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Drought impacts in Austria

Index selection and modelling in Forestry, Wild fires and Danube transport

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Abstract

Major drought events have recently become of high public and scientific interest. They cause complex chains of impacts. However, understanding of their relationship to drought indices are still in early stages. For investigating various impact categories, a broad number of observation frames and indicator characteristics have been suggested. This makes a comprehensive analyses of drought impacts a complex and difficult task.

In this master thesis, Spearman correlation analysis and logit regression models (i.e. likelihood of impact occurrence LIO about the event probability of damage) are employed to assess the relationship of drought indices and impacts in Austria. Impact indicators include drought and heat damage, wild fires and Danube transport for different spatial and time scales. Meteorological and hydrological indices include the SPI, the SPEI, precipitation sums, and streamflow (Annual Minima AM and total days below threshold). To aggregate data of different spatial units, various calculation metrics are tested.

From the results, areal means of $SPEI_3$ and $SPEI_6$ for the vegetation period and AM turn out to be the most suitable hydrometeorological indices. The LIO model shows a significant influence (α smaller 0.05) of the $SPEI_6$ and of the observation region on the logit for both wild fire occurrence and drought and heat damage occurrence. β_{SPEI} is at -0.81 for drought and heat damage and at -0.59 for wild fires, and the region has a higher influence than the SPEI. The A_{ROC} model quality shows relatively high values of 0.805 and 0.809, respectively. The linear regression model on Danube transport showed an R^2 of 0.2. Thus, results show an overview of the current situation and discuss aspects and further questions of feasibility.

Kurzfassung

Große Dürreereignisse mit komplexen und umfassenden Schäden stehen immer mehr im öffentlichen und wissenschaftlichen Interesse. Noch herrscht Unsicherheit darüber vor, ab welcher Intensität Schäden messbar sind und wie sich diese im Zusammenhang mit Dürremaßen entwickeln. Je nach Schadenskategorie existieren unterschiedliche Anforderungen an Monitoring und Messung, wodurch Herausforderungen in der übergreifenden Darstellung und Analyse entstehen.

In dieser Arbeit wird eine Spearman-Korrelationsanalyse durchgeführt und zwei Logit-Regressionsmodelle erstellt, um die Beziehung zwischen Dürremaßen und Schäden in Österreich zu beschreiben. Beobachtete Indikatoren umfassen Dürre- und Hitze-Forstschäden, Waldbrände und das Transportaufkommen auf der Donau. Zu den hydrometeorologischen Indizes gehören SPI, SPEI, Niederschlagssummen und jährliche Abflussminima und die Anzahl an Tagen mit Abflussmenge unter einem Grenzwert. Verschiedene Möglichkeiten zur räumlichen Aggregation der Daten werden getestet.

Die Ergebnisse zeigen, dass regionale Mittelwerte von $SPEI_3$ und $SPEI_6$ über die Vegetationsperiode sowie die jährlichen Abflussminima in diesem Zusammenhang am geeignetsten erscheinen. Die berechneten Spearman-Korrelationskoeffizienten für Dürre- und Hitze-Forstschäden sind höher als jene für Waldbrände, während jene für das Transportaufkommen auf der Donau am höchsten sind. Die Logit-Regressionsmodelle schätzen den Einfluss des $SPEI_6$ auf das logit-transformierte Auftreten von Schäden ($\beta_{SPEI} = -0.81$ für Dürre- und Hitzeschäden und $\beta_{SPEI} = -0.59$ für Waldbrände) als signifikant ein (α smaller 0.05). Noch ausgeprägter ist der Einfluss der Region. Der Modell-Qualitätswert A_ROC ergibt für beide Modelle mittlere bis gute Erklärungswerte (je 0.805 und 0.809). Für das

Modell des Transportaufkommens ergibt sich ein R^2 von 0.2. Die Ergebnisse zeigen die derzeitige Situation auf und weisen auf weitere Fragen zur Messung und Modellierung von Dürre-Schäden hin.

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1 Introduction

Reoccurring drought events and the high damages associated have led to a rising interest in understanding the underlying processes. They have drawn public and scientific attention to this particular type of extreme event. Such events were recently observed in Central and Southern Europe, e.g. in 2003 and 2015. In particular the year 2015 has been analysed, documented and followed by both science and public (Van Lanen et al., 2016; Van Loon, 2015) An increasing amount of literature exists describing various effects of drought (Mishra and Singh, 2011; Mishra and Singh, 2010) in describing the relationship, measurement and simulation of hydrological drought conditions (WMO, 2008; Van Loon et al., 2015; Parajka et al., 2016; Wagener et al., 2013). Drought events may have devastating effects on economy, society and ecosystems (Ding et al., 2011; Van Loon et al., 2015; Matthews and Marsh-Matthews, 2003). An increasing attention is also observed in the context of climate change (Austrian Panel on Climate Change, 2014), coming with a rising interest understanding drought process and drought impacts.

Drought events are characterized by a large area involved, a broad time frame, a slow onset and recovery, making it difficult to classify areas as being under drought conditions versus under non-drought conditions (Tallaksen, 2006). Such events have large impact, are difficult to identify (start, end, region), and are driven by slow reacting processes (Laaha et al., 2013; WMO, 2008). Characteristics differ across regions and climate zones (Tallaksen, 2006). Droughts most commonly are classified as meteorological drought, hydrological drought, or agricultural drought, but other classification schemes are in use and depend on the focus of the work (Van Loon et al., 2015; Bachmair et al., 2016b). Thus, the identification of drought impacts brings difficulties in monitoring, which have to be considered whenever trying to model, predict or estimate drought impacts.

Drought as a natural hazard is generated by a complex combination of processes with a difficult start- and end-date identification and therefore been subject of fewer investigations compared to other hazards, such as floods or mountain hazards.

There are different options to classify droughts. Drought events can be classified by the natural process which causes the drought (e.g. meteorological vs. hydrological) or by impact category (e.g. agricultural drought) (Bachmair et al., 2016b; Van Loon et al., 2015). Less common, there are also other characteristics to classify droughts: e.g. ecological drought. Drought impact, according to the European Drought Impact Inventory (EDII) (European Drought Center, 2016) and the United States Drought monitor (USDA) (Smith et al., 2014), is an event of smaller than average water availability that leads to a negative impact and this definition is considered within this master thesis. Drought impacts could also be positive, e.g. for tourism.

Observing, and even more so predicting drought impacts is a non-trivial matter. Currently there is still a lack in understanding the full connection between drought and impact, making it difficult to answer questions such as “what intensity of drought leads to which impacts?”, or when and under what conditions impacts start to occur (Bachmair et al., 2016b; Bachmair et al., 2016a).The number of studies investigating this effect on a regional and local level is increasing.

Different monitoring schemes are in operation, but they are rare and often based on different input. The USDM, the European Drought Observatory (EDO) and the EDII are most commonly used and recognized. Bachmair et al. (2016b) observe impact monitoring often performed on a smaller scale in many areas. The focus of attention is often in the category of agriculture or water supply. Monitoring, data collection and index selection, however seldom follow a defined structure or are evaluated at a broader level. The authors also conclude, that in fact it is quite useful, rather than hindering, to have diverse definitions of drought. This is due to the differences in processes and needs of drought monitoring. Bachmair et al. (2015) already state the necessity of a deeper understanding of the link between drought monitoring, impact occurrence and investigate this link for different indices for Germany.

The structure of this master thesis includes basic drought concepts and monitoring, reinforcing the above introduced issues, followed by an overview of drought impacts and options for drought monitoring in Austria (see Fig. 1.1). This section captures quantified and documented effects, gives an overview of indirect and qualitative effects, and the data availability according to different impact categories is analyzed. Impact category classification is taken from the EDII. The impacts are structured in the single categories stating the effects on more well-documented sectors like agriculture and forestry, and challenges facing evaluation of impacts in more complex ecosystems, terrestrial ecosystems and freshwater ecosystems.

The analytical part of the thesis consists of a statistical extreme value analysis of the Danube riverw in the context of inland waterborne transport, and a regression analysis of drought and heat damages in forestry and wild fire occurrence, and testing the ability of different drought indices to highlight drought impact occurrence. The selection of those fields was mainly driven by their data availability, i.e. no data availability in other sectors.

The following research questions are considered:

- Which drought impacts are relevant for Austria?
- How is the data availability concerning these drought impacts, and what are potential or applied drought impact indicators?
- What indices are appropriate to describe drought impact in various water related sectors?
- Is it possible to determine a risk function and if so, "What is the drought risk of negative economic impact within different sectors in Austria?"

In the conclusions, I will point out the possible benefits of drought monitoring, drought impact monitoring and the proper selection and investigation of the indices used. A deeper insight in technical questions, relations between drought intensity indices and occurring impacts would raise both efficiency as well as accuracy of drought early warning systems. At the same time, it could make new management options considerable.

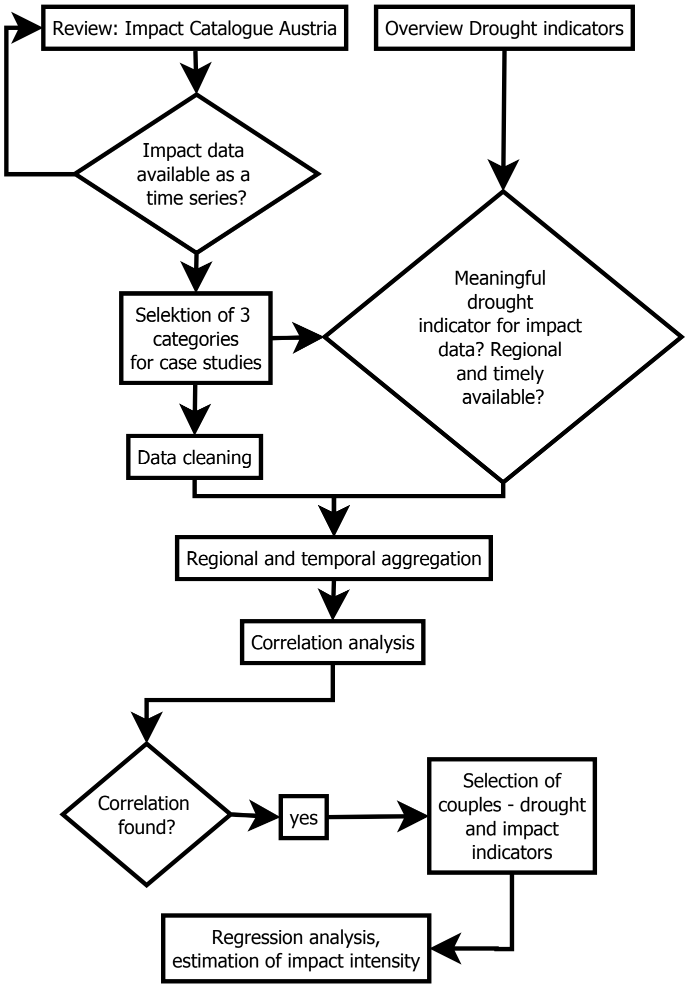

Figure 1.1: Schematic representation of the performed analysis of this master thesis

2 Concepts of drought, impacts and risk

2.1 Propagation of drought

Drought is a complex and multi-factorial process in the water cycle. It starts as a meteorological drought via a long-term lack of precipitation (Tallaksen, 2006, chapter1) and - if precipitation deficits remain - propagates through to different stages in the water cycle, becoming more severe and intense. Later on in the water cycle, deficits will occur in water bodies and in groundwater, leading to a hydrological drought (Van Loon et al., 2015). If water is missing for agricultural purposes, it is referred to as an "agricultural drought", and similar definitions for soil moisture, streamflow and groundwater exist.

A comprehensive definition of drought is difficult to establish. Mishra and Singh (2011) and Mishra and Singh (2010) describe drought as having the following characteristics: 1) low precipitation leading to missing water in the water cycle, 2) affecting a large area over a long period of time, and 3) an impact is seen due to the water deficits. Drought is an extreme event and shall not be confused with a dry climate (Van Loon et al., 2015). Moreover, a lack of water as a result of rise in demand is an issue of water scarcity and not the result of a drought (Van Loon and Van Lanen, 2013).

Tallaksen (2006, p.4) define drought as a "sustained and regional extensive occurrence of below natural water availability". They also describe the propagation of drought through the water cycle. Once a drought propagates through the soil moisture and hydrological components of the water cycle, it usually affects a large area and takes a considerably long period of time until the water availability is fully restored. Identifying and defining concrete onset and termination of a drought event remains challenging.

Precipitation deficits propagate through each stage in the water cycle with a time lag in between. This is determined by catchment characteristics, e.g. topographic slope, soil depth, land cover, (Laaha et al., 2013; WMO, 2008), geological and vegetational factors, climate and seasonal regimes, and previous hydrological water storage (Laaha et al., 2013; Parajka et al., 2016; Van Loon et al., 2015). See 2.1 for a schematic representation.

While water level and streamflow of small water bodies react very sensitively to periods of low precipitation, big rivers aggregate the precipitational situation of a wide area over a longer period (Laaha et al., 2013; WMO, 2008). Parts of the catchment suffering from low precipitation might be averaged out by other areas having precipitation above average. In large river basins like the Danube, precipitation situation over parts of Europe are aggregated. Depending on the catchment size, time lags of drought propagation may increase or decrease. For hydrological developments in Austria, seasonal patterns are highly relevant (Laaha et al., 2013; Laaha and Blöschl, 2006). The snow melting periods in spring bring high water flows in summer but weak flows in winter due to the precipitation being stored in the form of snow and ice. If drought occurs in a large area and many sectors, deficits throughout the water cycle might remain beyond the first re-occurring rainfalls until the water storages are refilled. The time lag of this process (Tallaksen, 2006) returning to normal levels of water availability depends on the suffered drought intensity and characteristics of the ecosystem. As described above, this again underlines the difficult definition of drought on- and termination of drought and the potential permanence of the condition.

Impacts on society, economy and ecology occur at various steps of the process of drought (see Fig. 2.1, based on Tallaksen (2006)). This will then influence the sectors, stakeholders and ecosystems hit. These impacts will be discussed more thoroughly in the following sections. The more general term of socio-economic drought (Van Loon et al., 2015) describe the impacts occurring on social and economic systems, caused by drought events. The severity of this may be independent of the severity of water deficit, e.g. in a highly vulnerable situation a water deficit can lead to over-proportional impact severity.

