than in wet times. The higher probability of violent raiding in times of abundant vegetation cover, is also supported by Meier et al. (2007). They investigated the environmental variables rainfall, vegetation cover and fodder availability for their inclusion in the CEWARN early warning system based on their effects on conflict in the Karamoja Cluster. They could not find any significant relationship between the rainfall variable and conflict incidences and therefore deem the variable as too indirect. However, they show that more vegetation during that period led to more conflict incidences. Therefore, Meier et al. (2007) reach the same conclusion as Witsenburg and Adano (2009), that environmental variables may reveal more about the strategic considerations. They see raiding as motivated by long-term access to resources rather than instantaneous contest for resources in the moment when they are scarce.

Two attempts have been made in the reviewed literature to reconcile the different findings (1) through a differentiation of the behaviour of different ethnic groups in response to drought or water abundance and (2) through a combination of seasonal and inter-annual climate variability called the Resource Abundance and Scarcity Theory (RAST).

A Different ethnic group responses

Ember et al. (2012) hypothesize that the responses to seasonal and climate variability are ethnic-group-specific. Based on an analysis restricted to Pokot attacks on Turkana, they conclude that Pokot are largely following the same patterns as Turkana of attacking predominantly in dry years and dry months. However, the signal is not found to be as strong as suspected.

In a follow-up research, Ember et al. (2014) investigate the patterns for different ethnic groups in Marsabit. They find that the pattern of more livestock-related violence in wet years only holds for the Borana. For all other groups, combined, most fatalities are observed in very dry years. However, even among these groups, patterns vary. For Garre conflict in dry years seems to be much more fatal, while for Gabra conflict is most fatal during normal years. For Dassanetch and Samburu patterns are more difficult to decipher as fatality of conflict varies a lot over the different anomaly classes. For Dassanetch, both, extremely negative and extremely positive DIs are found to have the highest fatality numbers. However Ember et al. (2014) still highlight their similarity in response to drought to the pattern of Turkana because of the high fatalities in extremely dry years.

In addition, a tendency towards more fatalities in the wet season is described for Borana and Gabra, while for Dassanetch and Samburu more conflict is recorded in very dry months. For Garre most fatalities are reported in average months.

Ember et al. (2014) center their explanation of these diverging patterns around the migratory behaviour of the different ethnic groups. While Dassanetch, Samburu and Turkana move towards other groups during drought and dry season, the seasonal transhumance patterns of Borana and Gabra are opposite and they are also more inclined to stay close to their base camps during drought.

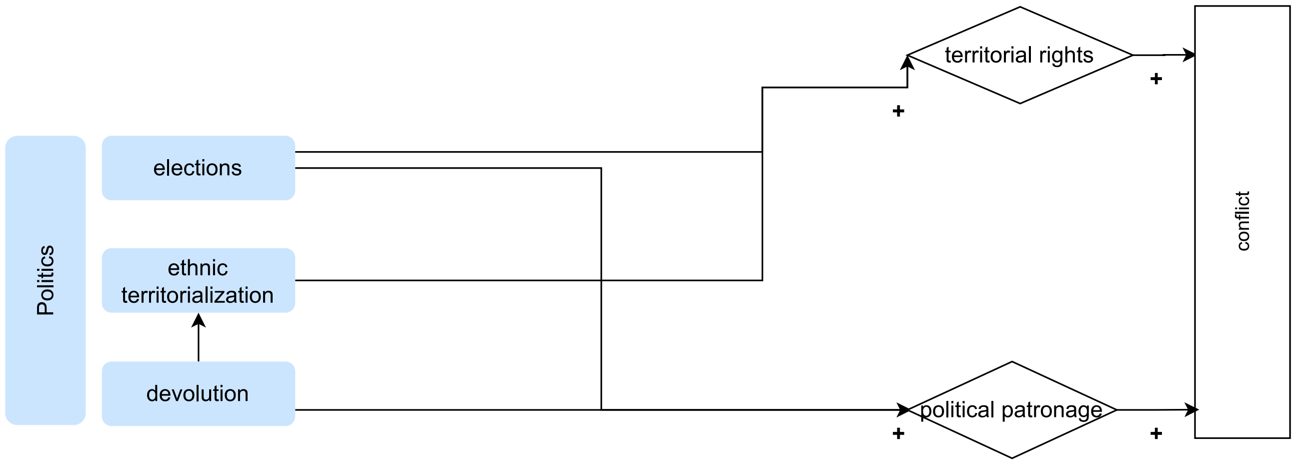


Figure 3.12.: Political Events and their impact on inter-ethnic conflict in North-Western Kenya

The different inter-annual transhumance patterns are primarily explained by climate vulnerability of the different groups. The main camps of Borana people are located in relatively water abundant regions. In times of droughts, Borana can move their cattle back to their camps. The Kenya Gabra are camel herders and the Ethiopica Gabra have water sharing arrangements with the Borana. Therefore, both groups are likely to be less vulnerable to drought than other groups.

However, drought vulnerability cannot explain why Borana are involved in more fatal violence in wet years. Ember et al. (2014) do not find Witsenburg and Adano (2009)'s explanation on strategic considerations underlying the timing of livestock raiding satisfactory. Therefore, they suggest that it may rather be related to age-set initiation practices which coincidentally have been in the same years as especially wet years.

For seasonal transhumance, Gabra and Borana are expected to also stay close to their cooler homebases in times of drought. In addition, the agricultural activities of Borana people are considered to cause the reversed mobility patterns of that ethnic group. During planting and harvest in the rain seasons cattle is considered to be moved into the arid lowlands (Ember et al., 2014).

B Resource Abundance Scarcity Theory

Another explanation by Schilling et al. (2014) for the diverging results is the RAST. Based on their results, they suggest that conflict is more likely in the wet season in regular years as the wet season provides the better conditions for raiding to restock their herds after the dry period. Thereby, they are following the argumentation of Witsenburg and Adano (2009) that strategic considerations like livestock health and vegetation cover are explanatory in the timing of raids in North-Western Kenya. In times of drought, on the other hand, pastoralists may not be able to delay their raiding until the wet season and raiding may happen out of the immediate need to gain access to resources (Schilling et al., 2014).

3.2.4 Politics

A Elections

Figure 3.12 illustrates the impact of national-scale political events on conflict in North-Western Kenya. Over the last decades, elections have repeatedly resulted in an outburst of politically motivated inter-ethnic violence in Kenya (Carrier & Kochore, 2014; Smith, 2009). Within the literature reviewed, underlying reasons for the 2007 and 2012 election violence have been discussed (Carrier & Kochore, 2014; Kanyinga, 2009; Smith, 2009).

Both, Kanyinga (2009) and Smith (2009) attribute the eruption of violence as part of the 2007 presidential election to a lack of addressing land grievances and political marginalization in colonial and post-colonial history. With the introduction of multipartyism in the 1990s and the reemergence of the idea of *Majimboism* stakes of elections had increased with regards to political patronage of one's ethnic group and a potential solution of the land question.

Majimboism, first proposed in the 1960s, was a countervision to the system of centralized power. Instead, administrative power should be given to the region for their respective territories. *Majimboism* was seen as a promise to address the marginalization of certain ethnic groups and the related land question. However, in the 2007 elections another party favouring the centralized state system won (Kanyinga, 2009).

Smith (2009) argues that the high stakes of elections related to political power and land grievances along with the consequent disillusionment, as elections did not yield the changes in power distribution or land rights, led frustrated ethnic groups to turn against those groups which they deemed to benefit from the status quo.

B Devolution

Despite hopes that the regionalisation of power could dissolve election violence, devolution as part of the 2010 constitution is not considered to have decreased electoral violence. Rather, accounts of violence during and after the 2012 general elections suggest a shift of the same motivations for patronage and related land struggles from the national to the regional scale, with the epi-centre of violence in the northern counties with a strong majority-minority distribution of different ethnic groups (Carrier & Kochore, 2014; Lind, 2018).

Marsabit, formerly of low importance in elections, was now considered a 'swing' region with great impact on the outcome of elections. The strategic use and encouragement of ethnic rivalry by politicians during the election phase has been reported multiple times in literature (Carrier & Kochore, 2014; Scott-Villiers, 2017). The devolved power system also increased the stakes of the political outcome at the local level, where Borana and Gabra had already long been competing for political dominance. While Marsabit was rearranged into constituencies which were ethnically more uniform, borders became sites of contestation for territorial rights. The loss of the Borana in the race for the governor position, hence, led to intense violence after the 2014 elections (Carrier & Kochore, 2014).

Furthermore, devolution is considered to have generally substantiated ethnic territorialization and tensions over the access rights to land through spatial modification of borders (Galaty, 2016; Scott-Villiers, 2017).

3.2.5 Economic development

The inflow of financial resources into the north-western counties as part of devolution has resulted in a recent rise of economic development projects in this marginalized region. The impact of these projects on conflict in the area has been a focal point of recent conflict literature for the study area (Johannes et al., 2015; Mkutu & Mdee, 2020; Schilling et al., 2015; Schilling et al., 2018; Schilling et al., 2016).

However, most of the impacts have not precipitated yet. As these projects are assumed to have a large impact in the near future, they are still considered within the perceptual conflict model (see Figure 3.13). To illustrate the uncertainty within the related findings, impacts of projects which partly or fully lie in the future are visualized through dashed arrows. While all links in the perceptual model are based on the hypotheses derived from the literature set, the following description is supplemented with up-to-date information on the progress of the projects.

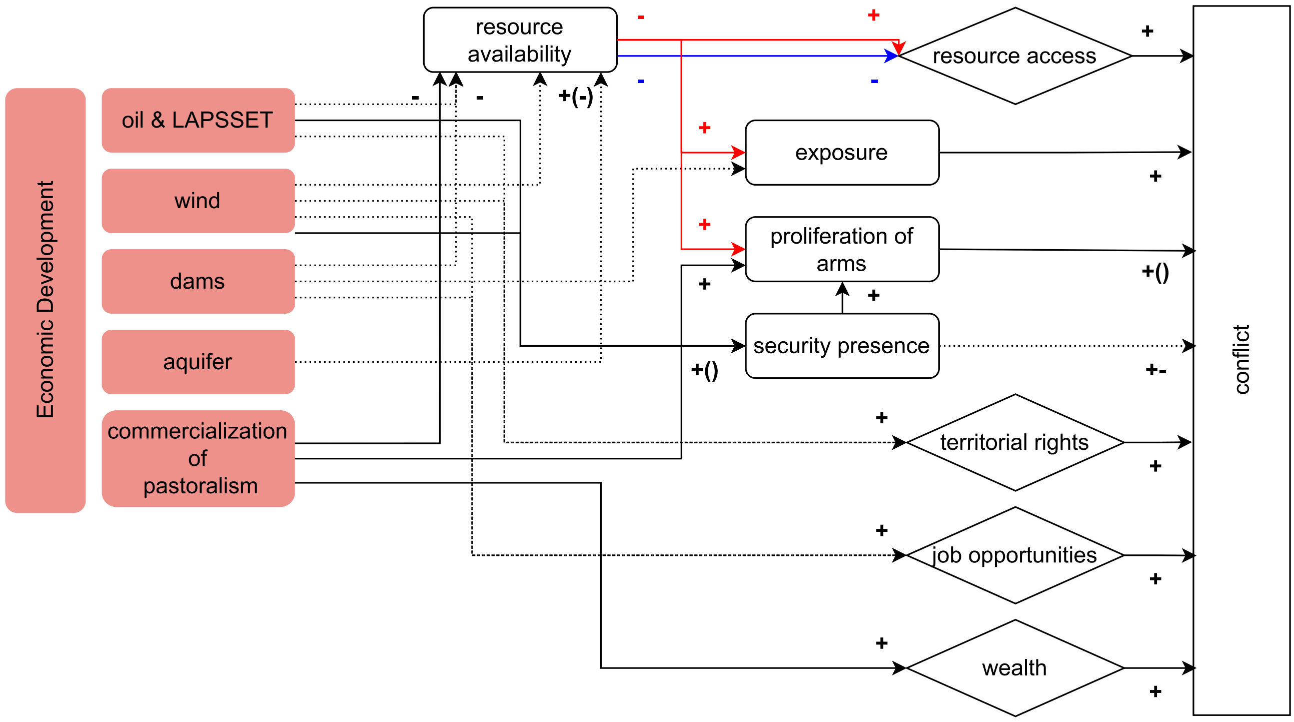


Figure 3.13.: Economic Developments and their impact on inter-ethnic conflict in North-Western Kenya

A Oil & related projects

The oil fields in Turkana were first discovered in 2012. Based on recent estimates they contain 585 million barrels of extractable oil volume (Ngugi, 2021). As part of the Early Oil Pilot Scheme, oil has already been exported in lower quantities (Okoth, 2020). However, full-field development has repeatedly been delayed with company Tullow oil running into financial difficulties. The following entrance of oil companies Africa Oil Corporation and Total has been overturned in May 2023 by these two partners' exit, leaving Tullow Oil once again in need of finding a new partner to finance the next development stage. At the same time, concerns about the viability of the project are increasing (Mutua, 2023a, 2023b).

The oil exploration is linked the construction of a crude oil pipeline from South Lokichar to Lamu in South Kenya. The pipeline is part of the larger Lamu Port and Lamu-Southern Sudan-Ethiopia (LAPSSET) Corridor infrastructure project consisting of interregional highways, oil pipelines, railway infrastructure connecting cities in Kenya, Ethiopia and South Sudan. In addition, three international airports, three resort cities and a dam along Tana River are part of the project. Along the axis connecting Isiolo with Juba in South Sudan, Turkana county is subject to the construction of railway, highway and oil pipeline infrastructure (LAPSSET Corridor Development Authority [LCDA], n.d.).

The literature reviewed has largely analysed the impact of oil development prior to the recent delay in progress, therefore representing scenarios of unhindered oil exploitation in the region. Apart from the tensions which have risen between the oil company and citizens, as well as the government and citizens, inter-ethnic tensions are projected to increase (Johannes et al., 2015; Lind, 2018; Schilling et al., 2018).

As illustrated in Figure 3.13, the increased value of land associated to the oil finds is assumed to intensify the conflict over territorial rights (Johannes et al., 2015; Lind, 2018; Schilling et al., 2018). Evidence of an increasingly expansionist attitude of Pokot people at the border to Turkana is provided by Lind (2018) and Schilling et al. (2018), however such accounts are only incidental among interviewees.

In addition, oil development is projected to and has already increased pressure on both, land and water resources. Extraction sites are fenced off, alleviating pastoralists of some of their grazing sites and access to water sources (Johannes et al., 2015; Mkutu & Mdee, 2020; Schilling et al., 2018). The struggle for land is prediced to intensify when the oil pipeline, highway and railway as part of the LAPSSET Corridor are constructed (Schilling et al., 2018; Schilling et al., 2016). However, the magnitude of effects of the LAPSSET corridor on pastoral migration routes, land and pasture availability depends on the extent to which the oil pipeline runs underground and on mandatory remedial measures taken to reduce the impact on livestock (Schilling et al., 2016).

The oil extraction will require large amounts of water, adding another pressure on already scarce water resources (Mkutu & Mdee, 2020; Schilling et al., 2018). Tullow Oil has installed water tanks along the road which are filled by water trucks. However, this source of water provision is considered to be unreliable and negligible in comparison to future water demands for oil extraction (Schilling et al., 2018). Schilling et al. (2015) also expresses worries with regards to potential pollution of air, water and soil resources.

To protect extraction sites, Tullow oil has employed security forces. While security forces have locally decreased conflict incidences in vicinity to the extraction sites, insecurity is said to have increased in other places (Schilling et al., 2018). Rather than trained police officers, Kenya Police Reservists (KPRs) have been employed. KPRs are people from the community who have been originally armed and trained by the police to protect the community. This does not only result in an additional source of arms in the area. The concern is also raised that thus empowered community members may misuse the arms in ethnic conflict (Mkutu & Mdee, 2020). Evidence for that has already been provided by Mkutu (2007) who found that KPRs were lending arms to raiders. As Tullow oil has employed security guards from cross-border tribes such as the Pokot, Turkana communities along the border are considered to be at higher risk of attacks by these communities (Schilling et al., 2016).

B Wind

In 2014, the construction of a wind farm at the eastern shore of Lake Turkana in Marsabit was started. The wind farm, owned and developed by Lake Turkana Wind Power Limited (LTWPL), consists of 365 wind turbines with a total capacity of 310 MW (Lake Turkana Wind Power Limited [LTWPL], n.d.).

Like for the oil resources, the wind farm is suspected to increase inter-ethnic tensions over territory. In addition, frustration over the distribution of jobs among ethnic groups has been expressed as part of interviews (Schilling et al., 2018).

However, the adverse impacts of the wind farm on land are lower, as the wind park is not fenced off. In addition, little water is needed for operation of the wind turbines and LTWPL has provided a more reliable water source to the residents than Tullow Oil through the drilling of wells. Therefore, the overall impact of the wind park on resource availability is considered to be rather positive (Schilling et al., 2018).

Like Tullow Oil, LTWPL is employing KPRs to protect the sites, resulting in increased security in proximity to the wind park. However, the same concerns, with regards to exposure in other areas and arming community members, are relevant (Schilling et al., 2018).

C Gilgel Gibe III & Turkwel dam

The Gilgel Gibe III dam was constructed in Ethiopia along the Omo River and started operation in 2015 (S. T. Avery & Tebbs, 2018). In combination with a heavy water abstraction for irrigation projects along the Omo River, the dam was projected to result in reduced inflow of the Omo River into Lake Turkana and a decrease of the water level of the lake by over 20m (S. Avery, 2013). While this has been a reason for concern in the literature reviewed, more recent estimates suggest limited impact of the dam on lake water level (S. T. Avery & Tebbs, 2018).

Turkwel dam is a dam in West Pokot County close to the border of Turkana County constructed between 1986 and 1991. With a capacity of 1.6 billion cubic metres it provides water for hydroelectric power generation, irrigated agriculture, tourism and fisheries (Government of Kenya & UNDP, 2021).

In conflict literature, Gilgel Gibe III is assumed to not only decrease water availability but also to increase the exposure of ethnic tribes to conflict through bringing them into direct contact with other ethnic tribes which they have been formerly separated from through the lake, or with tribes displaced by the dam and plans for irrigated plantations (Johannes et al., 2015; Schilling et al., 2016). Similarly to the displacement of Dassanetch and Nyangatom projected for the Gilgel Gibe III dam, the Turkwel dam is said to have the same effect on Turkana people (Johannes et al., 2015). In addition, inter-ethnic tension between Pokot and Turkana has arisen surrounding the job opportunities in operating Turkwel dam, thereby further increasing the presence of small arms in the study area (Noonan & Kevlihan, 2018).

D Aquifer

The discovery of groundwater sources in Turkana in 2013 has been mentioned by Schilling et al. (2016) and Johannes et al. (2015) as a potential source of high-quality water to improve water availability in the region and to counteract increasing pressure on existing water sources posed by oil extraction in the future. However, supplementary more recent information shows that the Kenyan government has abandoned the exploration of the aquifer in February 2022 due to high costs for the necessary desalination of the water source, even for the purpose of using it in oil extraction (Andae, 2022). The impact of the aquifer on resource availability is still open, as researchers at the University of Nairobi have objected that the aquifer may contain non-saline pockets of water (Chepkuto, 2022)

E Commercialization of pastoralism

Apart from the more recent economic development projects, the increasing integration of pastoralism into the market economy has been discussed by several authors. While denied by raiders, officials are seeing livestock raids increasingly motivated by wealth accumulation through sale of livestock (Schilling et al., 2012). Given the financial incentives, pastoralists are likely to scale up their herds, thereby increasing the risk of overgrazing and resource degradation (Schilling et al., 2014). In addition, wealthy actors have become active in sponsoring raiding and providing guns to young men to obtain livestock for sale (Omolo, 2011).

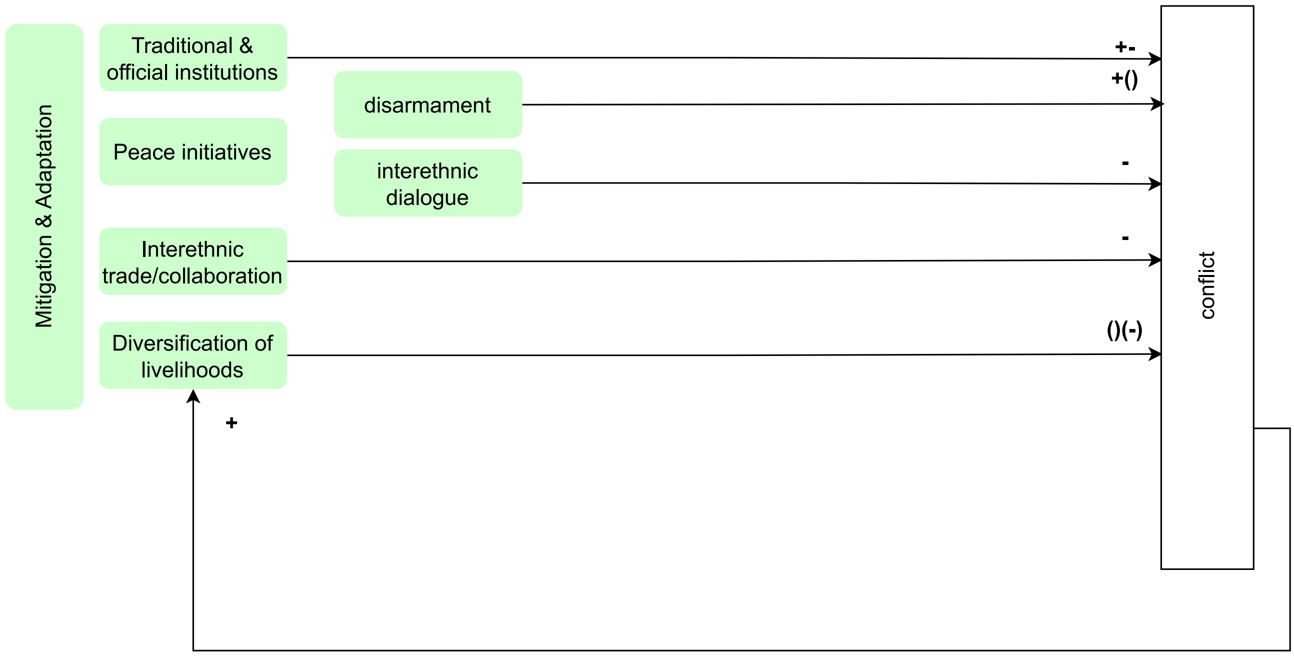


Figure 3.14.: Adaptive and mitigatory action and its effect on conflict

3.2.6 Mitigation & adaptation efforts

A Traditional & governmental institutions

Within the literature, the importance of communal leaders is repeatedly mentioned in securing peace but also in exacerbating inter-ethnic tensions (Adano et al., 2012; Carrier & Kochore, 2014; Noonan & Kevlihan, 2018; Schilling et al., 2012). Elders have been found to actively encourage raiding in times of conflict while trying to prevent the youth from raiding in times of peace (Schilling et al., 2012). Related to the 2013 election Carrier and Kochore (2014), stress the importance of elders in mobilizing voters and hardening lines of ethnic identity. On the other hand, they have enabled peace and resource sharing agreements and are considered to traditionally be the only institution which could deter conflict in the absence of state-control in the region (Adano et al., 2012; Carrier & Kochore, 2014). In addition to elders, the younger Kraal leaders have been mentioned as instrumental in the case of the siege of Loregon to uphold peace agreements (Noonan & Kevlihan, 2018).

The peace efforts of official authorities, on the other hand are only sporadically mentioned and are of limited success. Early warning and response to conflicts by public authorities in the area is reported to be undermined by a lack of funding (Omolo, 2011). Temporal successes in government peace efforts in the region, following the siege of Loregon, could not be maintained by the Police Authorities (Noonan & Kevlihan, 2018).

B Peace initiatives

A similar picture is obtained when investigating local peace initiatives. A significant pacifying impact of local peace initiatives on conflict occurrence has been found by Meier et al. (2007). However, accounts of different peace initiatives suggest their variable success. Government disarmament efforts in the region are generally considered to have had no impact or to have even amplified conflict. One-sided disarmament often left one group vulnerable to attacks by the other ethnic group (Mkutu, 2007; Schilling et al., 2012; Witsenburg & Adano, 2009).

On the other hand, there are several examples of successful inter-communal dialogue. Recent peace caravans, organized by the local youth, as well as intra- and inter-communal peace meetings are considered to be promising in mitigating conflict (Johannes et al., 2015; Lind, 2018; Noonan & Kevlihan, 2018; Schilling et al., 2016). A further point which is repeatedly mentioned is the importance of inter-ethnic collaboration and trade in sustaining peace. Meier et al. (2007) find a significant mitigating effect of *reciprocal exchanges* on conflict. This is illustrated by the case of the Samburu and Rendille. While borders between districts are commonly sites of conflict, conflict along the border between Samburu and Marsabit is largely absent due to the long-term alliance between Samburu and Rendille (Galaty, 2016).

C Diversification of livelihoods

Climate change and felt insecurity in the area, as a result of intense conflict, have motivated sedentarization and diversification of livelihoods among pastoralists. While this may reduce the pressure to fight over scarce resources, the impact on conflict in the study area is considered to be marginal, as agricultural potential in the area is low and livelihood diversification is therefore not considered to be sustainable (Omolo, 2011; Schilling et al., 2014).

3.3 Effect of DIs on conflict probability in North-Western Kenya

3.3.1 Overview of presented results

As part of the present thesis a large set of different logistic regression model set-ups has been tried to assess the effect of drought or water abundance on conflict. Within the results section only a subset of the models is visualized based on the most important findings. These findings are related to:

1. A comparative assessment of the four different model structures (Model 1, Model 2, Model 3 and Model 4)
2. An in-depth analysis of different ethnic-group-specific effects of drought or water abundance on conflict

A full overview of the odds ratios associated to a one unit decrease in negative DI or increase in positive DI for SPI and SPEI at different lag times, aggregation periods and for spatial statistics is given in Appendix E. Taking the 25th or 75th percentile of DI values across grid cells when spatially aggregating DIs to the admin1-level or ethnic territory did not result in systematically more significant values. Rather, results were largely consistent across the set of spatial statistics. Therefore, in the following, only the median is used to illustrate the results. The median is chosen over the mean, as the mean is expected to be more affected by the negative outliers in the SPEI.

In addition, the analysis of results focusses on the analysis of the SPEI. Corresponding figures for the SPI are provided in Appendix F to enhance the discussion on potential differences in the found relationships when choosing a different DI. The SPEI is chosen over the SPI for analysis due to its higher information content on the actual on-ground water budget. In addition, the SPI is considered to be less suitable for arid regions where many months without any rainfall are recorded. The underlying gamma distribution is not defined for zero. Therefore, the fit of the distribution becomes more uncertain, the higher the percentage of zero-records within the data for a certain grid cell and month of the year (European Commission, 2020).

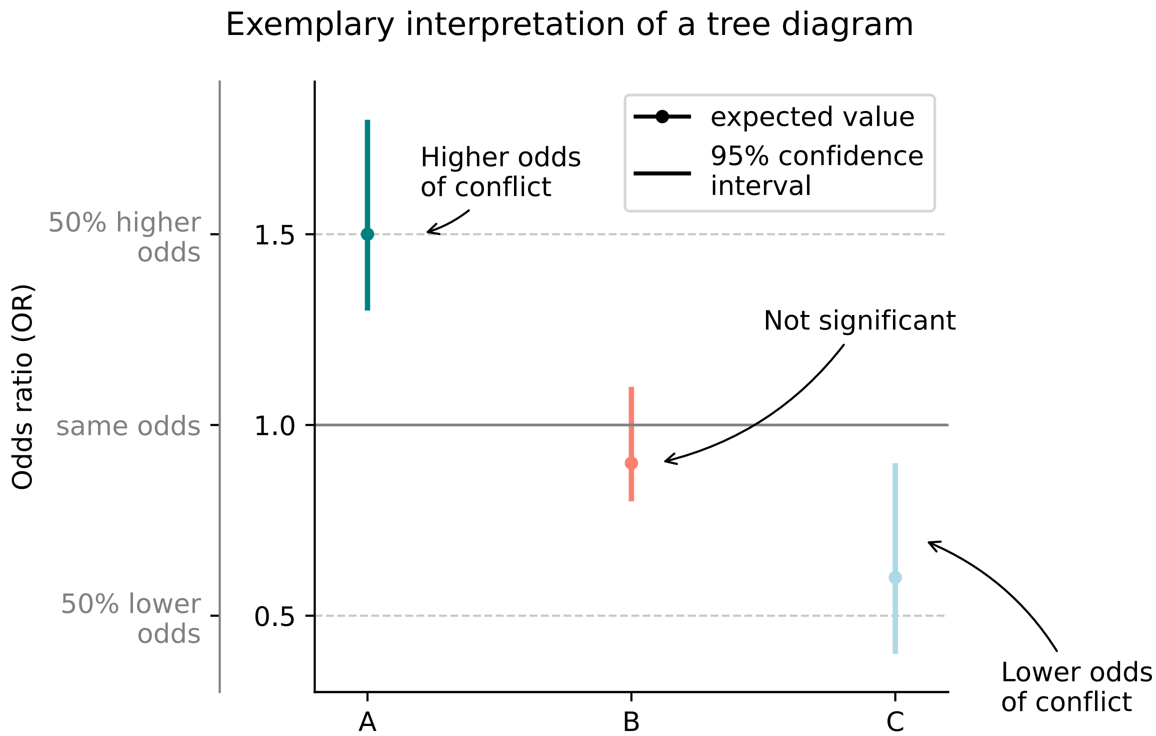


Figure 3.15.: Exemplary interpretation of a tree diagram. The odds ratio for a unit change in the drought indicator towards the extremes is displayed for Model A, B and C, where the marker represents the expected value and the whiskers represent the 95% interval. An odds ratio of one corresponds to no change in the odds of conflict. An odds ratio higher than 1 suggests an increase in the odds for more extreme dry or water abundant conditions, depending on the context of analysis (Model A). An odds ratio lower than 1 suggests a decrease in the odds for more extreme dry or water abundant conditions (Model C). If the confidence interval overlaps 1 (Model B), no significant impact of the drought indicator on conflict can be found at the 5% significance level.

For simplicity, in the following, an OR is referred to as significant if significant at the 5% level. This is a commonly used threshold in climate-conflict studies (Fjelde & von Uexkull, 2012). However, significance at alternative thresholds of 10% and 1% are provided as part of the tables in Appendix E.

The ORs are visualized in tree diagrams. To enable the reader to understand and analyse these figures, an exemplary interpretation of a tree diagram is given in Figure 3.15. The figure illustrates the expected value and the CI of an OR for three example models. It shall be recalled that the OR has been defined for a unit change towards the climatic extremes. If the effect of a negative DI is investigated, the y-axis therefore corresponds to the factor by which the odds are multiplied when the DI is one unit lower, i.e. conditions are drier. An OR of 1 suggests that the odds stay the same. For a model for which the 95% CI overlaps 1 (see Model B in Figure 3.15), it can be concluded that there is no significant effect of the DI on conflict probability at the 5% significance level. Therefore, 1 is marked by a dashed line in the following graphs. An odds ratio higher than 1 for which the 95% confidence interval does not overlap 1 suggests an increase in the odds of conflict for more extreme climatic conditions. For example, the odds of conflict for Model A increase significantly by 50% for a one unit lower negative DI or one unit higher positive DI. An odds ratio lower than 1 suggests the opposite. Hence, for Model C the odds of conflict decrease significantly by 40%.

3.3.2 Comparison of the four model structures

Figure 3.16 shows the OR of the negative SPEI-6 at all lag times for the four different model structures. The aggregation period of 6 months has been chosen here because of its common use in the climate-conflict literature (Fjelde & von Uexkull, 2012; Schleussner et al., 2016; von Uexkull, 2014). And the negative SPEI-6 is displayed instead of the positive SPEI-6 because of the special interest in drought as potential conflict contributor in the region. However, the qualitative patterns observed, when comparing the ORs across the models are consistent with the alternative SPEI-1, SPEI-3, SPEI-12 or any SPI or using positive DIs instead.

For all lag times there is no significant effect of the negative SPEI-6 on conflict in Model 1. The additional plots provided in Appendix F show similar results for other aggregation times and the SPI, where only few scattered results are significant. CIs are large suggesting little coherence in the effect of drought on conflict occurrence.

When comparing the results for Model 1 in Figure 3.16 to those of Model 2, it becomes evident that the smaller confidence intervals for temporal lags of 0 to 2 months in Model 1 coincide with relative homogeneity in the effect of the negative SPEI-6 across the three counties. For larger lags, on the other hand, almost opposite effects are observable in Model 2 for West Pokot and Turkana. For example, a unit decrease in negative SPEI-6 is associated to a significant increase in conflict odds in Turkana by 76% while for West Pokot a 19% decrease in conflict odds is estimated, although only significant at the 10% level (compare to Table E.4 and Table E.5).

Compared to Model 1, Model 3 shows much smaller confidence intervals, not only for the negative SPEI-6, displayed here, but also across all negative and positive DIs tested (compare to Appendix F. This suggests a more coherent universal effect of drought on conflict, when also considering the conflicts an ethnic group is involved in outside of its territory. A unit decrease in negative SPEI-6 is associated to a significant increase in the odds of conflict three to four months later.

Even though a global significant positive effect of the negative SPEI-6 on conflict occurrence is found, there are differences found in the magnitude and the direction of the effect for different ethnic groups in Model 4. For most groups a significant positive effect of the negative SPEI-6 is found four to five months later. However, for some groups the effect is not significant or even negative. These differences across ethnic groups against the backdrop of Ember et al. (2014)'s hypothesis that different ethnic groups may engage in conflict under different climatic conditions, have necessitated further analysis of ethnic-group-specific effects of drought or water abundance on conflict.

3.3.3 Interactions at ethnic group level

Figure 3.17 and 3.18 illustrate how a negative or positive unit change in median SPEI over the home territory of an ethnic group affects the odds that this ethnic group engages in conflict. In addition to SPEI-6, SPEI-1 is visualized. The choice of the DIs is driven by the observation of two distinct patterns in the results:

1. Many significant effects of single anomalous dry or wet months are found for the same or the subsequent month. These signals are interpreted in the following as the immediate response of ethnic groups to anomalies in CWB patterns.

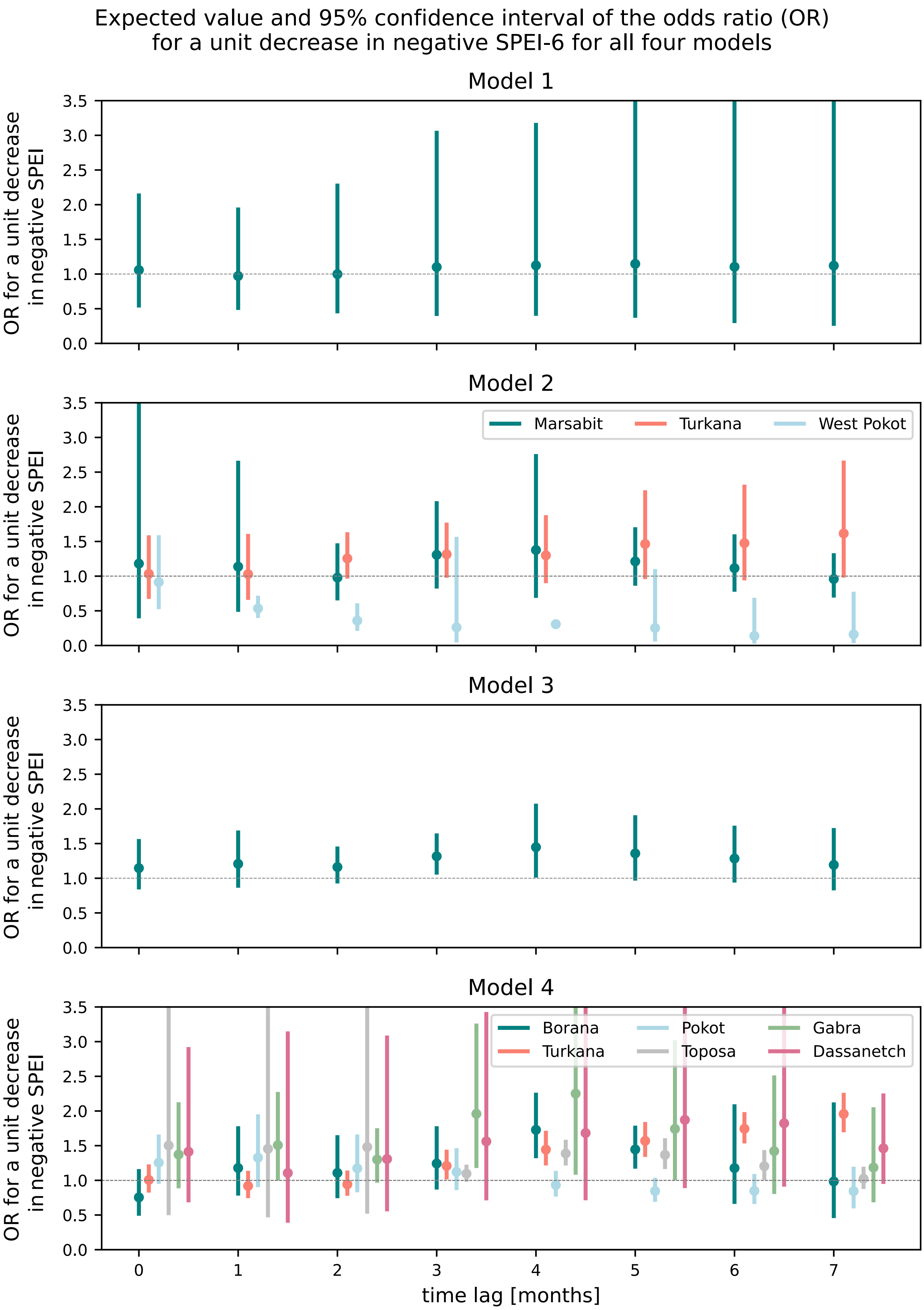


Figure 3.16.: Comparative figure of the OR of the median negative SPEI-6 for the four different model structures (Model 1 to 4 from top to bottom). ORs are provided for all lag times of zero to seven months.