2.2 Measuring drought

In order to establish drought early warning and monitoring systems, as well as implementing drought management, observing and measuring drought is highly interesting. This makes a choice of all the possible obervable apects necessary. To identify drought conditions, several different indices exist, each representing one measurements of drought characteristics (Tallaksen, 2006). Depending on the aspect of drought under observation, meteorological drought indices (e.g. precipitation), hydrological drought indices (e.g. streamflow) or soil moisture indices may be applicable. Moreover, there exists a wide range of combined drought indices ("composite indices"). These aim to combine many factors for a defined purpose: creating a warning system that enables adaptive management options, such as re-distributing water use or adaptation in agriculture. The EDO (Center, 2013) and the USDA (National Drought Mitigation Center, 2016b) provide represent such aggregated indices in form of drought warning levels. Nevertheless, those composite indices require a profound understanding of the various aspects of drought (meteorological drought, hydrological drought, propagation of drought) (Tallaksen, 2006, p. 141).

While meteorological drought indices focus predominately on precipitation (and sometimes also on evapotranspiration), hydrological drought indices characterize river streamflows and water body levels. Characteristics, behaviour under varying conditions and strengths and weaknesses highly depend on the prevalent climate, e.g. summer dry - winter wet climates. I.e. the choice of index depends on the regime under consideration. Mishra and Singh, 2011; Mishra and Singh, 2010 differentiate between aspects of hydrological drought such as duration of the event, affected area, drought intensity and drought severity, where intensity refers to the maximum intensity of missing water and severity to the accumulation of the negative water balance over the duration. In further chapters, their use effectiveness for identifying actual impacts will be assessed. In this context, where there is reference to a probability of impact occurrence, the term "drought indicator" will be used.

The meteorological indices "SPI" and "SPEI"

One commonly used index for meteorological drought is the Standardized Precipitation Index (SPI) (McKee et al., 1993; WMO, 2008). The SPI is calculated over an accumulation period, by normalizing the precipitation of each period (i.e. 1, 3 or also 12 months) by its long-term precipitation average. Therefore, the SPI_1, the SPI for the accumulation period of 1 month, is calculated by normalizing the precipitation sum in each month by its long term average. This is done by taking a time-series of the area under consideration and fitting a (two- or three-parameter) gamma distribution. The resulting values for each month are roughly between -3 and 3 and indicate the position along the standardized standard deviation of a normal distribution. Thus, an SPI value of approximately 0 indicates an average month in terms of precipitation, and an SPI of -3 indicates a very dry month. The advantage of this standardization lies in the better comparability of regions under different climates.

More recently, the SPI has become complemented by the "Standardized Precipitation Evapotranspiration Index (SPEI)" (Vicente-Serrano et al., 2009).Vicente-Serrano et al., 2009 introduce the SPEI, which also captures the potential evapotranspiration resulting from solar radiation. Thus, it is often applied in areas which have moderate dry climates as well as discharge response in Mediterranean climates. Those areas are characterized by high evapotransporational influences. (Lorenzo-Lacruz et al., 2010; López-Moreno et al., 2013). This brings advantages to vegetation analysis, as its water demand also depends on heat and vegetation consumes more water in hot periods.

Hydrological low flow indices

Tallaksen, 2006, chapter 3 describe hydrological drought as water deficit in river streamflow, lake or groundwater levels. Various indices exist for describing streamflow runoff and its properties, as changes in the runoff and also describing "seasonal normal" streamflows in contrast to extreme events like droughts (e.g. hydrological droughts). These include river streamflow quantiles (Q_x, defined as the streamflow reached or exceeded on x% of days in a year), mean annual minimum flows over d consecutive days (MAM_d), duration indices (indices measuring the number of days below a threshold), deficit volumes, and many more (WMO, 2008; Laaha et al., 2013). Groundwater levels are used to monitor aquifer development. Selection mainly depends on the research goal and on the impact under consideration (Laaha et al., 2013; Beyene et al., 2014), like stated before for meteorological indices.

Most commonly applied approaches for drought measurement are low flow characteristics and deficit characteristics (Tallaksen, 2006, chapter 5). Where low flow characteristics describe extreme situations of the streamflow within its typical variance, deficit characteristics define deficits and calculate deficit amounts, such as days under deficit. An important example of the low flow characteristics is the $MAMn - day$. An annual series can be obtained by taking the annual minimum flow of each year (AM). Other commonly used examples are "streamflow quantiles" (Q_x). They represent percentages of the flow duration curve, therefore streamflows, which are observed to be reached or exceeded in x percent of days.

An important example for the deficit characteristics is the threshold level method. It requires a specified threshold definition. Streamflows falling below this threshold suggest the presence of a deficit. Further, as an index, time periods or volumes of deficit are calculated (in days - d_{sum}, maximum consecutive days - d_{max}, volumes - v_{sum}, or volumes on maximum consecutive days- v_{max}) are calculated. Vectors of drought indices over an observation period can be derived by calculating the index for several consecutive periods of time, obtaining monthly or yearly series. Furthermore, thresholds can be varying, adapting the threshold to characteristic seasonal differences. The selection of the method and of the threshold will depend on the matter of investigation. The main challenge is the selection of an appropriate threshold. This should be prudently selected based on evidence rather than being arbitrary and potentially influencing the results, as well as defined by the impact category (e.g. water irrigation for agriculture, navigational depth, etc.) in order to improve the index' capability of indicating damage occurrence (Beyene et al., 2014). Suggestions in Tallaksen, 2006, chapter 5 are to use e.g. deficit volumes (analogous to deficit days, v_{sum} and v_{max}) when estimating effects on hydro-power plants. Table 2.1 presents an overview of those hydrological drought indices.

2.3 Drought monitoring and drought impact estimation

Recently, drought early warning and monitoring systems and protocols have been developed on a national and international level. While specific impacts such as wild fire monitoring on a national level had already been established, international monitoring, high data availability and standardization of indices and definitions are recent developments to a more comprehensive understanding of drought impacts.

2.3.1 European Drought Observatory (EDO)

The European Drought Observatory (EDO) operates an agricultural early drought early warning system. They do this by applying a composite index (of SPI_1 and SPI_3, soil moisture anomalies and remote sensing data fAPAR - fraction of observed photosynthetic active radiation), which indicates water availability for plants. A map is produced regularly (temporal scale

Table 2.1: Selection of hydrological drought indices, own illustration based on Tallaksen, 2006, 141ff

Variable	Name	Index characteristics
AM	annual minimum	flow
d_{sum}	total number of days below threshold	deficit
d_{max}	consecutive number of days below threshold	deficit
v_{sum}	total volume below threshold	deficit
v_{max}	volume on cosecutive days below threshold	deficit

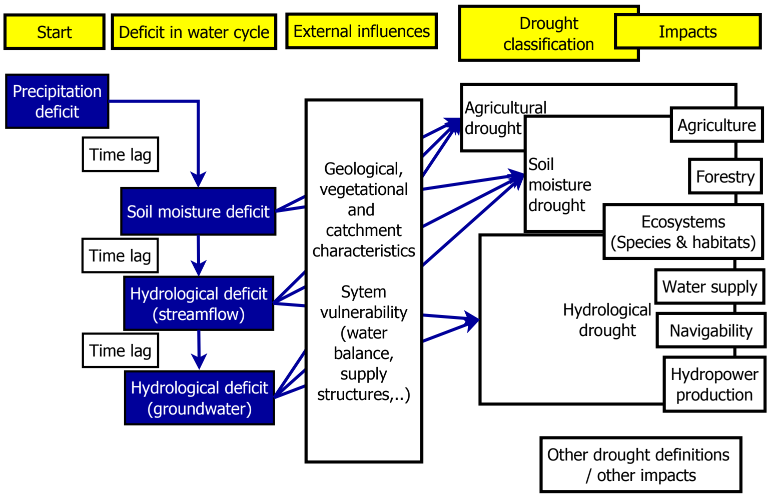

Figure 2.1: Schematic representation of drought propagation and impact influence. Source: own illustration, based on Van Loon et al. (2015)

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available every 10 days), that indicates the different warning levels across Europe (European Drought Observatory, 2016; Center, 2013).

2.3.2 European Drought Impact Report Inventory (EDII) and European Drought Reference Database (EDR)

European Drought Reference (EDR) and European Drought Impact Report Inventory (EDII) are major outcomes of the Drought R&SPI Project of the European Union (EU) FP7 programme that was carried out from 2011 to 2014. The aim of this project was to establish a database of historical drought events and to examine the impact drought events have on different areas or sectors in Europe (European Drought Center, 2016). Impacts are defined as effects resulting from drought conditions, that are 1) negative, 2) direct or indirect, and 3) monetary or non-monetary damages. Impacts are classified according to the European Commission's Nomenclature of territorial units for statistics (NUTS) areas (European Drought Center, 2013) and reported mostly via text-based information such as governmental reports. (Stagge et al., 2013). The database is available online and documented impacts can be viewed by region and time period. Impacts are further differentiated into 15 categories. Each category consists of various subcategories. These categories include e.g. "Agriculture", "Forestry", "Freshwater Ecosystems" and "Energy and Industry". An example of direct effects of drought in forestry would be financial losses due to reduced production. Indirect effects include higher vulnerability to parasites and pests due to water-stress. Various authors refer to the European Drought Impact Inventory (EDII) data base as a source of impact data (Giannikopoulou et al., 2015; Blauhut et al., 2015; Bachmair et al., 2015; Bachmair et al., 2016a; Bachmair et al., 2016b).

2.3.3 United States Drought Monitor (USDM)

The USDM reports a drought warning map on a weekly basis. Input data includes combinations of indices and various sources: precipitation, drought, and also local information from volunteers (Smith et al., 2014; National Drought Mitigation Center, 2016b; National Drought Mitigation

Center, 2016a). They publish a weekly update of the countrywide current risk and warning levels from D0-D4.

The calculation of the warning levels is based on various data inputs. These include the Palmer Drought severity index, SPI, other climatological inputs, Keech-Byram Drought index for fire, satellite-based assessment of vegetation health, various indices for soil moisture from data assimilation models, and hydrological data especially from the West such as surface water supply index and snowpack. Additionally, local information from observing partners is included in the calculations. Inputs are weighted differently according to the season and across regions, taking into consideration the different areas' properties (National Drought Mitigation Center, 2016b; National Drought Mitigation Center, 2016a). Smith et al. (2014) express the importance of local expertise and stakeholder involvement in the assessment of the current drought monitoring state, emphasizing the need for a fast local response and high local relevance.

The USDM is internationally highly recognized (Tallaksen, 2006). The effort-intensive construction of the composite index reflects the complex process of drought monitoring, drought propagation and difficulties of impact modelling.

2.3.4 Other drought monitoring

Other than specialized drought research centres focused on publishing drought development and impact information, monitoring occurs on various steps. Wild fire monitoring and a wild fire danger index is often reported on a national level, (e.g. the wild fire danger index for Austria by the Zentralanstalt fuer Meteorologie und Geologie (ZAMG) (ZAMG, 2017), or the wild fire warning for Germany by the German Meteorological service (DWD, 2017).

Bachmair et al. (2016b) performed research on the current practices utilised in drought early warning systems (DEWS) operated by global and regional providers both regionally and globally. Their results show, that where drought monitoring is practised the appropriateness of the used indices is seldom evaluated (agricultural drought is the exception). Instead, the selection is mainly based on practical issues such as data availability, timeliness of data and simplicity of interpretation.

There has been an increase in the number of different approaches to remote sensing analysis recently (AghaKouchak et al., 2015; Zhang et al., 2013). Furthermore, new approaches to measuring air moisture at ground level and carbon cycle characteristics have increased, thus contributing to better data availability.

2.4 Drought risk analysis

While there are no common standards yet applied, detailed drought risk analysis has been performed in regions that are highly vulnerable to drought. Risk is a concept widely investigated in the literature and across various disciplines. Perception of risk has been changing in recent decades (Smith and Petley, 2009, Part 1) and (Cardona, 2004). In the 1950s, risk was mainly influenced by engineering and natural science including a clear definition of risk as risk = occurrenceProbability * damage * presenceProbability.

In recent decades, Smith and Petley (2009) observe an additional focus on social dimensions of risk about acceptable and non-acceptable risks. This includes the diverse exposures to risk of social groups. The complex relationship of hazard and impacts, including long-term effects, has come into focus. Establishing a risk function - risk as a function of event-probability, presence-probability and occurring damage, like practised in natural science, requires a good knowledge of the probability distribution of hazard and about the thus resulting damage or disaster and got complemented by wider applicable concepts. Those concepts also include differences of vulnerability across socio-economic characteristics. Observations show, that often some parts of the population are more vulnerable to risk than others due to economic reasons, and at the same time less able to take preventive measures against/to offset (Cardona, 2004). Recent Concepts of vulnerability do not focus on a monetary risk estimation but include uncertainty aspects and qualitative aspects. König et al. (2014, 659fff) describe vulnerability as a potential danger or weakness of a system, being between possible impacts on one side and adaptive capacity on the other. Risk therefore comprehends not only the degree of exposition, but also the potential ability to take future measurements against exposition.

The concept of vulnerability in Smith and Petley (2009, 17ff) similarly comprehends potential weakness to threats. Vulnerability as a concept or characteristics of a system aims at identifying potential danger and adaption as well. It integrates the systems' reactions and stabilization mechanisms mitigation or adaption measurements. Stötter et al. (2014) underline the importance of such social aspects when aiming for risk assessment, to be able to establish scenarios and management options or even priorities.

Concerning complex hazards like droughts, some current analysis combine these different approaches, but the main focus is still on the derivation and calculation of a risk function Some relevant studies are presented hereafter:

- Giannikopoulou et al. (2015) perform a risk based analysis of mitigation options for Syros Island, Greece by comparing a baseline scenario to alternative scenarios. Considered sectors are agriculture and domestic water demand. Risk here is defined as "the economic losses associated with the probability of occurrence with a given return period".
- Giannikopoulou et al. (2015) perform a risk-based analysis of mitigation options for Syros Island, Greece by comparing a baseline scenario to alternative scenarios. Considered sectors are agriculture and domestic water demand. In their study, risk is defined as "the economic losses associated with the probability of occurrence with a given return period".
- Haro et al. (2014) examine decision support systems for water managers (based on Montecarlo simulation and SIMGES) on a reservoir system at Orbigo river, Spain. Aim is a status of risk, while at the same time providing a suggestion of management alternatives for drought mitigation based on streamflow development.
- Blauhut et al. (2015) calculate "vulnerability" as the likelihood-of-impact-occurrence (LIO). The idea is the calculation how much

the probability of impact occurrence rises together with the intensification of drought. A logistic regression of SPEI on the impact occurrence (yes/no) is performed for European supra-regions based on the EDII database. Results suggest a steep rise in vulnerability at $SPI_{12} < -1$. Different sectors and different areas show differences in vulnerability.

- Thompson and Calkin (2011, p. 1900) describe risk in wild fire assessment as the "intersection in the triangle burn probability, fire intensity, fire effects" and underline the importance of assessing public and social resource efficiently according to public perception.

3 State of drought impact monitoring in Austria

The EDII identifies 15 different categories of drought impacts (European Drought Center, 2013). For an overview over all impact categories, see Tab. 3.1. In order to present the current state of drought impact monitoring in Austria, a range of studies, research reports and data sources are summarized in this chapter.

Most categories of the EDII will be covered at least briefly. three impact categories were not considered in this master thesis, as they seem negligible for the current situation in Austria (Conflict, Air Quality and Public Safety). Guideline questions include: 1) the identification of drought processes leading to impact; 2) stakeholders involved in impact documentation, and 3) the status of impact documentation and availability and quality of data. Although this work does not focus on mitigation, potential mitigation measurements are named where mentioned important in the literature.

3.1 Agriculture

Among different drought impact categories, drought impacts in agriculture are amongst the most prominent and strongest perceived damages in Austria. Information about agricultural data in Austria is available on a high level compared to other impact categories. The impact category is represented by a high number of available scientific studies and governmental reports. The Österreichische Hagelversicherung (Austrian Hail Insurance) regularly reports damage caused by early frost, heat and drought, and hail (Österreichische Hagelversicherung, 2015; Österreichische Hagelversicherung, 2012; Österreichische Hagelversicherung, 2014).

Table 3.1: List of drought impact categories of the EDII (European Drought Center, 2013)

EDII Impact Category	impact example
Agriculture and Livestock Farming	Reduced availability of irrigation water
Forestry	Decreased tree growth and vitality
Freshwater Aquaculture and Fisheries	Reduced aquaculture production
Energy and Industry	Reduced hydropower production
Waterborne transportation	Impaired navigability of streams
Tourism and Recreation	Reduced number of short-stay tourists
Public Water Supply	Bans on domestic and public water use
Water Quality	Increased water temperature in surface waters
Freshwater Ecosystems: Habitats, Plants and Wildlife	Mid-term deterioration of wetlands
Terrestrial Ecosystems: Habitats, Plants and Wildlife	Lack of feed / water for terrestrial wildlife
Soil System	Drought - related erosion processes (loss of soil fertility)
Wildfires	Increased burned area
Air Quality	Air quality pollution effects / problems (dust bowl effect, wildfires, substitution of hydropower production by fossil energy)
Human Health and Public Safety	Increased respiratory ailments (heat wave and air quality)
Conflicts	Regional/local user conflicts

Scientific case studies on the economic situation of agriculture enterprises (Darnhofer et al., 2016; Toscani and Sekot, 2017), agriculture and ecosystem policy (Wüstemann et al., 2017; Kirchweger and Kantelhardt, 2015), climate change effects and adaptation (Steininger et al., 2015; Lexer et al., 2014; Steininger et al., 2016; Mitter et al., 2015; Mittre et al., 2017; Schönhart et al., 2014) and also drought effects (Strauss et al., 2013) affirm the importance of the sector in Austria. Recent case studies aim to assess the very specific effect of drought on different economic and social characteristics (e.g. Quiroga and Suárez (2016) and Mittre et al. (2017)). Annually, the governmental "Green Report" by the Bundesministerium für Landwirtschaft, Forstwirtschaft, Umwelt und Wasserwirtschaft (BMLFUW, Austrian Ministry for Agriculture and Forestry, (BMLFUW, 2016) is published, representing an overview and interpretation of the year's production, including drought events.

This high level of interest in the effects of drought in agriculture leads to the quick identification of risks, with losses regularly identified and calculated throughout the year. The fast reaction of crop production to precipitation deficits – faster than forestry - supports this higher level of available information. An overview for the years of known drought events show a wide range of reports. Press releases of the Austrian Hail Insurance have been found for the years of known drought events 2003 and 2012-2015 (Österreichische Hagelversicherung, 2015; Österreichische Hagelversicherung, 2012; Österreichische Hagelversicherung, 2014; Niederösterreichische Landesregierung, 2003). Mostly affected regions here are Eastern Austrian regions. Nevertheless, isolating and identifying drought effects is difficult. Usually, throughout the year, a variety of meteorological events influence crop production, of which drought is just one (*Starke, Holger: personal communication* 2016). Late frost in spring, extreme heat and pests are all influencing factors. This significantly affects the production data of a time series of years to derive drought damages.

The Austrian Hail Insurance present explicit quantifications are presented for 2015 of 175 million Euros for Austria (Österreichische Hagelversicherung, 2015). After the drought event in 2015, the Green Report by the BMLFUW (BMLFUW, 2016) shows a decrease in production resulting in an increase in price, which is attributed to the extreme drought and heat of the year. There has to be a bias assumed considering the type of insured crops, insured regions and attention to damage occurrence. Decreasing yields per hectare and rising prices have been registered for corn, potatoes and leguminous crops. 2015 was special considering the accountability of damage to drought, due to the lack of late spring frost. Those estimations represent the agricultural production sites covered by insurance, and therefore do not account for all cultivated areas or crops. Moreover, an interest in insurance is mainly assumed for vulnerable sites.

Drought compensation of the Austrian Hail Insurance is refunded according to crop type a local municipality-based precipitation thresholds (Österreichische Hagelversicherung, 2018). Refunds therefore occur in case precipitation in the critical growth period falls below a threshold. Depending on the insurance product, different regulations apply and other crop types are insured. In the most general product "Agrar Universal", most crop types are included, including most cereal types except maize (which has a different regulation). The threshold is reached either if precipitation (monitored for each municipality) in the defined vegetation period falls more than 10% below defined water demand (defined for crop and municipality), or if precipitation is below 10mm for 30 consecutive days in the vegetation period.

In a more general study, Strauss et al. (2013) specify the vulnerability of dry regions as potential losses of 0.6-0.9 % when annual precipitation sums decrease by 1%. Most important here were precipitation amounts in spring and summer. Mittre et al. (2017) estimate the losses due to drought under climate change scenarios in Austria from 1.7 - 6.9% per year and highest risk for eastern regions.

Drought impacts in Austria occur on various levels. Costs and income reduction occur at the level of farmers and insurance companies. Indirect effects, i.e. on market prices (BMLFUW, 2016) or raised costs of mitigation efforts (i.e. irrigation and changes in crop choices (Neugschwandtner et al., 2015; Grussmann et al., 2014) have been observed. Resource deterioration of soil and groundwater has also been noted (Neunteufel et al., 2016; ZAMG and TU Wien, 2011) but is not exclusively accountable to drought. The extent of vulnerability highly depends on vegetational and geological factors, i.e. the soil structure and the respective capability of water storage, as well as the period of precipitation deficit (Brázdil et al., 2008).

Depending on the timing of the drought, different crops are affected. A drought occurring later in the year, like that of 2015, leads to damages to the production of e.g. corn but not wheat. Mitigation efforts are focused on adaptive crops and mitigation, with the latter one putting pressure on water resources (Nachtnebel et al., 2014).

Summarized, the impact category is characterized by a competition in water use across other impact categories, already happening regular adaptions to drought events, a high amount of research but few data available for statistical time series analysis. High resolute data would be needed for this purpose, separating different crops as well.

3.2 Energy and industry

Effects on the energy sector are mainly caused by a low flow situation (i.e. the focus lies on river discharge). The decreased production of hydroelectric power, restrictions in industrial production and other thermal power production due to the scarcity of cooling water (European Drought Center, 2013) influence the costs and revenues of operators, but also effect energy production in general.

Amongst industrial plants, run-of-river hydro-power plants and thermal power stations depending on cooling water are most directly affected by restrictions of water use, which would result from water scarcity and ecological residual water sections. Small size hydro-power plants could be affected in a different way than big hydroelectric power plants. They are situated at small rivers and streams, which react to precipitation deficits much faster than big rivers.

Currently, there is no available data on the impact of such effects, but data needed for modelling could be presented by an electric production time series. Austrian energy market data is collected and documented by the e-control Austria (the federal agency for the energy market) and reported on a yearly basis (e.g. E-control (2016)). Due to the small number of market operators (Österreichs E-Wirtschaft, 2018), the availability of data is impaired by underlying privacy issues (*Nischkauer, Hans: personal* *communication* 2016). Sometimes as few as one or two companies are operating plants along a river (within a federal state). Moreover, this lack of stakeholders affects the availability of data, as none of the contacted suppliers had any interest in entering into a research partnership (Österreichs E-Wirtschaft, 2018). In order to find a suitable time series of hydroelectric power production several suppliers were contacted. However, no partnership was found due to a presumed lack of interest. Likewise, no partners were found for cooperation in researching the effects of drought and low flows on small hydroelectric power plants. For cooling water effects, no public available of data or an overview of production plants were found. The extent to which detailed information is available remains open, and many other factors influencing production exist.

The effect of drought on the "energy and industry" impact category has been estimated in the context of climate change. Nevertheless, there is no clear conclusion on the quantification of effects available. One study considers effects of drought on this impact category and concludes a high resilience of the same (Austrian Panel on Climate Change and Kromp-Kolb, 2014). They estimate a trend in rising winter low flows, and thus raising the usually scarce water availability for energy production in winter. This would bring demand and supply of energy production closer together. Other stakeholders in the sector assume that in the event of low flow there will be effects on hydroelectric production (*Nischkauer, Hans: personal communication* 2016; Buchsbaum, 2016). *Nischkauer, Hans: personal communication* (2016) confirmed that the effects would mainly depend on technical design and sizing. Österreichische Kleinwasserkraft (Austrian small scale hydroelectric power, Buchsbaum (2016)) also confirmed that small scale hydroelectric production is strongly affected by low flow events.

The ambiguity and uncertainty surrounding direct effects suggest the need for an in-depth analysis on the actual impacts, research partners from the private sector or a higher availability of public data. In the case of low discharge, ecological purposes, fishery, agriculture, tourism and industry all have an interest in the water use. Such conflicts are currently considered mainly in the context of hydropower plant usage (Austrian Panel on Climate Change and Kromp-Kolb, 2014; Niedermair et al., 2007; Jung, 2003; *Hinterhofer, Manuel: personal communication* 2017), and therefore the need for a more integrative approach of management is suggested. Additional planning and balance of interests surrounding conflicts of use would be in the interest of all stakeholders involved. These arguments will be further examined in the conclusion of this section.

3.3 Fishery and freshwater aquaculture, freshwater ecosystems and water quality

Drought influences freshwater ecosystems, aquaculture and fisheries across different pathways. It is therefore difficult to track consequences that are directly related to drought. This chapter will provide an overview of the impact of drought on freshwater ecosystems, with a specific focus on fishery and aquiculture. In the final section the possibilities for drought impact monitoring will be reviewed.

Drought impacts on freshwater ecosystems

According to the EDII, propagating drought has different forms of impact on freshwater ecosystems caused by factors such as food availability, water quality and water temperature (European Drought Center, 2013). While some drought impacts are visible in the short term (e.g. increased species mortality) others are only registered in later years (e.g. reduced rejuvenation) or occur in larger areas and time scales (e.g. habitat change).

Figure 3.1 gives an overview of various directions of impacts influencing freshwater ecosystems, in which droughts changes environmental factors of the ecosystems (Lampert and Sommer, 1999; Kalbe, 1997), causing an increase in fish mortality and a decrease in reproduction rates (own illustration, based on Mosley (2015), European Drought Center (2013), Lampert and Sommer (1999), and Kalbe (1997)). Figure 3.2 gives more detailed examples of the negatively influencing ecological situations, such as higher chemical concentrations and less Oxigen-availability. Smaller waterbodies could also result in increased competition between energy and agriculture productions, leading to greater water consumption (NÖN,

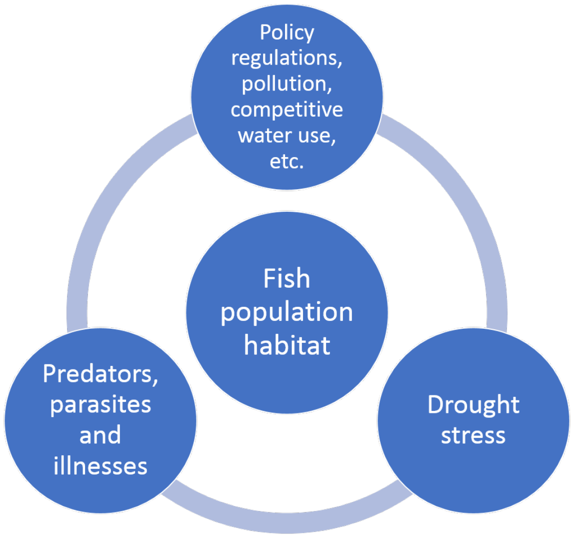

Figure 3.1: Schematic representation of hydrological drought impact processes in freshwater ecosystems and fishery

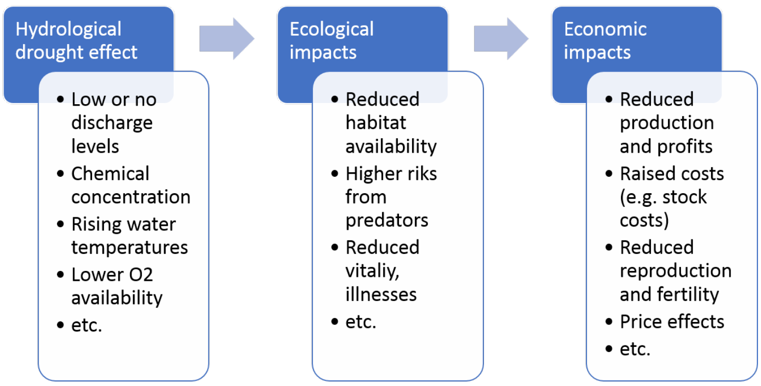

Figure 3.2: Listing of hydrological drought impact processes freshwater ecosystems and fishery

2015; Melcher et al., 2013; Niedermair et al., 2007; Bezirksrundschau, 2013). Thus, identifying concrete drought impacts on freshwater ecosystems is difficult and bears methodological barriers.

However, multiple studies have shown that the impact of drought is less intense in structurally diverse ecosystems. These include zones that are lower in temperatures, provide better protection against predators and have a wider variety and offer of food which strengthen the resilience of the ecosystem (Niedermair et al., 2007; Jung, 2013). These structurally diverse ecosystems provide better protection and more alternatives under extreme conditions.