2. There are also significant effects of single anomalous dry months at longer lags of five to seven months and significant effects of DIs with longer aggregation periods at short to intermediate time lags. Not every single-month negative or positive peak in DI translates to a long-term drought. However, the similarity in the direction and significance of effects results in a step-like visible pattern across these DIs in the colour-coded OR tables in Appendix E (see e.g. Figure E.22. This suggests that the visible effects are part of the same phenomena: the effect of a prolonged drought or water abundance on conflict occurrence. Therefore, it is stressed that effects at longer time lag should not necessarily be interpreted as effects occurring *after* a drought or water abundance phenomenon has ended. They may as well correspond to the effect of a prolonged time of anomalously high or low CWB.

In addition, the analysis is restricted to the most apparent ethnic-group-specific patterns. An interpretation and explanation of every ethnic group response to climate extremes has not only been beyond the scope of the thesis. It is also not advisable as it may treat artifacts in the results as signals. Determining significant effects at a 5% significance level still means that, statistically, 5% of these effects are incorrectly classified as significant.

For the negative SPEI in Figure 3.17 it can be seen that already short-term drier conditions suffice to increase the odds of conflict significantly for most groups. A significant increase in the odds of conflict is visible for Turkana, Gabra, Toposa, Dassanetch and Pokot in an anomalously dry month or the following month. However, also for longer time lags of six to seven months, a significant increase of conflict odds for most of these ethnic groups is found. This, and the observation of significant increases in odds of conflict a few months after a low SPEI-6 or SPEI-12 suggest that these ethnic groups are not only more likely to engage in conflict when a month is exceptionally dry but also when the consequences of prolonged drought for pasture availability and water resource availability become tangible. Intermediate time lags of three to five months on the other hand suggest that after the immediate response to an anomalously dry month, these groups are less inclined to engage in conflict.

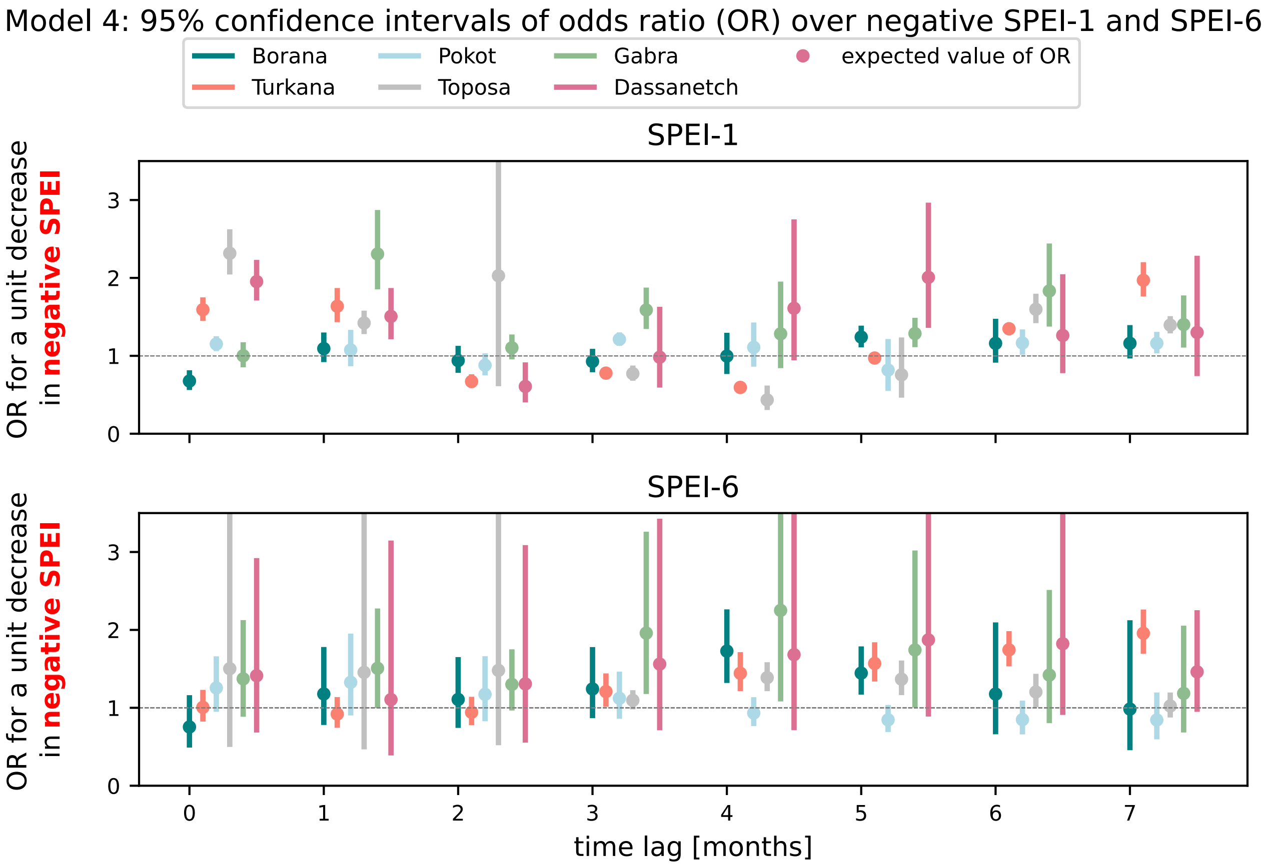


Figure 3.17.: Model 4: Estimates and 95% CIs of ethnic-group-specific ORs for a unit decrease in negative SPEI-1 and SPEI-6 as obtained from the LRM

These patterns are followed by most of the ethnic groups, although timing of the effects varies. Therefore, on a monthly basis, opposite responses between different ethnic groups are observable. In addition, differences in the response to short-term and longer-term drought phenomena are found. For Borana, a lower negative SPEI-1 significantly decreases the odds of conflict in the same month, while in the longer term, dry conditions are also found to increase the odds of conflict. On the other hand, the odds of conflict increase significantly for Dassanetch in a drier month or the following month, while for longer aggregation periods, like the SPEI-6, no significant effects are found and DIs are large.

An exception to the mentioned patterns, are the Pokot for which significant positive effects of drier conditions on conflict are scarce. For the SPI (compare to Figure F.13) evidence even suggests a lower probability for their engagement in conflict during and after prolonged droughts, as for SPI-6 and SPI-12, the odds are found to decrease significantly for a unit decrease in negative SPI.

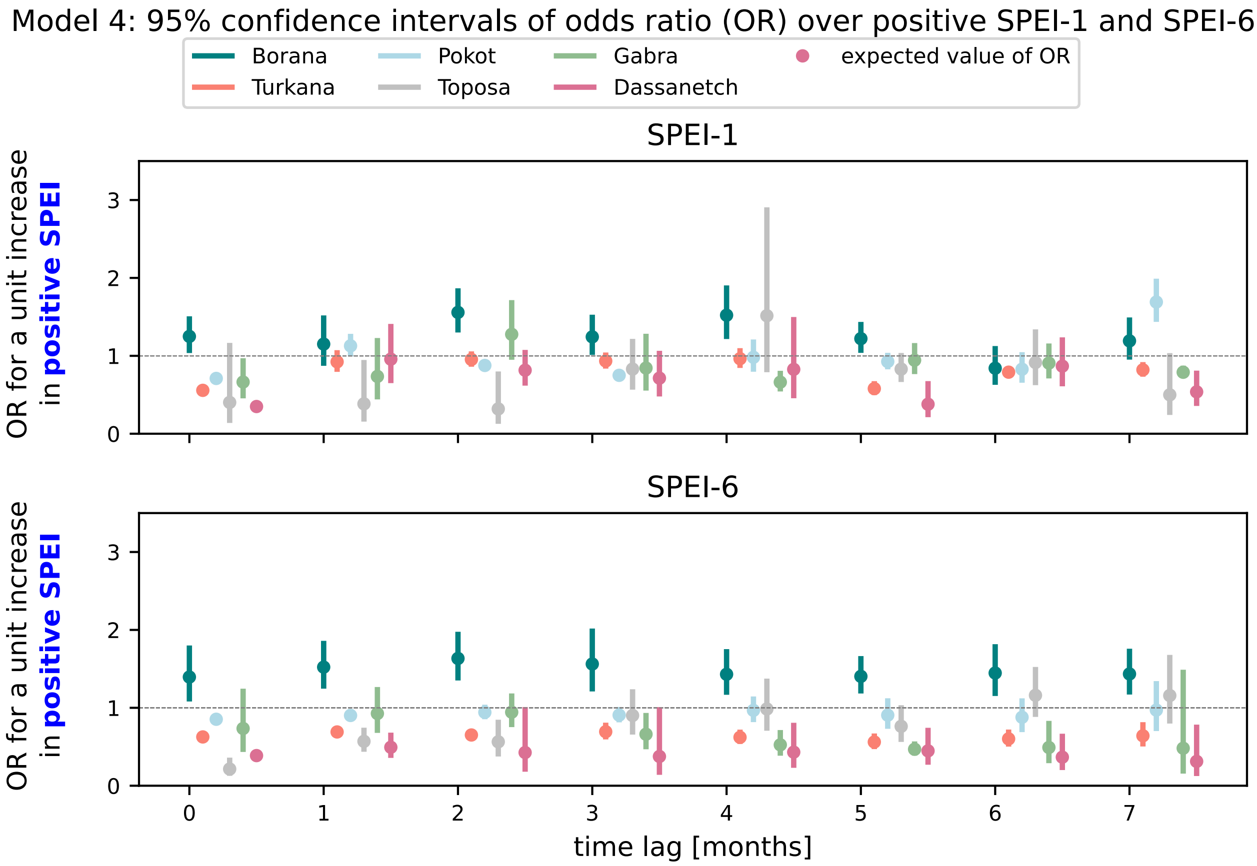


Figure 3.18.: Model 4: Estimate and 95% CI of ethnic-group-specific ORs for a unit increase in positive SPEI-1 and SPEI-6 as obtained from the LRM

For the positive SPEI, Figure 3.18 illustrates that confidence intervals are mostly visibly smaller than for the negative SPEI. This suggests higher coherence in the response of each ethnic group to times of water abundance. For most groups, short- but especially long-term water abundance have the potential of decreasing the odds of conflict. While there are exceptions, a unit increase in positive SPEI-6 or SPEI-12 are associated to significant decreases of conflict odds for Turkana, Pokot, Gabra, Toposa and Dassanetch over most of the following months. On the other hand, for Borana, the probability of conflict is higher in more water abundant situations. For almost all time lags and aggregation periods of the SPEI, a significant increase in conflict odds for the Borana is observable for a unit increase in positive SPEI.

3.4 Predictive power of drought indicators in a regional conflict model

3.4.1 Model performance

The confusion matrix in Figure 3.19 illustrates the percentage of *conflict* and *no conflict* months which are correctly and incorrectly classified in the testing dataset of the RF model.

Out of the 203 *conflict* months within the testing dataset 75% are correctly predicted as such. This comes at the cost of also predicting 27% of the 4045 *no conflict* months as *conflict*. The result is a low precision of conflict predictions. Only 12% of all conflict predictions are actual *True positives*.

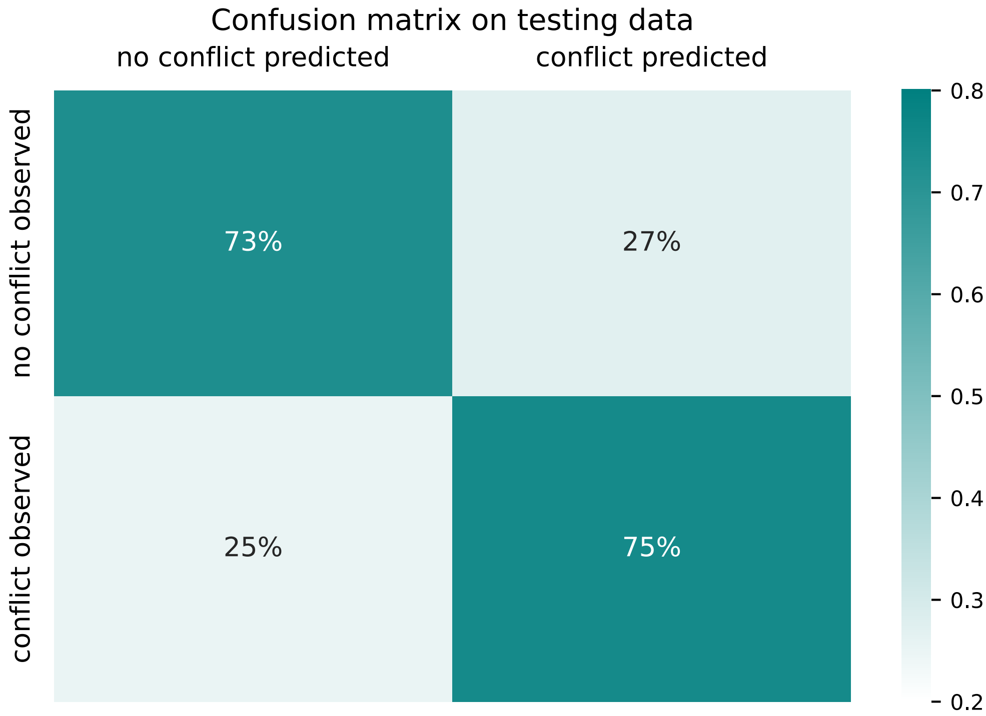


Figure 3.19.: Confusion matrix of conflict prediction on testing dataset

Table 3.3.: Comparison of RF model performance to predictive performance of common CEWS

	Own RF Model	**WPS Model**	**ViEWS Model**
Recall	0.75	0.86	0.59
Precision	0.12	0.39	0.63
F2 Score	0.37	0.69	0.60

Resulting precision, recall and f2 score metrics are given in Table 3.3 and compared to the RF model from the WPS Global Early Warning Tool (Kuzma et al., 2020) and the first version of the ViEWS model (Hegre et al., 2019). While desirable to report the performances of the most recent models from the two modelling systems, the lack of reporting on recall, precision and f2-scores or confusion matrices for these models has forced the use of performance metrics from the first model versions. Metrics scores of both models are taken from a comprehensive comparison of the two models by Kuzma et al. (2020).

The choice in models for comparison is based on the closest comparability of the models to the present RF model. Hence, the WPS RF model developed and assessed on Africa is used, as well as the ViEWS model on non-state conflict. Nonetheless several differences in between the models shall be mentioned:

1. **The spatial resolution:** While later WPS models were built at the admin-1 level, the first generation RF model was predicting conflict at the admin-2 level. ViEWS, on the other hand, is predicting conflict at the country and gridded level. As Kuzma et al. (2020) is not reporting precision and recall scores for the grid-level scale, here, the country level model metrics are reported.

Table 3.4.: Predictive performance of RF model on administrative units in North-Western Kenya for testing time period (2016-2021)

	West Pokot	Turkana	Marsabit
number of conflict months	3	9	11
Recall	0.33	0.89	0.91
Precision	0.02	0.15	0.20
F2-Score	0.09	0.44	0.53

2. **The conflict definition:** In terms of conflict definition the present RF model is comparable to the non-state ViEWS model. Both models attempt to predict non-state conflict occurrence at the monthly time scale based on UCDP-GED data. However, the RF model within the present thesis focusses on communal conflict as a sub-category of non-state conflict. The WPS model, on the other hand, predicts conflict occurrence as 10 or more fatalities over the next 12 months.
3. **The model structure**: Inspired by the WPS RF model, the model as part of this thesis is very similar WPS model. The ViEWS model, on the other hand, uses multiple LRMs and RFs which are aggregated to one prediction via Bayesian model averaging. Each of the models has a thematic focus, including a wider set of variables than the final WPS RF model.

Overall, performance of the present RF model is lower than for the WPS model. The percentage of conflict occurrence which is detected with the WPS model is higher with 75%. At the same time, less *no conflict* instances are predicted as *conflict*. While still low, 39% of the predicted *conflict* occurrences are real conflict, compared to the 12% for the present RF model. This results in a much higher F2 score for the WPS model than for the present model.

Compared to the ViEWS model, the present model has a higher recall. The ViEWS model only manages to detect 59% of the *conflict* occurrences as such. On the other hand, precision and F2 score are higher for ViEWS. Out of all predicted *conflict* instances, 63% are true *conflict* instances. The best F2 score is still obtained with the WPS model because of the higher weight given to recall than precision.

Table 3.4 displays the performance of the RF model on the three administrative units of West Pokot, Turkana and Marsabit in North-Western Kenya. Predictive performance for West Pokot is poor with only one third of the *conflict* months being detected while simultaneously many *no conflict* months are classified as *conflict*. Only 2% of the predicted *conflict* months are *True positives*.

For Turkana and Marsabit, the model performs better than globally, with 89% and 91% of the *conflict* events being detected, respectively. While precision is still low for both counties, it is higher than globally. These results and the much higher F2-score suggest a better separation of conflict and no conflict months for the case of Turkana and Marsabit.

3.4.2 Feature importance

Figure 3.20 displays the importance of individual features in the RF based on the decrease in recall when a feature is permutated. The height of the bars is the mean decrease in recall over 30 repetitions of shuffling a feature and the error bar is its standard deviation.

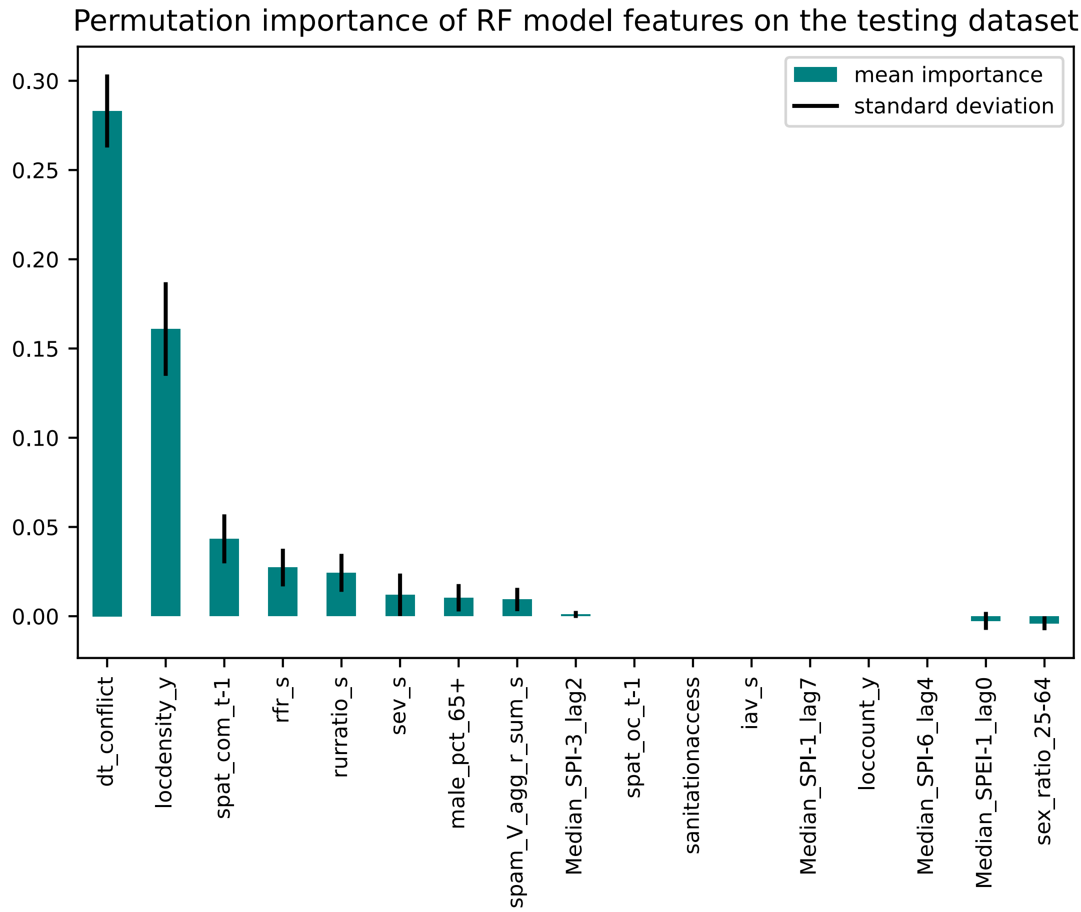


Figure 3.20.: Permutation importance as decrease in recall of RF model features on the testing dataset

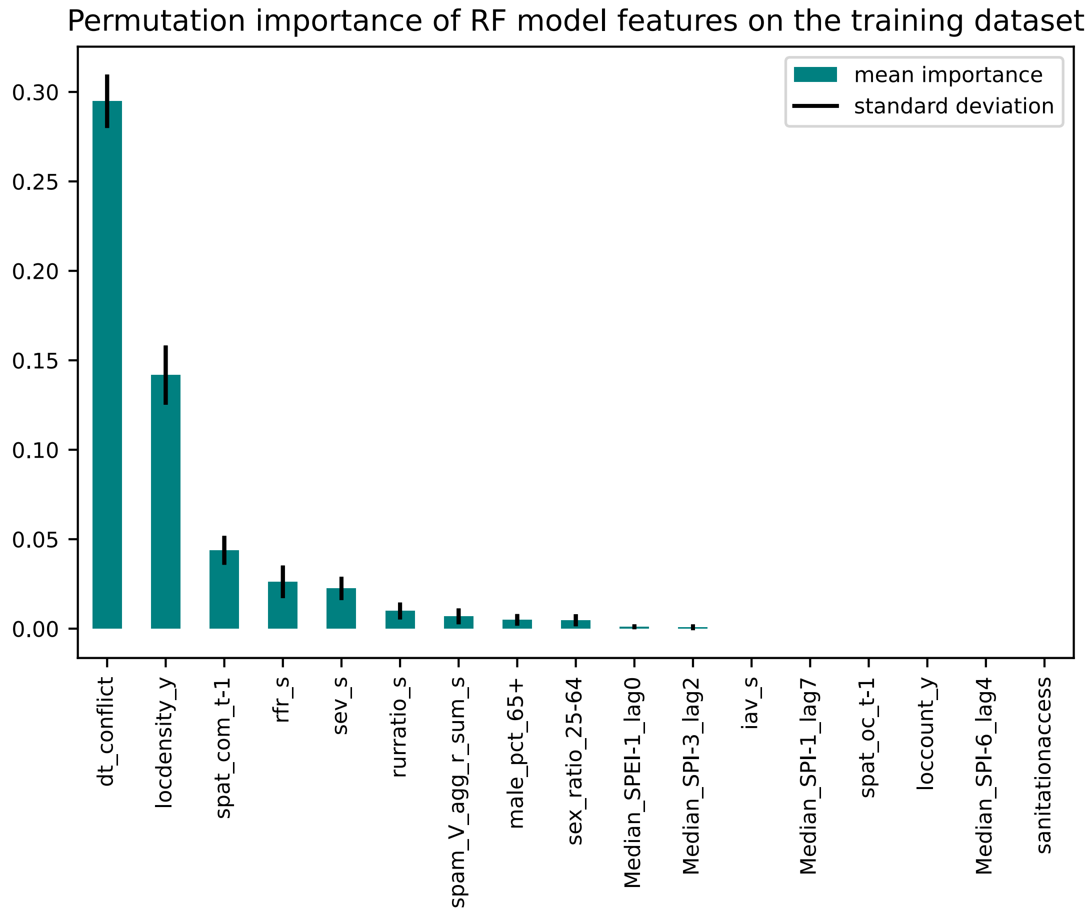


Figure 3.21.: Permutation importance as decrease in recall of RF model features on the training dataset

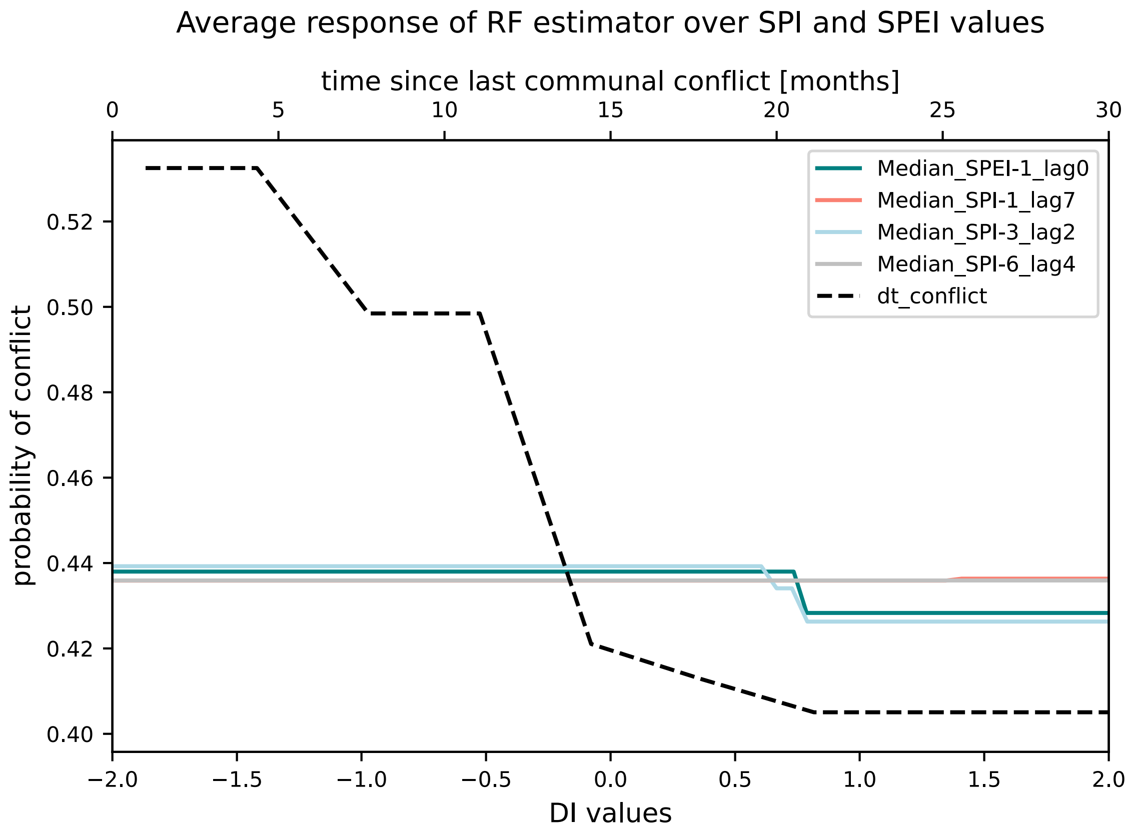


Figure 3.22.: Average effect of the DIs on conflict prediction by the RF model. The variable *dt_conflict* serves as a reference for how much a variable with high PFI affects the prediction of conflict probability.

It can be seen that the highest decrease in recall results from shuffling the variable *time since last communal conflict (dt_conflict)*. This variable has a high explanatory power for conflict prediction on the testing dataset. Instead of 75% of the *conflict* months only 47% are expected to be detected when *time since last communal conflict* is permutated. A further important variable is the *local population density (locdensity_y)* for which permutation reduced recall on average by 0.16. While of less importance, the variables *spatially lagged communal conflict(spat_com_t-1), riverine flood risk (rfr_s), rural to urban ratio (rurratio_s), seasonal variability (sev_s), ratio of males in age-group 65+ (male_pct_65+), value of rainfed crop (spam_V_agg_r_sum_s)* are also found to decrease recall when permutated.

All DIs show little to no visible impact on conflict prediction on the testing dataset. The median SPI-3 lagged by two months shows a very small average decrease in recall. However, the standard deviation is larger than the average of the importance. The median SPEI-1 lagged by zero months even has a negative mean value, suggesting that its permutation on average increases recall. However, again, the standard deviation is larger than the absolute value of the mean importance. One further variable which, when permutated, increases recall, is the *ratio of males in age-group 25-64 (sex_ratio_25-64)*

The permutation importance of individual features in the training dataset, depicted in Figure 3.21, is largely comparable. Minor differences in the magnitude are found, where, for example, *rurratio_s* is associated to a higher decrease in recall in the testing dataset than the training dataset. Such deviations result in a slightly different order of the features in terms of their PFI. More striking is, that the two features with a negative PFI for the testing dataset, have small but positive permutation importances in the training dataset.

The average marginal effect of the DIs on conflict probability, as the average change of conflict probability over the range of the DI, is illustrated in 3.22. Apart from the four DIs the marginal effect of *time since last communal conflict* is additionally displayed to serve as a reference of the change in conflict probability over the range of values for a variable of high PFI.

For *Median_SPEI-1_lag0 and Median_SPI-3_lag2*, months with a DI value lower than 0.7 are predicted to have a slightly higher probability of conflict than higher DI values. However, the total change in conflict probability over the range of values is small. The probability for low SPEI-1 and SPI-3 values is only 1.1 pp and 1.3 pp higher than for high values. In comparison, the probability of conflict over the range of *time since last communal conflict* increases by 13% for commmunal conflict in the last 4 months relative to no conflict within the last 20 months. The other two DIs show no to a very low effect on the conflict probability predicted by the RF model

For the three administrative units in North-Western Kenya, the response to the DIs follows the same pattern as globally. Conflict is more likely as the DIs drop below 0.75. The magnitude of the increase in conflict probability for the three counties is comparable but low. No effect is observed for the other two DIs.

For comparison, Figure 3.24 displays the marginal effects of the DIs on conflict probability as obtained from the LRM. It can be seen that the magnitude of changes in conflict probability are higher. For Turkana, the change in negative SPI-1 when moving towards more extreme values, is associated to an average increase in conflict probability of 16% per unit decrease in DI. The impact is of comparable magnitude as the impact of the *time since last communal conflict* variable in the RF model over its entire range of values.

Variables for which higher consistency has been found in the response to positive DIs, are also the variables for which an increase in conflict probability is predicted by the RF model for less water abundance.

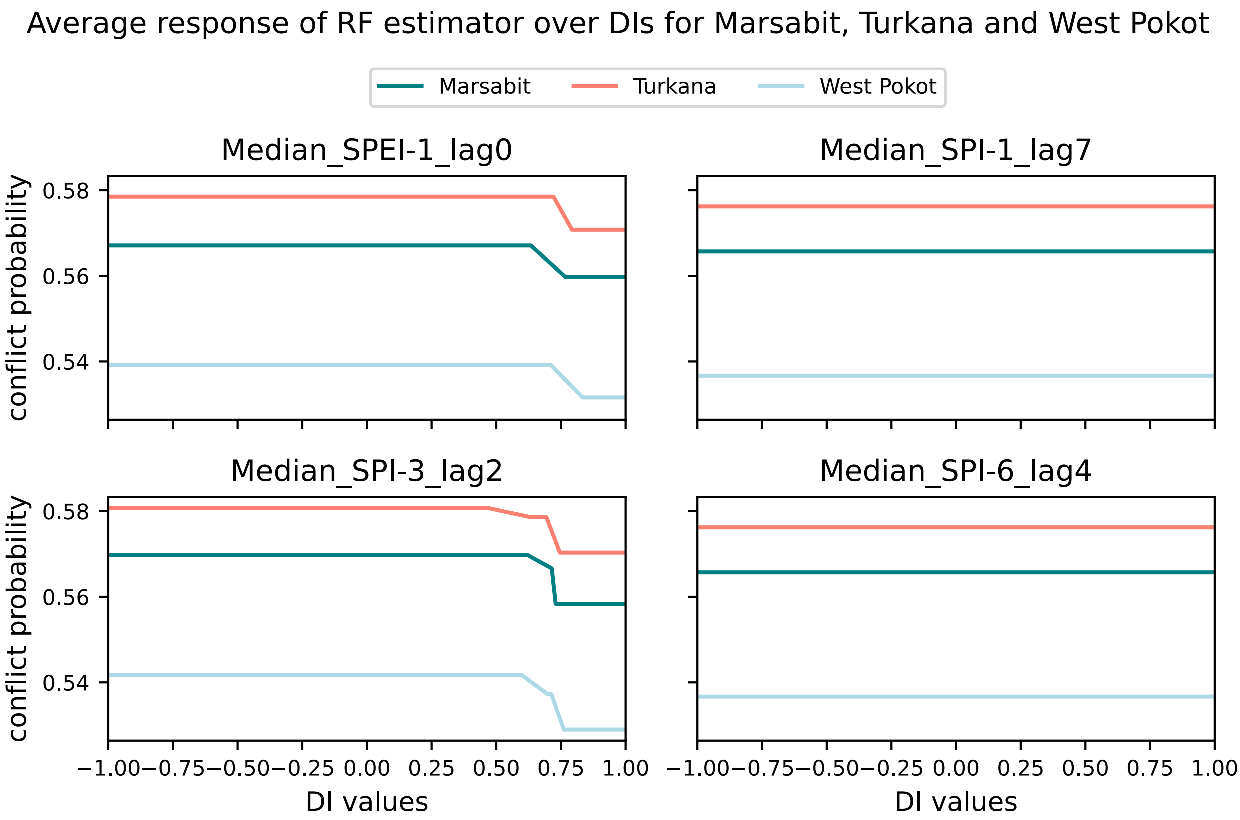


Figure 3.23.: Average marginal effect of DIs on conflict prediction by RF model for Marsabit, Turkana and West Pokot

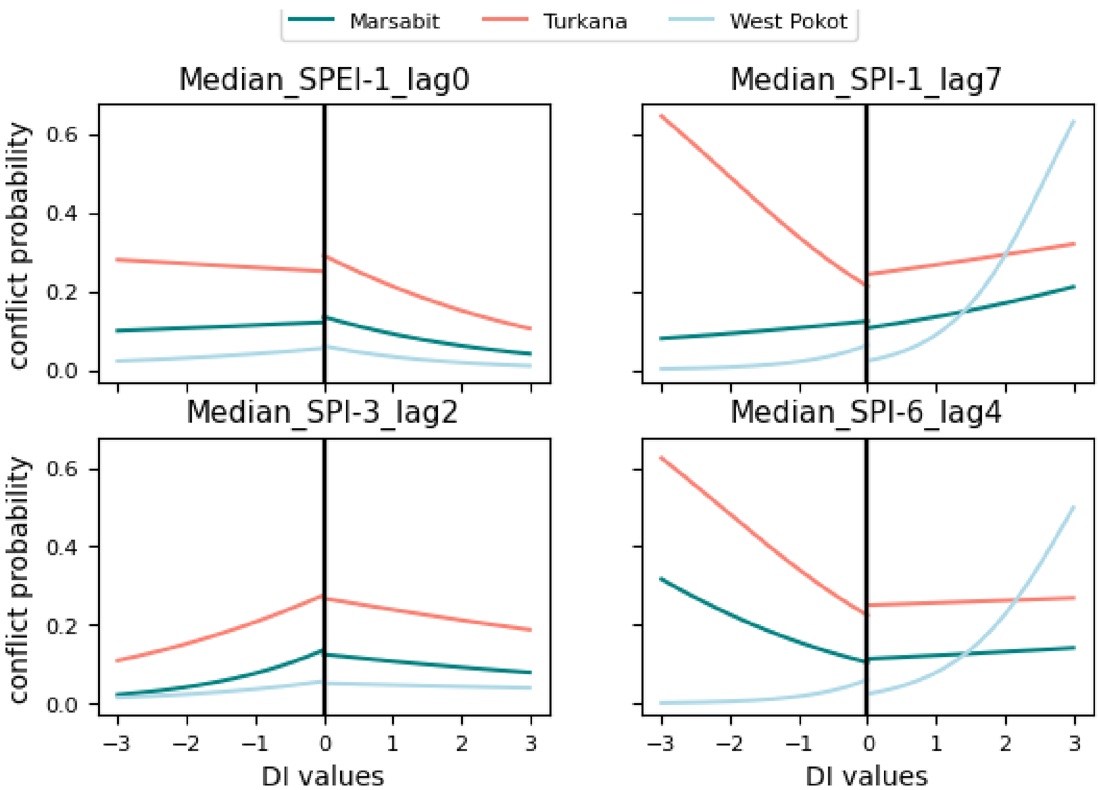


Figure 3.24.: Average effect of DIs on conflict probability, obtained from the Logistic Regression Model for Marsabit, Turkana and West Pokot

4 Discussion

The present thesis has set out to assess the impact that meteorological DIs can have on conflict prediction in a region for which the narrative of resource scarcity-driven conflicts between pastoralists exists.

In the prior chapter the results of each of the three research sub-questions have been presented. The following discussion follows the same structure. In Section 4.1 the findings in literature on the different conflict pathways are discussed and how these findings have influenced the further quantitative research as part of the thesis. Section 4.2, then, analyses the quantitative effect of DIs on conflict occurrence in the region, as obtained from the LRM and how the found patterns can be explained. How the effects reflect in the predictive model, is discussed in Section 4.3.

Only in Section 4.4, the interpretations of each of the sub-questions are combined to answer the overarching research question on the role of meteorological DIs in conflict prediction in North-Western Kenya. Finally, in Sections 4.5 and 4.6 the limitations of the research and its implications for further research and Conflict Early Warning practices are analysed.

4.1 Conflict dynamics in North-Western Kenya

4.1.1 The impact of drought and water abundance on conflict

Two pathways have been identified from literature to explain the impact of climate variability on conflict occurrence in the study area. While the one builds on the resource scarcity hypothesis and suggests that conflict in the region is a struggle over scarce resources, the other implies that strategic considerations underlie the decision to engage in conflict. As times of water abundance provide convenient conditions for raiding, this pathway suggests, that opposite to the prior hypothesis, conflict is more likely in times of water abundance. Both of these pathways are backed by empirical evidence from Turkana and Marsabit respectively.

Two hypothesis which try to reconcile the contrary findings lead to the assumption of a more contextual climate-conflict relationship, where the occurrence of conflict does not only depend on drought or water abundance, but also on the underlying seasonal cycle and the different responses by different ethnic groups.

The results have urged the consideration of the following aspects in the further research:

1. **Different responses per administrative unit and ethnic group**: Responses are observed to vary per administrative unit, with different results found by Ember et al. (2012) for Turkana and by Witsenburg and Adano (2009) for Marsabit. Within Marsabit, they are even varying per ethnic group. These differences in responses needed to be considered in the further analysis to avoid generalized statements where further distinction is necessary.

2. **Differentiation between positive and negative DIs**: A more detailed analysis of the different ethnic groups and their responses has shown that response to dry or wet conditions may not always be one directional (Ember et al., 2012). The example of the Dassanetch shows that both positive and negative rainfall anomalies can simultaneously increase or decrease the risk of conflict. Therefore, a separate consideration of positive and negative anomalies has been required for the development of the logistic regression model, which would otherwise assume a linear increase or linear decrease of the odds in the direction of a higher DI.

3. **Cross-border migration**: Results by Ember et al. (2014) on the importance of migratory behaviour in North-Western Kenya in combination with Detges (2014)'s warning to not be too restrictive on spatial delimitation of the units of analysis required a critical assessment of the definition of the administrative unit as the spatial unit of analysis. This is further emphasized by the visual inspection of conflict locations in 2.7, where many conflict events happen in close proximity to an administrative border, suggesting cross-border migration.

4. **The impact of different seasons**: Apart from yearly climate variability, literature has also identified differences in between seasons in conflict occurrence, or, following the RAST hypothesis, a combination of the two. This suggests the importance of accounting for seasonal variability when wanting to isolate the effect of DIs.

Despite the opposing pathways suggested in literature, there is consensus among the scientists that climate variability affects the conflict behaviour of the population in North-Western Kenya. This stresses the the suitability of the region for an in-depth analysis of the predictive value of DIs in conflict analysis.

4.1.2 Further conflict contributors

Further pathways have been identified as part of the perceptual model, suggesting a complex interplay of multiple macro-scale to individual contributing factors. While originally, livestock raiding may have been an adaptive response to the environmental challenges of the region, the increasing commercialization of livestock raiding coupled with the proliferation of small arms, the ethnic territorialization and the heightened stakes during election periods as well as devolution and the related windfall of public resources which have been partially used for economic development projects, have arguably increased the complexity of the underlying motivations behind inter-ethnic violence, including livestock raiding.

In addition, the results stress the importance of human agency in the mitigation or amplification of conflict through individual motives for conflict and the important role assigned to elders and kraal leaders in directing inter-ethnic relations towards dialogue and interethnic cooperation, on the one hand, or conflict on the other hand.

These results stress that even for the present study area, a singular attribution of conflict to climate variability would underestimate the impact of other factors. In particular, the role of elections shall be stressed here. General elections during the time period of analysis have taken place in December 2007, in March 2013 and in August 2017. Figure 3.3 illustrates that high numbers of conflict events are visible in the years 2008, following the general election in December 2007, and in 2013 surrounding the general election in March 2013. Especially, for Marsabit, violence after devolution is largely following electoral cycles with peaks occurrence of violence from 2012 to 2014 and from 2017 to 2019 as well as a renewed occurrence of conflict in 2021 preceding the election in August 2021.

Apart from elections, the high peak in conflict events in Turkana and West Pokot in 2014 may be additionally related to the siege of Loregon, where in November 2013 an armed Pokot militia attacked Loregon and killed members of the Turkana people. The incident was followed by several retaliatory attacks in 2014 which could only be interrupted through a combination of communal and governmental peace efforts. According to Noonan and Kevlihan (2018), the violent phase can not be explained by long-term or short-term struggle over pasture or water, as the micro region is relatively resource abundant. Rather the struggle over ownership of the Turkwel dam and the vulnerability of the community resulting from prior livestock raiding, are mentioned as contributing factor. While Noonan and Kevlihan (2018)'s explanation stresses how structural factors can exacerbate tension between different ethnic groups, they also point to the limited explanatory power in determining the exact timing of the outburst of conflict. The case of Loregon stresses the importance of micro-scale human agency in an intensification or mitigation of inter-ethnic tensions.

As the patterns are also visible within the binary monthly variable of the occurrence or non-occurrence of conflict in a particular month, the inclusion of a proxy which can account for inter-annual variability in conflict probability, related to elections or inter-ethnic peace efforts, is considered crucial.

4.2 The effect of drought and water abundance on conflict in North-Western Kenya

4.2.1 The effect of scale on modelling outcomes

Four different model set-ups were tried as part of the thesis to assess the statistical effect of DIs on conflict. The inter-comparison of the four models allows for a differentiated discussion of the effect of scale on the modelling outcome.

Globally, the logistic regression model (Model 1) lends little support to a hypothesis that DIs may affect conflict. As reported in the results section, no universal significant effect of SPEI-6 on conflict is found. There is more evidence of significant effects for SPI or SPEI (see Table F.2 and F.4), where a significant decrease in conflict odds during and 1 or 2 months after a unit decrease in positive SPI or SPEI is observed.

While these results could be interpreted as an indication that when water is abundant, pastoralists in the area are *generally* less inclined to engage in conflict than in all other situations, results for Model 2 illustrate that the smaller CIs are a consequence of more homogeneous responses across different administrative units than for other temporal lags or aggregation period (compare to Figure F.6 and F.8). Vice versa heterogeneous, sometimes opposite patterns, across different administrative units result in large CIs which render many of the global effects in Model 1 insignificant. As the comparison of Model 1 and Model 2 shows, a neglection of the differences between administrative units may conceal the local effect of drought or water abundance. The significant results found for Model 1 can therefore rather be attributed to relative homogeneity across the responses within the three counties for the particular DIs and temporal lags, while other confidence intervals may be inflated by the non-distinction between the different administrative units.

When analysing the full scope of results on county-specific effects of DIs on conflict (see Appendix F.2), Turkana seems to be largely following the narrative of resource scarcity. Especially long-term negative precipitation anomalies (represented through SPI-6 and SPI-12) significantly increase the odds of conflict up to several months later, while for positive deviations in the same DIs conflict odds are significantly decreased. In West Pokot, on the other hand, there is evidence that especially, in the months following prolonged relatively dry conditions the odds of conflict decrease.

The pastoralist livelihood in the region and the repeated mentioning of cross-border transhumance in the area raises the question whether differences in the patterns between different administrative regions could also be explained by the migratory behaviour of ethnic groups in the region. A lower probability of conflict may not be the result of little incentive to engage in conflict but rather that migration is leading to a shift in conflict locations into adjacent regions. Therefore, the alternative agent-level approach has been adopted for the third and fourth model, where the impact of positive or negative anomalies in DI in the respective territory of an ethnic group is mapped to conflict, the ethnic group has been involved in.

As the comparison of Model 3 to Model 1 in the results has shown, the CIs of effects of negative SPEI-6 on the odds of conflict significantly decrease when shifting the focus of analysis from the administrative unit level to the ethnic group level. This pattern also holds for all other specifications of DIs analysed. The smaller CIs and the higher number of significant relationships in Model 3 stress the importance of cross-border migration. Drought or water abundance better explain conflict at the agent-level of different ethnic groups than in a spatially restricted analysis where only conflict events occurring in the same administrative unit are considered.

This conclusion is also supported by the odds ratios per ethnic group, as obtained from Model 4. Most of the CIs are small, resulting in many significant odds ratios. Nonetheless, differences in the ethnic-group-specific effects of meteorological DIs on conflict occurrence, demanded an in-depth discussion of the differences in the effects (see Section 4.2.2).

The present comparison has illustrated that significant effects of DIs on conflict odds may be overseen if applying rigid spatial delimitations which do not meet the living reality of pastoralists in the area. With cross-border transhumance as an important part of their subsistence strategy, conflict may not occur in the same county as the factors which have triggered it. Based on the more consistent patterns obtained for the ethnic group level than for the administrative unit level, the restriction of the WPS Global Early Warning Tool to administrative units as the unit of analysis, raises the question whether the full predictive power of DIs in conflict analysis could be unravelled by this model set-up. This question has motivated the analysis of the role of DIs in a conflict prediction model at the administrative unit level as the final part of the thesis. Before analysing the predicitve power of DIs in the conflict prediction model, the next section discusses the differences between ethnic groups in more detail.

4.2.2 Ethnic groups' responses to drought and water abundance

As suggested by the results in Section 3.3.3, three distinctive patterns are observable among the ethnic group's responses to drought and water abundance:

1. Turkana, Gabra, Toposa and Dassanetch are found to have increased odds in times of dry climatic anomalies while showing lower odds of conflict in times of water abundance.
2. Borana partially follow the same pattern, as the odds of conflict also increase in times of prolonged drought. At the same time they show an opposite behaviour to the remaining groups with a significant increase in odds in times of water abundance.
3. Pokot show barely any significant relationships for drier conditions and only for long-term water abundance a decrease in conflict odds is observed.

These results partially align with the results obtained by Ember et al. (2014). Ember et al. (2014) suggests that Turkana and Dassanetch are more likely to engage in conflict in drier conditions. Like in the present thesis, the uncertainty of this trend is, however, much higher in the case of the Dassanetch. Ember et al. (2014) also find a clear trend of more conflict for Borana in times of water abundance. On the other hand, Ember et al. (2014) suggest that the odds of conflict for the Borana decrease in times of drought, contrary to the present findings of higher conflict odds as a result of prolonged drought. A potential reconciliation of the findings is the different temporal unit of analysis. Ember et al. (2014) use a yearly measure of precipitation anomaly and its impact on the number of fatalities in conflict in the same year. The vulnerability of Borana to prolonged drought may not be reflected in this measure due to the rigid temporal separation into calendar years. In addition, results by Ember et al. (2014) conclude that Gabra are most inclined to engage in conflict in normal years, while the present thesis suggests a pattern with higher odds under dry conditions and lower odds of conflict when water is abundant. Differences in the findings may be related to the changing relationship between Borana and Gabra. While Ember et al. (2014) consider Gabra to be less vulnerable to drought through resource sharing and cooperation with the Borana, fights over political patronage in Ethiopia and Kenya have rendered the relationship more hostile in recent years (Adugna, 2014; Galgallo, 2016). The different time period of analysis may therefore explain differences in the results obtained.

As many of the results align with Ember et al. (2014), their hypothesis, that differences in mobility patterns may explain the varying drought-conflict relationships among the groups, is considered to also plausibly explain many of the ethnic groups' responses found within the present thesis. Groups which live in arid regions are considered to move further away from their home territories during dry conditions, in search for pasture and water. A well explored example are the Turkana who, during drought, are forced to move towards the wetter, more mountaineous areas at the western, northern and southern periphery of Turkana county (Detges, 2014). This puts them in greater competition with neighbouring groups such as the Pokot. Similar patterns of outward mobility in times of drought have been reported for the Toposa and Dassanetch (Ember et al., 2014; Yongo-Bure, 2007). Therefore, the found increase in conflict odds in times of drought for all three groups is in line with Ember et al. (2014)'s mobility hypothesis. The similar pattern for the Gabra may be explained by their increased vulnerability to drought since amicable relationships to the Borana have broken down. This may also force them to move further from their home camps. However this hypothesis requires further testing. As all four groups show lower odds of engaging in conflict in times of water abundance, they are considered to support the resource scarcity narrative, where conflict is primarily motivated by the struggle for scarce resources.

The Borana have their main camps in a relative water abundant region. According to Ember et al. (2014), this explains why the Borana engage less in conflict during dry times. While this quantitative result is not fully supported by the present thesis, the lower drought vulnerability of the Borana, due to their less arid home territory and their additional subsistence on agriculture, suggests that their livelihood may not be as easily exacerbated. This may explain why Borana only engage in more conflict in times of prolonged drought. The strong increase in odds of conflict in times of water abundance suggests that Borana rather engage in conflict based on strategic considerations than out of the immediate necessity to raid to sustain their livelihood.

As Turkana move towards West Pokot in times of drought and are therefore likely to get into proximity of the Pokot, the question is raised why the Pokot do not follow the same pattern of more conflict in times of drought. This result can only partially be explained by the present theories. In fact, migration of Pokot from Pokot Central Sub-county towards the Pokot-Turkana border in times of drought have been reported which is likely to increase conflict between Pokot and Turkana. At the same time, Pokot from Pokot North Sub-county migrate towards Uganda (Naburi, 2021). As they are also populating the border-region of Uganda, conflict is less likely (Naburi, 2021). These different mobility patterns may in parts explain why the climate variability - conflict link is less evident for the Pokot. However, further ethnographic research is desired to solidify the relationship between the different mobility patterns and how they affect the Pokots' conflict engagement.

In coherence with Ember et al. (2014), the present results suggest a high value of mobility patterns in combination with relative climate vulnerability in explaining differences in the climate-conflict link across ethnic groups. However, a more differentiated account is achieved in the present thesis which stresses that even the subsistence strategies of less drought-vulnerable groups can be exacerbated by prolonged drought. In addition, the case of the Pokot illustrates the complexity of the case where additional factors such as the mobility destination and different mobility patterns among ethnic sub-groups needs to be acknowledged when trying to understand the relationship between DIs and conflict.

4.3 Predictive power of drought indicators in a regional conflict prediction model

4.3.1 Model performance

The inferior performance of the RF model, built as part of the thesis, compared to the WPS model, can at least partially be explained by the difference in the conflict variable. Firstly, WPS uses fatal violence, based on ACLED data as its target variable. In comparison, the more specific focus of the present thesis on communal conflict is considered to assess a type of conflict which shows little temporal continuity (Elfversson, 2019). This is also confirmed by the scattered nature of conflict months displayed in Figure 3.5. Much of the predictive power of the WPS model is assigned to the model's ability to predict ongoing conflict. In their overall performance metrics of the WPS model Kuzma et al. (2020) do not distinguish between ongoing and emerging conflict. Performance of the model in predicting emerging conflict is worse with a recall of 0.65 and a precision of 0.21 as well as an F2 score of 0.46. Another potential reason for the higher performance metrics of the WPS model is the temporal delimitation of the conflict variable. It is likely that their smoother conflict variable which indicates conflict occurrence over the next 12 months is easier to predict. In fact, a comparison of the time series of observed and predicted monthly conflict occurrence for Marsabit, Turkana and West Pokot, suggests that even the present RF model often predicts conflict for several subsequent months (see Figure 4.1). These prolonged intervals of *conflict* prediction are seen as a contributor to the low precision values.

The conflict definition, therefore, makes the present RF model more comparable to the ViEWS model. The lower recall for ViEWS can be explained by the fact that ViEWS has not been constructed with a focus on recall. This also precipitates through a much higher precision for ViEWS than for the present model. With the primary incentive of flagging conflict months, the performance of the RF model is still considered satisfactory, as recall is in between those of the two operational CEWS.

In addition, it shall be stressed again that overall model performance has not been at the core of the present research. Rather, a model with acceptable performance was needed to shed light on the predictive power of DIs in the model.

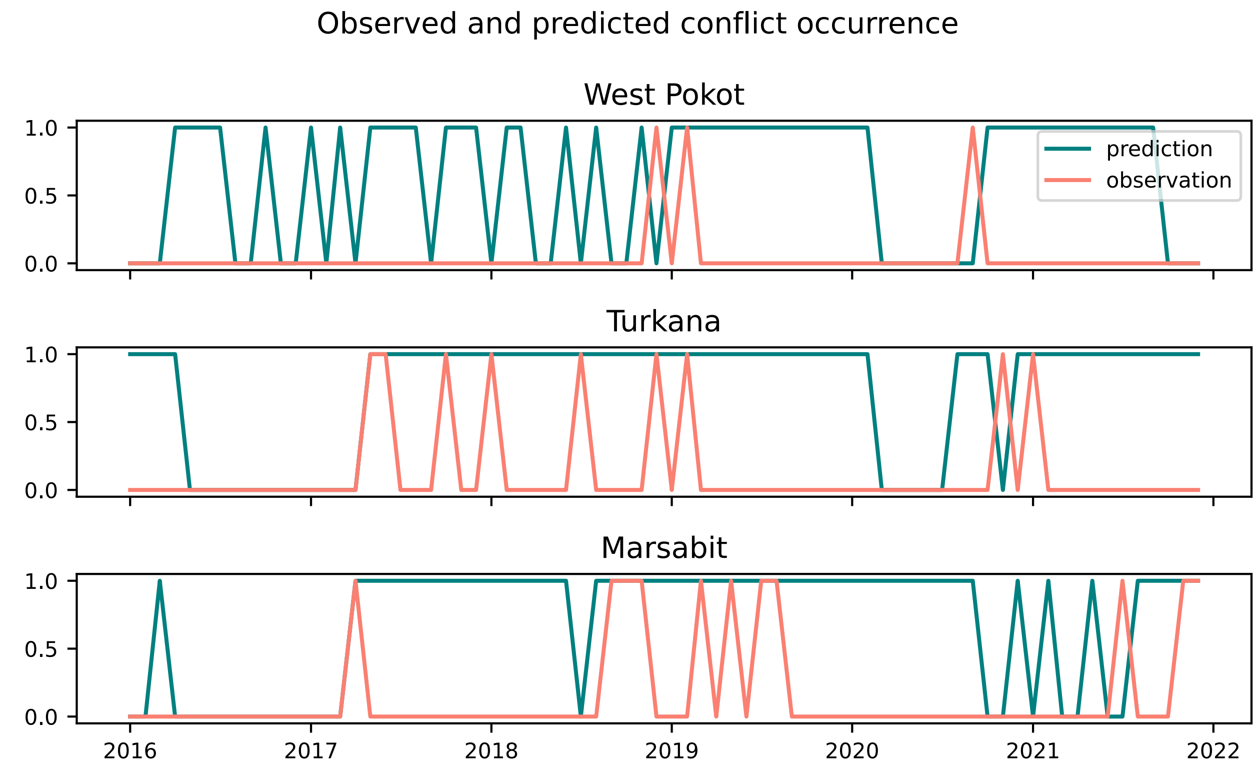


Figure 4.1.: Monthly conflict occurrence and prediction by the RF model for Marsabit, Turkana and West Pokot

4.3.2 Predictive power of drought indicators

The permutation of single features on the testing dataset provides a very similar picture of feature importance as obtained by Kuzma et al. (2020) for the original WPS model. The model heavily relies on conflict history to predict conflict. This is despite the fact that communal conflict is less continuous. It stresses that communal conflict still clusters in time - a phenomenon which can be explained by the fact that one inter-ethnic livestock raid may trigger further retaliatory raids. In addition, the local population density variable also features among the most important variables.

DIs, on the other hand, do not have any to a very low importance in conflict predictions. The negative PFI of the *Median_SPEI-1_lag0* for the testing data while positive for the training data, can be even seen as an indication of the model overfitting, based on provided SPEI-1 data.

The comparison of the marginal effects across the three counties of Marsabit, Turkana and West Pokot, suggests that the model is incapable of accounting for differences in between administrative unit responses to a change in DI. These differences in the direction of the response and its magnitude are visible when looking at the LRM marginal effects plots. In addition, the order of magnitude of marginal effects over DI values is much higher for the LRM.

These observations lead to the tentative suggestion, that the low predictive power of DIs can be at least partially explained by the limited capacity of conflict prediction models to account for different responses to changes in DIs at the admin-1 level. However, the generalizability of these results to other conflict prediction models is hampered by the narrow architecture of the present RF model. This reduces the model's ability to grasp complex relationships. Therefore, another more complex conflict prediction model may be able to account for some of the variability in marginal effects across administrative units.

At the same time, the results of the prior sub-questions suggest that, even the more complex WPS model, is unlikely to capture the different responses. At least for North-Western Kenya, the present thesis points towards the relevance of accounting for cross-border migration to unravel significant effects of DIs on conflict. In addition, different responses of ethnic groups to climate extremes are considered to be a result of differentiated climate vulnerability between these groups. The aridity of a region compared to the wider climate, as well as, differences in subsistence strategies and resource sharing agreements among ethnic groups are not accounted for in the limited set of features of the WPS model.

4.4 Combining sub-question 1 to 3: The role of meteorological drought indicators for conflict prediction

The three sub-questions, as part of the present thesis, have helped to shed light on the role that meteorological DIs play in conflict prediction and what may hamper their importance.

While the complexity of conflict dynamics in North Western Kenya warns against using DIs as the only explanatory variable for conflict occurrence, the in-depth LRM analysis suggests that climate variability affects conflict occurrence in the study area. However, different responses are observed for different ethnic groups. Based on the differences in between ethnic groups, it is suggested that relative drought vulnerability and related mobility patterns may play a role in determining how climate variability affects conflict behaviour of different ethnic groups.

These results are in line with the recent call in climate-conflict literature for a differentiated account of the impact of climate-related variables on conflict potential. While large-N studies have mainly identified structural drought vulnerability of regions due to the dependence on agriculture, marginalization and ethnic division as important conditional factors for increased conflict probability in times of drought, the present research shows that even on a scale where variability in these factors is relatively minor, responses by different ethnic groups in and after times of relatively dry or water abundant conditions differ. In addition, the results stress the importance of considering cross-border transhumance to unravel these patterns.

Therefore the thesis warns against the premature conclusion that DIs are not relevant in conflict prediction models, solely based on their lack of improving model performance of common CEWS and of the RF model constructed as part of the thesis. Rather, results point towards a misconceptualization of conflict prediction models at the administrative unit level for predicting conflict in a pastoralist area. In addition, they stress that disregard of differences in conflict response among different ethnic, may further hamper the role of DIs in conflict prediction.

4.5 Limitations

The set-up of the present thesis has been guided by the motivation to explore the role of DIs in conflict prediction based on a deeper understanding of the conflict dynamics in the study area. The local-scale literature review and logistic regression analysis have enhanced the thesis through insight into local-scale dynamics, which have proven important to unravel the effect of DIs on conflict. However, this local focus of the thesis comes at the cost of spatial inconsistency when moving from the local scale to a wider study scope to develop an RF model.

It can be concluded that for communal conflict prediction in North-Western Kenya, the conceptualization of the WPS conflict prediction model is unsuitable to account for the potential role of DIs on conflict. However, whether this has resulted in the little predictive power of DIs in the RF model, or whether conflict probability in other regions is not affected by climate extremes, cannot be determined with certainty. Nonetheless, the later option is considered to be unlikely. The criterion for the wider study area has been the high presence of pastoralism in these countries. Hence, people in the wider study area are considered equally prone to climate variability and struggle over resources.

Therefore, the results are considered indicative for future changes in conflict prediction models towards models which acknowledge the migratory behaviour of ethnic groups. However, no final verdict on the predictive power of DIs in such an alternative model specification can be reached. As highlighted by Ward et al. (2010), many variables which have been found to be significant in econometric conflict models, showed little predictive power when trying to predict conflict on an evaluation time period. In addition, different causal dynamics in other regions would require the additional consideration of other conditional factors to account for various ethnic groups' responses to climate extremes.

It shall also be stressed that the suggestions of important factors for differing migratory behaviour are based on a very limited body of literature. Therefore, even within the context of North-Western Kenya there may be additional factors which could support the linkage of DIs to conflict prediction.

Several assumptions have been made as part of the thesis which may affect the results. Although desirable to conduct sensitivity tests on all of these assumptions, this has been beyond the scope of the work. The most important assumptions are:

1. **The used drought input dataset**: ERA-5 data has been chosen for its coherence with potential further steps of evaluating the role of drought forecasts based on SEAS5. Thereby the model derived from ERA5 could serve as a benchmark. Alternative DIs may be tried but as DIs from ERA5 have been found to be robust in prior studies, the effect on results is expected to be low.

2. **The used drought variable**: The use of different spatial statistics and SPI and SPEI to assess the effect of DIs on conflict is considered to serve as a sensitivity test. Results suggest that, qualitatively, the derived patterns are the same. However, the significance level of the results may change. Especially at the administrative unit level, where confidence intervals are still large, the choice of the SPEI over the SPI was at times found to decrease the significance level. While this should be acknowledged, the most important results on the higher significance for models at the ethnic group level and the opposing patterns of different ethnic groups remain unchanged by the choice of DI. While assumed that the meteorological DIs could also incorporate changes in soil moisture, surface water and groundwater availability, testing alternative meteorological DIs may still be of interest. For Marsabit, Lam et al. (2022) find that the Standardized Soil Moisture Index represents the best indicator for assessing the impact of drought on pasture. Through a more accurate representation of the on-ground conditions, it may be possible to even reduce the uncertainty reflected in the CIs of the effect of drought on conflict. In addition, the monthly lag at which significant effects of negative SPI or SPEI occurred for aggregation periods of 6 or 12 months suggests that longer aggregation periods may be able to establish an immediate effect of prolonged drought on conflict.

3. **The used output dataset**: UCDP-GED has been a useful dataset to assess communal conflict and the ethnic-group-specific response to drought, as all records can be clearly assigned to a dyad. Nonetheless, the UCDP-GED dataset structure may still conceil differences in ethnic group behaviour as it cannot be distinguished between the aggressor and the victim based on dyad information in the dataset. If a group is attacked by several other groups which show different responses to climate variability, this may result in larger confidence intervals and the conclusion of an insignificant relationship. The importance of a distinction between aggressor and victim is also highlighted by Ember et al. (2012). When distinguishing between Turkana people as the attacker and Turkana people as the victim, different patterns emerge for livestock-raid related deaths in months with below normal or above normal water availability. Especially for Turkana as the attacker an almost linear decrease in mean number of deaths over the rainfall anomaly is found. Therefore, it is of interest to explore other datasets, such as ACLED which distinguishes between aggressor and victim. In addition, it serves as a sensitivity analysis of the results. This is especially of interest, to also assess the robustness of the results to the removal of conflict events of insufficient temporal or spatial precision. However, keeping the same focus on communal conflict may be challenging due to the different classification strategies used in different datasets. In addition, it needs to be acknowledged that conflict datasets can have a bias in reporting over time but also in between different groups. In their paper Scott-Villiers (2017) illustrate how large the distrust is in Kenya in politicians to impartially investigate violence. Therefore, it is highly likely, that violence between some groups gets more media attention than between others. In that context, the importance of the literature review and future field work is stressed, to supplement available data with on-the-ground observations.
4. **The definition of the conflict variable**: The focus on communal conflict has been intentional. Therefore, a lack of significant findings, if replacing the conflict variable with alternative types of conflict, is not considered to question the results obtained as part of the thesis. However, alternative definitions of the conflict variable in terms of fatalities or conflict events may be of interest for newer CEWS which are predicting these measures instead of the binary conflict month variable.
5. **The choice of a fixed-effect LRM**: Alternatives to the fixed-effect LRM exist. Most notably mixed-effect logistic regression models have been used which also relieve the need to cluster standard errors (von Uexkull et al., 2016). Thereby, they may overcome uncertainty associated to the standard errors in regression tasks with few clusters.
6. **Temporal dummies**: The 2-year dummies within the present LRM may be replaced by alternative time periods. Alternatively, based on the literature review, the explicit inclusion of contributing factors which have been found to affect conflict probability over time could be included and potentially interacted with the different spatial units. This would have the advantage that it could be accounted for spatial variability in the impact of these factors. For example, the recent elections have primarily affected the conflict risk in Marsabit. In addition, a more complex representation of seasonal dummies should be considered, as Schilling et al. (2014) suggest the dependence of the impact of wet and dry season on climate variability.
7. **The ML model**: The RF model may be replaced by other promising model structures which have been tried in the conflict prediction domain. Most notably, WPS has launched an additional LSTM model during the course of the present research, which predicts conflict for the next two months. In addition, gradient tree boosting and multilayer perceptrons have been found to be most promising for a good recall and F1 score, respectively, in a recent study which assessed the performance of different ML algorithms in conflict prediction (Musumba et al., 2021).

8. **The random seed**: While for larger models, the random seed is likely to not be of importance for performance and importance metrics, in the present case the model is quite narrow. Therefore, it is expected that some input features may coincidentally have been chosen more often than others. Therefore, the use of alternative random seeds, to obtain other variable combinations in the trees is considered to provide information on the results on model performance and feature importance.

4.6 Outlook & Recommendations

Based on results for North-Western Kenya it is advocated for a shift in conflict prediction by CEWS from the administrative unit level to the agent-level of individual ethnic groups. This is expected to unravel the potential of DIs as conflict predictors. It relaxes any assumptions on spatial containment of conflict locations in the area for which climate extremes are calculated.

However, the final call on the predictive power of DIs in such a setting needs to be awaited. Sensitivity tests of the present findings and further local analysis in other regions should be conducted to assess the generalizability of the significant relationships between DIs and conflict occurrrence at the ethnic group level. In addition, local studies of ethnic group responses to drought, including interviews, surveys and observations may broaden the limited understanding of the underlying factors of different migratory behaviour in response to climate extremes. A conflict prediction model at the ethnic group level including DIs and these contextual factors may then be able to provide an improved assessment of the role of DIs in conflict prediction.

The present thesis also illustrates the challenges of such an analysis in terms of data availability of ethnic territories which may hamper the employment of an ethnic-group centered approach on a larger scale. Data on ethnic groups, including the residents of North-Western Kenya, is difficult to find and for the present thesis, needed to be manually digitized. Therefore, it is called for an increased effort to harmonize and update existing data on ethnic group territories and combine it with conflict data. With ACD2EPR such a dataset already exists for politically powerful ethnic groups (Vogt et al., 2015). However, the present thesis highlights the importance of expanding such a dataset to politically and economically marginalized groups. As those groups are commonly considered to be among the most drought vulnerable, it is argued here, that especially in such cases, an accurate representation of climate variability in conflict models is crucial.

While desirable to account for the effect of DIs on conflict occurrence in quantitative conflict prediction, the present thesis also highlights its challenges due to the complexity of the climate-conflict relationship at hand. Not only, has it shown differences in ethnic responses to drought. The cases of the Gabra and Pokot also illustrate that responses may change over time or may vary across sub-groups. This raises the question, if a quantitative model can grasp the complexity underlying the climate-conflict dynamics at such a small scale.

It stresses the importance of local-scale expert judgement on the risk of conflict related to drought and water abundance to complement quantitative conflict risk assessments. For the present case of North-Western Kenya, where mobility was found to be crucial to understand the climate-conflict relationship, efforts to map and understand transhumance patterns, should be intensified.

5 Conclusion

In an effort to assess the role of meteorological DIs on conflict prediction for North Western Kenya, the present thesis has illustrated how a mismatch in between administrative units and scales of transhumance may hamper the predictive power of DIs in conflict prediction.

A comparative assessment of the effect of DIs on conflict occurrence in the same administrative unit, or along ethnic lines of identity has shown that the occurrence of conflict is much better explained when accounting for the transhumance of ethnic groups across administrative borders. The probability of conflict increases for most ethnic groups with more extreme drought conditions while water abundance decreases the probability of conflict, lending support to the resource scarcity theory. However, other ethnic groups follow opposite patterns. It is hypothesized that such differences in conflict behaviour may be explained by different mobility patterns. For the most drought-vulnerable, drought can be considered to exacerbate conflict, as it forces them to move into proximity of other ethnic groups in search of scarce resources. These results are considered to explain the low importance of DIs in the conflict prediction model developed. It is argued that the low importance of DIs says more about potential misconceptualizations of the model than about a generally limited predictive power of DIs. Due to its spatial delineation along administrative borders, conflict prediction models like WPS Global Early Warning Tool and ViEWS cannot account for cross-border migration as the link between drought occurrence and conflict.

The final verdict on (1) the sensitivity of these results to alternative model specifications or to other regional settings, and (2) on the importance of DIs in conflict prediction under alternative ethnic-group centered approaches still needs to be reached. Nonetheless, efforts towards a better understanding of differences among ethnic groups in their conflict engagement patterns, and an improved, homogenised data infrastructure on ethnic group territories and conflict events are considered crucial first steps for a comprehensive analysis of the potential role of DIs in quantitative conflict prediction. In addition, the found complexity of the local DI-conflict dynamics stresses the importance of supplementing quantitative conflict prediction with informed local expert judgement.

Code availability

The code for replication is available at https://github.com/cgasten/MasterThesis

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A Quotes used to construct the perceptual model

In the present tables, the elements, links and signs used in the perceptual models are backed by corresponding quotes. It is referred to the papers through the use of the following abbreviations of authors: A12: Adano et al. (2012); C14: Carrier and Kochore (2014); D14: Detges (2014); E12: Ember et al. (2012); E14: Ember et al. (2014); G16: Galaty (2016); J15: Johannes et al. (2015); Kanyinga (2009); L18: Lind (2018); M07: Meier et al. (2007); Mk07: Mkutu (2007); Mk20: Mkutu and Mdee (2020); N18: Noonan and Kevlihan (2018); O11: Omolo (2011); Sch12: Schilling et al. (2012); Sch14: Schilling et al. (2014); Sch15: Schilling et al. (2015); Sch16: Schilling et al. (2016); Sch18: Schilling et al. (2018); S09: Smith (2009); SV17: Scott-Villiers (2017); WA09: Witsenburg and Adano (2009)

Table A.1.: Sources and quotes for retrieval of conflict motives from literature

Source	**Quote**	**Page**
territorial rights		
Sch12	"In Turkana, several representatives of the government and NGO respondents stated that the expansion of the Pokot territory into the plains of Turkana and vice versa is one of the central drivers of violent conflicts. Several key informants suggested that this process is politically driven while few indications to support this notion were found during interviews with the communities."	p.8
N18	"disputes over the 'ownership' of the dam have focused on control of employment opportunities there, rather than control of the electricity generated by the dam itself."	p.142
WA09	"This informant refers to the current problems in pastoral societies, which cause politically motivated raids. Pastoral land in Marsabit, as in many other districts, is trust land that is controlled by the county council within whose area it is situated and governed by customary law. The usefulness of land is typically determined by availability of water. Water sources are usually owned by individuals or clans, but use rights traditionally override ownership rights. This means that every nomad has the right to use a well, also on the land governed by a neighbouring ethnic group, if he negotiates well. With the creation of boundaries, whereby new districts and constituencies (like Moyale district in 1995), new divisions and locations are meant to mark ethnically 'pure' territories, it is increasingly hard to maintain the traditional arrangement of water and land sharing."	p.532
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas."	p.93
C14	"Despite leaving the constituencies more uniform in terms of ethnic composition, the process did bring the unintended consequences of boundary contestation between the contiguous constituencies. For example, as Schlee notes, 'Turbi, a small trading post between Moyale and North Horr constituency' became a major site of contestation between the Borana and Gabra.43 With Moyale being a Borana constituency and North Horr Gabra, this boundary arrangement pitted the two groups against each other."	p. 7
G16	"While the exaggerated claim has sometimes been made that demarcating districts actually brought ethnic divisions into being, the enforcement of district frontiers clearly severed intimate ties between some long coexisting communities and lent some groups a state-based justification for attempting to deny access to others thought to have been allocated homelands elsewhere. So some borderlands between provinces and districts became long-term battlegrounds periodically tested by herders who felt that historical precedent and social familiarity should allow them entry and residence rights."	p.110

Continued on next page

Table A.1 – continued from previous page

Source	Quote	Page
J15	”Emerging evidence, including exclusion of local communities in oil-related-decision-making, land grabbing by outsiders at the expense of locals, corruption and incipient interethnic conflicts over discovered oil-field territories in Turkana County indicates increased vulnerabilities, risks, and perverse opportunities which suggest a high likelihood that oil will exacerbate interethnic conflicts in an already volatile region and even result in full-blown violent conflicts between the already marginalized Turkana and the government, national and foreign investors such as Tullow Oil, unless effective preventive and corrective actions are taken early. ”	p.156
S09	Previous commissions on land and suggestions for a land tribunal or land board have stalled-out, leaving land grievances to simmer, usually along ethnic and regional lines.87 In this setting, local militias and self-described ‘land defence forces’ have arisen. Increasingly, as Lonsdale argues, Kenyans ‘are learning more exclusive attitudes to territory’, even though ‘most Kenyans are migrants and have displaced others; very few are “autochthons”, deep-rooted sons of the soil’.88”	p.882
SV17	In pastoralist territories, for instance, livestock raiding had become a means to establish exclusive political and economic hold on a territory in the name of a single ethnic group.	p.252
L18	Yet, this is new violence, happening under the guise of ‘cattle raiding’, but which is driven by the revival of Pokot expansionist politics and attempts to stake ancestral claims to areas with rich resources inside Turkana County.	p.144
Sch15	”Disputed territory is already a driver of the Turkana–Pokot conflict (Schilling et al., 2012b; Adem et al., 2012;Vasquez, 2013). However, it is too early to say to what extent oil exploration will affect land rights and prices. But the oil exploration could further weaken the already weak social contract between the pastoral communities and the central government.”	p.712
M20	”Clemens Greiner’s case studies (2013a; 2013b) found that two of three Rift Valley conservancies had been created in areas with contested administrative borders, and these have experienced conflicts. Vague access rights correlate strongly with conflict, and borderlands conservancies overlap with the highly politicized struggle for ethnic territories. Even inter-communal cattle raids are now politicized and linked to the expansion of land and the fight for ethnically exclusive areas (Schlee 2010).”	p.548
Sch18	”Particularly two issues have the potential to aggravate existing conflicts or create new ones between and within communities. These are disputes over territory and competition for employment opportunities.” + ”Similar developments can be observed in Marsabit. The Deputy County Commissioner of Loiyangalani explains: ‘People from Samburu say the land is theirs, the Samburu, the Rendille all of them say the land is theirs’.123 A member of the Sarima community made this observation: ‘They [the Samburu] saw this project has come, they saw the Turkana will benefit from it, let us chase them and go to their land’.124” + Many interviewees in Sarima were particularly angry when jobs as security officers were given to Samburus. The ‘heads of G4S [a security company] are all Samburus’, complains one member of a small group interview in Sarima.126” ”Overall, the research findings suggest that the oil and wind extractive processes have an aggravating effect on existing violent conflicts between communities (e.g. between Turkana and Pokot) and a potential to create new, so far non-violent conflicts, within communities of the same ethnicity (e.g. between Turkana South and Turkana East).”	p.586, p.587

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Table A.1 – continued from previous page

Source	Quote	Page
K09	"The land redistributon policy of the 1960s and its outcome clearly shaped the outcome of the December 2007 presidential election dispute. Both the procedure by which land settlement schemes were established and the skewed bias in favour of certain groups are responsible for the recurrence of violence. Notably, these is a clear link between land, territory, and politics." + "Grievances over land continue to inform Kenya's local and national politics whenever political circumstances change. That was true in December 2007 general election" + "The landed elite are in control of both the politics and economy in the highlands and finance violence more often to deflect attention from inequalities in land ownership to inequalities in distribution of political power"	p.341 + p.339 + 334
resource access		
Sch12	"Watering points are a source of conflict particularly during dry periods. In Lokiriama, several exchanges of gunfire were witnessed between the Turkana and the Pokot who were trying to access the borehole at night."	p.11
N18	"Despite a relative local abundance in the immediate vicinity of Loregon, access to water and grazing lands remains very important to local livelihoods and survival. Encroachments without permission on a valued and controlled area can be perceived as an act of intrusion or aggression.80"	p.148
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250
O11	"According to Kirbride and Grahn (2008:21), resource competition also significantly increases the risk of conflict between different groups of land users. This risk is enhanced during times of stress (that is, during drought or floods). For example, it was reported that renewed clashes between the Turkana in northern Kenya and the Toposa in southern Sudan, both seeking to access grazing land and water in the Nadapal Belt, reportedly left more than 20 people dead and 60 000 animals stolen within three months (Daily Nation 2009b)."	p.88
D14	"Pastoralist violence is more likely close to permanent water sources and in wetter areas, where animals can be appropriated more easily. Not incidentally, these places are also strategically important in order to effectively use surrounding pastureland. This points to the complementary logic of pastoralist violence as a means for both obtaining short term material gains and securing long term access to essential resources."	p.63
WA09	"there is no evidence that the number of violent deaths is related to scarcity of resourcees. As previous studies have shown, water scarcity rather makes people stop their feuds until droughts and famine are over."	p.528