Drought impacts on fishery and aquaculture production in Austria

According to the EDII (European Drought Center, 2013), drought affects fishery and freshwater aquaculture primarily through reduced production or raised costs. Reasons for reduced production mostly lie in the categories of ecological drought impacts. These include missing water volume (e.g. low flows up to dry fallings), reduced water quality (e.g. chemical component composition, low oxygen rates, concentration effects, rising temperatures, etc.) and higher vulnerability to predators or illnesses due to weakened state. Matthews and Marsh-Matthews (2003) underline the diverse effects of drought on fish populations and a higher need of understanding. In the study performed in Oklahoma, United States, no medium-term effects were registered on the investigated fish species. Results do, however, suggest that habitat changes have resulted in long-term effects and a change in species and ecosystem equilibrium over decades, threatening vulnerable species. Mosley (2015) report worse water quality due to salinity and algal production. On the other hand, ZAMG and TU Wien (2011) conclude that, overall, the extent of effects by human activities on water quality is higher than those of climate, including droughts.

Drought impacts on aquaculture and fishery are assumed but not quantified, monitored or registered. A range of monetary estimations exists, which origins are unclear. Single reports make estimations about monetary losses ("couples of thousands of Euros" in Pesenbach in 2015 (Oberösterreichische Nachrichten, 2015b). Estimations of damage can reach large amounts, as seen in a report in the Austrian newspaper der standard, regarding damage of over €400 million at the Baikal-See shows in 2015 (Ballin, 2015), caused by dry circumstances and overuse together. A range of studies is available for climate change estimations which include assumptions about drought, but drought impacts cannot be directly derived. Regularly reported impacts although not on a standardized and regular scale are impacts on water quality and falling water levels in water bodies or dry-falling. Various authors mention low flows as a cause of water temperature and affecting water quality and also species movement according to their temperature preferences (Niedermair et al., 2007; Melcher et al., 2013). Dry-falling of rivers is in particular mentioned by local and regional newspapers (Bezirksrundschau, 2013; Oberösterreichische Nachrichten, 2015b; Oberösterreichische Nachrichten, 2015c; Oberösterreichische Nachrichten, 2015a; NÖN, 2015).

Data about drought effects is moreover difficult to achieve in the small and non-uniform structure of fishery in Austria. Drought impacts on fishery and aquaculture production in Austria are assumed by various stakeholders, but currently no estimations exist. Fishery and aquaculture production in Austria is characterized by small economic structures and spread over many different actors: owner of the area, leaseholder, external manager and license owner (BMLFUW, 2015; Statistik Austria, 2008). Furthermore, fishery is in many cases not the primary economic activity of suppliers (e.g. it is realized by restaurants) nor is the request for fishery licenses (e.g. it is seen as a hobby or lifestyle question). Experiences of the Austrian Fishery Association (*Hinterhofer, Manuel: personal communication* 2017) show change in the demand of fishing licenses for many different reasons, but less as a reaction to the fish situation in rivers, lakes or ponds. Cost structures and actual numbers are therefore not documented nor are decisions for direct economic reasons of the fishing activity (i.e. investments, price building, continuing or discontinuing of activities) made.

Further options for monitoring

Finding a drought damage indicator for direct impacts is difficult. Currently, there is no direct monitoring of additional costs or reduced profits induced by drought. Impacts to fishery and aquaculture are – if they exist - rather visible on a qualitative scale (impact categories) than a quantitative scale (actual costs). Estimations are provided by stakeholders' experience, but actual monitoring is not performed.

Considering the difficulties in obtaining quantitative impact data and the availability of single impact mentioning as illustrated in this section, text-based information such as newspaper articles is currently used by the EDII as primary source of information (European Drought Center, 2013). In order to assess direct impacts of drought on these categories, a closer understanding of the relation between drought and water temperature as well as between drought and low flow would be required. A possible attention bias has to be considered which draws attention to already observed effects instead of representative occurring effects (Thompson and Calkin, 2011). The category-specific complexity is also reflected by being under-represented amongst evaluations of the EDII (e.g. studies for impacts on agriculture, forestry or wild fires are already found, while currently there are no studies available for aquaculture production).

Where the exact impacts of drought on freshwater systems are not yet well understood, documented or monitored, the evolving of conflicts of use that might occur in drought periods is stated in different contexts (ZAMG and TU Wien, 2011; Niedermair et al., 2007; *Hinterhofer, Manuel: personal communication* 2017). Competing sectors are e.g. agriculture and fishery in using river water for irrigation, fishery and recreation at local lakes and ponds, and fishery and electric production in cases of low flow and high energy demand.

3.4 Forestry

Drought impact allocation in forestry is a complex objective. This section aims at highlighting the different manifestations of drought management in forestry and the channels that are currently used to show this damage.

Drought damage in forestry is closely related to heat damage and highly depends on the site characteristics. EDII sub-categories include direct impacts (e.g. reduced growth and vitality, die-backs of trees or increased costs and economic losses) as well as indirect impacts (i.e. increase of pests) (European Drought Center, 2013). Altenkirch et al. (2002) and Schwerdtfeger (1981) describe drought effects in forestry, occurring as a consequence of decreasing soil moisture and also on the availability of water for vegetation. Forest vegetation exposed to water stress and extreme temperature relies mainly on geological, soil and vegetational properties as well as pre-conditions of soil and vegetation. Moreover, secondary damages and long-term damage depend on other influence factors like management factors, fallen timber in the form of available breeding material, or the growth cycles of parasites.

The Austrian Research Center for Forests (BFW) documents forest damage at a variety of different impact indicators (BFW, 2013a; Steyrer et al., 2012), available under "documentation of forest damage factors" (DWF) on the BFW-homepage (BFW, 2017[a]). Most relevant for this context is the category "drought and heat damage" (d&h), here directly visible damage is reported. This category combines damages by drought and heat due to the similar visible symptoms which entail monetary and non-monetary damages as well as mortal and non-mortal damages (Institut für Waldschutz, 2016). Further on, the data will be analysed in respect to a comparison of different meteorological drought indices. The combined report of damage volume of drought as well as heat damage suggests using precipitation indices as drought indices for impact evaluation and especially for the SPEI.

Potential categories for indirect effects have been identified in cooperation with the BFW (*Steyrer, Gottfried: personal communication* 2016) including damage by the European spruce bark beetle and the six-toothed spruce bark beetle due to their infestation of drought-weakened trees (Netherer et al., 2015). Their population also depends on the availability of brooding substrates (e.g. fallen or damaged timber caused by heavy storms). Therefore, an isolation of the effect will be challenging.

Impact reporting in the DWF is performed by the local forest supervision authorities and reported by year, authority region (BFI) and damaged quantity, i.e. “reduced damaged areas” for “heat and drought damage” and “cubic meters” for “bark beetle damage”. Data is available at this level of information since 2002. It has to be underlined though, that indirect effects such as falling prices due to over-production could also arise. Therefore, the selected indicators presents an estimated, but incomplete overview of drought damage.

The DWF database show the highest damage for the years 2003 and 2015 (see Fig. 4.3) for direct drought and heat damage, but also relatively high damage in 2011 and 2013. A team of authors in "Nature" assesed a very high vulnerability of forests to drought in case of changing rain patterns (Choat et al., 2012). Regional media has shown interest by reporting drought damage in forestry in 2012, 2013 and 2015 (Österreichischer Rundfunk, 2012; Waldverband Österreich, 2013; Waldverband Österreich, 2015). Although the observation of drought damage is subject to various forms of detection and cognition biases (Institut für Waldschutz, 2016; *Steyrer, Gottfried: personal communication* 2016), the presented database provides a good starting point for estimating drought damage and its impacts. An analysis of the data will be presented below.

3.5 Public water supply

Impacts on public water supply caused by drought impacts consist of a variety of different occurrences. According to the EDII (European Drought Center, 2013), those include water shortage or water supply cuts on a local, regional or national level, bans of water use, needs of emergency actions to ensure water supply and increased economic costs or losses.

Public water supply mainly reacts to hydrological components of drought. Depending on the supply structure, water shortage is experienced from falling levels in reservoirs, lakes, rivers, springs or groundwater (European Drought Center, 2013). In Austria, water supply is mainly based on groundwater and springs, and only in few areas on surface water (Neunteufel et al., 2016). This renders the sector comparably resilient in direct damages of drought events. In case of water scarcity, decreasing groundwater levels, rising water temperatures and quality deterioration are potential impacts. Low discharges following drought events can also lead to corrosion effects and odour formation in waste water disposal (Austrian Panel on Climate Change and Kromp-Kolb, 2014).

Drought impacts on the water supply in Austria are currently not critical. Neunteufel et al. (2016) conducted a study performing a survey among main water supply providers in Austria for the years 2003, 2013 and 2015, in which water shortage was felt the most. No impacts were reported for 2013, and were on a higher level for 2015 compared with those of 2003. In both years, approximately 10% of survey respondents reported appeals for water saving, and 5% actual bans of activities like car washing. Those occurred mainly on a local level. Furthermore, occurrences of local water shortage and raising infrastructure costs in the short term but also in the long term arouse to raise supply security. An individualisation of drought effects is also in the public water supply difficult. The sector is demand-driven, facing situations of highest demand on hot summer days. Water shortage might therefore be caused also by heat days, which seems to be a more critical situation in Austria than drought events characterized by low flows. There is some indication that groundwater resource levels are decreasing in some regions in Austria and drought events playing a role due to missing groundwater recharge, but in the context of drought events have not been covered.

There exist more general evaluations of the sector for Austria underlying resilience towards climate and in particular drought events. Neunteufel et al. (2014) see an increased effort for removing sediments. North eastern parts of the country suffer vulnerability here. Main costs arise from heavy precipitation events and other extreme events caused by climate change, costs for infrastructure renewal, etc., but also mention deterioration of water quality after long drought events. Effects of human activities on water quality are estimated higher than those of climate (including droughts), pointing also here at the general drought resilient situation for Austrian public water supply. In an evaluation of climate change on water supply, ZAMG and TU Wien (2011) report a decline in groundwater levels for Carinthia, South-Eastern Styria, Burgenland and towards north until the Danube has been registered in the last years. Due to high resource level though there are critical situations in water supply only expected for small vulnerable areas but not on a general level. Austrian Panel on Climate Change and Kromp-Kolb (2014) find similar results. Authors speak of problems caused by conflicts of water use though possibly occurring on high demand days (hot summer days), and Neunteufel et al. (2016) explicitly mention agriculture.

These studies, in particular simulations for climate change, are based on uncertainty. Findings have therefore to be taken with care. Especially in presence of long term effects on water resources, a need for change in water management could become necessary. At the moment, this is not assumed, also due to high resource levels and water availability in Austria. A particular focus could be made on local level in specific, vulnerable regions in Eastern and Southern Austria, and on management methods to avoid conflicts of use for specific days or months. Concluding on the information of this section, estimations and individualisation of direct drought damages in this sector on a national level would be difficult and their added value is assumed to be low.

3.6 Waterborne transportation

Under enduring drought conditions, impairments in navigability may occur due to low flows in rivers. This is characterized by reduced profits due to real impairments and higher infrastructure costs, ensuring the navigability of the river way also under extreme conditions. The first one includes reduced amounts of transport volume, reduced loading rates and reduced number of shipments (*Simoner, Markus (via donau): E-mail communication* 2016). Loading rates of shipments decrease, until they are no longer economically efficient and the amount of transport volume decreases in total. In this case, other modes of transport are chosen. Most frequently transported goods in 2016 on the Danube were ores and metal wastes (32%), and petroleum products (20%) (Statistik Austria, 2017a). Raised infrastructure costs occur when freeing and deepening the water ways to guarantee a certain navigability level even under extreme conditions (via donau, 2016a). Indirect occurring costs would be higher amounts of CO_2 due to a shift to other transport modes (Krause, 2009).

There needs to be further research about the frequency and intensity of these effects.

In Austria, the main relevant river regarding waterborne transportation in Austria is the Danube. Waterway transport is less important than other modes of transport. The share in transport performance in ton-kilometers (tkm) in Austria of waterway transport is at 2.5% in 2006 (Statistik Austria, 2017c), where the transport volume in tonnes (t) times the transported space in kilometres (km) results in the transport performance tkm. Nevertheless, effects on specific product segments and on efforts to raise the sector's importance are high in case of extreme low flows. In 2016, 9.274 mio tkm of goods were transported on the Danube going at least partly through Austria (Statistik Austria, 2017c). Moreover, low flow impacts in some areas of the Danube have effects on the attractiveness of the waterway as a whole.

The Danube is the second largest river in Europe and as part of the waterway Rhein-Main-Danube it is significant to the transit and east-west connection of waterways (Krause, 2009). Other rivers in Austria are not relevant on an international level and impacts on shipment impairment on those might happen on a local or individual level, but are not covered here. Developments in transport volume and performance on the Danube depend on weather conditions, general trends in the transportation sector, navigability of the whole Rhein-Main-Danube waterway including infrastructure operations along the whole waterway. Navigability impairments due to weather conditions include days of low flow, floods and ice (via donau, 2016a). General trends depend on product trends, the economic situation of regions along the Danube and policy measurements (Krause, 2009). Navigability of the international waterway depends on missing infrastructure operations, e.g. no excavating in Hungary and Bulgaria in 2015 or the military crisis in former Yugoslavia 1993-1995 (BMVIT, 2006), or specific local conditions like the navigability of the Main-Danube canal (via donau, 2016a). Such events block only part of the waterway, yet lead to a decrease in transport volume along the whole path. For 2003 and 2015, moreover, decreases in transport volume and performance are accounted to the low flows (Statistik Austria, 2016b; via donau, 2016a; BMVIT, 2006). For 2015, transport performance in particular was 17% below 2014. Thus, the share is small and the importance smaller than other forms of transport, a decrease in transport volume has significant effects on specific product segments and forwarders. Conclusively, high data availability of statistical data and a clear assignment of this type of drought impact to low flow impacts render this impact category interesting for analysis.

Statistical data for Danube transport details is highly available. The "Via donau - Österreichische Wasserstraßen GmbH" manages and controls operational aspects of Danube river transport, which is the route for inland waterways transport (BMVIT, 2017a; BMVIT, 2017b; via donau, 2016b). The "Statistik Austria", the Austrian federal institute for statistics, publishes data on a yearly level (e.g. monthly transport volume, monthly transported tons and kilometres, and yearly ship loading rate). As data is highly available, a quantitative analysis of the impact category is provided in further chapters below.

3.7 Wild fires

The process of wild fires is multifactorial. According to Altenkirch et al. (2002, 217ff.), wild fires develop in the context of precipitation, ground humidity, availability of burnable material, temperature and ignition. Depending on geological and vegetational factors, some sites are more exposed to wild fires than others. The individual occurrence of wildfires is a very regional process, although, small summer thunderstorms can significantly decrease the risk of wild fires in an area of few square-kilometres, while the rest of the region still suffers critical conditions. High precipitation and ground humidity can limit the possibilities for fire to develop high temperatures and intensity. However, a high availability of burnable material supports the intensification of ignited fires and often depends on the management of the forest. There are two sources of ignition in Austria: Lightning and human causes, such as litter induced ignition or arson. Thus, critical and high alert situations still depend in ignition factors. However, the process remains to some extend unpredictable. Drought in this context raises the probability of wild fires occurring, rendering the vegetation more vulnerable and leading to a higher intensity and faster spreading of fire.