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Table A.1 – continued from previous page

Source	Quote	Page
M07	”The environmental variable vegetation also presented a positive relationship with the incidence of raids, and there appears to be cyclical influence of bi-modal seasons [. . .] This direct environmental measure then suggests that the raiding behaviour is strategically planned and tied to opportunities presented by the environment. Indeed, Turner (2004:877) argues that the high spatiotemporal variability of productive resources leads to a situation in which there is little spatial fixity in the competition over land” which means that ”conflicts are less likely to be ’in-the-moment’ struggles over a particular resource patch and more likely to resemble strategic contests to maintain resource access over the longer-term [...] Herders interviewed during related field research explain that, “raiders like to attack during wet years because of high grass, strong animals, dense bush to hide in and the availability of surface water, which makes it easier to trek with the animals.” (Adano & Witsenberg, 2005: 723).”	p.731
E12	”Why should the Turkana attack in drier conditions? Here our reasoning is speculative since we do not have interviews with Turkana individuals, but if pasture and water are scarce and access cannot be arranged peacefully during dry times, there may be little choice but to aggressively fight for access even if the attacking groups are small.”	p.176
livestock restocking		
E12	”In addition, livestock theft may make up for the loss of livestock lost in drought conditions or livestock theft of animals grazing in wetter conditions cushions against future losses.”	pp.176
Sch14	”In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources.”	pp.250
WA09	”Raiding is not only done for restocking purposes or for avenging previous attacks. Raiding is also related to traditional ceremonies and age-set changes of the pastoral peoples that are not connected to climatic patterns, as the month-reckoning is based on lunar cycles.”	p.525
D14	”Hence, armed raids against other pastoralist groups are considered a strategy to cope with the dire living conditions of ASAL. Livestock thus obtained compensates for the loss of animals to drought, disease and theft (Kr€atli & Swift, 2001: 22; Witsenburg & Adano, 2002: 13).”	p.58
political patronage		
C14	”This was the new devolved county system of government introduced by the 2010 constitution. This system transformed the political landscape: crucially, the post of county governor would give much power to incumbents at a regional level, meaning local rivalries were likely to coalesce around competition for the position.”	p.5
G16	”These reforms have led to intense electoral competition over political and administrative positions, accompanied by efforts at pushing members of certain communities out of ethnically mixed areas that others claim as their cultural homelands, since the benefit of devolved powers is not only greater local control over resources but also the exercise of patronage (Schlee & Shongolo 2012)”	p.111

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Table A.1 – continued from previous page

Source	Quote	Page
SV17	In pastoralist territories, for instance, livestock raiding had become a means to establish exclusive political and economic hold on a territory in the name of a single ethnic group.	p.252
L18	”Instead of pioneering a new type of politics, devolution has entrenched existing political dynamics through reproducing at the county-level a type of patronage politics and rent-seeking seen at the centre (Cornell & D'Arcy, 2014).”	p.140
retaliation		
WA09	”Raiding is not only done for restocking purposes or for avenging previous attacks. Raiding is also related to traditional ceremonies and age-set changes of the pastoral peoples that are not connected to climatic patterns, as the month-reckoning is based on lunar cycles.”	p.525
N18	”Pokots justified their raids in the vicinity of Loregon as counter-raids. Such thefts had a strong impact on both communities, with one interviewee reporting that ‘raids began until all animals were gone’.57”	p.143
Sch12	”Beyond the physical effects, insecurity negatively affects the inter-communal relations. Community members of both Pokot and Turkana have expressed strong negative feelings and distrust towards the other group. The distrust decreases the motivation and the capability of the communities to choose a cooperative path which is a prerequisite for peaceful and effective resources sharing (Eriksen and Lind 2009). Inter-communal relations particularly deteriorate when raids include the rape or abduction of women. This practice could increase the incentive for parents to marry off their daughters early into the ‘safe hands’ of a husband (see Little et al. 2009). Another response to such hostile attacks is retaliation which further fuels the conflict (Eaton 2008).”	p.18
L18	”Up to 100 were killed in the raid and retaliatory attacks by Pokot”	p.143
food insecurity		
Sch12	”In Turkana, the majority of raiders indicated hunger and drought as their primary and secondary motives for engaging in livestock raiding (Table 1). In Pokot, payment of dowry and accumulation of wealth were the strongest motives while the expansion of territory summarised as ‘land’ in Table 1 was still given by 25% of the Pokot raiders as a primary motive.”	p.7
O11	”According to Watson (2003:7), other motivation for raids in pastoral communities is the desire to reduce poverty and hunger, and acquire bridewealth.”	p.88
poverty		
Sch12	”During this research, 75% of the pastoralists and raiders reported to have lost livestock, partly due to raids and drought-related incidences. A reduction in livestock population, even by small numbers, is critical especially for the pastoralists who depend on livestock for income and food security.”	p.11
O11	”When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas.”	p.93
dowry		
Sch12	”In Turkana, the majority of raiders indicated hunger and drought as their primary and secondary motives for engaging in livestock raiding (Table 1). In Pokot, payment of dowry and accumulation of wealth were the strongest motives while the expansion of territory summarised as ‘land’ in Table 1 was still given by 25% of the Pokot raiders as a primary motive.”	p.7

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Table A.1 – continued from previous page

Source	Quote	Page
O11	"According to Watson (2003:7), other motivation for raids in pastoral communities is the desire to reduce poverty and hunger, and acquire bridewealth."	p.88
job opportunities		
Sch18	"Particularly two issues have the potential to aggravate existing conflicts or create new ones between and within communities. These are disputes over territory and competition for employment opportunities." + "Similar developments can be observed in Marsabit. The Deputy County Commissioner of Loiyangalani explains: 'People from Samburu say the land is theirs, the Samburu, the Rendille all of them say the land is theirs'.123 A member of the Sarima community made this observation: 'They [the Samburu] saw this project has come, they saw the Turkana will benefit from it, let us chase them and go to their land'.124" + Many interviewees in Sarima were particularly angry when jobs as security officers were given to Samburus. The 'heads of G4S [a security company] are all Samburus', complains one member of a small group interview in Sarima.126" "Overall, the research findings suggest that the oil and wind extractive processes have an aggravating effect on existing violent conflicts between communities (e.g. between Turkana and Pokot) and a potential to create new, so far non-violent conflicts, within communities of the same ethnicity (e.g. between Turkana South and Turkana East)."	p.586, p.587
N18	"disputes over the 'ownership' of the dam have focused on control of employment opportunities there, rather than control of the electricity generated by the dam itself."	p.142
wealth		
Sch12	"In Turkana, the majority of raiders indicated hunger and drought as their primary and secondary motives for engaging in livestock raiding (Table 1). In Pokot, payment of dowry and accumulation of wealth were the strongest motives while the expansion of territory summarised as 'land' in Table 1 was still given by 25% of the Pokot raiders as a primary motive."	p.7

Table A.2.: Sources and quotes for the climate-conflict pathway in the perceptual model

Source	Quote	Page	Sign
Pathway I: Scarcity-driven conflict			
dry season/drought - resource scarcity			
WA09	"These citations show the usual tension between pastoral groups in northern Kenya due to difficult ecological conditions. Tension between groups during the dry season increases, especially when scarce resources need to be shared. Relationships between groups are at peril, but therefore treated with utmost care, so as to avoid an escalation that could result in violence. These clippings also show that government officials help in negotiating access to and fair allocation of resources."	p.527	+
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas."	p.93	+
E12	"Central Turkana country is very dry, but it is suitable for pasturing more animals and more people during the wet season. As described above, when the pasture is disappearing, the Turkana head for wetter areas."	p.176	+
dry season x drought - resource scarcity			
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250	+
resource scarcity - motive: resource access			
Sch12	"Watering points are a source of conflict particularly during dry periods. In Lokiriama, several exchanges of gunfire were witnessed between the Turkana and the Pokot who were trying to access the borehole at night."	p.11	+
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250	+
WA09	"there is no evidence that the number of violent deaths is related to scarcity of resourcees. As previous studies have shown, water scarcity rather makes people stop their feuds until droughts and famine are over."	p.528	-
O11	"According to Kirbride and Grahn (2008:21), resource competition also significantly increases the risk of conflict between different groups of land users. This risk is enhanced during times of stress (that is, during drought or floods). For example, it was reported that renewed clashes between the Turkana in northern Kenya and the Toposa in southern Sudan, both seeking to access grazing land and water in the Nadapal Belt, reportedly left more than 20 people dead and 60 000 animals stolen within three months (Daily Nation 2009b)."	p.88	+

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Table A.2 – continued from previous page

Source	Quote	Page	Sign
D14	”Conversely, drought conditions and the depletion of resources can constrain pastoralist groups to venture further away from their home range into more dangerous peripheral areas, where they are susceptible to attacks by neighbouring groups (Leff, 2009). This pattern has been observed in Turkana county. Dry conditions in the inner area ofthe county regularly force Turkana herders to leave for wetter mountain ranges on the northern, western and southern borders of the county. This does not only facilitate raids by neighbouring groups such as the Toposa and Pokot, but frequently also involves disputes with these communities over the use of water points and shared dry season pastures (Eriksen & Lind, 2009: 826f; Opiyo, Wasonga, Schilling, & Mureithi, 2012; Schilling et al., 2011). This pattern is likely to be responsible for the frequency of pastoralist conflicts observed in the border areas of Turkana county”	p.58	+
E12	”Why should the Turkana attack in drier conditions? Here our reasoning is speculative since we do not have interviews with Turkana individuals, but if pasture and water are scarce and access cannot be arranged peacefully during dry times, there may be little choice but to aggressively fight for access even if the attacking groups are small.”	p.176	+
resource scarcity - exposure to conflict			
O11	”KVRT preliminary findings (KVRT 2009) point out that the Turkana migrate due to the following reasons: search for pasture and water (52,7%), conflicts (21,9%), search for larger pieces of land (6%), and culture (2%).”	p.89	+
E12	”Central Turkana country is very dry, but it is suitable for pasturing more animals and more people during the wet season. As described above, when the pasture is disappearing, the Turkana head for wetter areas. If necessary, the herds are divided by type of livestock with different groups of men going with different types of animals. In the driest months, the Turkana are furthest from base camps. But in drought years, they must go even further away to wetter areas close to the territory of other ethnic groups. These lands are more desirable as drought reserves, but they are also more dangerous. The herding groups are also small, making the group more vulnerable to attack.”	p.176	+
resource scarcity - proliferation of small arms			
Mk07	”At the time of writing (January 2006), 1.2 million Kenyan pastoralists were experiencing severe drought and Pokot pastoralists were moving into Uganda in search of water and pasture.108 Historically this has always led to tension and acquisition of arms. Although droughts have become frequent, no policy yet exists for provision of adequate land access to pastoralists within Kenya and the region”	p.69	+
dry season/drought - livestock (health, number)			
Sch12	”During this research, 75% of the pastoralists and raiders reported to have lost livestock, partly due to raids and drought-related incidences.”	p. 11	-
Sch14	”In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources.”	pp.250	-
resource scarcity - livestock (health, number)			

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Table A.2 – continued from previous page

Source	Quote	Page	Sign
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas." + "Whenever these extreme climatic conditions like drought and floods occur, they impact negatively on pastoralists' livelihoods through loss of human and livestock lives, starvation and destruction of property."	p.93 + 97	-
E12	"In addition, livestock theft may make up for the loss of livestock lost in drought conditions or livestock theft of animals grazing in wetter conditions cushions against future losses."	pp.176	-
Sch16	Particularly during dry periods, a loss of pasture can result in losses of livestock (Opiyo et al. 2014)	p.61	-
livestock loss - motive: poverty			
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas." + "Whenever these extreme climatic conditions like drought and floods occur, they impact negatively on pastoralists' livelihoods through loss of human and livestock lives, starvation and destruction of property."	p.93 + 97	+
Sch12	"During this research, 75% of the pastoralists and raiders reported to have lost livestock, partly due to raids and drought-related incidences. A reduction in livestock population, even by small numbers, is critical especially for the pastoralists who depend on livestock for income and food security."	p.11	+
livestock loss - motive: food insecurity			
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas." + "Whenever these extreme climatic conditions like drought and floods occur, they impact negatively on pastoralists' livelihoods through loss of human and livestock lives, starvation and destruction of property."	p.93 + 97	+
Sch12	"During this research, 75% of the pastoralists and raiders reported to have lost livestock, partly due to raids and drought-related incidences. A reduction in livestock population, even by small numbers, is critical especially for the pastoralists who depend on livestock for income and food security."	p.11	+
livestock loss - motive: livestock restocking			
E12	"In addition, livestock theft may make up for the loss of livestock lost in drought conditions or livestock theft of animals grazing in wetter conditions cushions against future losses."	pp.176	+
conflict - livestock number			
Sch12	"Indirectly, raiding contributes to loss of livestock through the spread of diseases (Bett et al. 2009; Oloya et al. 2006). The direct effect of raiding can be both positive (for the raiding community) and negative (for the raided community). From the raider's perspective, raiding can appear to be an effective and direct tool to increase their own herd, at the cost of those who are raided."	p.10	+-
N18	"Such thefts had a strong impact on both communities, with one interviewee reporting that 'raids began until all animals were gone'.57 Constant raiding dissipated herds, rendering some families destitute."	p.143	-
conflict - resource availability			

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Table A.2 – continued from previous page

Source	Quote	Page	Sign
Sch12	”While the abandonment of entire settlements is a rare case, the loss of pasture and water points is a common phenomenon in conflict-prone rangelands of north-western Kenya.” + ”Similarly, it was observed that the rangelands south of Loya, located between the Turkana plains and the highlands of Pokot, were rich in pasture. Yet, neither of the two groups was accessing the area because of insecurity. The insecurity is further increased by highway robbery of bandits who take advantage of the power vacuum. In addition, the underutilization of pasture bares the risk of encroachment of certain species which deplete the pasture or make it inaccessible (Opiyo et al. 2011; Bollig 1990; Huho et al. 2009). Unused boreholes can become a source of livestock poisoning (Mbaria et al. 2005). Along river Turkwel and Kerio, 78% of the pastoralists are forced by conflicts to migrate with their livestock to the neighbouring water sources in Karamoja of Uganda, while 10% are confined within the few safe riverbanks that remain. This concentration of people and livestock increases the likelihood of overuse ofresources and poses a potential source of new conflict. The majority of respondents reported that they are afraid to move freely when conflicts are ongoing in the study area.	p.11	-
N18	”Loregon and its immediate vicinity is known to be an area with good access to water and grazing. However, during periods of violence, access became difficult for both sides.59”	p.143	-
O11	”Self-imposed restrictions on mobility due to climate change-induced conflict can have very negative implications for the viability of herds. McCabe (1990:90), for example, estimated that up to one quarter of the territory of the Nginsonyoka, comprising Turkana's best highland grazing areas, was rarely used for fear of livestock raiding. Restrictions on mobility leads to the immediate problem of overgrazing which in the longer term, can lead to serious soil degradation.”	p.92	-
conflict -exposure			
Sch12	”Along river Turkwel and Kerio, 78% of the pastoralists are forced by conflicts to migrate with their livestock to the neighbouring water sources in Karamoja of Uganda, while 10% are confined within the few safe riverbanks that remain. This concentration of people and livestock increases the likelihood of overuse of resources and poses a potential source of new conflict.”	p.12	+
O11	”KVRT preliminary findings (KVRT 2009) point out that the Turkana migrate due to the following reasons: search for pasture and water (52,7%), conflicts (21,9%), search for larger pieces of land (6%), and culture (2%).”	p.89	+
Pathway II: Strategically planned conflict			
wet season - vegetation cover			
Sch14	”In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources.”	pp.250	+
WA09	”While conflicts over scarce resources may be largely explained by drought conditions, population pressure, and access problems, livestock raiding is more violent during wet seasons, when pasture and water are abundant and when the livestock is in good health”	p.514	+
wet season - livestock (health, number)			

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Table A.2 – continued from previous page

Source	Quote	Page	Sign
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250	+
WA09	"While conflicts over scarce resources may be largely explained by drought conditions, population pressure, and access problems, livestock raiding is more violent during wet seasons, when pasture and water are abundant and when the livestock is in good health"	p.514	+
wet season - resource availability			
A12	"Violent livestock raiding is mostly carried out during the wet season. The animals are stronger and fatter then, and the vegetation and surface water are more readily available, which is necessary during a long trek away from the area where the raid took place. The vegetation is also thicker, which makes it easier to hide after an attack. Raiders usually have to trek long distances, for which the animals should be fit and strong. Raiding is especially common during the rainy season because rain washes away tracks, which increases the chance of escaping with the raided livestock. Rainy seasons in pastoral areas are usually times of relative abundance, not only of pasture, water or milk. There is also a labour surplus, which makes it easy for young men to engage in raiding."	p.71	+
livestock (health, number) - motive: livestock restocking			
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250	+
vegetation cover - motive: livestock restocking			
Sch14	"In regular years with sufficient rain, raiding is mostly conducted before and during the long and short rains to make use of the fortunate raiding conditions (healthier animals, vegetation providing cover, own herds need less attention). But when rains partly or completely fail and a certain threshold of resource scarcity is reached, raids are conducted despite the less fortunate restocking conditions not only to compensate drought-related livestock losses but to protect or gain control over scare pasture and water resources. [...] While the rainy season is used for restocking herds, raiding in dry periods is mainly an instrument to control or gain access over resources."	pp.250	+
vegetation cover - motive: resource access			

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Table A.2 – continued from previous page

Source	Quote	Page	Sign
M07	The environmental variable vegetation also presented a positive relationship with the incidence of raids, and there appears to be cyclical influence of bi-modal seasons [. . .] This direct environmental measure then suggests that the raiding behaviour is strategically planned and tied to opportunities presented by the environment. Indeed, Turner (2004:877) argues that the high spatiotemporal variability of productive resources leads to a situation in which there is little spatial fixity in the competition over land" which means that "conflicts are less likely to be 'in-the-moment' struggles over a particular resource patch and more likely to resemble strategic contests to maintain resource access over the longer-term [...] Herders interviewed during related field research explain that, "raiders like to attack during wet years because of high grass, strong animals, dense bush to hide in and the availability of surface water, which makes it easier to trek with the animals." (Adano & Witsenberg, 2005: 723)."	p.731	+

Table A.3.: Sources and quotes for the impact of politics on inter-ethnic conflict in the study area

Source	Quote	Page	Sign
elections, devolution - territorial rights			
N18	Interviewees also noted that the boundary issue is used as a mobilising device by politicians and others who have personal status and ambitions within their community, particularly in the run-up to elections. During such periods, politicians can reportedly exert considerable influence, often mobilising support by paying out money to secure supporters.55	p.142	+
S09	"Kenya's recent political violence has many roots, including historical inequalities and marginalization of members of certain groups and a failur to institutionally address critical policy sectors such as land and resettlement."	p.885	+
K09	"The land redistributon policy of the 1960s and its outcome clearly shaped the outcome of the December 2007 presidential election dispute. Both the procedure by which land settlement schemes were established and the skewed bias in favour of certain groups are responsible for the recurrence of violence. Notably, these is a clear link between land, territory, and politics." + "Grievances over land continue to inform Kenya's local and national politics whenever political circumstances change. That was true in December 2007 general election" + "The landed elite are in control of both the politics and economy in the highlands and finance violence more often to deflect attention from inequalities in land ownership to inequalities in distribution of political power"	p.341 + p.339 + 334	+
SV17	"In Marsabit County there was a growing sense among pastoralists that their hold on land and all that it meant in terms of wealth, identity, culture and power, was tenuous.74 This precariousness was crucial in people's acceptance of the political messages embodied in the violence in 2013. At stake was 'the disappearance from under the feet of local inhabitants of the resources that provide them livelihood security [. . .]'.75"	p.259	+
elections, devolution - political patronage			
SV17	In pastoralist territories, for instance, livestock raiding had become a means to establish exclusive political and economic hold on a territory in the name of a single ethnic group. Elite actors were said to use the funds raised through livestock raids to finance political campaigns and, once in power, to supply patronage to their 'ethnic group' in return.41 Political candidates who could leverage the support of customary leaders by availing them exclusive control of a constiuency or ward were then able to offer national parties voting blocs in national elections.42 Once in power, politicians pressed the national government to carve out constituencies that created ethnically homogenous jurisdictions."	p.252	+
C14	"This was the new devolved county system of government introduced by the 2010 constitution. This system transformed the political landscape: crucially, the post of county governor would give much power to incumbents at a regional level, meaning local rivalries were likely to coalesce around competition for the position.	p.5	+

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Table A.3 – continued from previous page

Source	Quote	Page	Sign
G16	”It is noteworthy that on the basis of the 2010 constitutional reforms, defensive boundary processes initiated during the colonial period have recently been reawakened due to the devolution of governance powers to newly founded counties with essentially the same boundaries as the traditional administrative districts. These reforms have led to intense electoral competition over political and administrative positions, accompanied by efforts at pushing members of certain communities out of ethnically mixed areas that others claim as their cultural homelands, since the benefit of devolved powers is not only greater local control over resources but also the exercise of patronage (Schlee & Shongolo 2012)”	p.111	+
L18	”Instead of pioneering a new type of politics, devolution has entrenched existing political dynamics through reproducing at the county-level a type of patronage politics and rent-seeking seen at the centre (Cornell & D'Arcy, 2014).”	p.140	+()
ethnic territorialization - territorial rights			
G16	”While the exaggerated claim has sometimes been made that demarcating districts actually brought ethnic divisions into being, the enforcement of district frontiers clearly severed intimate ties between some long coexisting communities and lent some groups a state-based justification for attempting to deny access to others thought to have been allocated homelands elsewhere. So some borderlands between provinces and districts became long-term battlegrounds periodically tested by herders who felt that historical precedent and social familiarity should allow them entry and residence rights.”	p.110	+
WA09	”This informant refers to the current problems in pastoral societies, which cause politically motivated raids. Pastoral land in Marsabit, as in many other districts, is trust land that is controlled by the county council within whose area it is situated and governed by customary law. The usefulness of land is typically determined by availability of water. Water sources are usually owned by individuals or clans, but use rights traditionally override ownership rights. This means that every nomad has the right to use a well, also on the land governed by a neighbouring ethnic group, if he negotiates well. With the creation of boundaries, whereby new districts and constituencies (like Moyale district in 1995), new divisions and locations are meant to mark ethnically 'pure' territories, it is increasingly hard to maintain the traditional arrangement of water and land sharing.”	p. 532	+
C14	”Despite leaving the constituencies more uniform in terms of ethnic composition, the process did bring the unintended consequences of boundary contestation between the contiguous constituencies. For example, as Schlee notes, 'Turbi, a small trading post between Moyale and North Horr constituency' became a major site of contestation between the Borana and Gabra.43 With Moyale being a Borana constituency and North Horr Gabra, this boundary arrangement pitted the two groups against each other.”	p. 7	+

Table A.4.: Sources and quotes for the impact of economic development on inter-ethnic conflict in the study area

Source	Quote	Page	Sign
oil, LAPSSET - resource availability			
J15	"local pastoralists have already experienced other negative livelihoods impacts, particularly the loss of grazing lands. Tullow Oil has fenced off 50 sq. km of land that the Turkana previously used for grazing and watering livestock. The Turkana are concerned because the perimeter fence separates them from these important natural resources (see also Ng'etich, 2012)."	p.155	-
Sch15/18	"Exposure to pollution of water, land and air is a major concern (Fig. 3). It has long been known that oil spills on land can "pose long term threats to groundwater quality" (Duffy et al., 1980). [...] The respondents did not mention the pollution of water, possibly because they are not noticeable yet as the exploration in Turkana only started in 2012. In addition to water, land could be polluted for instance by the dumping of oil wastes without proper sealing and treatment (Khaitan et al., 2006; da Silva et al., 2013). But again, the pollution of land did not feature strongly in the responses of the communities." + While the chosen approaches by the wind project and the oil exploration are different, both have improved the local communities' access to water, at least in the short to medium term. However, as water is needed for the extraction of oil, Tullow needs the same water resources as the communities." + "Tullow has chosen a different approach. Instead of drilling boreholes, the company mostly set up water tanks along the main road and nearby communities like Nakukulas.62 These water tanks are filled on a regular basis by water trucks but because Tullow can decide to stop filling the water tanks, the source is less reliable than a borehole." + "In contrast to the wind project, all oil sites for exploration, storage of oil and others are fenced and inaccessible for local communities. The inaccessibility of land and disruption of pastoral migration routes is likely to become worse when the construction for the planned oil pipeline starts.91"	p.708/p.508, p.583	-(+)?
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Table A.4 – continued from previous page

Source	Quote	Page	Sign
M20	""Tullow Oil PLC established thirty well pads in Turkana between 2012 and 2015 (Tullow n.d.). Fencing of these sites has at times happened completely unexpectedly for communities, causing livelihood insecurity and fear."+ "Displacement from water sources is as important as displacement from land. Twenty-nine boreholes have been drilled by the oil company, and several of these are available for use by the surrounding community. The community is also free to use some of the water from bowsers brought from the Turkwel river. However, the oil industry is likely to need much larger quantities of water in the future, and how competing claims over water resources will be resolved is unclear."	p.838/p.840	-(+)?
Sch16	The LAPSSET infrastructure is planned to cut through major pastoral areas located in northwest and north central Kenya (Fig.1). Land, pasture and migration routes will likely be significantly affected by LAPSSET. In the feasibility study, it is acknowledged that "from the viewpoint of environmental conservation, the LAPSSET [. . .] railway, highway and pipeline must have remedial measures against the impacts on wildlife and livestock. An example is the influence of their construction works to migration/movement of these animals across the facilities. The corridor shall not block them completely. It is necessary to construct culverts and/or other appropriate passages across the corridor bank" (LCDA 2015). Particularly, the degree of the oil pipeline running under ground will determine how strongly it will interrupt pastoral migration routes.	p.63	-?
oil - motive: territorial rights			
J15	"Emerging evidence, including exclusion of local communities in oil-related-decision-making, land grabbing by outsiders at the expense of locals, corruption and incipient interethnic conflicts over discovered oil-field territories in Turkana County indicates increased vulnerabilities, risks, and perverse opportunities which suggest a high likelihood that oil will exacerbate interethnic conflicts in an already volatile region and even result in full-blown violent conflicts between the already marginalized Turkana and the government, national and foreign investors such as Tullow Oil, unless effective preventive and corrective actions are taken early. "	p.161	+
L18	Yet, this is new violence, happening under the guise of 'cattle raiding', but which is driven by the revival of Pokot expansionist politics and attempts to stake ancestral claims to areas with rich resources inside Turkana County.	p.144	+

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Table A.4 – continued from previous page

Source	Quote	Page	Sign
Sch18	"Particularly two issues have the potential to aggravate existing conflicts or create new ones between and within communities. These are disputes over territory and competition for employment opportunities. The borders between Turkana and West Pokot have been a source of conflict for a long time.118 The Turkana claim parts of West Pokot and the Pokot claim parts of Turkana.119 Now that oil has been found on the Turkana side, concerns are increasing that the resource may aggravate the conflict between the Turkana and the Pokot. For instance, a teacher interviewed in Turkana South states that 'Pokots are here [in Turkana South], being pushed by their leaders with the intention of land and oil'.120" + "Overall, the research findings suggest that the oil and wind extractive processes have an aggravating effect on existing violent conflicts between communities (e.g. between Turkana and Pokot) and a potential to create new, so far non-violent conflicts, within communities of the same ethnicity (e.g. between Turkana South and Turkana East)."	p.586, p.587	+?
oil - security presence			
Sch15	Regardless of the exact number, members of all three research locations have indicated that, on the one hand, the increased presence of KPR officers has improved the security situation where the oil exploitation is taking place.	p.712	+()
wind - resource availability			
Sch18	"For Sarima a borehole was drilled which allowed the community to access groundwater + "While the chosen approaches by the wind project and the oil exploration are different, both have improved the local communities' access to water, at least in the short to medium term. However, as water is needed for the extraction of oil, Tullow needs the same water resources as the communities." + "In the case of the wind park, competition for water is unlikely to become an issue as the amount of water needed to operate and cool the (V52–850) turbines is expected to be minimal.97" + "While members of the Sarima community did not seem to have received any financial compensation for the land given to the wind project, the turbines are not fenced and the area surrounding them was still accessible to the community members at the time of the research."	p.580, p.582	+(-)?
wind - motive: job opportunities			

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Table A.4 – continued from previous page

Source	Quote	Page	Sign
Sch18	”Particularly two issues have the potential to aggravate existing conflicts or create new ones between and within communities. These are disputes over territory and competition for employment opportunities.” + ”Similar developments can be observed in Marsabit. The Deputy County Commissioner of Loiyangalani explains: ‘People from Samburu say the land is theirs, the Samburu, the Rendille all of them say the land is theirs’.123 A member of the Sarima community made this observation: ‘They [the Samburu] saw this project has come, they saw the Turkana will benefit from it, let us chase them and go to their land’.124” + Many interviewees in Sarima were particularly angry when jobs as security officers were given to Samburus. The ‘heads of G4S [a security company] are all Samburus’, complains one member of a small group interview in Sarima.126” ”Overall, the research findings suggest that the oil and wind extractive processes have an aggravating effect on existing violent conflicts between communities (e.g. between Turkana and Pokot) and a potential to create new, so far non-violent conflicts, within communities of the same ethnicity (e.g. between Turkana South and Turkana East).”	p.586, p.587	+?
wind - motive: territorial rights			
Sch18	”Particularly two issues have the potential to aggravate existing conflicts or create new ones between and within communities. These are disputes over territory and competition for employment opportunities.” + ”Similar developments can be observed in Marsabit. The Deputy County Commissioner of Loiyangalani explains: ‘People from Samburu say the land is theirs, the Samburu, the Rendille all of them say the land is theirs’.123 A member of the Sarima community made this observation: ‘They [the Samburu] saw this project has come, they saw the Turkana will benefit from it, let us chase them and go to their land’.124” + Many interviewees in Sarima were particularly angry when jobs as security officers were given to Samburus. The ‘heads of G4S [a security company] are all Samburus’, complains one member of a small group interview in Sarima.126” ”Overall, the research findings suggest that the oil and wind extractive processes have an aggravating effect on existing violent conflicts between communities (e.g. between Turkana and Pokot) and a potential to create new, so far non-violent conflicts, within communities of the same ethnicity (e.g. between Turkana South and Turkana East).”	p.586, p.587	+?
wind - security presence			

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Table A.4 – continued from previous page

Source	Quote	Page	Sign
Sch18	"The oil and wind extraction affects the overall security situation in each region as it changes its security architecture. The oil company and LTWP concentrate security forces to protect the extraction sites. This tends to improve the security around the oil sites and wind park."	p.587	+()
security presence - conflict			
Sch15/Sch16	"Several community members, for example in Lokwamosing, reported that the raiding by the Pokot had decreased. "The home guards are patrolling," notes one community member. On the other hand, insecurity in other areas such as the raiding hotspots along the Turkana–Pokot border was reported to have increased due to a lack of KPR officers./To deal with these interruptions, Tullow has placed security personnel to protect the operations. On the one hand, community members reported that this has decreased livestock raiding in the vicinity of the oil sites. On the other hand, however, it has left Turkana communities along the borders with enemy tribes (particularly the Pokot) exposed to attacks as Tullow recruited community guards (so called Kenya Police Reservists, KPRs) from those communities to protect oil sites (see also Schilling et al. 2015; Mkutu 2015)."	p.712/p62	+-?
M20	"The security governance issues of conservancies are significant. Since private security companies cannot carry arms (Diphoorn 2016; Dobson 2019), there is a provision that allows National Police Reservists (NPRs) to act as rangers and scouts to guard conservancies against poaching and other incursions and to receive wages for their services. NRT provides NPRs with training and equipment, meaning they are better resourced than the police (Lorogoi 2013). This has implications for state sovereignty and arms proliferation, and raises the possibility that these empowered community members could revert to ethnic conflict and other illicit activities."	p.849	+?
security presence - proliferation of small arms			
Mk07	"Arms may also originate from legal sources, such as official security forces and militias armed for the defence of th community"+ "On the Kenyan side of the border, the government has provided arms to the KPRs who are under the control of the police and district commissioners" + "guns issued to the reservists are frequently hired out or used in banditry and raiding. This subsequently undermines the security they are supposed to protext and creates instability"	p.53+p.56	+

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Table A.4 – continued from previous page

Source	Quote	Page	Sign
M20	"The security governance issues of conservancies are significant. Since private security companies cannot carry arms (Diphoorn 2016; Dobson 2019), there is a provision that allows National Police Reservists (NPRs) to act as rangers and scouts to guard conservancies against poaching and other incursions and to receive wages for their services. NRT provides NPRs with training and equipment, meaning they are better resourced than the police (Lorogoi 2013). This has implications for state sovereignty and arms proliferation, and raises the possibility that these empowered community members could revert to ethnic conflict and other illicit activities."	p.849	+?
dams - resource availability			
Sch16	"Velpuri/Senay (2012) calculated that the Gibe III dam could reduce Lake Turkana's depth by about 1.5–2 m with extremes ranging from less than a meter to more than 3 m reduction depending on the used rainfall scenario. Another study from the University of Oxford estimates the impact to be even more severe, with a reduction of over 20 m at an average lake depth of only 30 m (Avery 2013). This would mean at least a splitting of the lake into two parts. Avery (2013, 3) even warns of an "Aral Sea disaster". [...] The community members reported violent engagements with other groups from the east side of Lake Turkana and Ethiopia. Should Lake Turkana partly dry up, there is a risk of increased conflict between communities who have been previously been separated by the lake (see also Allibhai 2015; Guardian 2015a)."	p.65	-?
dams - exposure			
Sch16	"Velpuri/Senay (2012) calculated that the Gibe III dam could reduce Lake Turkana's depth by about 1.5–2 m with extremes ranging from less than a meter to more than 3 m reduction depending on the used rainfall scenario. Another study from the University of Oxford estimates the impact to be even more severe, with a reduction of over 20 m at an average lake depth of only 30 m (Avery 2013). This would mean at least a splitting of the lake into two parts. Avery (2013, 3) even warns of an "Aral Sea disaster". [...] The community members reported violent engagements with other groups from the east side of Lake Turkana and Ethiopia. Should Lake Turkana partly dry up, there is a risk of increased conflict between communities who have been previously been separated by the lake (see also Allibhai 2015; Guardian 2015a)."	p.65	+?