Economic costs of wild fires are mainly represented by first the costs of suppressing wild fires and second, the direct damage in the forest caused by wild fires. The suppression of fires often costs more than the damage incurred. Arpaci et al. (2013) describe the importance of wild fire suppression in Austria, independent costs and resources needed. Therefore, it is difficult to distinguish between resilience of wild fire danger and extinguishing measurements (i.e. drought mitigation measurements as high indirect costs of drought). The effective suppression of wild fires mainly depends on the availability of measurements (water or sand, see Altenkirch et al. (2002, 221f.)) and the reduction of (human-related) ignition causes (awareness raising and early warning methods to prevent carelessness, see (Altenkirch et al., 2002, 219f.)).

In wildfires, early warning and monitoring systems, developed for the Northern American areas (United States and Canada), play an important role also in Europe. Different indices for wildfire warning systems have been established and used, and reflect the dominating process characteristics of the season, e.g. temperatures, wind or other climatic factors which vary with the season and thus may or may not be critical for wild fire development. Wild fire prone conditions occur at a mix of climatological and soil moisture conditions. For the US and Canada, indices have been tested and developed. Most are composite indices, which take more than one input value to form a risk evaluation. Most focus in their input factors on precipitation and ground humidity. Nevertheless, there remains many uncertainties as effects vary from regional perspectives.

Developed indices for the USA or Canada might not be valid for Central Europe. The European Forest Fire Information System (EFFIS) offers up-to-date information of occurrences additionally to a wild fire danger forecast based on the Canadian Forest Fire Weather Index (FWI) (Center, 2017; San-Miguel-Ayanz et al., 2012). The FWI focuses on soil properties and fire behaviour, taking as input values mainly temperature, wind speed, 24-hours rainfall and relative humidity (Canada, 2017; Lee, 1996). The adaptability of these indices for Austria and Alpine climate conditions has been discussed, with suggested findings and different methodological approaches.Müller et al. (2015) investigate fire anomalies considering the number of reported fires and the area burned. The findings suggest anomalies (peaks) of fire occurrence in 2012, 2013 and 2014, where in

2014 the earliest lightning-induced fire recorded occurred. To refer to the seasonal patterns of wildfires, seasons were examined.

Arpaci et al. (2013) test various indices for the Austrian fire regime. Most promising indices were maximal registered temperature, Keetch Byram (KBDI), BUI (Canadian) for summer, and M68dwd for winter. Wild fire estimation based only on precipitation and SPI or SPEI is strikingly limited in forecasting, but could provide useful insights in drought impact estimation, being a determinant variable on larger regional and timely scales (Blauhut et al., 2015). Gudmundsson et al. (2014) and Thompson and Calkin (2011) used logistic regression analysis used for predicting event occurrence probability (between 0 and 1), thus modelling the probability of wild fire occurrence (where wil dire occurrence is a binary variable) on independent variables.

Data availability of wild fire occurrence in Austria is high. The Boku Institute for Silviculture operates a database about wild fires (Institute for Silviculture (WALDBAU), 2016) and kindly supported this work by providing highly detailed data on the occurrence of Austrian wild fires over the last 30 years. For small areas (< 1 ha) the details of reporting increased in this time (Müller et al., 2015), so these small fires will be left out of analysis to guarantee homogeneous data. Details about the data set will be discussed below. For the quantitative analysis in this master thesis, drought indices in form of precipitation and evapo-transpiration measurements and modellings were considered.

3.8 Other impact categories

In the previous chapters, the impact categories with the highest literature availability have been covered. The EDI also foresees other potential impacts of drought which might be less obvious or where estimations and data availability are still unavailable. Of these, soil systems, terrestrial ecosystems, and tourism and recreation are covered here to give a fuller overview of the various implications of drought. Three impact categories were not considered in this master thesis, as they seem negligible for the current situation in Austria: conflict, air Quality and public safety).

Austrian Panel on Climate Change and Kromp-Kolb (2014) consider health and infrastructure to be mainly affected by temperature and heavy precipitation events in Austria and not by droughts. Water supply and waste water infrastructure is discussed as well in the section about public water supply.

3.8.1 Soil systems

Direct effects of drought on soil systems include soil erosion and loss of fertility and impacts of structural damages (European Drought Center, 2013). Accounting for the first, there was no individual reporting source found for the situation in Austria. Klik and Eitzinger (2010) assess climate change impacts on soil erosion and find low increased impacts due to climate change when mitigated according to the modelled measurements. Most effects here become visible at the level of agriculture or forest damage (and potentially terrestrial ecosystems). Case studies do exist, and Strohmeier et al. (2016) show the contribution of extreme occurrences of soil erosion for 2 sites in Austria. Austrian Panel on Climate Change and Kromp-Kolb (2014) expect pedosphere variations following changes in temperature and precipitation. This development will result for some regions in positive effects, while negative for others. This will depend on the changes in water balance and the stability of the region's water balance. Developments therefore are of a high level of uncertainty. This might result in positive or negative changes. Where dry soil systems contribute to structural damages in infrastructure, there are no registered effects. Different institutes collect and publish data about soil (e.g. the digital soil map "eBOD" (BFW, 2013b)) but no time series were found. Therefore, this category, while considered important, is not covered further in this master thesis.

3.8.2 Terrestrial ecosystems

Information for impacts on terrestrial ecosystems is mainly available in combination with information on risks to biodiversity and effects of climate change. Niedermair et al. (2007) describe risks for biodiversity in

Austrian forests mainly through temperature rises and slight shifts of biocenosis in northern and higher regions. This might present high risks and uncertainties to ecosystems, but quantification - especially concerning drought effects - has not yet been performed. Potential indicators include individuals of specific indicative species, but there is a need for further research before performing an analysis on drought effects. Climate change studies agree here on this need (Lexer et al., 2014). Kirchner et al. (2015) perform an analysis of ecosystem services using indicators of e.g. biomass production, ecological integrity or the Shannon Diversity Index for Landscape Aesthetics Here again, effects from other causes are expected to be a lot higher than impacts from drought. On the other hand, effects on moors, which are largely anticipated, could be dominated by changes in the water balance cycle. (Niedermair et al., 2007). More research on impact indicators will have to be done before concluding about drought indices; a potential focus could be on remote sensing data and precipitation indices.

3.8.3 Tourism and recreation

Tourism in Austria mainly faces negative impacts of drought in winter due to its high dependency on snow fall and potentially positive and negative impacts in summer (König et al., 2014). Concerning summer tourism, negative impacts would result from impairments to bathing possibilities due to low flows. Conversely, positive impacts could occur as a result of less rainfall and better weather conditions. Rising temperatures would lead to comparable effects. Different statistical data concerning the number of overnight-stays, arriving guests and income within the sector are available by the federal statistic office, Statistik Austria (Statistik Austria, 2017b). An impact evaluation is not covered here, as the focus of the analytical part of this work rested on negative summer impacts and a complete consideration was contextually irrelevant. For 2016 and 2017, there were some reports on water shortage for winter tourism destinations in Austria (Essl, 2016; Roth, 2017; Hahn, 2014). A high stakeholder interest in this potential developments roots in the potential competition of water across different categories, like tourism and fishery and tourism and freshwater ecosystems (ZAMG and TU Wien, 2011; Niedermair et al., 2007; *Hinterhofer, Manuel: personal communication* 2017).

3.9 Summary

In the first part of this thesis, the state of drought impact monitoring in Austria amongst different sectors was explored and different drought indicators were used or applied. For most drought impact categories, a distinction between impacts exclusively caused by droughts and those potentially caused by other factors appears difficult. Most drought impacts in Austria are not monitored on a regular basis. Best documented impacts are agriculture, forestry, wild fires, waterborne transportation and public water supply (Tab. 3.2 and Fig. 3.3). Stakeholders' interest in such indicators and follow up research showed to be high, although considerations and doubts of the required methodology prevailed.

For most impact categories there is not enough evidence to clearly identify monitorable impact indices at this state. In particular, ecological impacts on ecosystems and long-term impacts are characterised by complex damage processes and require profound indicator design and testing. Both drought generation and impact chains are highly complex systems, depending on a high variety of on-site and individual factors and monitoring will to some extend remain imperfect. Moreover, evidence from those results also suggests conflicts of interest of water use under drought events, i.e. in situations of water supply shortage.

Where impact monitoring exists, approaches are different amongst impact categories. Most documented damages are in agriculture. Common forms of documentations are based on regional and local weather data and derived from values below thresholds per crop type and season. Therefore, this indicator is a direct function of rainfall. Monitoring in forestry is available as direct reported "drought damage" by foresters. Although general standards for reporting exist, indicators are susceptible to subjective evaluation, high attention as well as presence bias. In the category of water supply, enquiries amongst water suppliers were found, questioning about their situation in especially dry years. In ecosystem science, mainly species migration (of bio-indicators) and endangered species development have been mentioned as indicators for drought. Wild fires as a direct consequence are documented on a high spatial resolution. In the categories of waterborne transport and energy and industry, direct transport volume statistics as well as energy production statistics could be put into correlation with water levels of rivers in questions.

In the next sections forestry, wild fire and Danube transport data will be taken for regression modelling approaches to make conclusions about the relationship between the tested drought indices and drought impact indicators and about index selection.

Table 3.2: Overview of drought impacts and data availability of EDII impact categories in Austria. (++) very high, (+) high, (-) nothing found, (x) not covered

EDII Impact Category	intensity of impacts	data availability and impact documentation	adaption in progress
Agriculture and Livestock Farming	++	-	+
Forestry	++	++	-
Freshwater Aquaculture and Fisheries	+	-	-
Energy and Industry	+	-	-
Waterborne transportation	+	++	+
Tourism and Recreation	-	-	-
Public Water Supply	-	+	+
Water Quality	+	-	-
Freshwater Ecosystems: Habitats, Plants and Wildlife	++	-	-
Terrestrial Ecosystems: Habitats, Plants and Wildlife	++	-	-
Soil System	+	-	-
Wildfires	+	++	-
Air Quality	x	x	x
Human Health and Public Safety	x	x	x
Conflicts	x	x	x

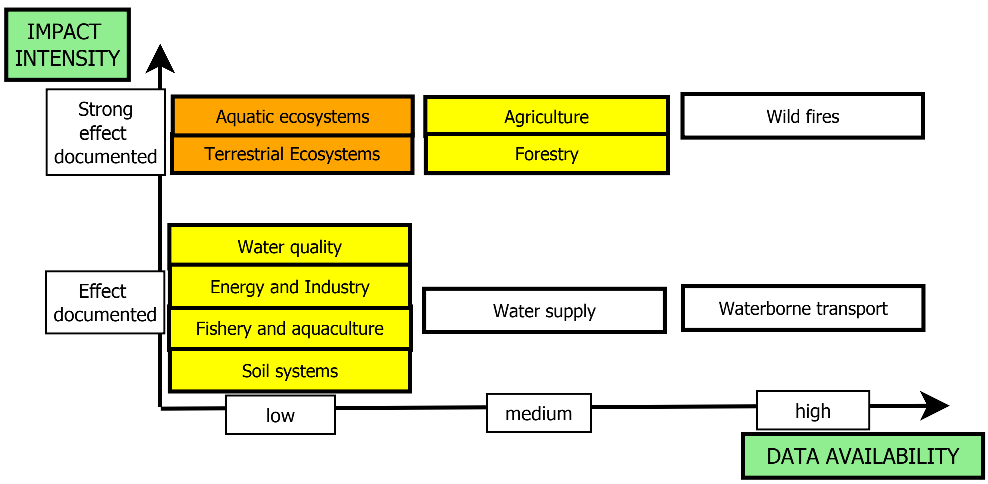

Figure 3.3: Impact intensity and data availability for drought impact categories in Austria with at least moderate registered impacts.

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4 Methods and Data

Difficulties in drought index selection and drought impact monitoring have been discussed previously, as well as the recent efforts of filling this gap (Pasho et al., 2011; Potop et al., 2012; Vergni and Todisco, 2011; Gudmundsson et al., 2014; Bachmair et al., 2015; Bachmair et al., 2016a; Stagge et al., 2015). For Austria, no comprehensive analyses have been found so far. This master thesis assesses different indices and calculation metrics in their ability to estimate the occurred impact in Austria, performing correlation- and regression analyses. To structure this analysis, meteorological and hydrological drought impacts were separated, as suggested in Bachmair et al., 2016a. In a second step, regression models were performed to give deeper insight into the relation and quantify the response of impact to drought indices.

4.1 Data

Selected meteorological and hydrological drought indices are discussed in the following sections, as well as drought impact data indicators, including drought and heat forest damage (d&h forest damage), wild fires and Danube transport.

4.1.1 Meteorological and hydrological drought indices

The SPEI, SPI and monthly precipitation sums are the meteorological drought indices applied in this master thesis. Tab. 4.1 gives an overview of the meteorological and hydrological indices included. Data sets available include monthly precipitation sums (mm), and the monthly SPEI and SPI-values for five accumulation periods (1, 3, 6, 8, 12 months), SPI_a and $SPEI_a$. Data is provided by the Zentralanstalt für Meteorologie und Geodynamik (ZAMG, 2016). Indices were modelled by the ZAMG for a regular 8km grid for Austria and cover the years 1993–2011. Fig. 4.1 shows the location of the grid points of the meteorological data sets on a map for Austria. The federal regions visible represent Federal Forest Districts (BFIs).

Fig. 4.2 shows yearly precipitation sums, SPI_{12} and $SPEI_{12}$ (both from December, therefore reflecting the whole year) for the years 2002–2011 which is the period, for which also impact data is available. The distribution of the boxplots represents the administrative unit of Federal Forest Districts (BFIs). While the behaviour of SPI and SPEI seems quite similar (with years of very low SPEI and SPI values in 2003 and 2011), this is less obvious for precipitation. A high variation among BFIs for SPEI and SPI can be seen for the years 1996, 2000–2002, 2008–2010. For the years 2002–2011, it can be seen that most BFIs show low values in $SPEI_{12}$ means for the years 2003 and 2011. The plots show very low SPEI indices for 2003 for all BFIs, and diverging climatic conditions, e.g. for 2005 and 2009. In the bottom of Fig. 4.2 the divergences in BFIs can be seen. In 2003 and 2007, low SPEI values for a majority of the BFIs are identifiable, while 1999–2001 some BFIs lie below and some above their average.

To present the hydrological data of Danube transport in Austria, the daily streamflow Q time series at the Hainburg gauge was used, provided by the Hydrographical Service of Austria (Hydrographical Service of Austria (HZB), 2016) for the years 1993–2015. From the streamflow, the annual minima (AM) and the deficit indices total number of days under threshold d_{sum} and maximum consecutive days under threshold d_{max} are derived. It is also represented in Tab. 4.1.

4.1.2 Forest damage

The Austrian Research Center for Forests (BWF) reports and publishes yearly forest damage factors (BFW, 2017(a)). Among those there is the factor of "drought and heat forest damage (d&h forest damage)" as a

Table 4.1: Drought indices used for analysis

Category of index and data	*Specification and characteristics*
Meteorological index	Precipitation sums, SPI and SPEI Aggregation periods 1, 3, 6, 8, 12 months Time period 1980-2011 Areal aggregation grid resolution 8 km, Austria Source ZAMG, 2016
Hydrological index	Daily mean discharge Q Danube gauge Hainburg Time period 1971–2015 Source Hydrographical Service of Austria (HZB), 2016

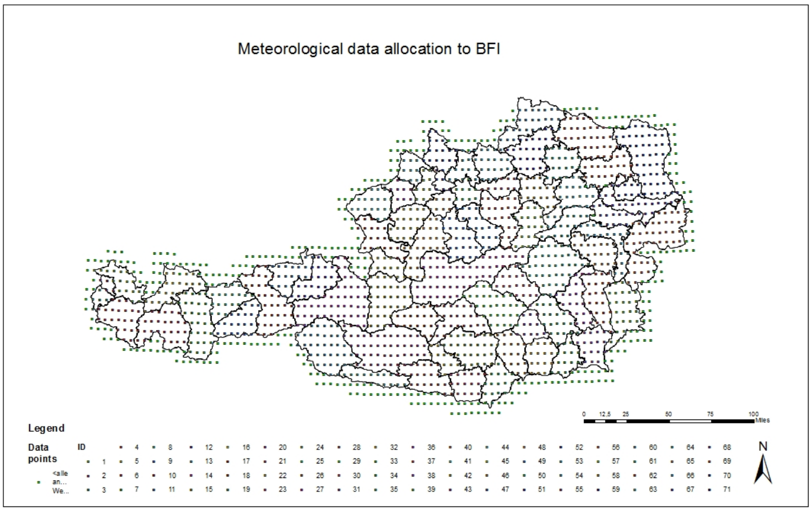


Figure 4.1: Meteorological grid data points relative to respective BFI administrative regions. Data source: ZAMG 2016, BFW 2016.

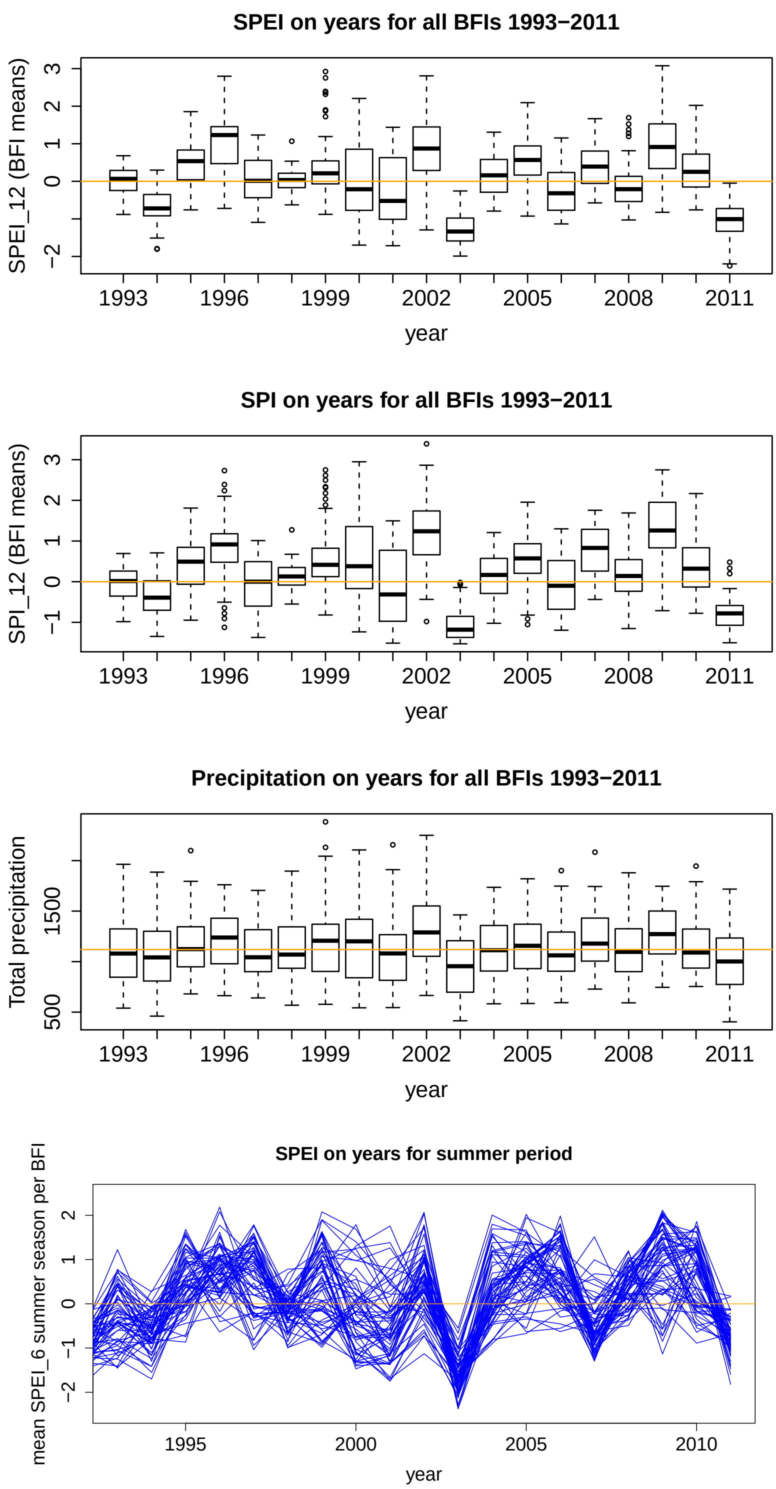


Figure 4.2: Overview of meteorological index data by year. Variations show values for BFI administrative regions in Austria. Data source: ZAMG, 2016

direct reported value and the factors "European spruce bark beetle (Ips typographus) damage" and "six-toothed spruce bark beetle damage", which are indirect indicators of drought damage, as they need weakened trees to flourish which is described in previous chapters. However, there are numerous other factors which influence bark beetle spreading, e.g. the availability of breeding material (after storms), temperature, or human management factors.

The data is reported by the local foresters once a year for d&h forest damage. Guidelines for reporting exist and refer to visible damage on trees, which includes physical damage, economic damage and non-economic damage (not differentiated in the data base) (Institut für Waldschutz, 2016). A certain individual range and estimation influence (i.e. bias) cannot be excluded. Damages are aggregated and reported on the level of federal forest districts (BFI) (which approximate the size of Austrian federal districts, slightly below NUTS3 level), year, and in hectares of reduced damage area (which corresponds to the area of actual affected trees and not to the whole area where damages have been noticed, see Institut für Waldschutz, 2016). They are available on this scale since 2002 (and for this analysis are considered until 2015).

Regional districts and BFIs have changed in the course of the last 15 years due to administration issues and time-series were re-built to the level of the BFIs in 2015 to assure that the BFI-definitions are identical for all observed years. Most BFIs affected by changes got consolidated in the last years and were simply added up for consolidation. In few cases, BFI borders changed and areas of few hectares got redistributed. This change cannot be corrected for completely. Nevertheless, those changes never concerned more than 5% of the forest area of this BFI, therefore these changes were accepted and the BFIs were kept for analysis in the definition of 2015. Fig. 4.1 shows the area of BFIs and the grid points of available SPEI and SPI data. In all cases, one BFI corresponds to several grid points. This will be discussed later.

Observing the d&h forest damage data of the data base, it can be seen in Fig. 4.3 that major years of forest drought damage were 2003, 2013 and 2015. 2013 and 2015 show an increase in damage less intense than in 2003. The BFI Horn has been removed from the data set, because it includes a major outlier for 2015. In this case, drought damage was assumed to hit the complete forest area because of the experienced dry conditions in this year. This is not following the reporting criteria of clearly observed drought stress indicators and not assumed water stress. Drought and heat impacts in 2015 affected more than half of the BFIs (the 75%quantiles are visible in the boxplots), and not only single BFIs like in other years. Fig. **??** shows d&h damage relative to other damage categories. A parallel development can be seen at wild fire occurrence as well.

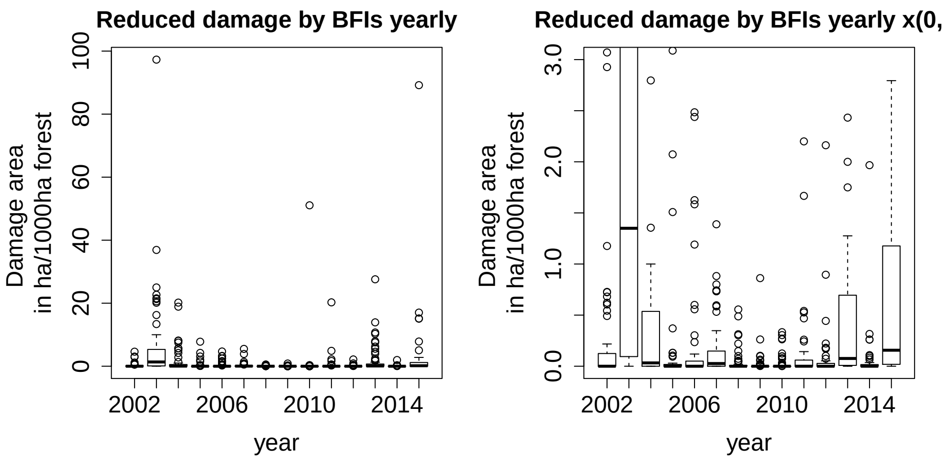


Figure 4.3: Distribution of d&h forest damage (in ha) per year at regional BFI level. Data source: BFW 2015

A geographical display of damage in single BFIs shows, that the areas in the northern and south eastern part of the country are more strongly affected by damage (Fig. 4.4). In the Alpine region, effects are less so visible. The map shows damage respective to the total forest area in each BFI, and thus does not show total vulnerability of BFIs but relative damage occurrence.

4.1.3 Wild fires

Wild fire registrations for this analysis were taken from the BOKU wild fire database, which is documented by the Institute of Silviculture (WALDBAU)

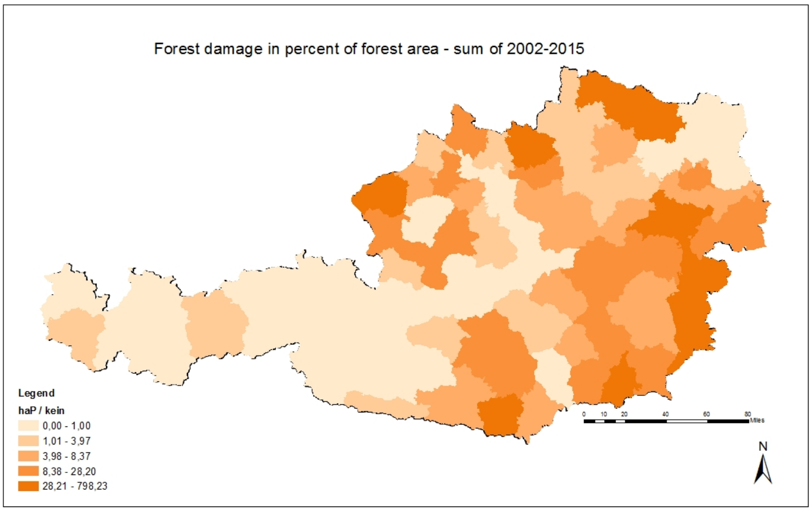


Figure 4.4: Map of d&h forest damage in each BFI relative to BFI forest area. Data source: BFW 2016.

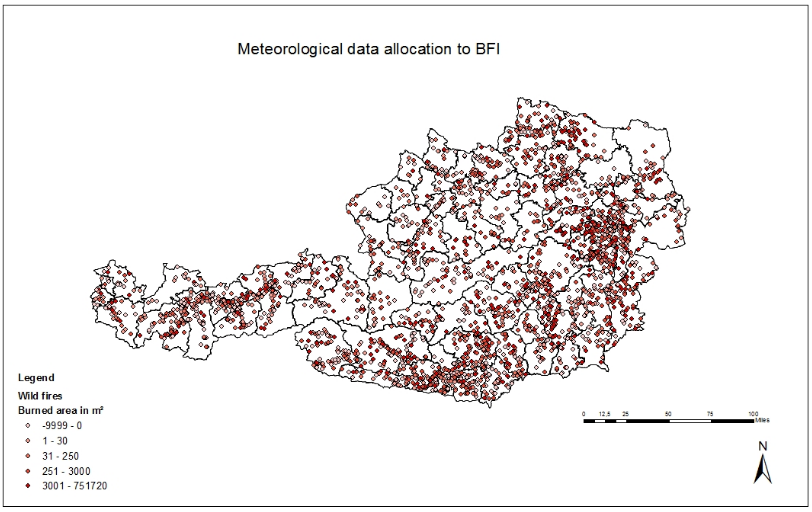


Figure 4.5: Map of wild fire events in the observation period in BFI. Colour intensity represents size of the area burned. Data source: BFW 2016, WALDBAU 2016.