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Source	Quote	Page	Sign
J15	"Of note here are impacts of the Turkwel Dam on the Turkana people and of Gibe III Dam on ethnic groups in the lower reaches of the Omo River, including the Nyangatom and Dassanech who are perennial opponents of the Turkana. As these groups are displaced by the dams and planned irrigated plantations, they will move farther afield, likely into the Ilemi triangle where conflicts with the Turkana are likely to intensify (International Rivers, 2013)."	p.151	+?
dams - motive: job opportunities			
N18	"disputes over the 'ownership' of the dam have focused on control of employment opportunities there, rather than control of the electricity generated by the dam itself."	p.142	+
aquifer - resource availability			
J15	"Using, some of the oil proceeds to develop and distribute the discovered ground-water resources, preferably even before actual oil production begins, could benefit thousands of drought-hit pastoralists who currently walk for many kilometers looking for water (Muchangi, 2012), as poignantly illustrated in Figure 7, and enhance local goodwill while defusing some tensions. However, care should be taken to prevent the pollution of this rich water resource through oil exploration and exploitation activities. Further, efficient supply of water from this reservoir may involve the resettling of Turkana populations, which would pose new social challenges."	p.158	+?
Sch16	"discovered aquifers in Turkana have the potential to significantly improve the water situation in Turkana."	p.66	+?
commercialization of pastoralism - motive: wealth			
Sch12	"In Pokot, a connection between the accumulation of wealth and commercialised raiding was more pronounced in the interviews with government officials and experts, while raiders denied that they sell a large portion of the captured livestock."	p.8	+?
commercialization of pastoralism - resource scarcity			
Sch14	"In addition, increased herd sizes which are a necessary element of commercialised pastoralism bear the risk of overgrazing and resource depletion (Wasonga et al. 2011)."	p.254	+?
commercialization of pastoralism - proliferation of small arms			

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Table A.4 – continued from previous page

Source	Quote	Page	Sign
O11	"In Turkana, the increase in 'commercial' raiding includes cases of 'sponsored' raiding where guns are provided to young men by wealthy people who wish to acquire livestock for sale. This has been facilitated by the general economic stagnation in the Horn of Africa which has contributed to the development of informal 'parallel' economies. [...] . The outcome, due to the use of modern weapons in raids, has been more destructive and has led to lasting hostilities among the Turkana and their neighbouring tribes: the Toposa (Sudan), the Karamojong (Uganda), the Donyiro (Ethiopia), the Merille (Ethiopia) and the Pokot (Kenya)."	p.88	+
proliferation of small arms - conflict			
Sch14	"raiding itself is reported to have become more violent. In the period considered here, the number of deaths and injured during raids rose from 139 and 27 in 2006 to 190 and 80 in 2009 (TUPADO 2011). While the cause of death is not listed in the TUPADO register, the ratio between people killed and injured could point to an increased use of semi and fully automatic small arms (see also Mkutu 2008)."	p.252	+
WA09	"Increasing small arms purchases by pastoralists are often seen as causing more violent deaths. There is, however, no evidence that this is true. Raiding with spears and machetes was probably equally, if not more deadly."	p. 534	()
O11	"When pastoralists lose their livelihoods, through loss of access to pastures and water due to climate variability and change, destitution threatens and they turn to violence. This is exacerbated by other factors, including the proliferation of small arms, breakdown in customary control and the absence of State governance in remote border areas."	p.93	+
C14	"Tension of whatever origin is rendered more dangerous by the large numbers of guns accumulated in the region, some smuggled in from across the national borders,34 others obtained through more legitimate means, for example, by the Kenya Police Reserves – the 'Home Guard' allocated rifles by the state to protect against bandits."	p.5	+
J15	"Findings also illustrate the extent of gun proliferation and challenges in addressing this problem. Many Turkana pastoralists encountered during fieldwork carried an assault rifle (Figure 4). Many explained that they needed the guns to protect themselves and their families from hostile neighbors as the government had failed to do so. However, most also admitted that these rifles made confrontations more likley, destructive and potentially deadly"	p.149	+

Table A.5.: Sources and quotes for the impact of mitigatory and adaptive action and its impact on inter-ethnic conflict in the study area

Source	Quote	Page	Sign
traditional, official institutions - conflict			
Sch12	”the majority of Turkana and Pokot raiders report that the elders encourage or even assist their raids with blessings and information (for example, where to find the enemy’s livestock). Further, several raiders stated that the elders receive a share of the livestock, sometimes even ‘the biggest bull’. On the other hand, most elders claim to discourage the raiding. Some acknowledged that they occasionally benefit from the raids or the raiders ‘just go on their own’, as one woman phrased it. One focus group discussion with both raiders and elders in Lokiriama was instrumental to match these seemingly opposing views. During times of peace with the Pokot, the elders discourage the youth to raid the Pokot, while during times of conflict, the elders hardly ever refuse a pre-raid blessing. [...] The village chiefs are in a difficult position. On the one hand, they are the representation of the national government on the ground and hence have to prevent or sanction raiding; on the other hand, they understand why the community engages in raiding.”	pp.8	+-
N18	”The conflict management process that is now in place has re-established an effective institution at the local level that has both managed and prevented conflict, creating a basis for broader improvements in cross-community relations. + ”In the past elders were held in high esteem by the community and represented key interlocutors. In this instance, however, it is the younger kraal leaders who are actually ensuring that peace agreements are maintained and enforced in a collaborative way. These local leaders have direct access to the local government administrative chief as well as other government bodies to prevent conflict.”	p.147+ p.149	-
D14	”Over the last centuries, customary institutions have evolved in northern Kenya, which define under what circumstances raids are legitimate, how stolen animals are redistributed and how resulting hostilities between different groups can be settled through compensation (Hendrickson, Mearns, & Armon, 1996; Meier et al., 2007).”	p.58	+-
A12	”During drought periods, pastoralists in northern Kenya deploy social institutions that mediate agency toward cooperation and guarantee access rights to resources (water) for all, thereby reducing violent conflicts. [...] The absence of overt violent conflict in Marsabit is clearly not due to lack of scarcity, which is a common feature of marginal and deteriorating environmental conditions. [...] From each of the two case studies emerges the significant role of institutions, be they traditional or ‘official’, in preventing avoidable conflicts and allowing reconciliatory situations to prevail within competing interest groups and between rivalry communities in Loita and Marsabit.” + ”. The results reveal a rare insight into the importance of hybrid customary-cum-legal institutions and ingenuity as to whether or not a common-pool resource becomes a curse. Therefore, human agency ultimately determines whether natural resources turn into a curse, but we need the historical contextual analysis of institutional structures to inform us about the potential threats and opportunities.”	p.77	-
O11	”There do exist conflict-mitigating institutions at local and national levels, with officers seconded to them from government, as well as district peace committees. However, their effectiveness in practical early warning of conflicts and rapid response is hampered by a lack of funding and resources from government.”	p.89	(-)

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Table A.5 – continued from previous page

Source	Quote	Page	Sign
C14	”Councils of elders were a key part of these dynamics. With the weak state in parts of the north, such councils have considerable authority, and can be a force for the good in applying customary law: ‘the revival and application of customary law by clan elders has, in the absence of an effective state police and judiciary, been the single most powerful deterrent of crime’.61 However, they can also ‘be venal, corrupt, and inclined to foment ethnic divisions’.62”	p.8	+-
disarmament efforts - conflict			
Sch12	”However, as governmental disarmament efforts of the past were selective and poorly coordinated, they predominantly failed, partly aggravating conflicts between communities (Mkutu 2008; Wepundi et al.).”	p.14	+()
WA09	”Among peace organisations, the issue of disarmament is very popular, yet intervention efforts in this direction have been grossly unsuccessful.47”	p.534	()
Mk07	”According to local community representatives, these operations have often been unduly harsh and heavy-handed, leading to a paradoxical increase in arms acquisition. The cross-border pastoralists have always seent themselves as enemies of the state, with the Karimojong word for state, ’anyang’, meaning the same as enemy!”	p.64	+
peace caravans - conflict			
N18	”When asked which peace initiatives played a role in resolving the conflict, respondents identified a wide range of initiatives, including (in declining order of frequency) inter- and intra-community meetings, peace caravans, local chiefs holding baraza (i.e. councils), inter-communal trading and sporting activities, peace workshops and seminars and an inter-community agreement between politicians.”	p.144	-
J15	”Local youth, who are generally used as cattle raiders or interethnic warriors, have taken the initiative to bring peace among themselves through the so-called ‘peace caravans,’ which have resulted in several ‘peace agreements’ being signed among youth groups from rival ethnicities (Okumu, 2013).”	pp.159	-
Sch16	”It is noticeable that in each month of 2014 the number of raids was higher than the number of banditry incidences. This relationship is reversed in 2015 (with the exception of February). Between June and September, no raids were recorded in Turkana. The reduction of raids could be attributed to a peace caravan launched by 15 politicians from Turkana, West Pokot and Baringo in late May 2015 (Daily Nation 2015c).	p.60	-
interethnic dialogue - conflict			
N18	”When asked which peace initiatives played a role in resolving the conflict, respondents identified a wide range of initiatives, including (in declining order of frequency) inter- and intra-community meetings, peace caravans, local chiefs holding baraza (i.e. councils), inter-communal trading and sporting activities, peace workshops and seminars and an inter-community agreement between politicians.”	p.144	-
L18	”in some areas of northern Kenya there were effective efforts to maintain peace and prevent more serious conflict and violence in the lead up to the March 2013 elections. These centred on dialogue across familiar ethnic and clan divides between influential opinion-makers and leaders from different sides, resulting in informal agreements on how to divide political seats before the election. ”	p.142	-()
interethnic trade and cooperation - conflict			
M07	”As would be expected of ”peace indicators,” reciprocal exchanges and peace initiatives are both negatively related to the incidence of raids”	p.730	-

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Table A.5 – continued from previous page

Source	Quote	Page	Sign
N18	"When asked which peace initiatives played a role in resolving the conflict, respondents identified a wide range of initiatives, including (in declining order of frequency) inter- and intra-community meetings, peace caravans, local chiefs holding baraza (i.e. councils), inter-communal trading and sporting activities, peace workshops and seminars and an inter-community agreement between politicians."	p.144	-
E14	"With regard to very dry years, which predicted more Turkana violence, such years predict for Dassenech, Samburu, and Garre, but not for Borana and Gabra. [. . .] Our reading of the ethnography of the Marsabit groups suggests that the Dassenech and Samburu mostly follow a pattern similar to the Turkana and move toward other groups that have been their enemies during droughts. But this is not the pattern of the Borana and Gabra. For example, for the Borana, if years are hard, herds can be brought back to their main camps where there is usually ample water from deep wells. The Ethiopian Gabra, as we discussed above, have benefited from established water sharing arrangements with the Borana, providing labor in exchange for access to water.56 And the Kenya Gabra, who rely more on camels, are not as vulnerable during drought because camels adapt to more arid conditions and herd groups can stay longer in arid lands, such as the Chalbi desert.57"	p.320	-
G16	"But in some cases borders are neither contested nor sites of conflict. For instance, the frontier between Marsabit and Samburu districts is noteworthy for its benign status, since the Samburu and the Rendille of the Koroli Desert in central and south Marsabit have long enjoyed a comfortable alliance based on the complementarity of their cattle- and camel-keeping economies, their marital, linguistic, and livelihood interactions having given rise to an interstitial bicultural community called the Ariaal (Spencer 1973 ; Fratkin 1991 , 2012)."	p.111	-
O11	"Kirbride and Grahn (2008:22) state that community agreements governing access to and the sharing of resources have been developed to prevent recurring conflicts, but these agreements have not been well disseminated."	p.89	(-)
diversification of livelihood - conflict			
Sch14	"To a limited extent, subsistence farming and fishing around Lake Turkana is used to supplement pastoralism (see Figure 3 and Yongo et al. 2011). In general, the diversification of food sources strengthens food security and hence reduces the pressure to engage in conflict over scarce resources. However, in practice the climatic conditions in Turkana strongly limit the potential of agricultural efforts."	p.253	(-)
O11	"Eriksen and Lind (2005:21) observe that the high prevalence of diversification as a livelihood strategy signals efforts by the Turkana to actively manage vulnerability by increasing the reliability of livelihood assets." + "Nevertheless, livelihood diversification by pastoralists has not resulted in sustainable livelihoods, because it is being done out of desperation or distress"	p.91	()
conflict - diversification of livelihood			
WA09	"This trend line indicates the rapid settling of pastoral people who, due to herd losses and impoverishment, increasingly inhabit towns and villages on Marsabit Mountain where they engage in arable farming, trade, or casual employment. Impoverishment is partly a result of frequent droughts associated with heavy livestock losses and increasing insecurity."	p.516	+

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Table A.5 – continued from previous page

Source	Quote	Page	Sign
O11	"According to Eriksen and Lind (2005:15), raiding and killing have led to several women losing their husbands. Women-headed households are particularly vulnerable because women have poor customary rights to land, wells and livestock. [. . .] Additionally, according to Hendrickson et al. (1998:195), women and children are the first to leave the pastoral sector in times of crisis. They are sent to stay with distant relatives or, ever more, to urban areas where their vulnerability to food insecurity may not be relieved. [...] Herders dispossessed of livestock are themselves often forced out of the pastoral sector into relief camps or into a search for wage labour. These gradual changes threaten the hopes of recovery as the crucial social ties needed to resume herding are often irrevocably severed."	p.89	+

B Wet and dry season months for each county and ethnic group

	Dry season [months of the year]	**Wet season [months of the year]**	**Source**
County			
Turkana	1,2, 7,8,9,10	3, 4, 5, 6, 11, 12	NDMA (2022b)
West Pokot	1, 2, 7, 8, 9	3, 4, 5, 6, 10, 11, 12	NDMA (2022c)
Marsabit	1, 2, 3, 7, 8, 9	4, 5, 6, 10, 11, 12	NDMA (2022a)
Ethnic group			
Turkana	1,2, 7,8,9,10	3, 4, 5, 6, 11, 12	NDMA (2022b)
Pokot	1, 2, 7, 8, 9	3, 4, 5, 6, 10, 11, 12	NDMA (2022c)
Toposa	1, 2, 3, 12	4, 5, 6, 7, 8, 9, 10, 11	World Bank (2021)
Dassanetch	1, 2, 3, 7, 8, 9, 12	4, 5, 6, 10, 11	Ember et al. (2014)
Borana	1, 2, 3, 7, 8, 9, 12	4, 5, 6, 10, 11	Ember et al. (2014)
Gabra	1, 2, 3, 7, 8, 9, 10	4, 5, 6, 11, 12	Ember et al. (2014)

C Spearman's rank-order correlation coefficient

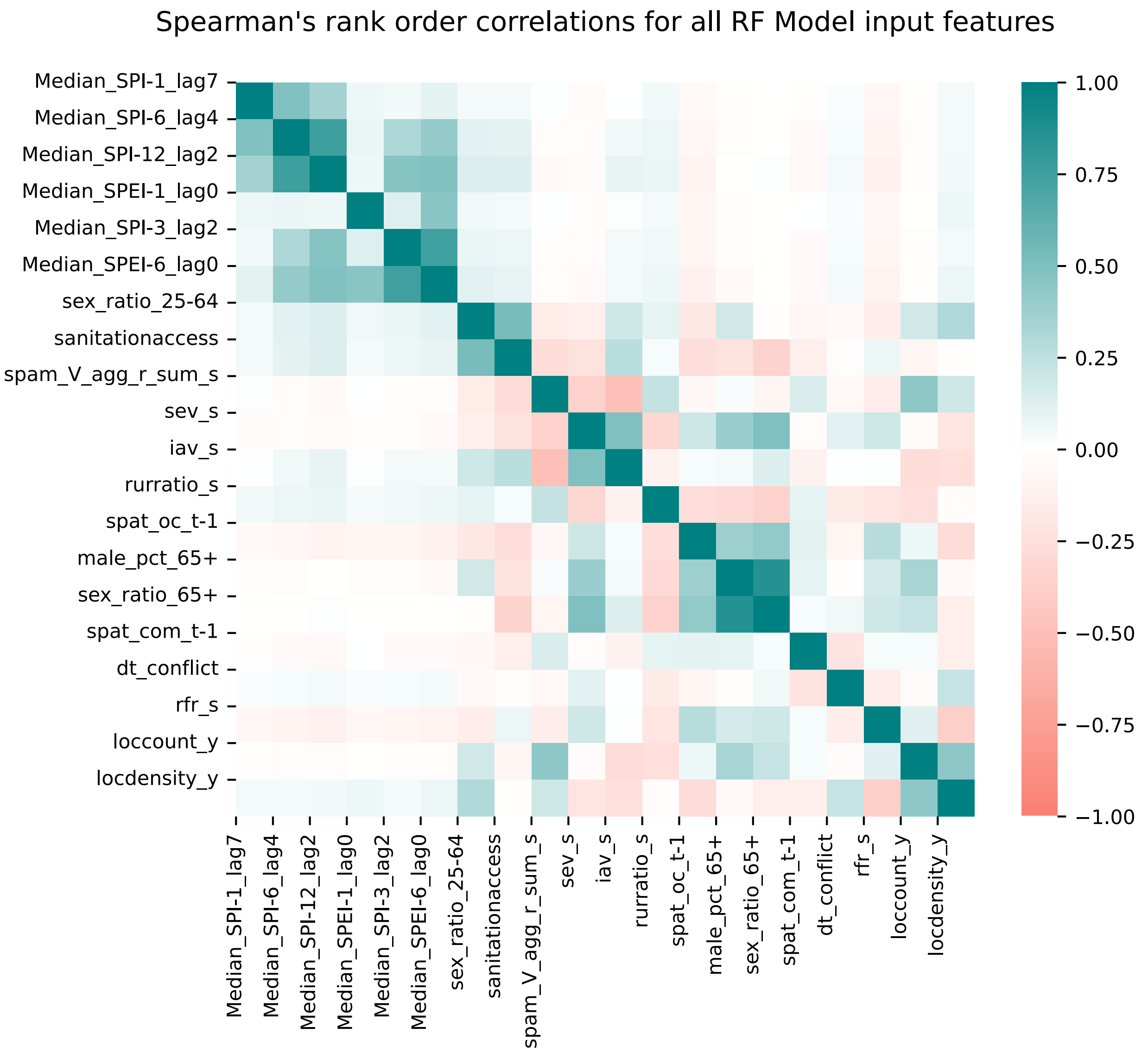

Figure C.1.: Spearman's rank-order correlation coefficient of input features of the Random Forest model

D Calculation of reference evapotranspiration

$$\mathrm{ET_o} = \frac{0.408\Delta(R_n - G) + 900/T_{mean}\gamma w_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{D.1}$$

Δ	slope of the vapour pressure curve [kPa °C^{-1}]
R_n	net radiation [MJ m^{-2} day^{-1}]
G	soil heat flux [MJ m^{-2} day^{-1}]
T_{mean}	daily mean air temperature [°C]
γ	psychrometric constant [kPa °C^{-1}]
w_2	wind speed at 2m height [m s^{-1}]
e_s	daily saturation vapour pressure [kPa]
e_a	daily actual vapour pressure [kPa]

Daily saturation vapour pressure

e_s is calculated from the hourly minimum and maximum hourly air temperature values following Allen et al. (1998). The saturation vapour pressure e^o at temperature T is given by:

$$e^o(T) = 0.6108exp\left[\frac{17.27T}{T + 237.3}\right] \tag{D.2}$$

The daily saturation vapour pressure e_s is consequently calculated through averaging the saturation vapour pressure for the minimum and maximum hourly temperature values T_{min} and T_{max}.

$$e_s = \frac{e^o(T_{max}) + e^o(T_{min})}{2} \tag{D.3}$$

Daily actual vapour pressure

e_a is calculated using Formula D.2 on dewpoint temperature T_{dew}. As the dewpoint temperature is also available from ERA5 at hourly time steps, e_a is here also calculated as the average the saturation vapour pressure at minimum and maximum dewpoint temperature $T_{dew,min}$ and $T_{dew,max}$.

$$e_a = \frac{e^o(T_{dew,max}) + e^o(T_{dew,min})}{2} \tag{D.4}$$

Wind speed at 2m height

w_2 is computed from the two wind components u_{10} and v_{10} through Pythagoras' theorem and adjustment of the height following Allen et al. (1998). Wind speed at 10m w_{10} height is therefore given by:

$$w_{10} = \sqrt{u_{10}^2 + v_{10}^2} \tag{D.5}$$

The height adjustment is based on the assumption of a logarithmic wind speed profile as given by Allen et al. (1998). For the present case of available wind speed data at 10m above the ground, the formula for wind speed at 2m height is given by:

$$u_2 = u_{10}\frac{4.87}{672.58} \tag{D.6}$$

The psychrometric constant

γ [kPa °C^{-1}] is the psychrometric constant is derived by Allen et al. (1998) from the surface pressure P [kPa] as :

$$\gamma = 0.665x10^{-3}P \tag{D.7}$$

$$P = P_{msl}\left[\frac{T_{ref}+zl}{T_{ref}}\right]\exp\left[-\frac{Mg}{Rl}\right] \tag{D.8}$$

P_{msl}	mean sea level pressure [kPa]
T_{ref}	reference temperature: 288.15 K
z	elevation above sea level [m]
l	lapse rate: -0.0065 K m^{-1}
R	universal gas constant: 8.3144621 J (mol K)$^{-1}$
M	molar mass of the air: 0.0289644 kg mol^{-1}
g	gravitational acceleration: 9.80665 m s^{-2}

The surface pressure is here calculated from the mean sea level pressure P_{msl} by adjustment for the elevation through an elevation measurement z [m] obtained from the Digital Elevation Model (DEM). The elevation adjustment is based on the barometric formula for the troposphere, as defined by National Oceanic and Atmospheric Administration et al. (NOAA, 1976)

The daily mean air temperature

T_{mean} is derived from hourly temperature data. To keep consistency with the calculation of vapour pressure, described below, it is advised to not be based on hourly temperature measurements but rather the mean of daily maximum temperature T_{max} [°C] and minimum temperature T_{min} [°C] (Allen et al., 1998).

$$T_{mean} = \frac{T_{max} - T_{min}}{2} \tag{D.9}$$

The soil heat flux

G [MJ m^{-2} day^{-1}] can be assumed to equal zero at daily time scales (Allen et al., 1998).

The net radiation

R_n [MJ m^{-2} day^{-1}] can be calculated from surface net shortwave radiation R_{sns} [MJ m^{-2} day^{-1}] and surface net longwave radiation R_{snl} [MJ m^{-2} day^{-1}] (Allen et al., 1998). Both variables are available from ERA5. They are defined positively in downward direction. Therefore the formula for R_n is written as

$$R_n = R_{sns} + R_{snl} \tag{D.10}$$

The slope of the vapour pressure curve

Δ [kPa $°C^{-1}$] is calculated from the mean air temperature T_{mean} [°C], following Allen et al. (1998) :

$$\Delta = \frac{4098[0.6108 * \exp\frac{17.27T_{mean}}{T_{mean}+237.3}]}{(T_{mean}+237.3)^2} \tag{D.11}$$

E Tables of odds ratios for all models

Table E.1.: Model 1: Odds ratio for a negative unit change in negative DI

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	1.302	0.993	0.925	1.088	0.736	1.06	1.02	1.428
	Median	1.312	1.009	0.92	1.069*	0.718*	1.041	0.999	1.427
	P25	1.29	1.12	1.026	1.076*	0.783	1.074	0.997	1.299
	P75	1.306	0.901	0.937	1.088	0.697	0.976	1.123	1.557
SPI-3	Mean	1.069	1.055	0.837**	0.92	1.034	1.259	0.994	1.156
	Median	1.078	1.068	0.829**	0.881	1.005	1.257	0.969	1.159
	P25	1.24	1.059	0.866**	0.915	1.02	1.153	0.903	1.036
	P75	0.888	0.84*	0.765	0.923	1.066	1.333	1.097	1.235
SPI-6	Mean	0.981	0.962	1.084	1.155	1.304	1.228	1.181	1.182
	Median	0.986	0.924	1.056	1.145	1.279	1.213	1.126	1.142
	P25	1.048	1.028	1.18	1.056	1.161	1.139	1.187	1.175
	P75	0.806***	0.87	1.05	1.29	1.45	1.143	1.073	1.187
SPI-12	Mean	1.234	1.155	1.313	1.325	1.356	1.688	1.572	1.802
	Median	1.254	1.194	1.361	1.359	1.223	1.507	1.501	1.852
	P25	1.088	1.088	1.245	1.335	1.281	1.68	1.682	1.707
	P75	1.274	1.129	1.189	1.177	1.335	1.412	1.362	1.852
SPEI-1	Mean	1.117	1.469	0.876	1.1	0.967	1.112	1.07	1.224
	Median	1.131	1.476	0.885*	1.076	0.949	1.098	1.012	1.222
	P25	1.179*	1.511	0.921	1.087	0.958	1.06	0.991	1.07
	P75	1.059	1.331	0.792	0.991	0.904	1.09	1.042	1.283
SPEI-3	Mean	1.121	1.091	0.838*	0.993	1.066	1.181	0.904	0.996
	Median	1.144	1.106	0.843	0.972	1.068	1.155	0.878	0.979
	P25	1.232	1.083	0.928	0.988	0.988	1.029	0.796	0.886
	P75	0.988	0.975	0.712	0.992	1.065	1.309	0.984	1.067
SPEI-6	Mean	1.021	0.973	0.992	1.09	1.115	1.169	1.144	1.162
	Median	1.057	0.972	0.999	1.1	1.124	1.147	1.104	1.121
	P25	1.092	1.017	1.026	1.007	1.016	1.046	1.056	1.083
	P75	0.829**	0.866	0.901	1.08	1.131	1.169	1.12	1.136
SPEI-12	Mean	0.928	0.909	1.066	1.209	1.219	1.395	1.263	1.337
	Median	0.948	0.94	1.064	1.214	1.142	1.296	1.207	1.349
	P25	0.908	0.94	1.068	1.189	1.159	1.355	1.23	1.28
	P75	0.914	0.855	0.983	1.151	1.183	1.319	1.23	1.446

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.2.: Model 1: Odds ratio for a positive unit change in positive DI

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.621*	0.668	0.791*	0.847	1.07	0.866	1.116	1.384
	Median	0.609*	0.675	0.832	0.804	1.019	0.879	1.117	1.399
	P25	0.556	0.652	0.715*	0.844	0.989	0.911	1.248	1.577
	P75	0.69**	0.746	0.914	0.846	1.14	0.847	1.048	1.181
SPI-3	Mean	0.574*	0.677**	0.82**	0.968	1.025	1.214	1.404	1.207
	Median	0.577*	0.647***	0.777**	0.944	0.997	1.206	1.383	1.209
	P25	0.553*	0.616**	0.753**	0.956	1.036	1.358	1.59	1.34
	P75	0.634**	0.659**	0.845	0.969	1.02	1.107	1.269	1.106
SPI-6	Mean	0.634**	0.851	0.98	1.194	1.101	1.037	1.087	0.964
	Median	0.628**	0.836	0.97	1.173	1.094	1.033	1.076	0.974
	P25	0.631*	0.883	1.086	1.333	1.295	1.201	1.267	1.059
	P75	0.644***	0.841	0.934	1.094	0.979	0.91	0.99	0.938
SPI-12	Mean	0.768	0.786	0.771	0.808	0.957	1.016	1.195	1.377
	Median	0.775	0.812	0.796	0.834	0.957	1.023	1.206	1.364
	P25	0.711	0.759	0.79	0.874	1.06	1.223	1.477	1.614
	P75	0.786	0.801	0.777	0.801	0.911	0.954	1.174	1.311
SPEI-1	Mean	0.568**	0.682	0.805*	0.793	1.124	0.895	1.048	1.318
	Median	0.581**	0.685	0.833	0.776	1.093	0.902	1.042	1.259
	P25	0.548**	0.647	0.668*	0.805	1.093	0.944	1.059	1.392
	P75	0.63**	0.72	0.892	0.798	1.104	0.862	0.992	1.149
SPEI-3	Mean	0.532***	0.594**	0.749**	0.89	1.027	1.151	1.294	1.175
	Median	0.536***	0.574**	0.706***	0.832	0.999	1.126	1.263	1.161
	P25	0.515***	0.572***	0.743	0.948	1.077	1.269	1.377	1.254
	P75	0.587***	0.61**	0.762**	0.857	0.957	1.048	1.183	1.084
SPEI-6	Mean	0.583**	0.748	0.898	1.134	1.077	1.074	1.173	1.078
	Median	0.571**	0.731	0.877	1.11	1.059	1.066	1.179	1.097
	P25	0.598	0.761	0.941	1.258	1.221	1.19	1.319	1.176
	P75	0.564***	0.728*	0.828	0.98	0.931	0.934	1.008	0.995
SPEI-12	Mean	0.751	0.715	0.765	0.897	1.084	1.138	1.375	1.67
	Median	0.761	0.731	0.759	0.892	1.057	1.13	1.368	1.656
	P25	0.714	0.728	0.811	0.986	1.156	1.255	1.427	1.807
	P75	0.766	0.715	0.743	0.856	1.019	1.113	1.457	1.742

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.3.: Model 2: Odds ratio for a negative unit change in negative DI for Marsabit

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.875	1.581*	0.715	0.839	0.633	0.855	0.939	0.982
	Median	0.899	1.59**	0.745	0.888	0.621*	0.8	0.915	0.974
	P25	0.975	1.972**	1.191	0.98	0.763	0.934	1.197	0.869**
	P75	0.854	1.546*	0.613**	0.718	0.519**	0.68	0.857	0.997
SPI-3	Mean	1.339	1.147	0.643**	0.771**	1.07	0.847	1.117	1.504**
	Median	1.336	1.222	0.669*	0.707**	1.033	0.826	1.141	1.615**
	P25	1.637**	1.2	0.818	0.797**	1.276	0.887**	0.997	1.144
	P75	0.983	0.607*	0.324*	0.643**	1.047	0.629	1.017	1.645**
SPI-6	Mean	1.028	1.223	0.949	1.172*	1.907*	1.465*	1.491	1.237
	Median	1.068	1.089	0.853**	1.174*	1.933*	1.449*	1.456	1.154
	P25	1.174	1.53*	1.377*	1.115	1.562	1.175	1.254	0.927
	P75	0.686	1.044	0.708	1.197*	1.824**	1.48***	1.747**	1.99**
SPI-12	Mean	2.309**	1.733	1.6*	1.912	2.121**	2.053*	1.655	1.78
	Median	2.289**	1.798	1.64	2.139	1.918**	1.983**	1.787	2.141
	P25	1.843*	1.39	1.424	1.924	1.61*	1.761**	1.714	1.89
	P75	2.441**	1.8*	1.237**	1.223	2.445**	2.301*	1.999	1.96
SPEI-1	Mean	0.953	2.339**	0.739**	1.35	1.361	0.94	1.435*	0.98
	Median	1.013	2.206**	0.817*	1.353	1.308	0.883	1.349	0.982
	P25	1.069	2.304***	0.917	1.293	1.29	0.808**	1.179	0.78**
	P75	0.811	1.914**	0.528**	1.202	1.195	0.945	1.328	1.001
SPEI-3	Mean	1.302	1.092	0.797	1.099	1.229	1.043	1.086	1.073
	Median	1.299	1.139	0.836	1.048	1.237	0.994	1.077	1.063
	P25	1.287	1.129	1.017	1.068	1.138	0.829*	0.865	0.855
	P75	1.191	0.72*	0.405**	1.049	1.175	1.176	1.175	1.219
SPEI-6	Mean	1.088	1.142	0.983	1.25	1.363	1.271*	1.227	1.064
	Median	1.18	1.137	0.979	1.307	1.377	1.212	1.115	0.959
	P25	1.165	1.214	1.049	1.106	1.146	0.991	0.963	0.847
	P75	0.637**	0.827	0.721***	1.064	1.259*	1.319*	1.356**	1.272*
SPEI-12	Mean	1.158	1.059	1.062	1.366	1.269	1.221	1.042	1.101
	Median	1.176	1.081	1.052	1.406	1.152	1.117	0.98	1.137
	P25	1.073	1.054	1.121	1.348	1.158	1.129	1.028	1.212
	P75	1.198	0.923	0.891	1.199	1.255	1.252	1.15	1.18

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

Table E.4.: Model 2: Odds ratio for a negative unit change in negative DI for Turkana

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	1.705**	0.984	1.067	1.233	0.87	0.973	1.432	2.242***
	Median	1.724**	1.006	1.049	1.186	0.836	0.979	1.4	2.213***
	P25	1.578***	1.042	1.044	1.166	0.89	1.007	1.233	1.964***
	P75	1.761*	0.866	1.124	1.31	0.871	0.894	1.767**	2.696***
SPI-3	Mean	1.152	1.089	0.928	0.916	1.32	1.983**	1.239	1.319
	Median	1.16	1.1	0.902	0.888*	1.287	1.987**	1.182	1.287
	P25	1.211	1.087	0.925	0.945	1.165	1.67*	1.101	1.235
	P75	1.047	0.945	0.928	0.963	1.466**	2.434**	1.51*	1.426*
SPI-6	Mean	1.038	1.072	1.577**	1.767**	1.697**	1.791**	1.712*	1.816*
	Median	1.063	1.063	1.554**	1.756**	1.642**	1.746**	1.601*	1.782*
	P25	1.081	1.025	1.456**	1.405*	1.366*	1.576**	1.732*	1.897*
	P75	0.921	1.084	1.811**	2.585**	2.327**	1.764**	1.496*	1.644*
SPI-12	Mean	1.566*	1.772*	2.589**	2.36	2.109	2.817	2.296	2.605
	Median	1.605**	1.824**	2.633**	2.313*	1.815	2.324	1.973	2.343
	P25	1.289	1.501	1.959*	2.054	1.849	2.536*	2.332	2.127
	P75	1.949***	2.13**	3.455**	3.426**	2.403	2.299	1.704	3.159*
SPEI-1	Mean	1.303*	1.332	1.012	0.927	0.837	1.141	1.212	1.749**
	Median	1.299	1.379	0.993	0.885	0.819	1.142	1.166	1.709**
	P25	1.31**	1.337	1.007	0.993	0.871	1.163	1.172	1.624**
	P75	1.292	1.335	0.976	0.807	0.803	1.088	1.271	1.874**
SPEI-3	Mean	1.144	1.122	0.873	0.894	1.247	1.566*	1.007	1.176
	Median	1.177	1.128	0.867	0.897	1.248	1.555*	0.967	1.152
	P25	1.252*	1.1	0.907	0.948	1.125	1.392	0.934	1.119
	P75	1.022	1.117	0.84*	0.881	1.306	1.774*	1.107	1.212
SPEI-6	Mean	1.012	1.024	1.241*	1.329*	1.309*	1.485*	1.494*	1.631*
	Median	1.033	1.029	1.255*	1.315*	1.299*	1.464*	1.475*	1.615*
	P25	1.093	1.027	1.221*	1.204	1.171	1.374*	1.465*	1.622**
	P75	0.917	1.012	1.221	1.491**	1.402*	1.516*	1.436	1.49
SPEI-12	Mean	1.144	1.192	1.596	1.72	1.732	2.09*	1.727	1.76
	Median	1.168	1.253	1.605	1.702	1.648	1.969*	1.674	1.748
	P25	1.093	1.21	1.473	1.616	1.589	1.961*	1.636	1.527
	P75	1.155	1.224	1.634*	1.777	1.793	2.021*	1.558	1.975*

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.5.: Model 2: Odds ratio for a negative unit change in negative DI for West Pokot

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.915	0.296**	0.788	1.013	0.416**	1.633*	0.003**	0.344**
	Median	0.889	0.308**	0.766	0.971	0.439**	1.592*	0.001**	0.4**
	P25	0.982	0.447*	0.743	0.935	0.422**	1.503*	0.028**	0.393***
	P75	0.848	0.268**	0.841	0.971	0.356*	1.629	0.0***	0.283**
SPI-3	Mean	0.552	0.867	0.819	1.114	0.251**	0.267*	0.177***	0.354**
	Median	0.583	0.825	0.815	1.081	0.227**	0.281*	0.164***	0.359**
	P25	0.914	0.825	0.755	0.986	0.314*	0.299*	0.161***	0.302**
	P75	0.333	0.821	0.874	1.133	0.16**	0.253*	0.22**	0.434*
SPI-6	Mean	0.826	0.502*	0.387**	0.176*	0.282**	0.13*	0.023**	0.057*
	Median	0.77	0.489*	0.443*	0.185*	0.302**	0.197	0.029**	0.066*
	P25	0.855	0.59	0.482*	0.27*	0.405*	0.213*	0.037**	0.065**
	P75	0.712	0.337**	0.33**	0.021**	0.312**	0.051*	0.0*	0.013*
SPI-12	Mean	0.048	0.027*	0.008**	0.0***	0.034*	0.371	0.735	1.052
	Median	0.059*	0.034*	0.039*	0.0***	0.027**	0.299	0.713	1.118
	P25	0.1*	0.141*	0.109*	0.0*	0.144**	0.499	0.745	0.931
	P75	0.008	0.0***	0.0***	0.0***	0.0*	0.157	0.573	0.993
SPEI-1	Mean	0.908	0.557*	0.729	1.224	0.685	1.437	0.097**	0.419*
	Median	0.89	0.606*	0.68	1.195	0.708	1.493*	0.049**	0.508*
	P25	1.037	0.717	0.644	0.962	0.584	1.412**	0.161*	0.369
	P75	0.852	0.481	0.734	1.302	0.745	1.416	0.037**	0.39**
SPEI-3	Mean	0.737	0.985	0.792	1.17	0.305***	0.399**	0.269*	0.297*
	Median	0.762	0.971	0.776	1.099	0.307**	0.41**	0.259*	0.299*
	P25	1.057	0.935	0.826	0.97	0.34**	0.423**	0.227*	0.23*
	P75	0.57	0.965	0.825	1.313	0.251***	0.375**	0.324**	0.384*
SPEI-6	Mean	0.936	0.556**	0.339***	0.259*	0.262***	0.223*	0.12**	0.129**
	Median	0.913	0.534**	0.358**	0.261*	0.308***	0.252*	0.138**	0.16**
	P25	0.95	0.637*	0.442**	0.304*	0.354**	0.247**	0.113***	0.112***
	P75	0.871	0.498**	0.314***	0.15*	0.313***	0.158*	0.051**	0.075*
SPEI-12	Mean	0.04*	0.014**	0.026**	0.0***	0.098*	0.449	0.768	0.969
	Median	0.055*	0.015**	0.036**	0.0***	0.098*	0.408	0.739	0.994
	P25	0.134*	0.068**	0.062**	0.0**	0.178*	0.512	0.687	0.798
	P75	0.0*	0.0*	0.0*	0.0***	0.01*	0.314	0.784	1.09

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^*p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.6.: Model 2: Odds ratio for a positive unit change in positive DI for Marsabit

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.601**	0.389**	0.786	1.103*	0.861	1.149**	1.022	1.416
	Median	0.555**	0.413**	0.908	0.976	0.799	1.209**	1.105	1.427*
	P25	0.405**	0.234***	0.634	1.19**	0.709	1.416**	1.397	1.801*
	P75	0.742*	0.614**	1.051	1.051	1.022	1.048	0.993	1.124**
SPI-3	Mean	0.508**	0.714*	0.849*	1.243**	0.989	1.387	1.358	1.094
	Median	0.522**	0.658*	0.787*	1.176**	0.939	1.323	1.368	1.072
	P25	0.436**	0.538*	0.72**	1.243**	1.033	1.551	1.772	1.379
	P75	0.616*	0.717*	0.927	1.142	1.053	1.271	1.101	0.906
SPI-6	Mean	0.69*	1.01	1.252	1.36	1.092	1.049	1.18	1.201
	Median	0.692*	0.994	1.249	1.383	1.065	0.995	1.147	1.17
	P25	0.811*	1.19	1.563	1.554	1.386	1.296	1.428	1.308
	P75	0.64	0.984	1.187	1.226	0.853*	0.835	0.995	1.132
SPI-12	Mean	0.988	1.133	1.245	1.365	1.69	2.28*	2.342**	2.383*
	Median	0.971	1.159	1.277	1.447	1.657	2.248**	2.352**	2.351*
	P25	1.136	1.349	1.577	2.041	2.282*	3.228**	3.182**	3.107*
	P75	0.839	0.971	1.04	1.038	1.313	1.803*	2.109**	2.1
SPEI-1	Mean	0.634	0.518**	0.847	1.078	1.19	1.397**	1.031	1.482*
	Median	0.646	0.558**	0.949	0.992	1.163	1.403**	1.041	1.301**
	P25	0.777	0.458**	0.542	1.345*	1.369	1.738**	1.142	1.714*
	P75	0.67	0.591**	1.071	0.938	1.017	1.137	0.831	1.106
SPEI-3	Mean	0.525**	0.507	0.822*	1.213	1.03	1.334	1.198	0.993
	Median	0.559**	0.516*	0.73**	1.038	0.985	1.203	1.147	0.935
	P25	0.487**	0.483	0.93	1.487*	1.397	1.781	1.449	1.196
	P75	0.608**	0.538**	0.808	0.982	0.827	1.025	0.932	0.843
SPEI-6	Mean	0.7*	0.913	1.167	1.281	1.068	1.152	1.247	1.288
	Median	0.703	0.934	1.17	1.251	1.024	1.105	1.217	1.266
	P25	0.895	1.128	1.513	1.668	1.459	1.392	1.434	1.372
	P75	0.547*	0.755	0.879	0.91	0.748**	0.833	0.958	1.146
SPEI-12	Mean	0.903	0.96	1.108	1.609	2.024*	2.676**	2.688*	3.0*
	Median	0.904	1.002	1.112	1.596	1.934*	2.627**	2.727**	2.952*
	P25	1.131	1.412	1.729	2.738	2.735*	3.552**	3.082*	3.634*
	P75	0.758*	0.761	0.899	1.156	1.525*	2.131**	2.755*	3.021*

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.7.: Model 2: Odds ratio for a positive unit change in positive DI for Turkana