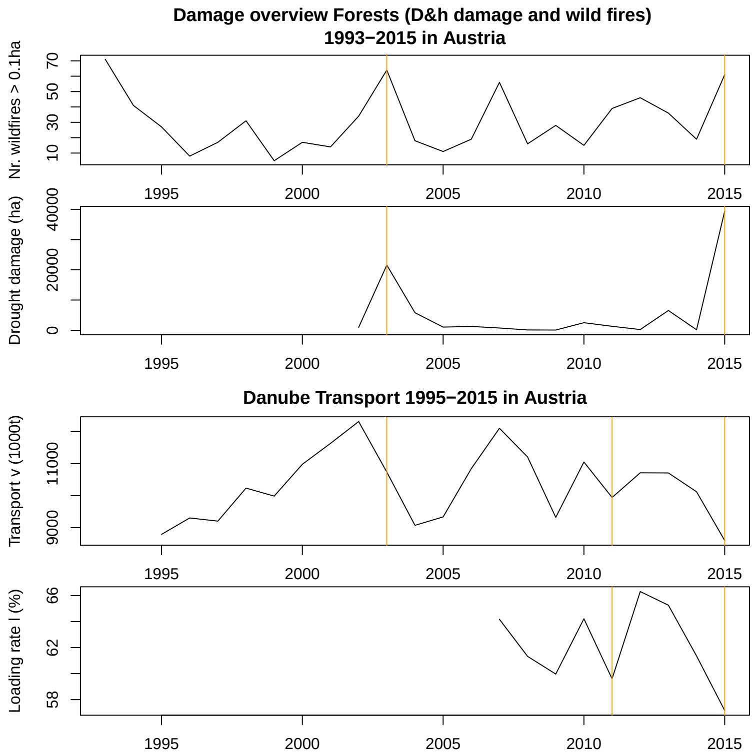


Figure 4.6: Overview yearly drought impact indicators. Top: Drought and heat forest damage and wild fires, source: BFW, 2016; WALDBAU, 2016. Bottom: Danube transport statistics, source: Statistik Austria, 2016; via donau, 2016

(Institute for Silviculture (WALDBAU), 2016). Fig. 4.5 shows wild fires for the years 1993–2003 and their location. Intense coloured data points indicate a larger burned area. Data from the 1990s is assumed possibly incomplete concerning small wild fires below one hectare of area affected. Thus, registered wild fires in Austria 1993–2011 greater than $1000m^2$ were used for analysis.

Fig. **??** shows wild fire events since 1993. Numbers of wild fires peaked in 1993, 2003, 2007, 2012 and 2015. 2003 and 2015 are years of intensive drought events, and years of high forest damage as well. While there are peaks in wild fire occurrence between 2007–2012, there are no peaks visible in forest drought damage registrations. The Figure shows for comparison the Danube transport statistics over the same period. Years with peaks were identified by a vertical orange line.

4.1.4 Danube Transport Shipment

For the analysis of the effects on Danube transport, data about the transport volume and the loading rate are used. Transport volume (v) per month is obtained from Statistik Austria (Statistik Austria, 2016a, for the years 1993-2015), and information about the monthly loading rate (l) from via donau by e-mail conversation (*Simoner, Markus (via donau): E-mail communication* 2016, for the years 2007-2015). Yearly statistics can be seen in Fig. **??**. Comparing the Danube transport drought indicator to the forest drought indicators, no clear correlation is visible at that level between peaks of damage and lows of transport volume. The years 1993-1994 were excluded from the data. Blockades in shipping during the political and military crisis in Yugoslavia in this period (BMVIT, 2006) resulted in outliers.

The relationship between the two variables t and l, is amongst others influenced by low flow processes. Generally speaking, if transport volume in shipment decreases, ships may not be fully loaded (as there are time-schedules to fulfil) and loading rates start decreasing. However, loading rates only decrease until a transport is no longer profitable. Therefore, transport volume decrease leads to loading rate decrease and ship tour decrease (*Simoner, Markus (via donau): E-mail communication* 2016).

Empirical analysis of the data available shows the Pearson correlation coefficient $r = 0.75$ and Spearman rank correlation coefficient $\rho = 0.62$, indicating also an empirical relation. This will be further discussed in the regression analysis.

4.2 Methods

This master thesis assesses different indices and calculation metrics in their ability to estimate the occurred impact for Austria, performing correlation- and regression analyses.

An extreme value analysis of the discharge data was performed using the lfstat package in R (R Development Core Team, 2017; Koffler et al., 2016). For further data analysis in this master thesis, R software is used (R Development Core Team, 2017) including following packages: lfstat (Koffler et al., 2016), Rfit (Kloke and McKean, 2012), pROC (Robin et al., 2011), ggplot2 (Wickham, 2009), lattice (Sarkar, 2008), pscl (Jackman, 2015), quantreg (Koenker, 2018), betareg (Cribari-Neto et al., 2016)).

4.2.1 Extreme value analysis

Tallaksen, 2006; WMO, 2008 give a good overview of the theoretical background of extreme value statistics and analysing hydrological drought events and characteristics. To analyse extreme events, GEV distributions are suggested. A special case of GEVs is the Weibull-Distribution, characterised by three parameters (Equ.4.1 shows the cumulative distribution function CDF). It is commonly used to model low flows.

$$F(x) = 1 - exp(-(\frac{x - \zeta^{\kappa}}{\alpha})) \tag{4.1}$$

where: ζ is the location parameter and the minima bound
α is the scale parameter
κ is the shape parameter

There are more variations, details and applications of this family of distribution (Tallaksen, 2006; WMO, 2008), but for this thesis only the lower bounded Weibull-distribution is mentioned, it is the most commonly used for low flow modelling, and therefore is applied here as well.

Different indices of low flow can be fitted to a Weibull distribution. Those which were used in this thesis are: (i) the Annual Minima Series (AMS) and (ii) the Total amount of days below threshold (d_{sum}). Annual series of AM and d_{sum} are aggregated from the daily discharge data. The AM is the yearly minimum daily discharge, and d_{sum} - as a deficit index - furthermore requires the definition of a threshold.

The selected threshold for analysing Danube transport is the defined RNQ_{2010} ($980 m^3/s$), which is the regulatory low flow discharge for the measuring station Hainburg. It is a relevant indicator gauge for Danube transport in Austria and obtained by calculating the 94%-quantile of the flow duration curve 1980–2010 (Hydrographical Service of Austria (HZB), 2016). It is the analogue index for low flow discharge of the RNW_{2010}, the regulatory low flow water level at Hainburg for shipment. For infrastructural capacity and restrictions, it is the main indicator for infrastructural capacity and restrictions. Although discharge and water levels do not correspond linearly, their relationship can be assumed as highly positively correlated for the station of Hainburg. If discharge lowers, water level will decrease. Therefore they are equivalent in their use for this purpose.

Tallaksen, 2006 mentions possible strengths and weaknesses of low flow indices. AMS are likely to include also AM for years, where discharge is quite high, and the AM is the minimal flow but no considerable low flow. Deficit indices, however, may include different days or periods of a year which refer to the same event and are correlated. Furthermore, they highly depend on the chosen threshold which defines a clear and sudden change from non-deficit to deficit, which usually does not reflect drought conditions and impacts. Their calculation will be further discussed below.

Model assumptions for time series analysis include stationarity (no change of distribution parameters with time) and independence. Tests were performed for both low flow indices. An augmented Dickey-Fuller (ADF, SAID and DICKEY, 1984) was performed to test for non-stationarity, as well as the auto-correlation test ADF and the auto-correlation function ACF (Cowpertwait and Metcalfe, 2009). Both tests do show low non-stationarity for AM and d_{sum}, and are considered neglectable for this analysis (AM: KPSS p-value > 0.1, ADF-Test p-value < 0.03, auto-correlation of 0.4 at time lag 1 of the ACF; d_{sum}: KPSS p-value > 0.1, ADF-Test p-value < 0.06, auto-correlation of 0.4 at time lag 1 of the ACF). The Ljung-Box test (LJUNG and BOX, 1978) is performed to test for independence. While independence for the AM can be assumed (p-value < 0.1), it is less obvious for the d_{sum} (p-value > 0.5).

4.2.2 Correlation analysis

The correlation analysis is based on the Spearman correlation (and on Pearson correlation coefficient ρ in the case of Danube transport). Its advantage compared to the Pearson correlation index lies primarily in its robustness to outliers and non-linear correlation and has been implied in this context before (e.g. Bachmair et al., 2015; Van Loon et al., 2015). Calculations, Significance Intervals and argumentations follow Schönwiese, 2006.

Regionalisation

To perform correlation analysis, it is necessary to find an aggregational method for the meteorological grid data to the administrative unit of BFI (Fig. 4.1). This issue is named "regionalisation" in Tallaksen (2006, 179ff). There is no consensus on how to best achieve areal aggregations of drought indices. Damage indicators (the reduced affected area of forest damage, the occurrence of forest damage, the burned area of wild fires and wild fire occurrence) were compared to the selected meteo-hydrological drought indices (SPI, SPEI and precipitation). Calculation metrices for precipitation diverge from those for the SPEI and the SPI, because sums of SPEI and SPI do not have an interpretable meaning. For precipitation, calculations can be taken from Equ. 4.2–4.4. They include the "deficit area", the "total areal deficit", and the "maximum areal deficit" (Tallaksen (2006, 179ff)).

Definitions of calculations for the regionalisation of precipitation sums are taken from Tallaksen, 2006, p. 179 and presented by Equ. 4.2–4.4:

Deficit area

$$A_{def} = \sum_{i=1}^{n} I_{\phi \leq \phi_0}(\phi_i) \tag{4.2}$$

where: $I_{\phi \leq \phi_0}(\phi_i) = 1$ for $\phi_i \leq \phi_0$ and
$= 0$ for $\phi_i > \phi_0$
$\phi_i =$ precipitation measurement ϕ at the grid point i
$\phi_0 =$ is a precipitation threshold

Total areal deficit

$$v_{area} = \sum_{i=1}^{n} (\phi_0 - \phi_i) I_{\phi \leq \phi_0}(\phi_i) \tag{4.3}$$

Maximum areal deficit

$$m_{max} = \phi_0 - min(\phi_1, \phi_2, ..., \phi_n, \phi_0) \tag{4.4}$$

ϕ_0 in the following analysis is defined as the amount of monthly precipitation below 40mm.

In order to achieve an areal aggregation SPI and SPEI data points, the calculations performed for precipitation were slightly adapted. An areal mean, an areal intensity, an area-index considering the proportion of the area affected, and a duration-index considering previous months were considered (see Equ. 4.5–4.8).

Following equations describe the aggregations of SPI and SPEI:

(Areal) mean M

$$M_a = \overline{SPI_{p,a}} \tag{4.5}$$

Intensity I

$$I_a = min(SPI_{p,a}) \tag{4.6}$$

(Proportional deficit) area A

$$A_{a,t} = 1/P * \sum_{p=1}^{P} I_{p,a,t} \tag{4.7}$$

where: $I_{p,a,t}$ =1 for $SPI_{p,a} \leq$ a threshold t and
=0 for $SPI_{p,a} > t$
$SPI_{p,a}$ = is an SPI value at the grid-point p and the accumulation period a

(Mean deficit) duration D

$$D_m = 1/P * \sum_{p=1}^{P} (\sum_{m=1}^{M} I_{m,p,t}) \tag{4.8}$$

where: $I_{m,p,t} = 1$ if $SPI_{1,p}$ in month m and for grid-point $p \leq$ threshold t;
$= 0$ if $SPI_{1,p}$ in month m and for grid-point $p >$ threshold t

M_a in Equ. 4.5 represents the areal mean SPI at the accumulation period a, I_a in Equ. 4.6 the areal minimum intensity at the accumulation period a, A_a in Equ. 4.7 the proportional deficit area considering the proportion of $SPI_{a,p} < t$ and D_m in Equ. 4.8 the mean deficit duration of the previous m months with $SPI_{1,p}$ under threshold t. Calculations are performed for SPEI analogous. a and m represents the accumulation and observation periods of 1, 3, 6, 8 and 12 months, and the selected threshold $t = -1$.

Calculating the areal mean SPI does not represent an SPI but an aggregated areal mean, as SPI and SPEI values for different grid points are based on different standardisations and are therefore not additive. Nevertheless, it reflects climate conditions of an area. Blauhut et al., 2015 applied this areal aggregation. Bachmair et al., 2015 applied different metric approaches including the mean, the minimum and percentiles of the area. In this context, the mean is considered as a meaningful areal indicator to signalise drought conditions.

For the transformation of forest damage in hectares to occurrences, binary values of 0 and 1 have been assigned to each BFI and year for "no event occurrence" and "event occurrence" (if the reported hectares were > 0). For the transformation of wild fires to occurrences (by BFI), which were presented with their geographic coordinates in the data base, numbers of wild fires and affected areas were aggregated by year and BFI.

As a reference period of forest damage and wild fires, the damage occurring month was set to August, as this represents the month when the damage becomes mostly obvious. Forest damage from drought conditions in autumn and winter will mostly be visible in the following year and then be documented (*Steyrer, Gottfried: personal communication* 2016), and wild fires mostly occur during the summer season (see Fig. 4.7).

To make damage comparable between BFIs of different sizes, the damage area was divided by the forest area in this BFI (data source: forest inventory 2007–2009, BFW, 2017(b)). The indicator is therefore the affected area by drought an heat (d&h) damage by $1000ha$ forest area. The BFIs "Reutte", "Hallein", "Eferding", "Linz-Land", "Tamsweg", "Melk" and "Korneuburg" were excluded from the analysis of forest damage as the number of years with a damage greater than zero is smaller than three (out of 14 years observed). Therefore, completeness of documented data was not assumed.

4.2.3 Logistic regression LIO

Logistic regression (Hosmer and Lemeshow, 2000; Menard, 2001) has been applied for this purpose before (Blauhut et al., 2015; Gudmundsson et al., 2014; Stagge et al., 2015). Blauhut et al., 2015 interpreted the results as the likelihood of impact occurrence. Outcomes lie on a scale between 0 and 1, and the event occurrence is transformed to a binary variable, 0 indicating no impact, and 1 indicating impact occurrence. The logit transformation is

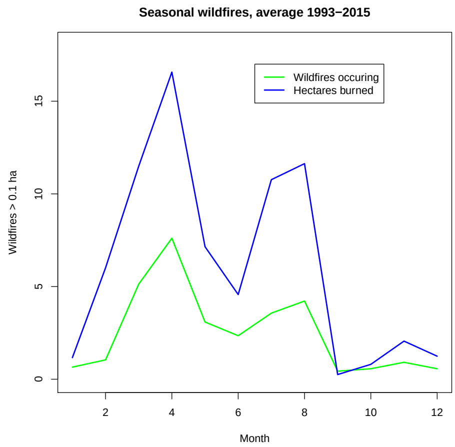


Figure 4.7: Seasonal mean wild fire occurrence. Data Source: WALDBAU, 2016

used, shown in Equ. 4.9 in its basic version.

$$log(\frac{LIO}{1-LIO}) = \beta_0 + \beta_{SPEI} * SPEI_6 \tag{4.9}$$

where LIO is the Likelihood of impact occurrence (a probability $0 < LIO < 1$). Realisations of observations in empirical data will be binary (event or no event, event occurrence = $\{0,1\}$).