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.668*	0.889	0.698	0.657*	1.383	0.703**	1.061	0.974
	Median	0.669*	0.896	0.711	0.667*	1.35*	0.697**	1.054	1.007
	P25	0.651	0.966	0.629	0.658*	1.423	0.661**	1.094	1.094
	P75	0.683**	0.839	0.75	0.665**	1.371*	0.738**	0.997	0.915**
SPI-3	Mean	0.609*	0.607*	0.763**	0.769	1.06	0.901**	1.018	0.755*
	Median	0.617*	0.614	0.766*	0.768	1.031	0.929*	1.02	0.773*
	P25	0.595*	0.609	0.759*	0.791	1.102	0.977	1.011	0.712*
	P75	0.632*	0.59*	0.765**	0.811	0.982	0.848**	1.034	0.801*
SPI-6	Mean	0.579**	0.732**	0.718**	0.926	0.857	0.69**	0.68**	0.536**
	Median	0.588*	0.736**	0.737**	0.919*	0.865	0.697**	0.685**	0.559**
	P25	0.541*	0.743*	0.771**	1.022	0.924	0.702**	0.718*	0.533**
	P75	0.607*	0.72**	0.687**	0.869*	0.824*	0.675**	0.688**	0.587**
SPI-12	Mean	0.514***	0.476**	0.444*	0.477*	0.567*	0.527*	0.673	0.876
	Median	0.526***	0.496**	0.466*	0.487*	0.569*	0.522*	0.665	0.859
	P25	0.394***	0.372	0.363	0.416	0.526*	0.501	0.712	0.896
	P75	0.596**	0.558***	0.513**	0.558**	0.621*	0.574*	0.732	0.91
SPEI-1	Mean	0.563*	0.779	0.701	0.64*	1.201	0.721**	0.941	0.9
	Median	0.574*	0.786	0.709	0.652*	1.184	0.723**	0.943	0.909
	P25	0.503	0.783	0.642	0.645	1.187	0.683**	0.878	0.907
	P75	0.622**	0.78	0.73	0.661**	1.212	0.746***	0.977	0.892
SPEI-3	Mean	0.508*	0.565*	0.682**	0.717	1.028	0.859**	0.907	0.76
	Median	0.516	0.566*	0.683**	0.702	0.992	0.878**	0.912	0.765*
	P25	0.489	0.555*	0.673**	0.747	1.015	0.857*	0.885	0.718*
	P75	0.546*	0.583*	0.694***	0.731*	0.985	0.867**	0.951	0.811
SPEI-6	Mean	0.504**	0.635***	0.679**	0.883	0.815*	0.688**	0.745	0.641*
	Median	0.515**	0.634***	0.679**	0.881	0.823*	0.696**	0.753	0.662*
	P25	0.478**	0.61**	0.666**	0.919	0.84*	0.706**	0.802	0.669
	P75	0.531**	0.647***	0.666**	0.837*	0.773**	0.668**	0.698*	0.63*
SPEI-12	Mean	0.526**	0.465***	0.482**	0.552**	0.661	0.641*	0.85	1.137
	Median	0.528**	0.47***	0.484**	0.553**	0.651	0.628*	0.825	1.117
	P25	0.444**	0.418**	0.447**	0.517*	0.624	0.617	0.815	1.141
	P75	0.577**	0.507**	0.506**	0.578*	0.676	0.676*	0.901	1.182

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.8.: Model 2: Odds ratio for a positive unit change in positive DI for West Pokot

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.472	0.542	1.292	1.148	0.588	0.977	1.655	4.255***
	Median	0.488	0.522	1.231	1.013	0.521	0.968	1.44	4.035***
	P25	0.441	0.385	1.346	1.065	0.271	1.217**	1.605	3.75**
	P75	0.569	0.799	1.265	1.083	0.741	0.77	1.477	3.474**
SPI-3	Mean	0.569	0.939	1.015	1.214	0.973	2.471*	4.316***	6.421***
	Median	0.535	0.786	0.798*	1.188	1.002	2.434*	3.967**	6.592***
	P25	0.6	0.822	0.802**	1.042	0.799**	2.815*	4.641***	6.957**
	P75	0.697	0.823	0.976	1.208	1.095	2.059*	3.725**	5.406***
SPI-6	Mean	0.786	1.068	1.798	2.33	2.876*	4.394*	5.112*	5.05*
	Median	0.692	0.965	1.571	2.065	2.799	4.552**	4.93**	4.962*
	P25	0.696	0.857	1.565	2.425	3.517**	5.675**	6.209**	6.085*
	P75	0.84	1.095	1.741*	2.083*	2.562	3.399*	4.15*	3.919*
SPI-12	Mean	1.891	2.119	2.025	1.931	2.098	2.045	2.434	2.563
	Median	1.88	2.143	1.997	1.888	2.049	2.074	2.39	2.398
	P25	1.87	2.201	2.227	1.88	2.301	2.731	3.216	3.157
	P75	1.807	1.988	1.959	1.878	1.979	1.919	2.305	2.288
SPEI-1	Mean	0.475	0.587	1.233	1.03	0.745	0.922	1.614	3.992***
	Median	0.491	0.527	1.198	0.943	0.656	0.884	1.521	3.609***
	P25	0.42	0.399	1.042	0.757	0.398	1.089	1.878*	4.03**
	P75	0.576	0.794	1.242	1.116	0.918	0.817	1.469	3.035***
SPEI-3	Mean	0.667	0.933	0.931	1.139	1.018	2.455*	4.691**	6.216**
	Median	0.586	0.734	0.767*	1.046	1.058	2.35*	4.317***	6.301**
	P25	0.704	0.823	0.767**	1.013	0.822	2.558	4.653***	6.322**
	P75	0.72	0.914	0.965	1.166	1.136	2.114*	3.924**	4.705**
SPEI-6	Mean	0.774	1.002	1.573	2.272	2.934*	4.424*	5.341*	5.089*
	Median	0.614	0.837	1.355	2.056	2.635	4.137*	5.212**	4.878*
	P25	0.705	0.871	1.357	2.282	3.168*	4.84*	5.804**	5.801*
	P75	0.754	1.061	1.599	1.967*	2.617*	3.769*	4.374*	4.136*
SPEI-12	Mean	1.872	1.923	2.058	1.987	2.359	2.302*	2.989*	3.281
	Median	1.888	1.892	1.875	1.825	2.155	2.209*	2.795*	3.03
	P25	1.855	1.877	2.04	1.982	2.612	2.879*	3.342	3.755
	P75	1.9	1.918	1.935	2.002	2.234	2.247**	3.014**	3.222*

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.9.: Model 3: Odds ratio for a negative unit change in negative DI

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	1.356*	1.235**	0.864	0.887	0.88	1.023	1.356***	1.431**
	Median	1.38**	1.238**	0.867	0.877	0.858	0.994	1.328**	1.398**
	P25	1.314*	1.284**	0.94	0.946	0.906	1.058	1.282**	1.378**
	P75	1.374*	1.169	0.783	0.824	0.828	0.931	1.409***	1.438*
SPI-3	Mean	1.403**	1.055	0.795	1.018	1.26	1.437	1.346	1.495*
	Median	1.394**	1.048	0.796	1.007	1.22	1.406	1.337*	1.454*
	P25	1.336**	1.032	0.843	1.048	1.215	1.339	1.236*	1.411*
	P75	1.42	0.992	0.717	0.974	1.246	1.554	1.449	1.526*
SPI-6	Mean	1.153	1.228	1.224**	1.357**	1.622	1.504	1.437	1.284
	Median	1.166	1.214	1.213**	1.376**	1.605	1.498	1.385	1.249
	P25	1.155	1.224	1.244***	1.309**	1.504	1.423	1.381	1.222
	P75	1.1	1.188	1.15	1.283	1.537	1.419	1.397	1.376
SPI-12	Mean	1.342	1.232	1.382	1.682	1.893	2.373**	1.736	1.662
	Median	1.311	1.186	1.351	1.658	1.748	2.161**	1.602	1.61
	P25	1.234	1.145	1.375	1.68	1.864*	2.346**	1.816*	1.675
	P75	1.271	1.145	1.133	1.325	1.524	1.86	1.533	1.557
SPEI-1	Mean	1.243	1.486**	0.88	1.047	0.969	1.133	1.407***	1.379**
	Median	1.256	1.442**	0.903	1.034	0.953	1.101	1.352***	1.388**
	P25	1.213	1.436**	0.894	1.084	1.007	1.101	1.322***	1.237
	P75	1.262	1.453**	0.84	0.924	0.904	1.104	1.404***	1.456**
SPEI-3	Mean	1.324**	1.062	0.838	1.071	1.254*	1.417**	1.333*	1.379**
	Median	1.317**	1.061	0.856	1.071	1.229*	1.384**	1.314*	1.353**
	P25	1.241*	1.03	0.888	1.066	1.203**	1.32**	1.244**	1.304**
	P75	1.374*	1.061	0.771	1.042	1.228	1.471**	1.345*	1.397**
SPEI-6	Mean	1.149	1.218	1.169	1.309**	1.441*	1.367*	1.308*	1.22
	Median	1.146	1.208	1.161	1.316**	1.447**	1.358*	1.284*	1.193
	P25	1.13	1.212	1.168*	1.27**	1.383**	1.335**	1.281**	1.228
	P75	1.113	1.176	1.099	1.249**	1.369*	1.292	1.239	1.198
SPEI-12	Mean	1.183	1.075	1.207	1.45	1.612**	1.852**	1.493	1.372
	Median	1.163	1.066	1.182	1.431	1.531*	1.77**	1.421	1.345
	P25	1.166*	1.108	1.273	1.524*	1.621**	1.894***	1.585*	1.442
	P75	1.189	1.005	1.03	1.193	1.423	1.585**	1.277	1.211

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.10.: Model 3: Odds ratio for a positive unit change in positive DI

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.643***	0.896	0.94	0.857	0.934	0.675**	0.904	0.973
	Median	0.636***	0.917	0.962	0.858	0.924	0.697**	0.901	0.976
	P25	0.561***	0.915	0.889	0.845	0.902	0.642*	0.95	1.05
	P75	0.687**	0.897	0.976	0.899	0.959	0.707**	0.87*	0.928
SPI-3	Mean	0.783**	0.926	0.896	0.808*	0.817**	0.878	0.896	0.836
	Median	0.793*	0.915	0.89	0.801*	0.812**	0.883	0.902	0.823
	P25	0.753***	0.91	0.853	0.79*	0.801*	0.877	0.902	0.877
	P75	0.792*	0.888	0.926	0.811*	0.824**	0.873	0.891*	0.819
SPI-6	Mean	0.757*	0.861	0.847	0.852	0.823	0.752*	0.811	0.815
	Median	0.768	0.878	0.871	0.864	0.831	0.749*	0.815	0.81
	P25	0.753	0.883	0.835	0.843	0.839	0.764	0.827	0.822
	P75	0.755*	0.842	0.845	0.849	0.791*	0.734**	0.804*	0.826
SPI-12	Mean	0.662**	0.733**	0.652**	0.619**	0.637**	0.643*	0.726*	0.833
	Median	0.665**	0.743**	0.664**	0.63**	0.643**	0.652*	0.735*	0.839
	P25	0.572**	0.658**	0.625**	0.624**	0.677*	0.736	0.838	0.932
	P75	0.711**	0.762**	0.679**	0.646***	0.636***	0.618**	0.736*	0.82
SPEI-1	Mean	0.626***	0.929	0.94	0.866	0.998	0.745*	0.828***	0.973
	Median	0.64***	0.934	0.969	0.87	0.996	0.762*	0.838***	0.964
	P25	0.568***	0.955	0.843*	0.894	0.977	0.753	0.851**	0.984
	P75	0.681**	0.909	0.994	0.859	1.017	0.749**	0.826***	0.925
SPEI-3	Mean	0.774**	0.836*	0.875	0.845	0.855*	0.842**	0.823*	0.808
	Median	0.788*	0.835*	0.868	0.839	0.861	0.857*	0.835	0.806
	P25	0.748**	0.814*	0.873	0.867	0.878	0.871	0.818	0.819
	P75	0.777**	0.835*	0.867	0.811**	0.814**	0.819**	0.811*	0.803
SPEI-6	Mean	0.723*	0.826	0.82	0.814	0.776	0.718*	0.75*	0.776
	Median	0.73*	0.841	0.838	0.818	0.788	0.731*	0.757*	0.782
	P25	0.731*	0.864	0.831	0.807	0.782	0.715*	0.765*	0.785
	P75	0.689**	0.779**	0.782**	0.786*	0.735**	0.702**	0.736*	0.784
SPEI-12	Mean	0.646**	0.661**	0.611***	0.61**	0.623**	0.629**	0.673**	0.812
	Median	0.654**	0.663**	0.613***	0.612**	0.621**	0.633**	0.67**	0.806*
	P25	0.607**	0.638**	0.609**	0.641*	0.647**	0.7	0.744	0.919
	P75	0.68**	0.675**	0.621***	0.6***	0.603***	0.581***	0.644**	0.763**

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.11.: Model 4: Odds ratio for a negative unit change in negative DI for Borana people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.856	1.075	1.228**	0.445***	0.81	1.381***	1.643***	1.282**
	Median	0.851	1.038	1.139	0.426***	0.729	1.251**	1.535***	1.17*
	P25	0.779*	1.197**	1.251***	0.632***	0.883	1.296***	1.47***	1.256**
	P75	0.921	0.773***	1.077	0.282***	0.708	1.23	1.595***	1.211**
SPI-3	Mean	1.33*	0.915	0.556**	1.016	2.348***	1.656***	1.793***	1.606***
	Median	1.224	0.875	0.527**	0.974	2.149***	1.506***	1.635***	1.5***
	P25	1.031	0.873	0.682*	1.118	1.872***	1.484***	1.401***	1.556***
	P75	1.704**	0.89	0.463***	0.594**	2.291***	1.892***	2.116***	1.76***
SPI-6	Mean	0.769	1.593*	1.485*	1.729**	3.08***	2.493***	2.102***	1.391
	Median	0.74	1.539*	1.429	1.662**	2.829***	2.318***	1.874***	1.274
	P25	0.862	1.5**	1.498**	1.74**	2.434***	2.065***	1.537***	1.151
	P75	0.623*	1.463	1.238	1.503*	2.885***	2.61***	2.528***	1.904**
SPI-12	Mean	1.236	1.417*	1.657**	2.479***	2.564***	3.302***	2.546***	2.726***
	Median	1.169	1.326	1.547*	2.381***	2.359***	3.127***	2.532***	2.821***
	P25	1.091	1.247	1.477**	2.175***	2.324***	2.999***	2.228***	2.144***
	P75	1.062	1.195	1.32	1.961**	2.087**	2.766***	2.769***	2.931***
SPEI-1	Mean	0.712***	1.235**	0.988	0.952	0.987	1.398***	1.288**	1.199***
	Median	0.676***	1.093	0.939	0.927	0.997	1.241***	1.16	1.161*
	P25	0.679***	1.242**	0.904*	1.067	1.082	1.14***	1.232*	1.052
	P75	0.744***	1.049	1.094	0.63***	0.987	1.317***	1.174	1.411***
SPEI-3	Mean	0.916	0.77*	0.668*	1.155	1.547**	1.334***	1.47***	1.111
	Median	0.833	0.703**	0.664*	1.173	1.362*	1.221**	1.299**	1.079
	P25	0.761*	0.83	0.776*	1.114	1.325**	1.302***	1.246*	1.086
	P75	1.253*	0.782*	0.601**	0.947	1.558**	1.263**	1.405**	1.068
SPEI-6	Mean	0.793	1.239	1.154	1.268	1.782***	1.485***	1.222	0.982
	Median	0.754	1.178	1.107	1.242	1.728***	1.446***	1.177	0.984
	P25	0.771	1.189	1.109	1.299*	1.525***	1.343***	1.103	1.061
	P75	0.723*	1.201	0.972	1.061	1.684***	1.395**	1.202	1.026
SPEI-12	Mean	0.966	1.086	1.196	1.66**	1.62**	1.905***	1.6**	1.674***
	Median	0.923	1.044	1.122	1.609**	1.558**	1.832***	1.556**	1.687***
	P25	0.943	1.107	1.29**	1.718***	1.729***	1.989***	1.696***	1.627***
	P75	0.918	0.914	0.904	1.067	1.065	1.338	1.249	1.406

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.12.: Model 4: Odds ratio for a negative unit change in negative DI for Dassanetch people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	2.423***	1.391**	0.462***	1.254	1.478	1.649**	1.524*	2.05**
	Median	2.564***	1.401**	0.474***	1.222	1.507	1.737**	1.562*	1.983**
	P25	2.252***	1.48**	0.549***	1.242	1.438	1.705**	1.434*	1.862**
	P75	2.664***	1.3	0.389***	1.243	1.552	1.482***	1.627*	2.173**
SPI-3	Mean	1.051	0.632	1.037	1.776*	1.624	2.61***	1.491	1.898**
	Median	1.062	0.605	1.054	1.772*	1.613*	2.594***	1.532	1.886**
	P25	1.038	0.647	1.026	1.714*	1.53	2.17***	1.402	1.774**
	P75	1.049	0.627	0.992	1.82*	1.751*	2.956***	1.767*	1.947***
SPI-6	Mean	1.378	0.82	1.441	1.79	1.95	2.553***	2.303**	1.523***
	Median	1.487	0.846	1.442	1.894*	1.969	2.536***	2.235**	1.508**
	P25	1.255	0.858	1.279	1.68	1.812	2.097**	1.848*	1.299**
	P75	1.399	0.805	1.643	1.947	2.148*	2.98***	2.513**	1.723***
SPI-12	Mean	2.441**	1.793	2.301*	2.077*	1.931*	2.151***	0.893	0.711**
	Median	2.51**	1.839	2.265*	2.115*	1.929*	2.048***	0.895	0.702**
	P25	2.039*	1.563	1.862	1.663	1.76*	2.175**	1.074	0.949
	P75	2.632**	1.802	2.691**	2.112*	1.897	2.174***	0.714*	0.593**
SPEI-1	Mean	1.934***	1.5***	0.575**	0.973	1.592*	1.973***	1.25	1.311
	Median	1.953***	1.506***	0.607**	0.982	1.61*	2.007***	1.262	1.3
	P25	1.832***	1.527***	0.613***	1.004	1.561*	1.943***	1.239	1.305
	P75	2.048***	1.441**	0.567*	0.968	1.658*	1.999***	1.29	1.315
SPEI-3	Mean	1.226**	0.929	1.065	1.631	1.548	1.914**	1.341	1.434*
	Median	1.257**	0.934	1.091	1.626	1.562	1.923**	1.35	1.442*
	P25	1.2**	0.897	1.087	1.643*	1.542	1.791*	1.362	1.477**
	P75	1.272**	0.955	1.004	1.598	1.589	2.055**	1.315	1.368
SPEI-6	Mean	1.439	1.092	1.29	1.574	1.665	1.861*	1.804*	1.458*
	Median	1.412	1.106	1.307	1.561	1.682	1.872*	1.823*	1.462*
	P25	1.473	1.147	1.28	1.559	1.66	1.786*	1.709*	1.376*
	P75	1.39	1.036	1.296	1.587	1.658	1.884*	1.812*	1.511*
SPEI-12	Mean	1.989	1.501	1.845	1.861	1.734	1.792	1.008	0.933
	Median	1.98*	1.53	1.816	1.828	1.694	1.722	0.977	0.924
	P25	1.919*	1.496	1.769	1.819	1.801	1.959	1.145	1.056
	P75	1.937	1.44	1.782	1.782	1.557	1.489	0.822	0.781*

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: *$p < 0.1$, **$p < 0.05$ and ***$p < 0.01$.

Table E.13.: Model 4: Odds ratio for a negative unit change in negative DI for Gabra people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.928	1.483***	0.694***	0.858*	0.726*	1.332***	1.36**	1.151
	Median	0.96	1.511***	0.732***	0.908*	0.749*	1.277**	1.36**	1.153
	P25	0.952	1.802***	1.007	1.05	0.895	1.349***	1.372**	1.132
	P75	0.849	1.273***	0.653***	0.744**	0.509**	1.072	1.323***	1.0
SPI-3	Mean	1.364**	1.506***	0.803	1.33**	1.942***	1.556**	2.098***	2.421***
	Median	1.347**	1.499***	0.823	1.287**	1.856***	1.489**	2.037***	2.38***
	P25	1.406**	1.308*	0.954	1.311**	1.851***	1.442***	1.676***	2.053***
	P75	1.264**	1.217*	0.515***	1.237*	2.08***	1.508*	1.981***	2.237***
SPI-6	Mean	1.077	1.756**	1.264	2.143***	3.542***	2.734***	2.312***	1.866***
	Median	1.125	1.62**	1.134	2.222***	3.607***	2.858***	2.382***	1.88***
	P25	1.158	1.869***	1.605**	2.065***	3.061***	2.418***	2.252***	1.598**
	P75	0.833	1.543**	0.933	1.851***	3.114**	2.531***	2.231***	2.386***
SPI-12	Mean	2.527***	2.306***	2.447**	3.827**	4.388***	3.96***	2.5***	2.503***
	Median	2.288***	2.095***	2.265**	3.721**	3.879***	3.37***	2.19***	2.561***
	P25	2.17***	2.009***	2.727***	4.256***	4.031***	3.528***	2.735***	2.564***
	P75	1.927**	1.672**	1.351**	2.111**	3.53***	3.746***	2.375***	2.521***
SPEI-1	Mean	0.942	2.335***	1.033	1.614***	1.316	1.347***	1.923***	1.399**
	Median	1.001	2.307***	1.103	1.588***	1.282	1.286***	1.832***	1.401**
	P25	0.963	2.215***	1.06	1.455***	1.328*	1.143**	1.563***	1.161*
	P75	0.927	1.844***	1.006	1.444***	1.151	1.426***	1.785***	1.388*
SPEI-3	Mean	1.569***	1.642***	1.13	1.473***	1.712***	1.576***	2.043***	1.771***
	Median	1.581***	1.639***	1.132	1.396***	1.679***	1.537***	2.034***	1.701***
	P25	1.32**	1.41**	1.163	1.284**	1.48***	1.305***	1.646***	1.538**
	P75	1.732***	1.559***	0.897	1.677***	1.799***	1.704***	2.008***	1.727***
SPEI-6	Mean	1.381	1.612**	1.429*	1.988**	2.293**	1.818**	1.497	1.279
	Median	1.372	1.507*	1.3*	1.959**	2.25**	1.742**	1.42	1.185
	P25	1.299*	1.538**	1.391**	1.825**	2.021**	1.659**	1.409	1.261
	P75	1.144	1.436*	1.248*	1.733**	1.994**	1.607**	1.237	1.132
SPEI-12	Mean	1.666**	1.567**	1.676**	2.102**	2.069***	1.837***	1.332	1.244
	Median	1.613**	1.513**	1.642**	2.1**	1.9***	1.712***	1.257	1.271
	P25	1.505***	1.555**	1.87**	2.306**	1.986***	1.763***	1.444*	1.385*
	P75	1.768**	1.429**	1.332*	1.676*	2.012***	1.882***	1.288	1.235

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.14.: Model 4: Odds ratio for a negative unit change in negative DI for Pokot people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	1.14**	1.008	0.817***	0.97	1.019	0.829	1.08	1.051
	Median	1.171***	0.991	0.842**	0.944	0.985	0.804	1.027	1.052
	P25	1.223***	1.018	0.868***	1.029	0.967	0.837	1.035	1.05
	P75	1.067	1.002	0.724***	0.843**	1.029	0.847	1.125	1.014
SPI-3	Mean	1.024	1.002	0.961	1.109	0.914	0.831**	0.868	0.924
	Median	1.051	1.006	0.962	1.102	0.909	0.834**	0.899	0.92
	P25	1.114*	1.002	0.953	1.104	0.917	0.871*	0.914	0.911
	P75	0.912	0.967	0.893	1.146	0.927	0.825*	0.839	0.944
SPI-6	Mean	1.159	1.188	0.996	0.921	0.796*	0.701**	0.724**	0.716*
	Median	1.167	1.196	1.02	0.961	0.806*	0.708**	0.716**	0.711*
	P25	1.124	1.127	1.022	0.967	0.886	0.809*	0.845	0.805
	P75	1.239	1.289	0.952	0.771	0.682**	0.523***	0.62**	0.639**
SPI-12	Mean	0.675*	0.547**	0.548**	0.669	0.836	1.358	1.406	1.287
	Median	0.667*	0.502**	0.534**	0.637	0.783	1.206	1.249	1.162
	P25	0.778	0.658*	0.734	0.911	1.106	1.729*	1.601	1.388
	P75	0.675	0.479**	0.399**	0.425**	0.524*	0.808	1.005	1.131
SPEI-1	Mean	1.09*	1.097	0.829**	1.225***	1.179	0.835	1.239**	1.064
	Median	1.152***	1.075	0.879*	1.212***	1.108	0.817	1.164**	1.161**
	P25	1.199***	1.062	0.868**	1.295***	1.105	0.868	1.156**	0.939
	P75	1.018	1.197**	0.744***	1.097*	1.117	0.866	1.335**	1.112
SPEI-3	Mean	1.038	1.109*	1.107	1.281	1.074	0.94	0.901	1.003
	Median	1.073	1.129**	1.122*	1.272	1.058	0.932	0.926	1.001
	P25	1.129**	1.061	1.115*	1.243	1.03	0.936	0.937	0.978
	P75	0.908	1.109	1.061	1.296	1.073	0.918	0.903	1.047
SPEI-6	Mean	1.241	1.331	1.158	1.085	0.901	0.841*	0.86	0.842
	Median	1.255*	1.327	1.173	1.122	0.933	0.846*	0.848	0.844
	P25	1.185	1.232	1.146	1.083	0.979	0.915	0.977	0.926
	P75	1.333*	1.446*	1.153	1.027	0.813	0.701**	0.757*	0.801
SPEI-12	Mean	0.816	0.616**	0.715	0.827	1.125	1.679*	1.673	1.283
	Median	0.801	0.608**	0.705	0.799	1.041	1.54	1.53	1.179
	P25	0.937	0.748*	0.851	1.032	1.289	1.902**	1.744*	1.366
	P75	0.787	0.561**	0.554**	0.63	0.899	1.291	1.392	1.126

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.15.: Model 4: Odds ratio for a negative unit change in negative DI for Toposa people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	2.176***	1.529***	1.841	1.396***	0.586***	0.642**	1.594***	1.452***
	Median	2.181***	1.598***	1.807	1.457***	0.583***	0.602**	1.653***	1.448***
	P25	2.022***	1.582***	1.842	1.307***	0.675**	0.814	1.465**	1.329***
	P75	2.57***	1.448***	1.581	1.548***	0.434***	0.555***	1.66***	1.737***
SPI-3	Mean	3.443**	2.123	1.402	0.751***	1.248	1.675*	1.308***	1.343**
	Median	3.328**	2.15	1.434	0.78**	1.183	1.669*	1.37***	1.293**
	P25	2.973**	2.226*	1.275	0.839**	1.114	1.463	1.262**	1.361***
	P75	3.867***	1.813	1.485	0.681***	1.319	1.964**	1.493***	1.164
SPI-6	Mean	2.356	2.039	2.525	1.465*	1.908**	1.632**	1.57**	1.3
	Median	2.241	1.957	2.606	1.504**	1.908***	1.676**	1.499*	1.304
	P25	2.341*	1.989	1.929	1.254	1.548*	1.32**	1.349***	1.154
	P75	2.169	1.866	2.894	1.606**	2.078***	2.11*	1.733	1.59
SPI-12	Mean	2.201*	2.606***	2.087**	1.78**	1.106	1.009	0.577***	0.76
	Median	2.205**	2.594***	2.126**	1.868***	1.044	0.954	0.526***	0.767
	P25	1.766**	1.672*	1.447**	1.167	0.912	1.041	0.774	0.829
	P75	2.218*	3.693***	2.611*	2.403**	1.209	0.579***	0.714**	0.631*
SPEI-1	Mean	2.387***	1.489***	1.963	0.813***	0.426***	0.764	1.59***	1.38***
	Median	2.316***	1.422***	2.028	0.771***	0.434***	0.756	1.597***	1.394***
	P25	2.278***	1.506***	2.024	0.875**	0.458***	0.889	1.456***	1.248***
	P75	2.52***	1.475**	1.751	0.721***	0.412***	0.57	1.583*	1.581***
SPEI-3	Mean	2.815*	1.379	0.804	0.51**	0.899**	1.426**	1.286**	1.373***
	Median	2.743*	1.47	0.887	0.514**	0.872**	1.413***	1.304**	1.384***
	P25	2.861*	1.574	0.851	0.619**	0.92	1.4**	1.22*	1.359***
	P75	2.604**	1.25	0.816	0.369**	0.863	1.398***	1.3**	1.389***
SPEI-6	Mean	1.481	1.448	1.406	1.065*	1.396***	1.37***	1.23**	1.058
	Median	1.502	1.454	1.48	1.096*	1.387***	1.367***	1.203**	1.024
	P25	1.626	1.595	1.378	0.99	1.328**	1.274***	1.103*	1.076
	P75	1.336	1.239	1.295	1.065	1.543***	1.531***	1.351**	1.017
SPEI-12	Mean	1.269	1.408	1.139	1.165	1.03	0.964	0.776*	0.889
	Median	1.301	1.419	1.157	1.178	1.001	0.993	0.727**	0.904
	P25	1.297	1.253	1.095	0.997	0.882	0.964	0.96	1.009
	P75	1.288	1.526	1.136	1.215	1.142	0.885	0.607*	0.796*

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.16.: Model 4: Odds ratio for a negative unit change in negative DI for Turkana people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	1.545***	1.329***	0.738***	0.822***	0.744***	0.861**	1.371***	2.025***
	Median	1.54***	1.351***	0.744***	0.804***	0.727***	0.853**	1.35***	1.986***
	P25	1.506***	1.262***	0.757***	0.839***	0.775***	0.926*	1.283***	1.935***
	P75	1.437***	1.457***	0.727***	0.812***	0.7***	0.764***	1.527***	2.12***
SPI-3	Mean	1.671***	0.948	0.541***	0.686***	0.951	1.778***	1.538***	1.935***
	Median	1.682***	0.945	0.545***	0.687***	0.933	1.775***	1.497***	1.862***
	P25	1.511***	0.912	0.626***	0.746***	0.991	1.599***	1.337***	1.709***
	P75	1.795***	0.957	0.477***	0.683***	0.858*	2.114***	1.893***	2.19***
SPI-6	Mean	1.093	0.849	1.004	1.426**	1.75***	1.838***	1.882***	2.37***
	Median	1.122	0.861	1.004	1.384**	1.756***	1.878***	1.827***	2.269***
	P25	1.096	0.909	1.074	1.248*	1.504***	1.662***	1.827***	2.073***
	P75	1.007	0.766	0.919	1.688**	1.894***	1.896***	1.793***	2.593***
SPI-12	Mean	1.429*	1.359*	2.178***	2.438***	3.868***	4.9***	3.148***	2.613**
	Median	1.439*	1.444**	2.284***	2.512***	3.314***	4.402***	2.66***	2.345**
	P25	1.239*	1.215	1.781***	2.085***	2.746***	3.322***	2.558***	2.322**
	P75	1.613*	1.634*	2.466***	3.606***	5.892***	6.417***	3.101**	2.494**
SPEI-1	Mean	1.564***	1.634***	0.668***	0.791***	0.602***	0.95	1.36***	2.02***
	Median	1.592***	1.636***	0.67***	0.778***	0.594***	0.971	1.348***	1.97***
	P25	1.554***	1.492***	0.687***	0.822***	0.702***	1.053**	1.4***	1.906***
	P75	1.422***	1.86***	0.634***	0.757***	0.505***	0.884**	1.392***	2.061***
SPEI-3	Mean	1.451***	0.908	0.54***	0.684***	1.065*	1.758***	1.434***	1.82***
	Median	1.465***	0.906	0.555***	0.699***	1.08**	1.746***	1.405***	1.763***
	P25	1.385***	0.864**	0.602***	0.742***	1.115**	1.607***	1.333***	1.672***
	P75	1.517***	0.942	0.485***	0.648***	0.962	1.956***	1.599***	1.929***
SPEI-6	Mean	0.99	0.893	0.926	1.224**	1.439***	1.554***	1.739***	2.039***
	Median	1.006	0.919	0.942	1.209**	1.443***	1.569***	1.744***	1.957***
	P25	1.029	0.944	0.998	1.164*	1.366***	1.551***	1.688***	1.859***
	P75	0.974	0.857	0.886	1.28**	1.429***	1.567***	1.675***	2.023***
SPEI-12	Mean	1.218*	1.106	1.413**	1.708**	2.482***	3.166***	2.434**	2.033**
	Median	1.229*	1.152	1.407**	1.731**	2.399***	3.1***	2.323**	1.933**
	P25	1.176	1.123	1.371**	1.657**	2.104***	2.666***	2.129***	1.885**
	P75	1.21*	1.079	1.339**	1.685***	3.005***	3.5***	2.421**	1.949**

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.17.: Model 4: Odds ratio for a positive unit change in positive DI for Borana people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.975	1.073	1.169*	1.152*	1.121	0.854	0.789***	0.794***
	Median	1.002	1.14*	1.237**	1.206**	1.141	0.905	0.813***	0.782***
	P25	0.76**	1.222*	1.347**	1.172	1.121	1.134	0.953	0.814***
	P75	1.022	0.98	1.075	1.191**	1.114*	0.777**	0.719***	0.811***
SPI-3	Mean	1.155	1.373***	1.316***	1.19**	1.051	1.011	1.07	1.015
	Median	1.223	1.375***	1.345***	1.189**	1.055	1.004	1.079	0.973
	P25	0.965	1.452***	1.237**	1.178**	1.213**	1.082	1.184	1.179**
	P75	1.126	1.232**	1.333***	1.089	0.888	0.965	0.967	0.972
SPI-6	Mean	1.283**	1.357**	1.443**	1.509**	1.368**	1.234*	1.399**	1.375**
	Median	1.374***	1.419**	1.53***	1.56**	1.388**	1.266**	1.416**	1.365**
	P25	1.28**	1.552***	1.521***	1.692***	1.601***	1.382**	1.446**	1.41**
	P75	1.261**	1.177	1.337**	1.458**	1.157	1.103	1.238	1.36*
SPI-12	Mean	1.413	1.549*	1.456*	1.349	1.186	1.246*	1.237	1.535**
	Median	1.404	1.533*	1.457*	1.385	1.201	1.245	1.236	1.509**
	P25	1.37	1.588	1.612*	1.745*	1.539*	1.773**	1.782***	2.087***
	P75	1.314	1.38	1.281	1.151	1.025	1.023	1.079	1.256*
SPEI-1	Mean	1.219*	1.129	1.392***	1.255*	1.495***	1.14	0.772**	1.193
	Median	1.249**	1.151	1.557***	1.243**	1.521***	1.221**	0.841	1.192
	P25	1.01	1.174	1.301*	1.498**	1.577***	1.478**	1.002	1.27*
	P75	1.165**	1.057	1.381***	1.124	1.39***	0.931	0.76**	1.042
SPEI-3	Mean	1.334**	1.202*	1.462***	1.485***	1.223*	1.036	1.225	1.258**
	Median	1.478***	1.262**	1.49***	1.552***	1.282**	1.067	1.25	1.275**
	P25	1.227*	1.195*	1.462**	1.599***	1.537***	1.314**	1.437**	1.44***
	P75	1.273**	1.212**	1.427***	1.186*	0.899	0.852**	0.996	1.106
SPEI-6	Mean	1.322**	1.453***	1.538***	1.486**	1.409***	1.343***	1.442**	1.405***
	Median	1.395**	1.522***	1.634***	1.563***	1.431***	1.404***	1.447***	1.435***
	P25	1.36**	1.654***	1.629***	1.679***	1.653***	1.5***	1.534***	1.528***
	P75	1.163	1.219*	1.316**	1.35*	1.105	1.151	1.326	1.471**
SPEI-12	Mean	1.672**	1.685**	1.53**	1.59**	1.338*	1.419**	1.255	1.627**
	Median	1.708**	1.678**	1.557*	1.64**	1.379*	1.462**	1.248	1.651**
	P25	1.953**	2.062**	1.957**	2.407***	1.886***	2.07***	1.872***	2.247***
	P75	1.354	1.346	1.256	1.094	0.994	0.994	0.96	1.166

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.18.: Model 4: Odds ratio for a positive unit change in positive DI for Dassanetch people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.334***	0.961	1.058	0.867	0.72	0.261***	0.97	0.65**
	Median	0.327***	0.986	1.085	0.921	0.739	0.279***	0.983	0.645**
	P25	0.272***	0.981	1.063	0.853	0.704	0.195***	0.999	0.651*
	P75	0.364***	0.919	1.069	0.874	0.735	0.325***	0.962	0.627***
SPI-3	Mean	0.575*	0.888	0.84	0.534***	0.466*	0.522*	0.642***	0.716*
	Median	0.603*	0.897	0.852	0.551**	0.494*	0.54*	0.643***	0.716*
	P25	0.506*	0.891	0.87	0.524***	0.408*	0.504*	0.691**	0.806
	P75	0.632*	0.884	0.828	0.55**	0.545*	0.509**	0.671**	0.664**
SPI-6	Mean	0.451***	0.585**	0.46*	0.421*	0.472**	0.527**	0.474**	0.379**
	Median	0.464***	0.588**	0.464*	0.445*	0.481**	0.515**	0.457**	0.347**
	P25	0.424***	0.558**	0.424**	0.337**	0.443**	0.509**	0.427**	0.329**
	P75	0.507***	0.644*	0.478*	0.477*	0.497**	0.527***	0.456**	0.418**
SPI-12	Mean	0.235***	0.299***	0.216***	0.195***	0.195***	0.22***	0.34***	0.323***
	Median	0.242***	0.306***	0.222***	0.194***	0.185***	0.213***	0.342***	0.324***
	P25	0.182***	0.25***	0.158***	0.126***	0.135***	0.219***	0.327***	0.265***
	P75	0.28***	0.336***	0.275***	0.252***	0.24***	0.266***	0.395***	0.401**
SPEI-1	Mean	0.348***	0.954	0.798	0.689*	0.814	0.363***	0.866	0.547**
	Median	0.349***	0.957	0.815	0.714*	0.826	0.379***	0.868	0.537**
	P25	0.305***	1.005	0.734*	0.661*	0.808	0.356***	0.884	0.512**
	P75	0.379***	0.926	0.853	0.745	0.845	0.386***	0.87	0.569***
SPEI-3	Mean	0.543**	0.71**	0.727*	0.555**	0.537*	0.58*	0.524**	0.499***
	Median	0.554**	0.713**	0.734*	0.568**	0.541*	0.591*	0.532***	0.503***
	P25	0.486**	0.684**	0.735*	0.568**	0.475*	0.59	0.522**	0.479***
	P75	0.596**	0.724**	0.724*	0.559**	0.584	0.568*	0.528***	0.528***
SPEI-6	Mean	0.357***	0.469***	0.405**	0.358**	0.416**	0.435**	0.373***	0.316**
	Median	0.387***	0.493***	0.426*	0.376*	0.431**	0.448**	0.366***	0.312**
	P25	0.352***	0.482***	0.4**	0.318**	0.384**	0.438**	0.372**	0.284**
	P75	0.382***	0.498***	0.421*	0.412*	0.44**	0.43***	0.382***	0.35**
SPEI-12	Mean	0.232***	0.254***	0.252***	0.228***	0.19***	0.191***	0.256***	0.323***
	Median	0.231***	0.253***	0.255***	0.238***	0.195***	0.193***	0.255***	0.323***
	P25	0.195***	0.238***	0.241***	0.221***	0.18***	0.209***	0.254***	0.316***
	P75	0.267***	0.266***	0.265***	0.253***	0.207***	0.176***	0.262***	0.331***

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.19.: Model 4: Odds ratio for a positive unit change in positive DI for Gabra people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.659**	0.501**	1.067	0.81	0.585**	0.831***	1.135	0.9
	Median	0.6**	0.526*	1.133	0.699	0.588**	0.836***	1.101	0.9
	P25	0.417***	0.394*	1.028	0.811	0.427***	0.932	1.422	1.029
	P75	0.748**	0.678***	1.228	0.921	0.722**	0.764***	1.045	0.816
SPI-3	Mean	0.794*	0.964	0.91	0.831**	0.813*	1.042	0.971	0.626***
	Median	0.816	0.952	0.912	0.809**	0.731***	0.964	0.946	0.608***
	P25	0.704**	0.833	0.819	0.81**	0.794*	1.094	1.158	0.802*
	P75	0.863	0.916	0.965	0.836**	0.841**	0.979	0.813**	0.559***
SPI-6	Mean	0.7	1.021	1.054	0.865	0.65***	0.548***	0.619**	0.591
	Median	0.739	1.044	1.058	0.876	0.632***	0.53***	0.634**	0.591
	P25	0.784	1.188	1.28*	1.005	0.788	0.649***	0.733***	0.618
	P75	0.661*	0.963	0.989	0.784**	0.573**	0.519***	0.63**	0.631
SPI-12	Mean	0.649**	0.703**	0.66**	0.592	0.713	1.025	1.073	1.099
	Median	0.649**	0.722**	0.703**	0.64	0.725	1.039	1.089	1.09
	P25	0.684*	0.77	0.869	0.902	0.994	1.415**	1.388*	1.337
	P75	0.558***	0.616**	0.584**	0.472	0.593*	0.856	1.049	1.044
SPEI-1	Mean	0.621*	0.684*	1.188	0.899	0.628**	0.896	0.871	0.872**
	Median	0.663**	0.736	1.276*	0.843	0.662***	0.944	0.907	0.789***
	P25	0.585	0.659**	1.093	1.038	0.555**	1.167	1.002	1.034
	P75	0.726**	0.695*	1.233*	0.793	0.702***	0.755***	0.738***	0.75***
SPEI-3	Mean	0.858	0.825	0.889	0.798**	0.684***	0.789*	0.697**	0.511***
	Median	0.913	0.881	0.87	0.747***	0.663***	0.767**	0.709**	0.532***
	P25	0.785	0.873	0.989	0.893	0.833	1.033	0.821	0.632***
	P75	0.864	0.745	0.81	0.729***	0.6***	0.673***	0.575***	0.49***
SPEI-6	Mean	0.695	0.892	0.974	0.71**	0.538***	0.471***	0.489**	0.48
	Median	0.735	0.927	0.944	0.661**	0.525***	0.468***	0.491**	0.481
	P25	0.875	1.133	1.26*	0.928	0.702**	0.565***	0.621***	0.577
	P75	0.534*	0.721	0.732	0.539**	0.414**	0.42***	0.443**	0.491*
SPEI-12	Mean	0.528**	0.494***	0.467**	0.521	0.641**	0.919	0.882	0.974
	Median	0.553**	0.515***	0.481**	0.545	0.649**	0.967	0.901	0.956
	P25	0.699	0.736	0.81	1.01	0.95	1.353	1.182	1.294
	P75	0.449***	0.41***	0.404***	0.416*	0.537**	0.737*	0.864	0.978

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.20.: Model 4: Odds ratio for a positive unit change in positive DI for Pokot people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.674***	1.102	0.829***	0.675***	0.957	0.88**	0.862*	1.859***
	Median	0.661***	1.167*	0.847***	0.707***	0.923	0.916	0.84*	1.861***
	P25	0.66***	1.111	0.717***	0.659***	0.97	0.788***	0.812**	2.109***
	P75	0.696***	1.098	0.861***	0.679***	0.907	0.903	0.878	1.627***
SPI-3	Mean	0.773***	0.845***	0.856*	0.821**	0.832*	1.082	1.085	1.277*
	Median	0.74***	0.823***	0.823*	0.786**	0.841	1.127	1.118**	1.281*
	P25	0.791***	0.81***	0.865*	0.829**	0.806**	1.064	1.049	1.285
	P75	0.776***	0.83***	0.81*	0.784**	0.864	1.096	1.142***	1.265**
SPI-6	Mean	0.875***	0.868**	0.906**	0.898	0.934	0.912	0.885	0.983
	Median	0.851**	0.883*	0.928	0.901**	0.956	0.895	0.893	0.981
	P25	0.902**	0.854***	0.859**	0.827	0.915	0.915	0.905	1.003
	P75	0.871**	0.85*	0.911	0.878***	0.959	0.893	0.913	0.976
SPI-12	Mean	0.754**	0.803*	0.691**	0.64***	0.722*	0.693*	0.769	0.87
	Median	0.758**	0.816*	0.693***	0.641***	0.728*	0.707*	0.778	0.88
	P25	0.675***	0.697***	0.653***	0.59***	0.759	0.786	0.863	0.98
	P75	0.855	0.874	0.758**	0.708**	0.736*	0.661**	0.763	0.857
SPEI-1	Mean	0.703***	1.098	0.868***	0.717***	0.993	0.941	0.837*	1.704***
	Median	0.71***	1.128*	0.877***	0.75***	0.981	0.927	0.828*	1.69***
	P25	0.672***	1.128*	0.766***	0.717***	1.015	0.924*	0.786*	1.807***
	P75	0.741***	1.1	0.901***	0.731***	0.96	0.936	0.885	1.493***
SPEI-3	Mean	0.799***	0.865***	0.863*	0.886	0.927	1.067	1.034	1.223
	Median	0.768***	0.823***	0.843*	0.865*	0.948	1.108	1.053	1.212
	P25	0.796***	0.806***	0.881	0.9	0.93	1.046	1.0	1.259*
	P75	0.782***	0.863***	0.81**	0.856*	0.926	1.066	1.059	1.19
SPEI-6	Mean	0.877***	0.897**	0.925*	0.904	0.941	0.916	0.869	0.981
	Median	0.853***	0.902**	0.942	0.907*	0.967	0.906	0.879	0.971
	P25	0.869***	0.909**	0.902*	0.846	0.91	0.894	0.879	0.995
	P75	0.85***	0.857**	0.899*	0.887**	0.947	0.9	0.867	0.981
SPEI-12	Mean	0.737**	0.721**	0.65***	0.603***	0.7**	0.674**	0.769	0.891
	Median	0.747**	0.73**	0.651***	0.59***	0.675**	0.661**	0.758	0.866
	P25	0.696***	0.664***	0.613***	0.57***	0.709**	0.762	0.836	1.009
	P75	0.812*	0.782*	0.687**	0.646**	0.688**	0.619***	0.708*	0.833

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

Table E.21.: Model 4: Odds ratio for a positive unit change in positive DI for Toposa people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.642	0.414*	0.289***	0.606**	1.221	0.549***	0.796*	0.872
	Median	0.662	0.373*	0.281***	0.606*	1.2	0.547***	0.861	0.879
	P25	0.711	0.195*	0.311***	0.542**	1.317	0.579***	0.801	0.804
	P75	0.651	0.572	0.251***	0.656**	1.243	0.683***	0.72***	0.955
SPI-3	Mean	0.279***	0.092***	0.285	0.576**	1.163	0.73	0.706*	0.986
	Median	0.321***	0.107***	0.292	0.615**	1.225	0.703*	0.752**	0.93
	P25	0.44**	0.084**	0.112**	0.535***	1.089	0.703	0.797***	1.08
	P75	0.302***	0.166***	0.459	0.662	1.138	0.74*	0.709**	0.855
SPI-6	Mean	0.131**	0.342***	0.385**	0.695**	1.181	0.838	1.388**	1.462**
	Median	0.141**	0.379***	0.399**	0.725	1.139	0.803*	1.419**	1.521**
	P25	0.032***	0.192**	0.154**	0.715	1.261	0.913	1.679***	1.743**
	P75	0.217**	0.424***	0.512**	0.738**	1.047	0.815*	1.216*	1.317**
SPI-12	Mean	0.502**	0.982	1.021	1.259*	1.235	1.116	1.238	1.566**
	Median	0.52**	0.965	1.046	1.24*	1.243	1.126	1.261	1.592**
	P25	0.388**	1.013	0.913	1.264	1.232	1.332*	1.488*	1.682**
	P75	0.551**	0.888	0.994	1.245	1.22	1.024	1.37*	1.546**
SPEI-1	Mean	0.409*	0.435**	0.335**	0.851	1.556	0.85	0.878	0.518*
	Median	0.402*	0.384**	0.319**	0.83	1.515	0.83*	0.914	0.499*
	P25	0.356*	0.238**	0.33**	0.912	1.57	0.89	0.906	0.318**
	P75	0.49	0.593*	0.35**	0.835	1.553*	0.827**	0.834	0.659**
SPEI-3	Mean	0.189***	0.147***	0.413	0.779	1.232	0.786*	0.698	0.775
	Median	0.215***	0.171***	0.405	0.764	1.3	0.784*	0.74*	0.752
	P25	0.199**	0.11***	0.331	0.869	1.196	0.679***	0.664	0.865
	P75	0.224***	0.254**	0.531	0.784	1.268	0.86	0.71*	0.753
SPEI-6	Mean	0.233***	0.554***	0.528**	0.903	1.036	0.717*	1.13	1.117
	Median	0.214***	0.57***	0.564**	0.902	0.985	0.762*	1.16	1.158
	P25	0.163***	0.525**	0.456**	0.892	1.084	0.643	1.193	1.12
	P75	0.318***	0.547***	0.566***	0.886	1.075	0.812*	1.082	1.098
SPEI-12	Mean	0.532***	0.861	0.909	1.195	1.202	1.125	1.073	1.416*
	Median	0.558***	0.854	0.914	1.229*	1.233*	1.145	1.061	1.438*
	P25	0.511***	0.875	0.872	1.151	1.125	1.194	1.205	1.646**
	P75	0.619***	0.842	0.921	1.18	1.214	1.085	1.046	1.279

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $^{*}p < 0.1$, $^{**}p < 0.05$ and $^{***}p < 0.01$.

Table E.22.: Model 4: Odds ratio for a positive unit change in positive DI for Borana people

	time lag [months]	0	1	2	3	4	5	6	7
SPI-1	Mean	0.975	1.073	1.169*	1.152*	1.121	0.854	0.789***	0.794***
	Median	1.002	1.14*	1.237**	1.206**	1.141	0.905	0.813***	0.782***
	P25	0.76**	1.222*	1.347**	1.172	1.121	1.134	0.953	0.814***
	P75	1.022	0.98	1.075	1.191**	1.114*	0.777**	0.719***	0.811***
SPI-3	Mean	1.155	1.373***	1.316***	1.19**	1.051	1.011	1.07	1.015
	Median	1.223	1.375***	1.345***	1.189**	1.055	1.004	1.079	0.973
	P25	0.965	1.452***	1.237**	1.178**	1.213**	1.082	1.184	1.179**
	P75	1.126	1.232**	1.333***	1.089	0.888	0.965	0.967	0.972
SPI-6	Mean	1.283**	1.357**	1.443**	1.509**	1.368**	1.234*	1.399**	1.375**
	Median	1.374***	1.419**	1.53***	1.56**	1.388**	1.266**	1.416**	1.365**
	P25	1.28**	1.552***	1.521***	1.692***	1.601***	1.382**	1.446**	1.41**
	P75	1.261**	1.177	1.337**	1.458**	1.157	1.103	1.238	1.36*
SPI-12	Mean	1.413	1.549*	1.456*	1.349	1.186	1.246*	1.237	1.535**
	Median	1.404	1.533*	1.457*	1.385	1.201	1.245	1.236	1.509**
	P25	1.37	1.588	1.612*	1.745*	1.539*	1.773**	1.782***	2.087***
	P75	1.314	1.38	1.281	1.151	1.025	1.023	1.079	1.256*
SPEI-1	Mean	1.219*	1.129	1.392***	1.255*	1.495***	1.14	0.772**	1.193
	Median	1.249**	1.151	1.557***	1.243**	1.521***	1.221**	0.841	1.192
	P25	1.01	1.174	1.301*	1.498**	1.577***	1.478**	1.002	1.27*
	P75	1.165**	1.057	1.381***	1.124	1.39***	0.931	0.76**	1.042
SPEI-3	Mean	1.334**	1.202*	1.462***	1.485***	1.223*	1.036	1.225	1.258**
	Median	1.478***	1.262**	1.49***	1.552***	1.282**	1.067	1.25	1.275**
	P25	1.227*	1.195*	1.462**	1.599***	1.537***	1.314**	1.437**	1.44***
	P75	1.273**	1.212**	1.427***	1.186*	0.899	0.852**	0.996	1.106
SPEI-6	Mean	1.322**	1.453***	1.538***	1.486**	1.409***	1.343***	1.442**	1.405***
	Median	1.395**	1.522***	1.634***	1.563***	1.431***	1.404***	1.447***	1.435***
	P25	1.36**	1.654***	1.629***	1.679***	1.653***	1.5***	1.534***	1.528***
	P75	1.163	1.219*	1.316**	1.35*	1.105	1.151	1.326	1.471**
SPEI-12	Mean	1.672**	1.685**	1.53**	1.59**	1.338*	1.419**	1.255	1.627**
	Median	1.708**	1.678**	1.557*	1.64**	1.379*	1.462**	1.248	1.651**
	P25	1.953**	2.062**	1.957**	2.407***	1.886***	2.07***	1.872***	2.247***
	P75	1.354	1.346	1.256	1.094	0.994	0.994	0.96	1.166

All cells are coloured according to the magnitude of the change in odds factor. Significance levels of change in odds factor: $*p < 0.1$, $**p < 0.05$ and $***p < 0.01$.

F Odds ratios and confidence intervals for SPI

F.1 Model 1

F.1.1 SPI

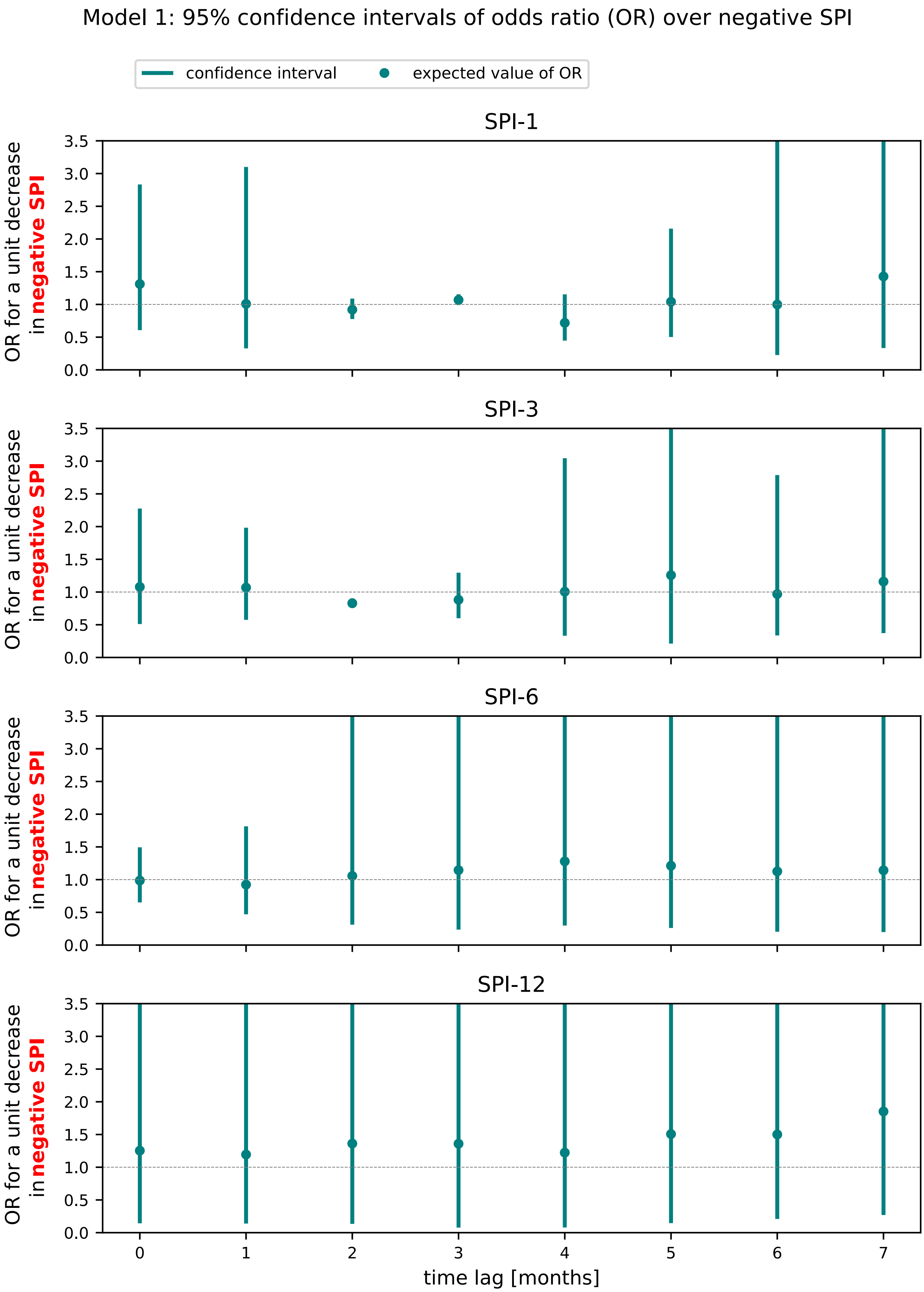

Figure F.1.: Model 1: Estimate of odds ratio and 95% confidence interval for a unit decrease in negative SPI for lags of 0 to 7 months

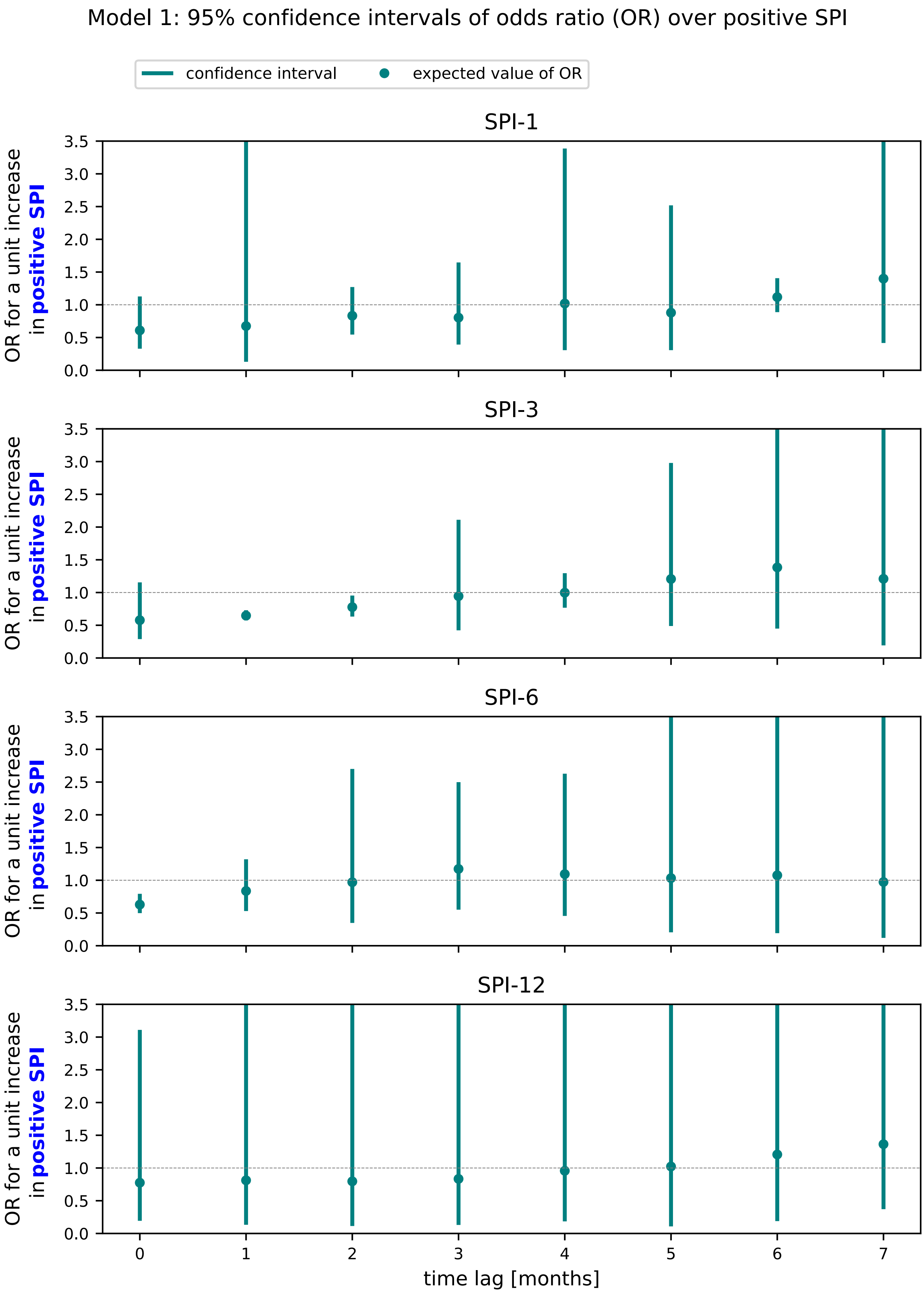

Figure F.2.: Model 1: Estimate of odds ratio and 95% confidence interval for a unit increase in positive SPI for lags of 0 to 7 months

F.1.2 SPEI

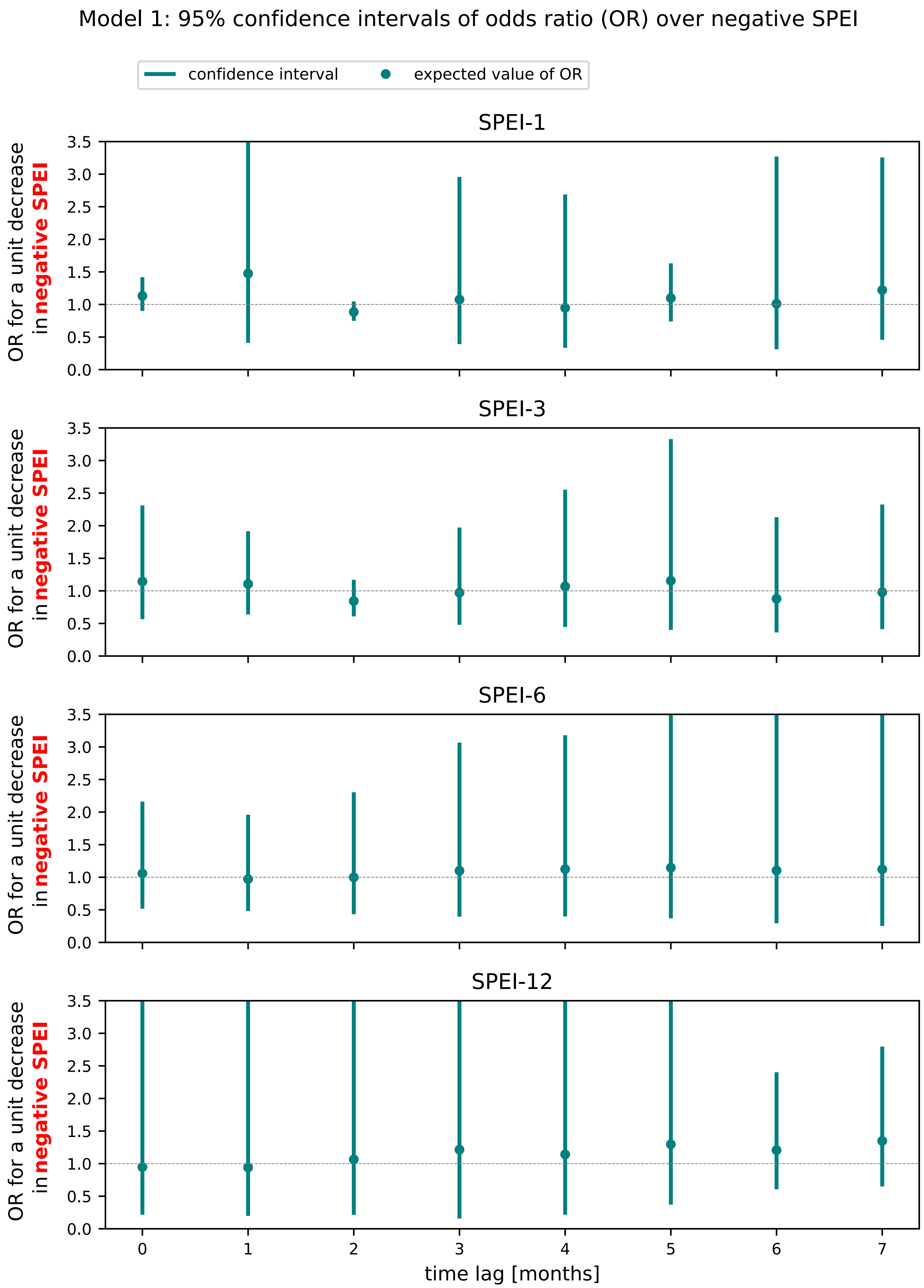

Figure F.3.: Model 1: Estimate of odds ratio and 95% confidence interval for a unit decrease in negative SPEI for lags of 0 to 7 months

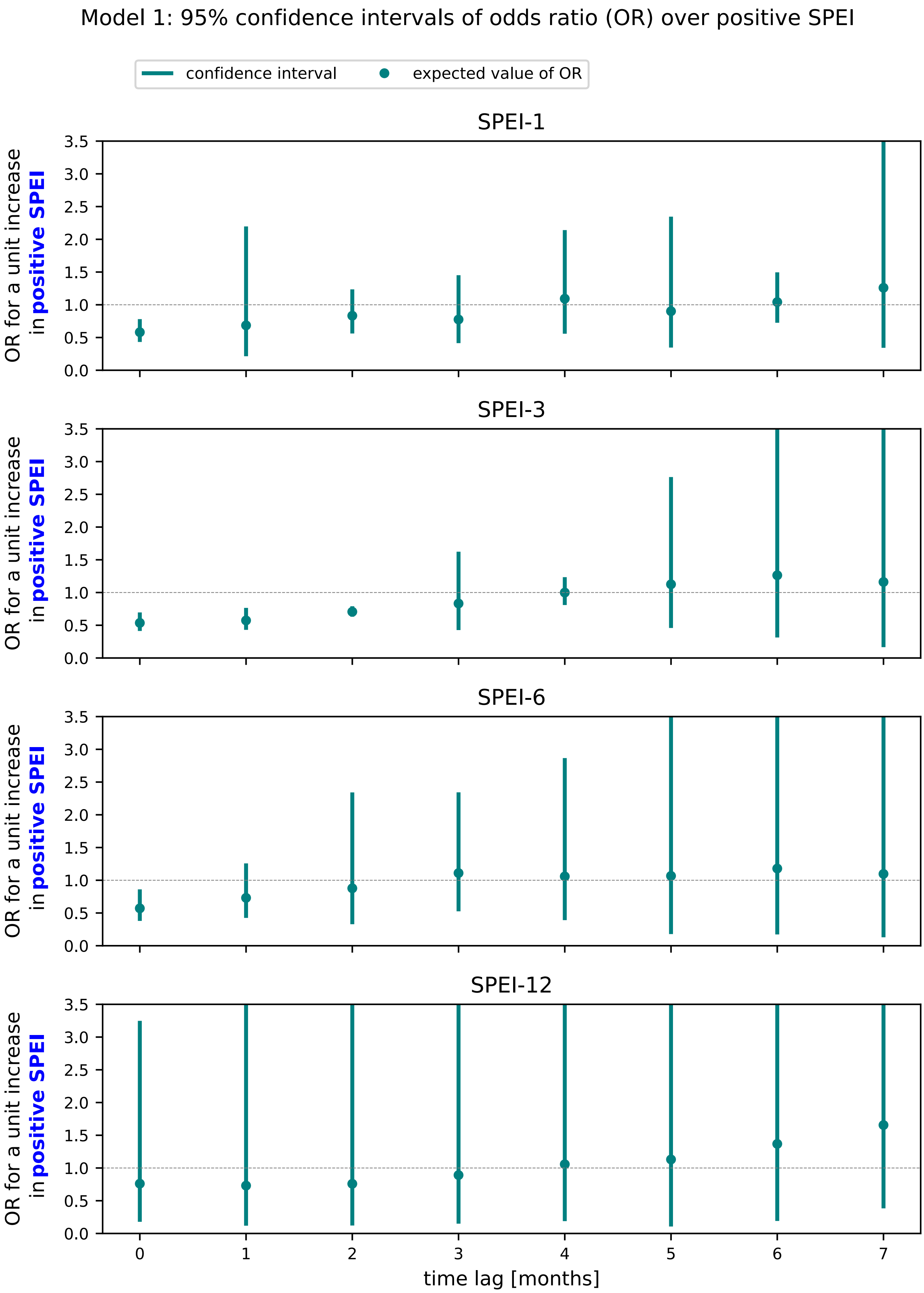

Figure F.4.: Model 1: Estimate of odds ratio and 95% confidence interval for a unit increase in positive SPEI for lags of 0 to 7 months

F.2 Model 2

F.2.1 SPI

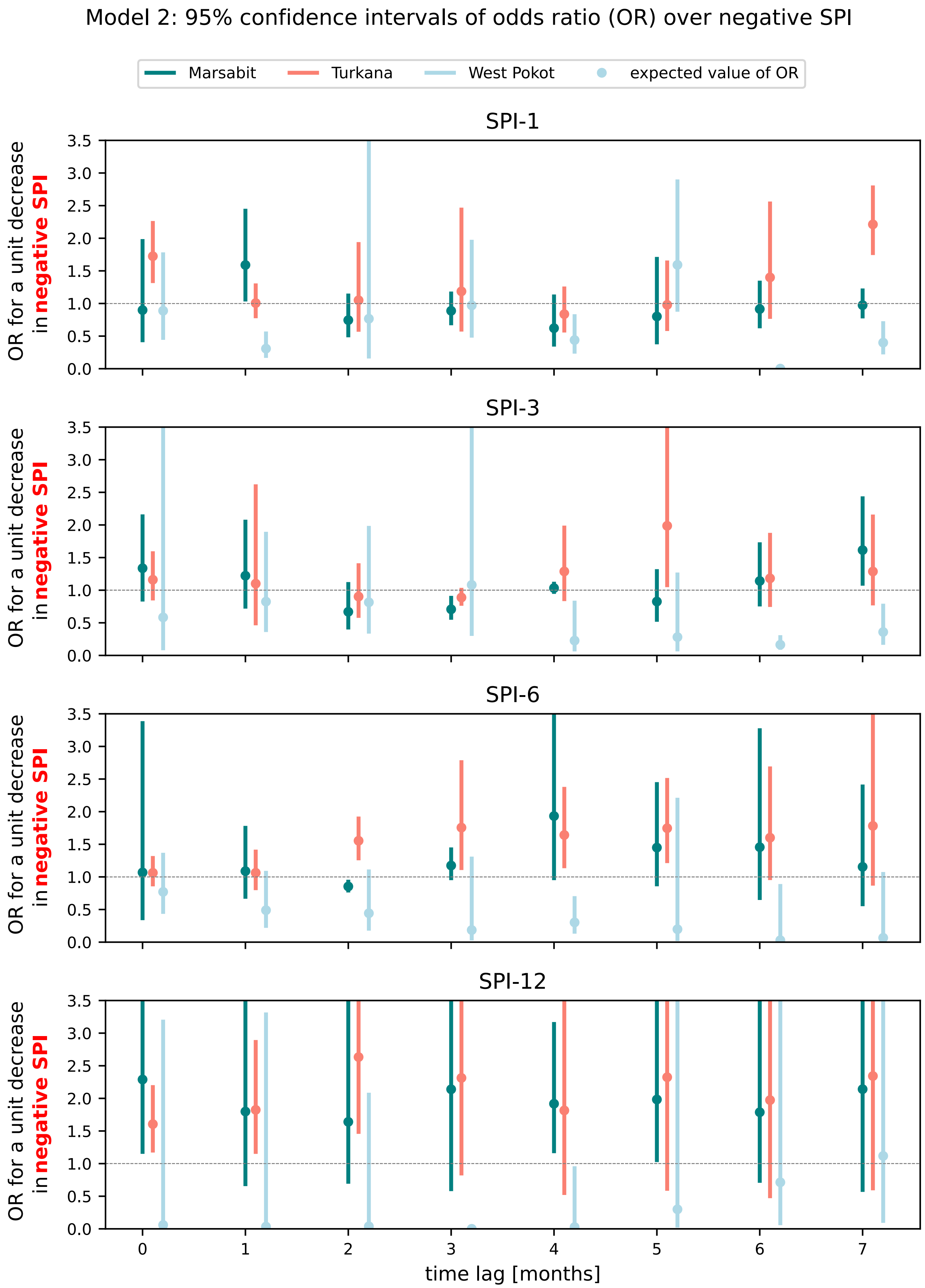

Figure F.5.: Model 2: Estimate of odds ratio and 95% confidence interval for a unit decrease in negative SPI for lags of 0 to 7 months

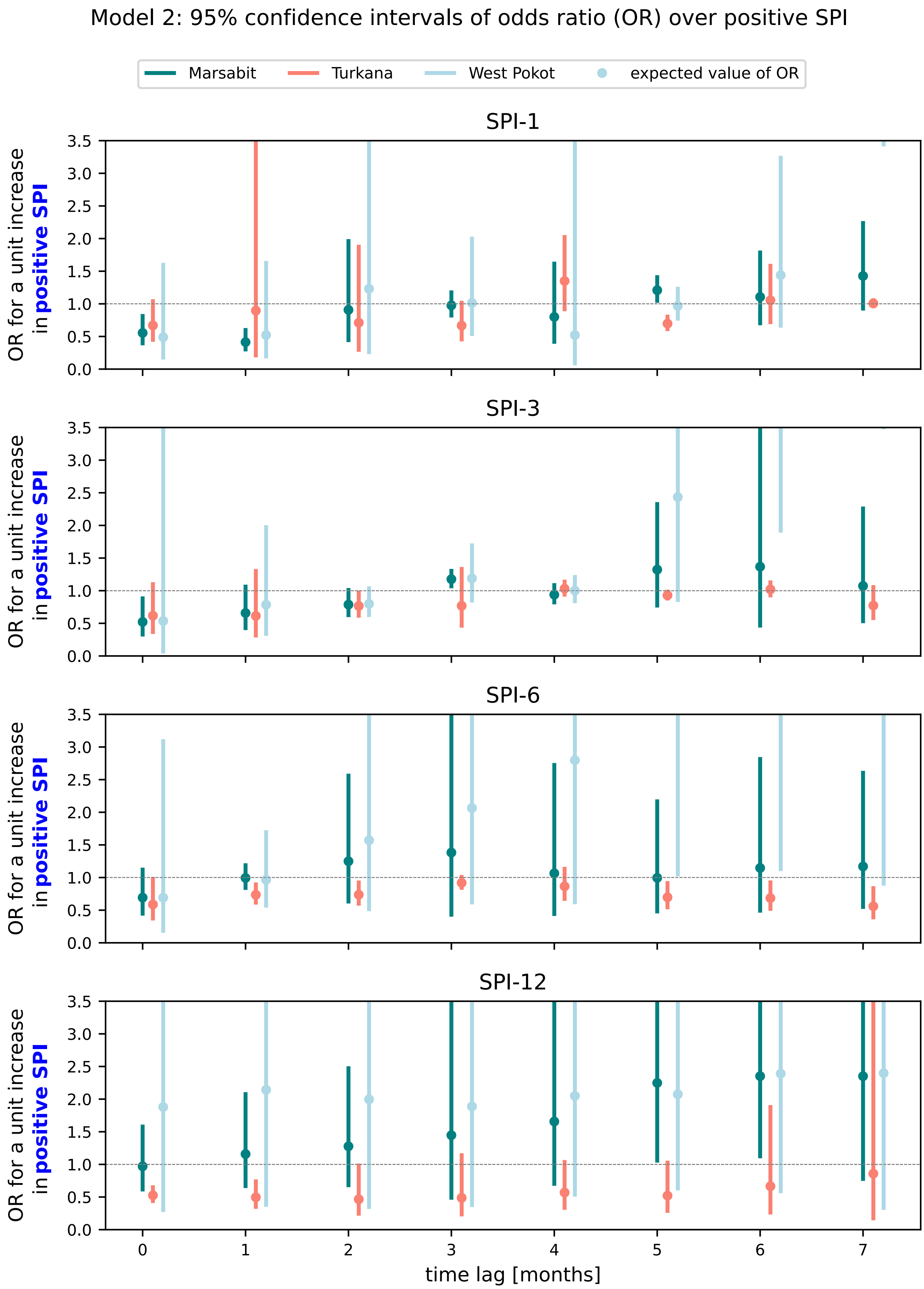

Figure F.6.: Model 2: Estimate of odds ratio and 95% confidence interval for a unit increase SPI for lags of 0 to 7 months

F.2.2 SPEI

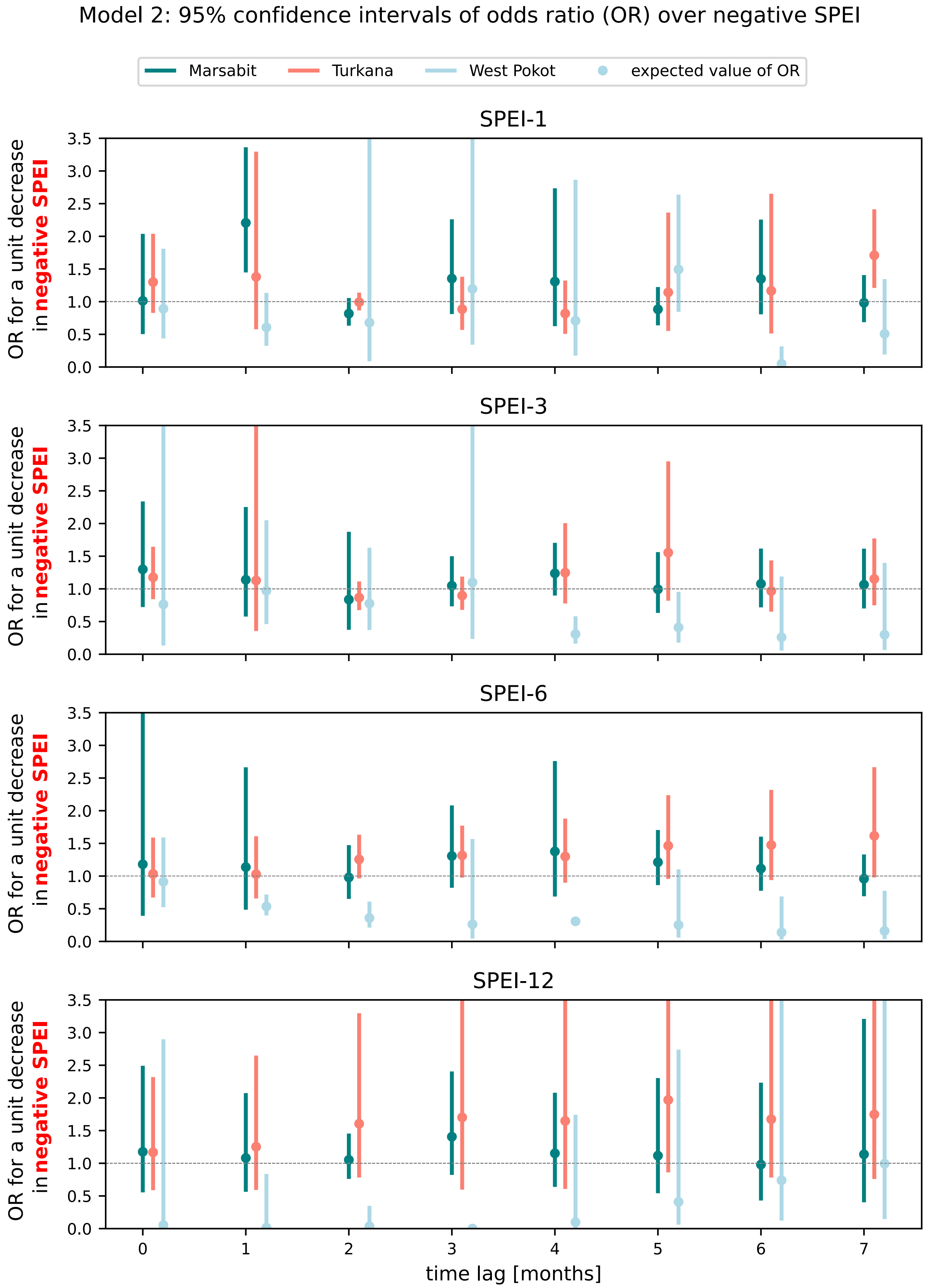

Figure F.7.: Model 2: Estimate of odds ratio and 95% confidence interval for a unit decrease in negative SPEI for lags of 0 to 7 months

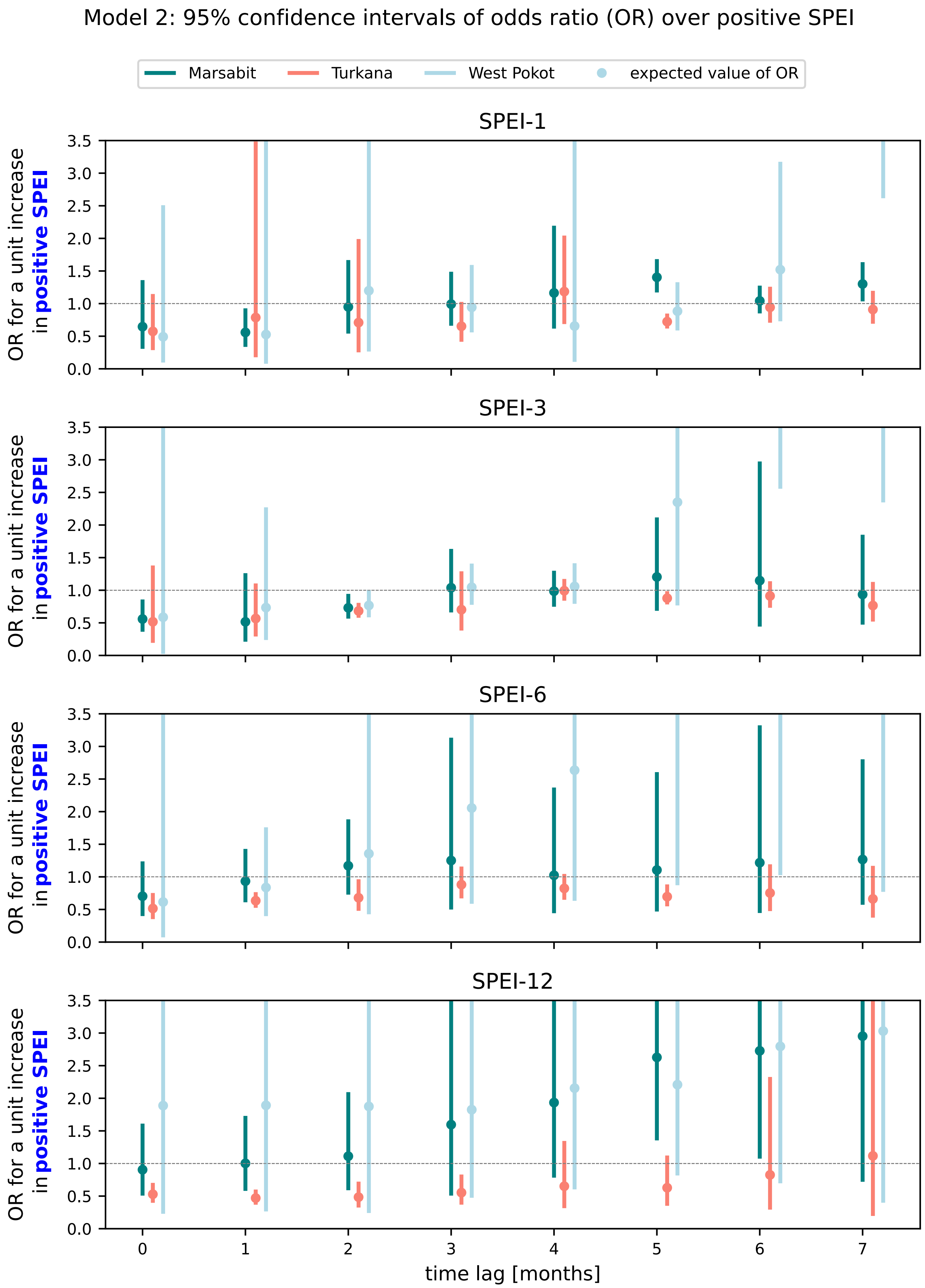

Figure F.8.: Model 2: Estimate of odds ratio and 95% confidence interval for a unit increase SPEI for lags of 0 to 7 months

F.3 Model 3

F.3.1 SPI

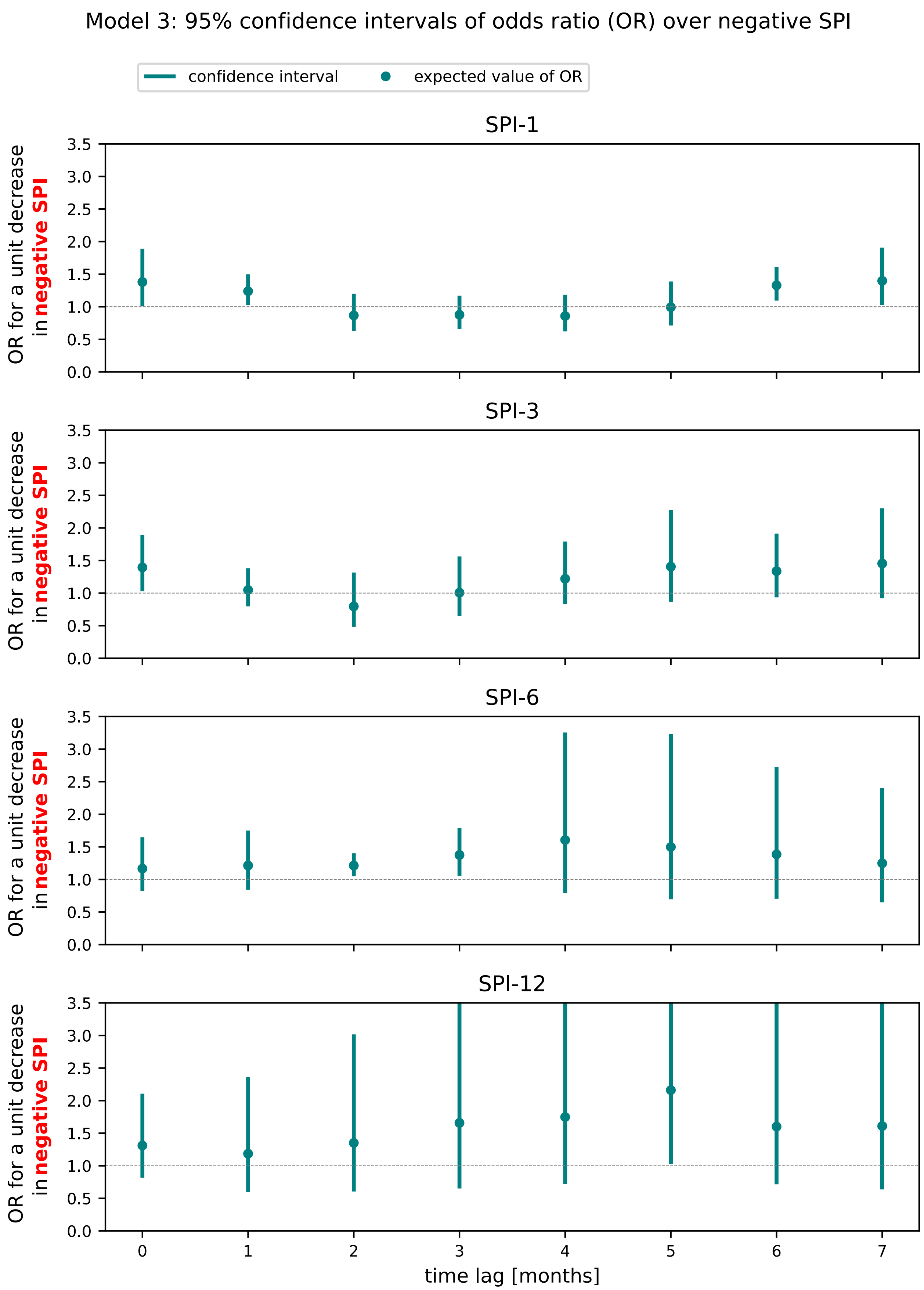

Figure F.9.: Model 3: Estimate of odds ratio and 95% confidence interval for a unit increase SPI for lags of 0 to 7 months

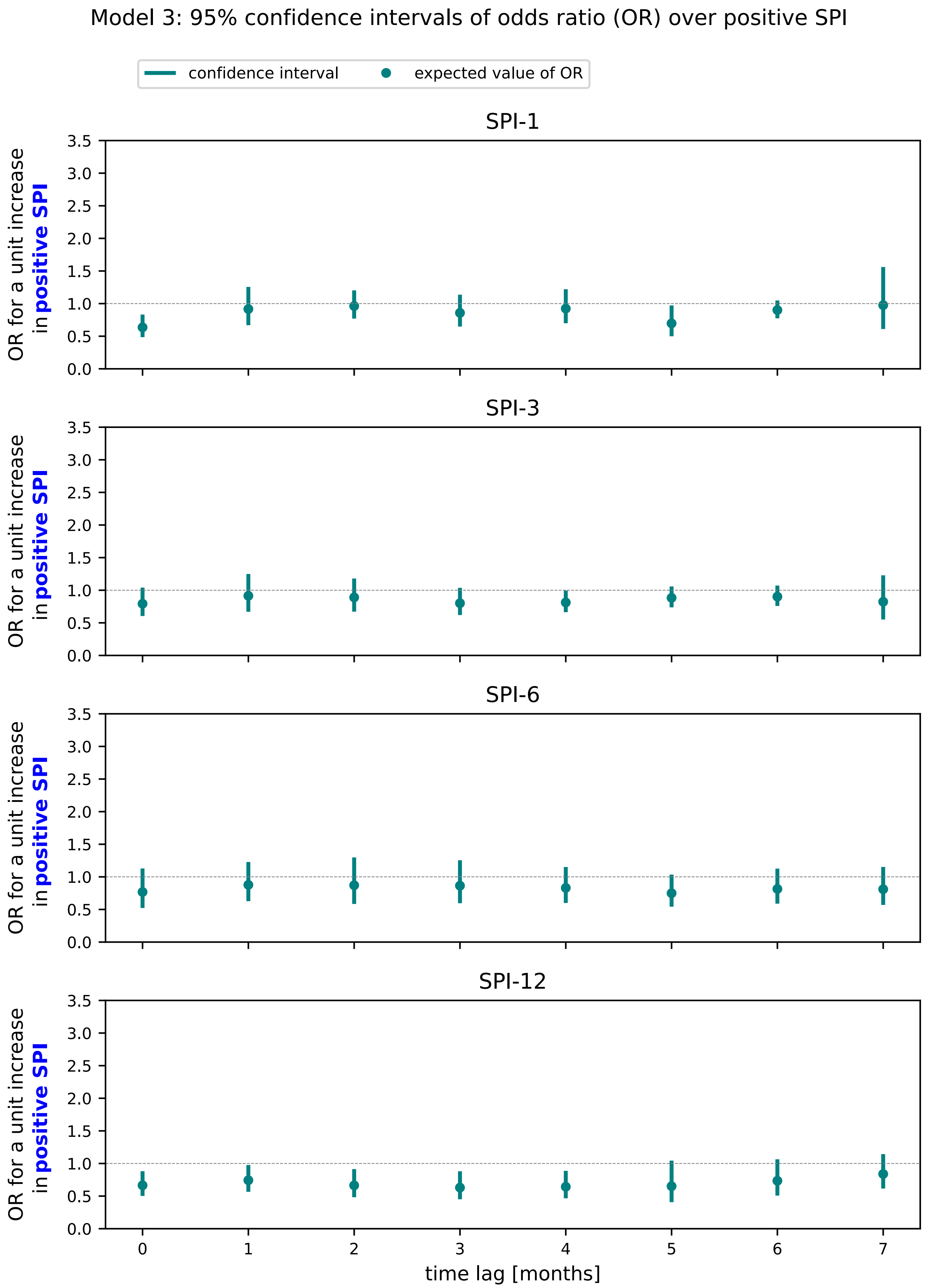

Figure F.10.: Model 3: Estimate of odds ratio and 95% confidence interval for a unit increase SPI for lags of 0 to 7 months

F.3.2 SPEI

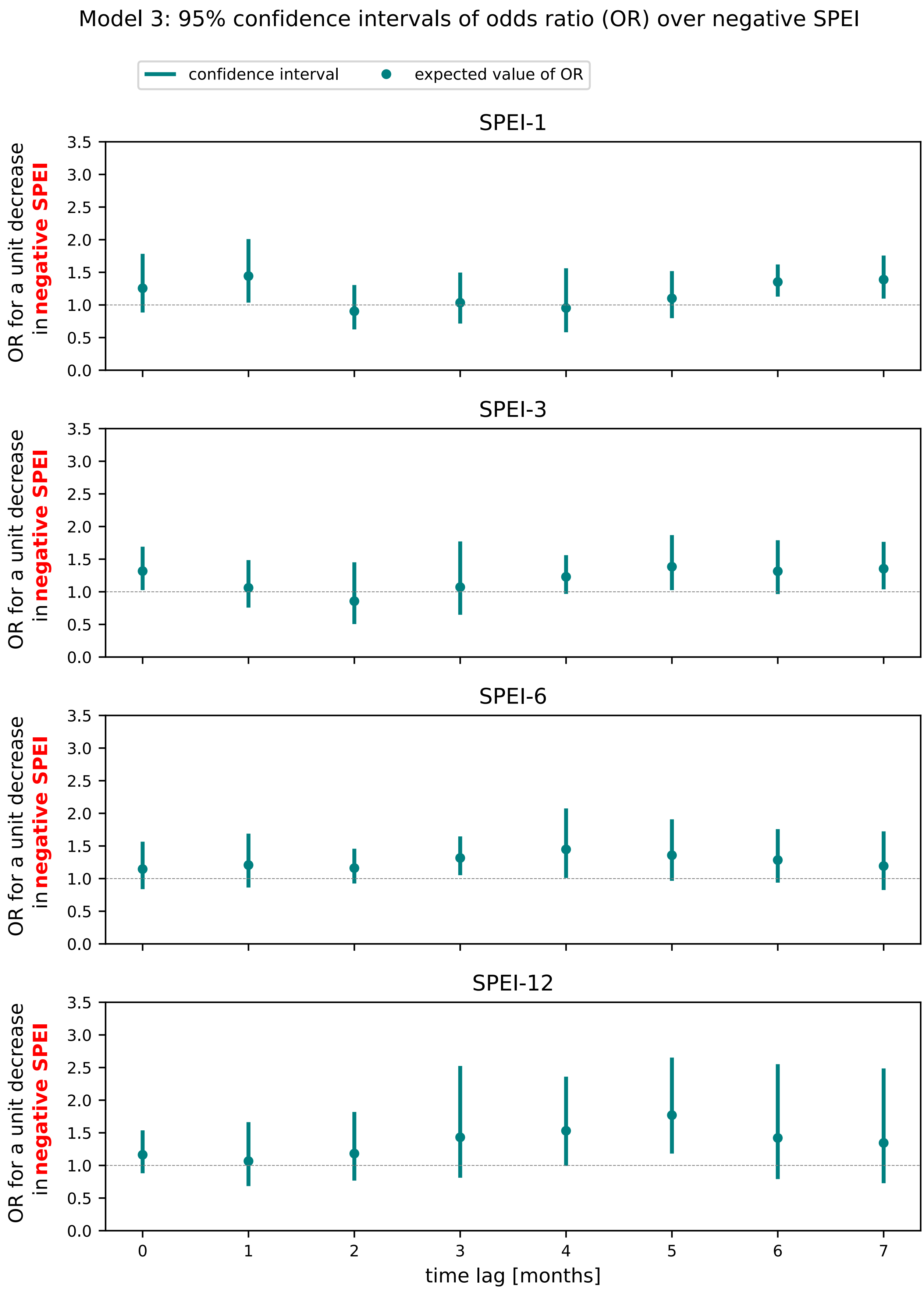

Figure F.11.: Model 3: Estimate of odds ratio and 95% confidence interval for a unit increase SPEI for lags of 0 to 7 months

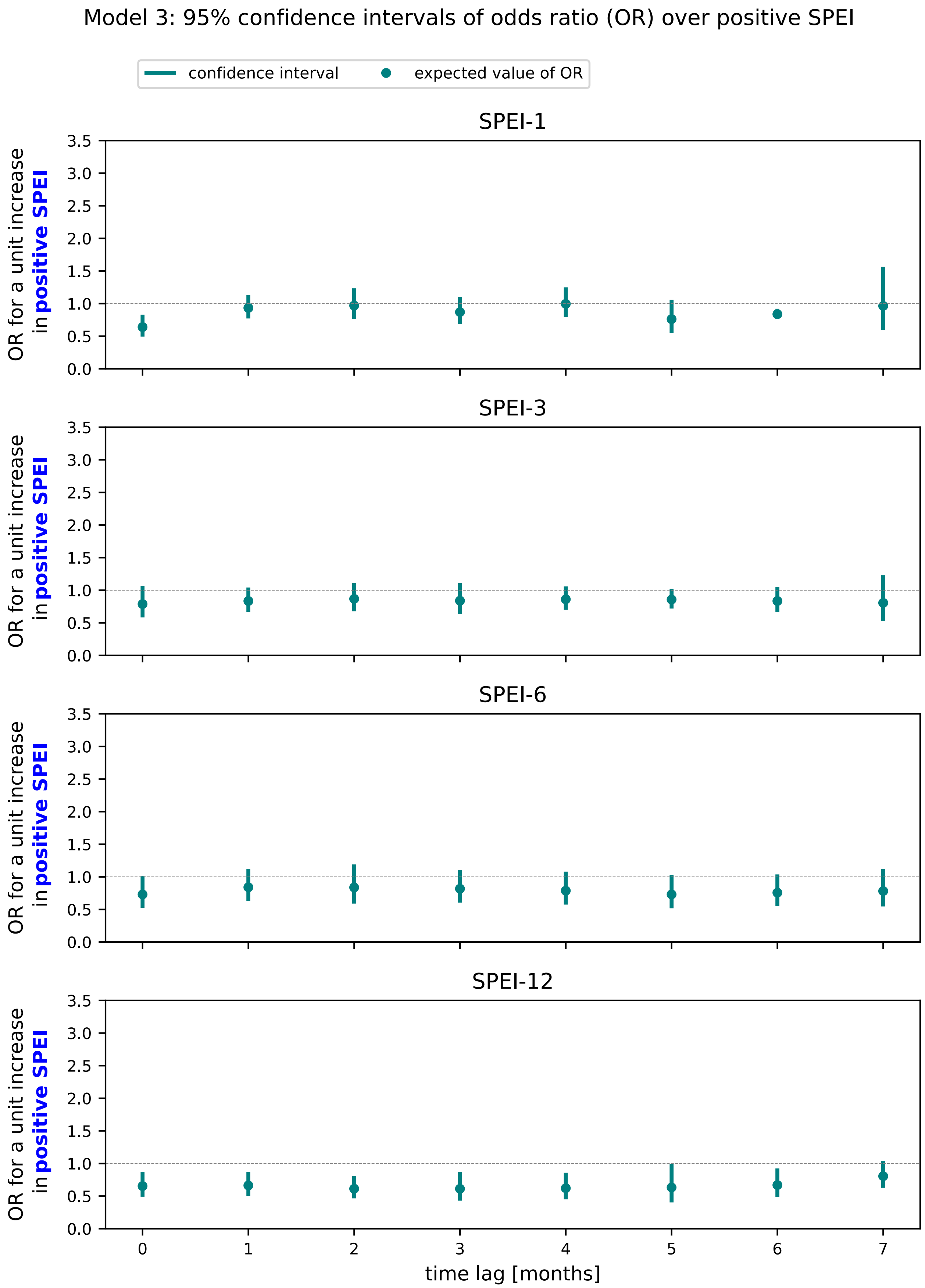

Figure F.12.: Model 3: Estimate of odds ratio and 95% confidence interval for a unit increase SPEI for lags of 0 to 7 months

F.4 Model 4

F.4.1 SPI

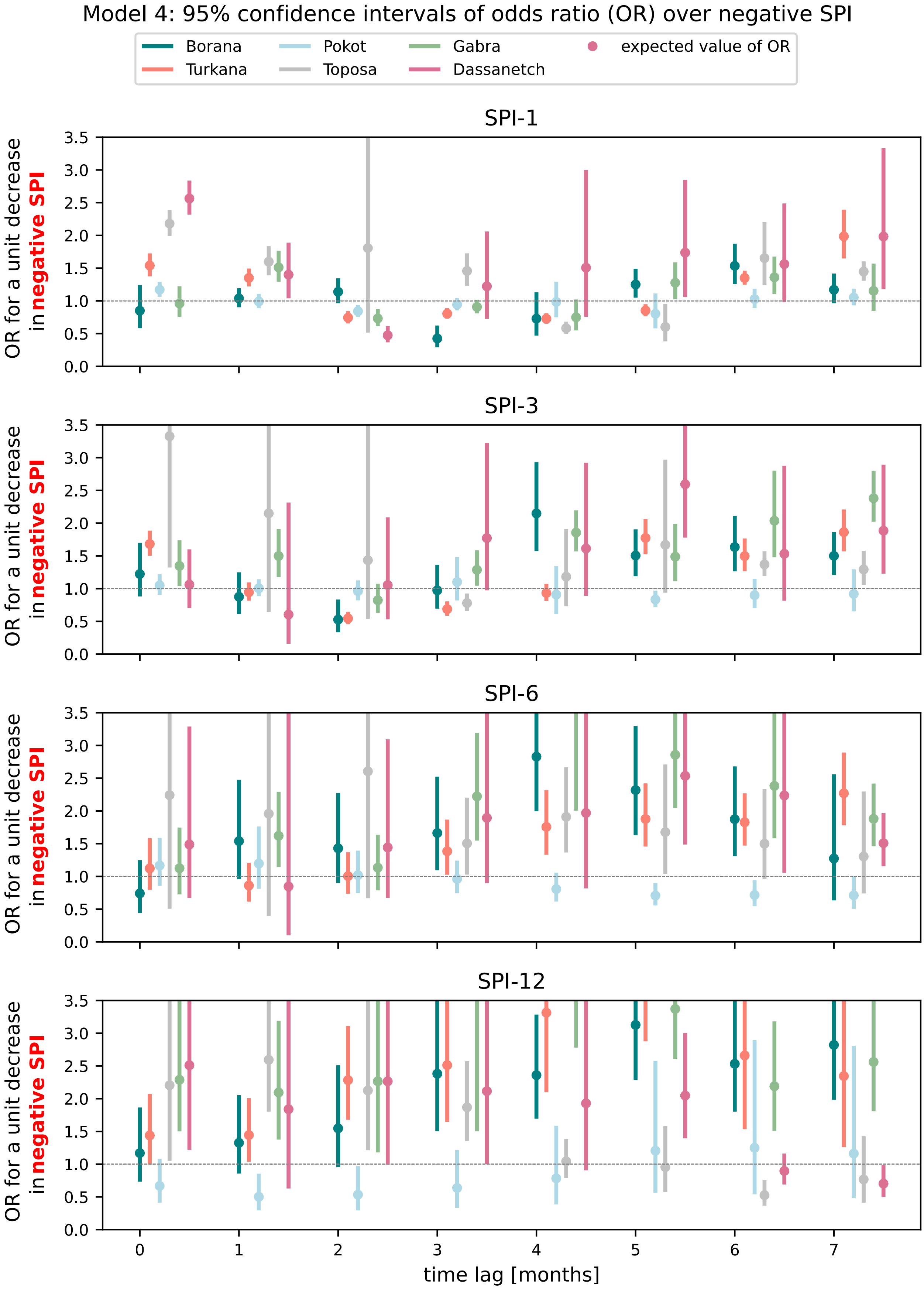

Figure F.13.: Model 4: Estimate of odds ratio and 95% confidence interval for a unit increase SPI for lags of 0 to 7 months

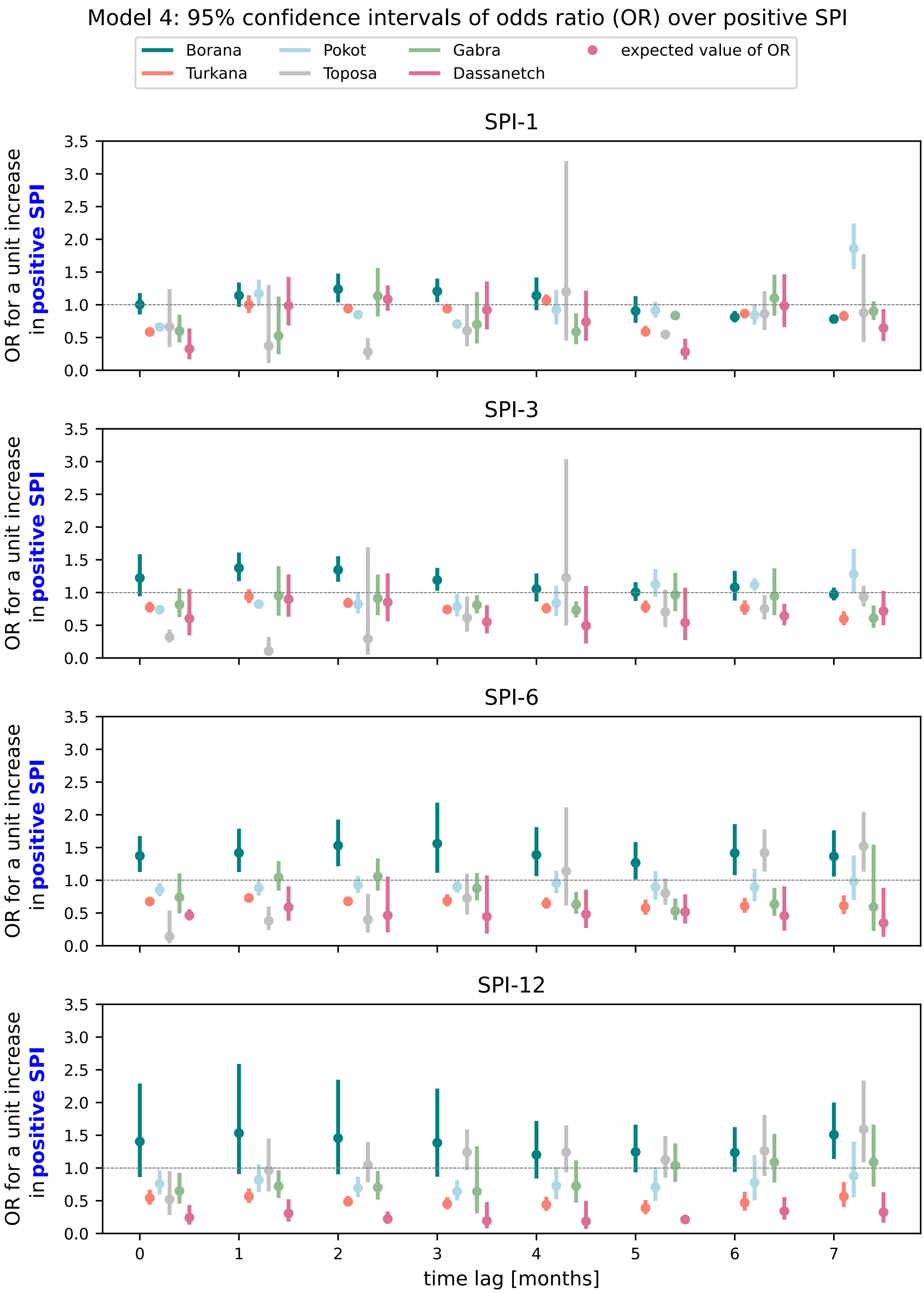

Figure F.14.: Model 4: Estimate of odds ratio and 95% confidence interval for a unit increase SPI for lags of 0 to 7 months

F.4.2 SPEI

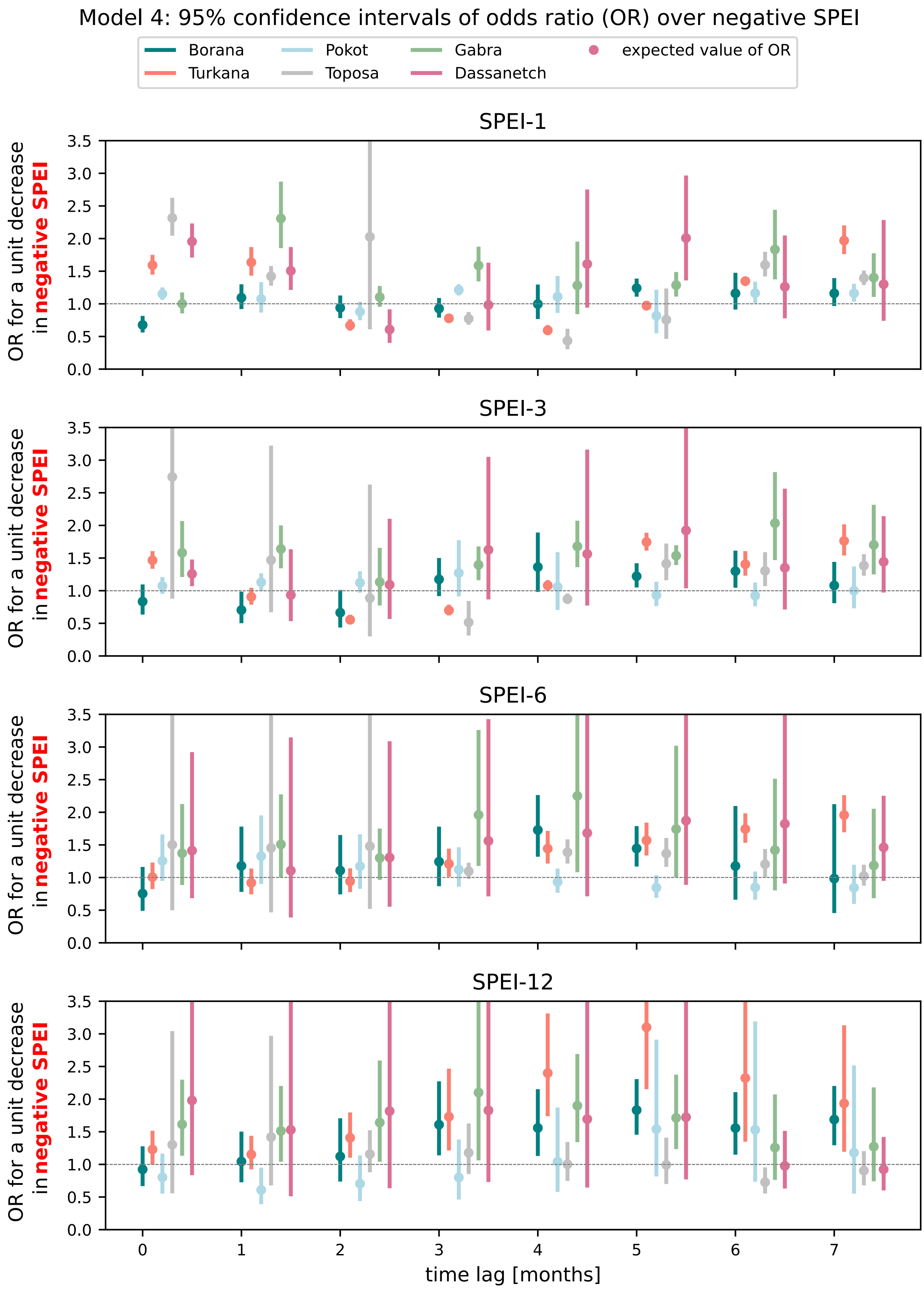

Figure F.15.: Model 4: Estimate of odds ratio and 95% confidence interval for a unit increase SPEI for lags of 0 to 7 months

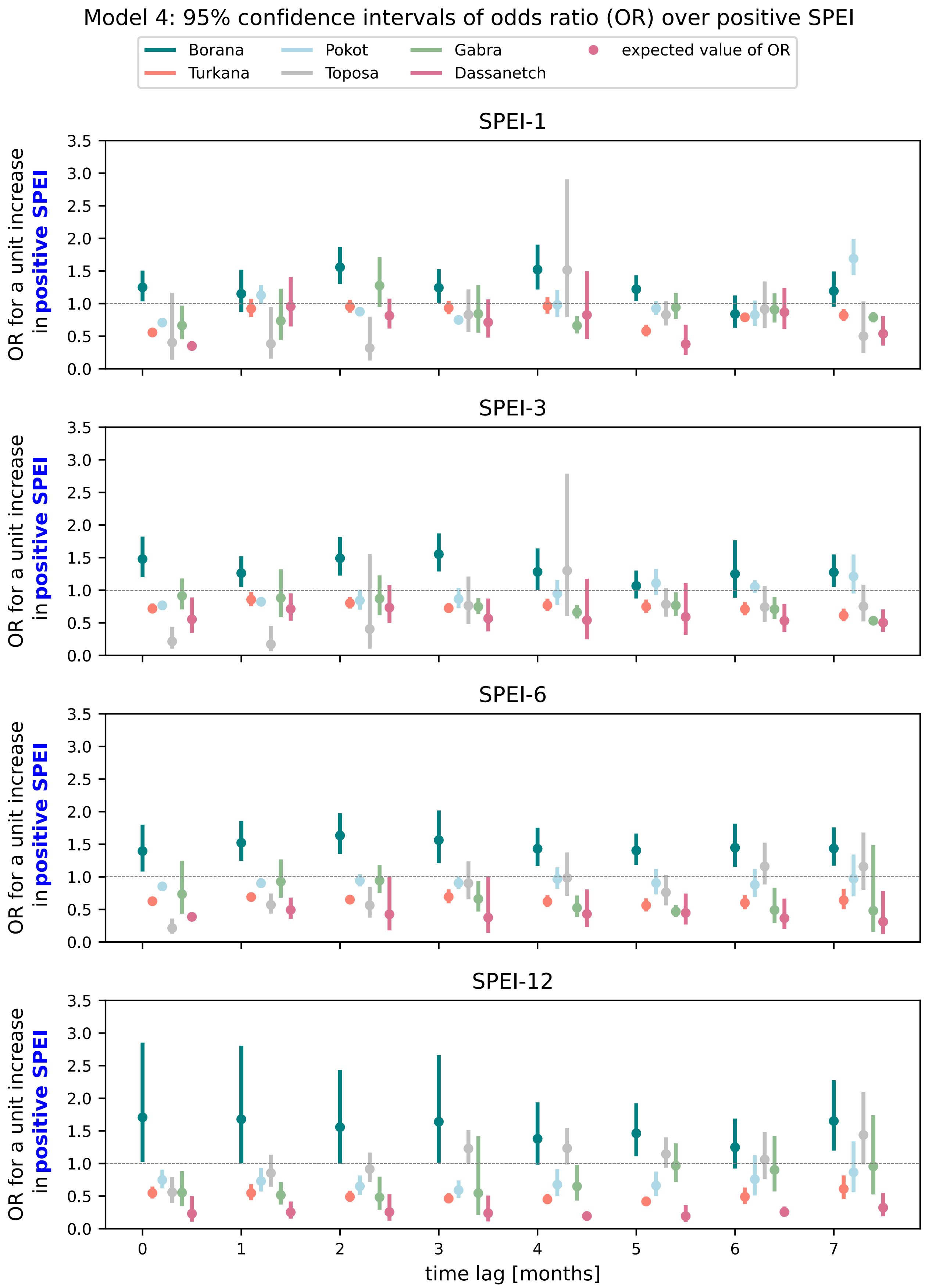

Figure F.16.: Model 4: Estimate of odds ratio and 95% confidence interval for a unit increase SPEI for lags of 0 to 7 months