An advantage of this approach is the robustness to differences in data availability (Blauhut et al., 2015). The size of the area affected underlies uncertainties, where the primary occurrence of a damage is more reliable. Furthermore, results are easily interpreted. However, they do not give any information about the size of the impact. The covariate BFI is included because it had high effect in terms of error reduction of the model and model performance increased. As the $SPEI_6$ gave the most promising results in the correlation analysis, it was used for further modelling.

A generalised linear model with the binomial logit transformation (R Core Team, 2015) (possible factor combinations between $SPEI_6$ and BFI were tested but rejected) is the following:

$$log(\frac{LIO}{1-LIO}) = \beta_0 + \beta_{SPEI} * SPEI_6 + \beta_{BFI} * BFI \tag{4.10}$$

where LIO is the Likelihood of impact occurrence (a probability $0 < LIO < 1$). Realisations of observations in empirical data will be binary (event or no event, event occurrence = $\{0,1\}$).

There exist various methods for assumption testing and evaluating the independent variables for regression analysis. Hosmer and Lemeshow, 2000; Menard, 2001 refer to local polynomial regression fitting and grouped mean plots. To evaluate the effect of the regressors before the modelling, smoothed scatterplots were applied. Fig. 4.8 shows the relation between d&h forest damage (top) and wild fires (below) to the $SPEI_6$, showing the potential logistic relationship as LIO. This relationship is more evident for the d&h forest damage. Lines represent smoothed loess lines, points represent observed data points. Smoothing is performed via local polynomial regression functions of the loess-function of the R stats package (smoothing factor $\alpha = 2/3$)

T-tests for the difference in $SPEI_6$ under damage occurrence compared to no damage occurrence were used to test the effect of the binary variable. They are significant as well, showing a relationship between SPEI and damage occurrence. BFI significance is supported by a Pearsons Chi-squared test and a p-value of 0 (wild fires) and 0.02 (forest damage).

The performance an fit of the model was not evaluated by selecting test datasets and keeping them out of modelling at first. This was not done because the number of different BFIs (n=63) and the low number of years per BFI (n=10) would cause difficulties in parameter estimation. A Receiver Operating Characteristic curve (ROC-curve) is used instead to assess the model quality (Fawcett, 2006). The area under the ROC-curve indicates moderate explanation value if $A_{ROC} > 0.5$. If $A_{ROC} > 0.8$, a considerable explaining capacity is assumed.

4.2.4 Linear rank regression

Linear rank regression is a linear model calculated on rank coefficients (Hettmansperger and McKean, 1998; Hettmansperger et al., 2000). In order to evaluate the intensity of damaged area in forests, burned area in wild fires and of Danube transport, linear rank regression is applied. It is more

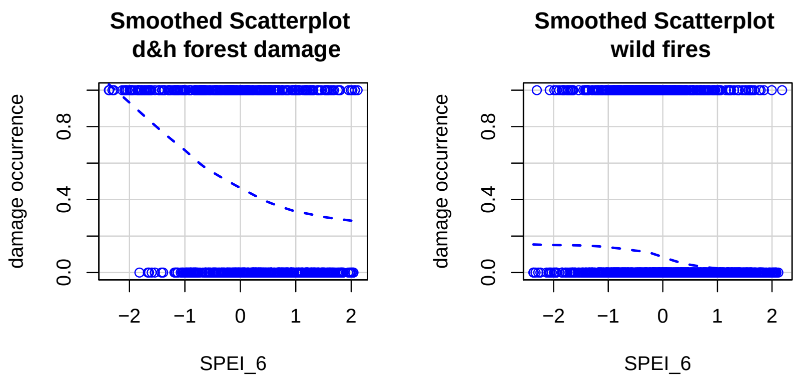


Figure 4.8: Smoothed scatterplots of $SPEI_6$ effect on log-transformed *d&h* forest damage and wild fires with local polynomial regression fitting and the smoothing factor $\alpha = 2/3$ of the R-package stats

robust concerning outliers than the ordinary least squares estimator (OLS) of standard linear regression models (Hettmansperger and McKean, 1998; Hettmansperger et al., 2000) and is applied by using the R package Rfit (R Development Core Team, 2017; Kloke and McKean, 2012).

(i) A model of log-transformed forest and wild fire impacts (Kloke and McKean, 2012)

$$log(damage) = \beta_0 + \beta_1 * droughtIndex + \beta_{BFI} * BFI + e \tag{4.11}$$

Model assumptions and their tests are similar to those of OLS modelling (Hettmansperger and McKean, 1998; Hettmansperger et al., 2000; Hosmer and Lemeshow, 2000). For linear rank based regression those observations of registered damage (> 0) were considered and log-transformed for the linear regression. The logarithmic transformation showed a better fit than values without transformation. Damage was standardised by the forest area, which varies in each BFI. No test datasets were selected and kept out of modelling to evaluate the performance and fit of the model in a second step. The number of different BFIs (n=63) and the low number of years per BFI (n=10) would lead to difficulties in parameter estimation. To assess model performance, the MacFadden Pseudo R-squared (Menard,

2001) is used (Fawcett, 2006). Diagnostic plots of the models are shown in the results.

Fig. 4.9 shows the relation between *d&h* forest damage (top) and wild fires (bottom) to the $SPEI_6$. For both plots, some step in the distribution is indicated for $SPEI_6$ values above 0. This leads to problems in model building and is discussed below in model evaluation as well. Smoothing in the plot is performed via local polynomial regression functions of the loess-function of the R stats package (smoothing factor $\alpha = 2/3$). Lines represent smoothed loess-lines, points represent observed data points.

(ii) For Danube transport, the following linear regression model was considered:

$$\hat{v}_i = \beta_0 + \beta_1 * DanubeTransport + \hat{e}_i \qquad (4.12)$$

4.2.5 Quantile regression

Quantile regression is a statistical method to describe relations between the independent and the dependant variable along the whole distribution (Koenker and Bassett, 1978; Koenker and Hallock, 2001). Where typical OLS fittings in linear regression focus on the mean influence of the regressors on the dependent variable, quantile regression adds information on the highest and the lowest ranges (quantiles) of the dependent variable and describe, if the distribution and the effect of the regressor increases or decreases on these parts of the dependent variables. While used already in social sciences, Cade and Noon (2003) also describe the benefits especially for ecological purposes.

Its advantages occur in situations, where not all necessary influencing factors can be observed, as it is often the case in ecological observations. Furthermore, they provide insight to the upper and lower parts of the distribution, in particular of interest in the context of drought events as extreme events. They provide good aspects in interpretability, as the parameters of the distribution estimate the regressor's effect on the dependent variable. This is the same as in OLS-regression. However, those parameters are estimated based on a certain quantile range of the empirical data. There is no normality assumption of the error term ϵ as in

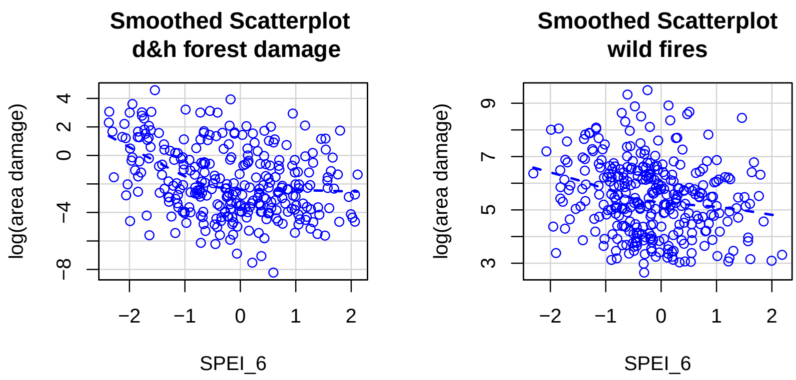


Figure 4.9: Smoothed scatterplots of $SPEI_6$ effect on $d\&h$ forest damage and wild fire occurrence with local polynomial regression fitting and the smoothing factor $\alpha = 2/3$ of the R-package stats

OLS-estimation, and it is possible to display heteroskedasticity via the regression quantiles (Koenker and Bassett, 1978; Cade and Noon, 2003).

Quantile regression is applied in this work as an interesting alternative of investigating the relation between drought indices and drought impacts across various quantiles of the distribution. In this data set, the yearly damage is auto-correlated only on a low level, therefore no corrections were considered in the model (see Hosmer and Lemeshow, 2000; Menard, 2001 for autocorrelation). Within years and across BFIs auto-correlation is high - 0.4–0.6 in the ACF graphics (Cowpertwait and Metcalfe, 2009) and positive in the ACD Test (SAID and DICKEY, 1984). However, BFIs were not included in the model. The number of observations within each BFI is low, and quantile regression requires high amounts of observations. This may lead to an biased estimation of the SPEI.

As in the previous models, percentage of damaged area as dependent variable was log-transformed by the natural logarithm, to reflect the relationship to the SPEI, which is log-linear for lower SPEI values. The relationship can be seen in Fig. 4.9 (left side). Only damage values above zero were considered to perform a log-transformation.

The model tested here for the percentage of area affected by drought damage (pArea) is the following:

$$log(pArea) = \beta_0 + \beta_{SPEI} * SPEI_6 + \epsilon \tag{4.13}$$

5 Results

Results presented in this section include an extreme value analysis of low flow indices for a Danube gauge, a correlation analysis of three selected impact categories (forest damage, wild fires, Danube transport) to evaluate drought indices and a regression analysis for drought effect estimation.

5.1 Extreme value analysis

(i) Fitted distribution of AM:

$$F(x) = 1 - exp(-(\frac{x - \zeta}{\alpha}^{\kappa}) \tag{5.1}$$

where: $\zeta = 620.915$
$\alpha = 304.448$
$\kappa = 2.37962$

L-moments: $L_1 = 890.76, L_2 = 68.19, L_3 = 0.07, L_4 = 0.10$

(ii) Fitted model of d_{sum} (valid only for $d_{sum} > 0$):

$$F(x) = 1 - exp(-(\frac{x - \zeta}{\alpha}^{\kappa}) \tag{5.2}$$

where: $\zeta = 0$
$\alpha = 30.0124$
$\kappa = 1.0238$

L-moments: $L_1 = 29.72, L_2 = 14.62, L_3 = 0.25, L_4 = 0.10$

with p_0 of $(d_{sum}$ equals $0) = 0.256$

Two considered low flow indices for the gauge Hainburg (Danube) are represented in Fig. 5.1 and their parameters are shown in Equ. 5.1 and Equ. 5.2, the annual minimum (AM) and the total number of days under threshold (d_{sum}). The fitted distribution for the annual minimum (AMS) shows that the 94%-quantile of the time series ($1095.2 m^3/s$) is slightly above the RNQ_{2010} ($980 m^3/s$). This results from the different time series underlying (1977–2015 compared to 1981–2010 for RNQ_{2010} calculations). It is estimated that the RNQ_{2010} is reached almost every year (slightly less than every 1.3 years). Every 5 years, the AM is expected to be lower than $783.01 m^3/s$ (Fig. 5.1, left).

The distribution fitted to for the d_{sum} was slightly adapted to a mixed distribution, because values of d_{sum} took the value 0 (Koffler et al., 2016) ($\zeta = 0$, $p_0 = 0.256$). Considering Fig. 5.1 (right), in most years d_{sum} will be at least 1 day, although there are years with no days below threshold ($d_{sum} = 0$). A 3-year-event is at 24 days, a 5-year-event is at 39 days (Fig. 5.2). The development of d_{sum} can also be taken from Fig. 5.1 (right). A 30-year-event ($d_{sum} = 91$) was reached in 1991 and 2003, which are also known as years of extreme drought events. The year 2011 sticks out as extreme as well, which was also visible in the SPEI and SPI data (Fig. 4.2).

The two low flow indices d_{sum} and maximum consecutive days under threshold d_{max} show strong similarities in their behaviour for the investigated period of time (Fig. 5.2). The Figure also shows that the extremes of d_{sum} are twice as high than those of d_{max}. A 3-year-event at the d_{sum} (24 days) corresponds to a 3-year-event at the d_{max} of 9 days. However, peaks occur simultaneously (e.g. in the years 1983, 1985, 1991, 2003, 2011). Following their characteristics, years with $d_{sum} = 0$ will mean $_{max} = 0$. Their Spearman correlation coefficient r_R is 0.98. Further on, results will be used for a regression analysis. In this context, a likewise capability of damage estimation is argued here.

Interesting differences to the AM series are visible. The year 2004 shows a similar level of AM compared to the year 2003, but a strong decrease in d_{sum} and d_{max}. Similarities between the AM and the deficit indices d_{sum} and d_{max} are visible especially in the years of peaks. All parameters are estimated on Weibull-distributions, however, the AM indicates low flows

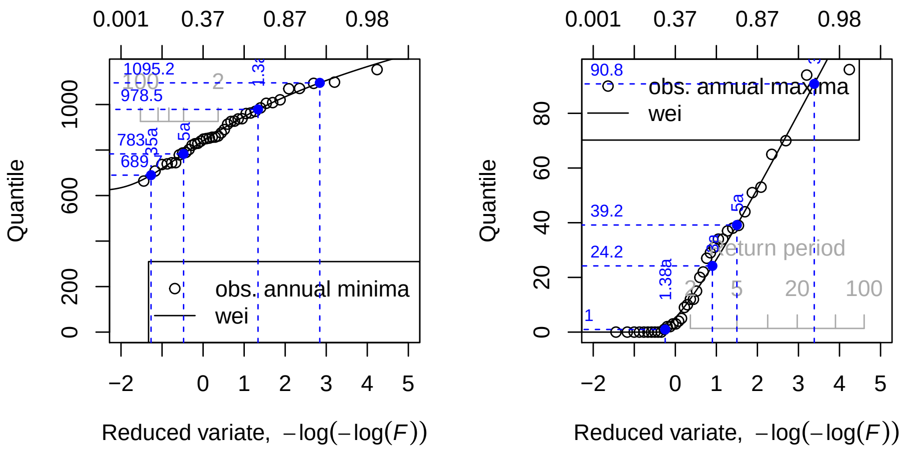


Figure 5.1: Low flow quantile calculations for the Danube gauge Hainburg. Left: AM. Right: d_{sum}. Data source: HZB, 2016.

with low values of AM. The d_{sum} and d_{max} indicate low flows with a high number of days a year (Their correlation r_R is -0.83). Furthermore, the AM does not have an absolute minimum or maximum and is less steep closer to the extreme event (the minimum for d_{sum} and d_{max} is 0, and the curves are steeper closer to the extreme event). Further on, those characteristics lead to advantages of the AM in regression analyses.

5.2 Correlation analysis

Correlation analysis of the drought indices to the impact indicators show category-specific differences. Results of d&h forest damage and wild fire damage follow similar procedures and the same drought indices and will be compared.

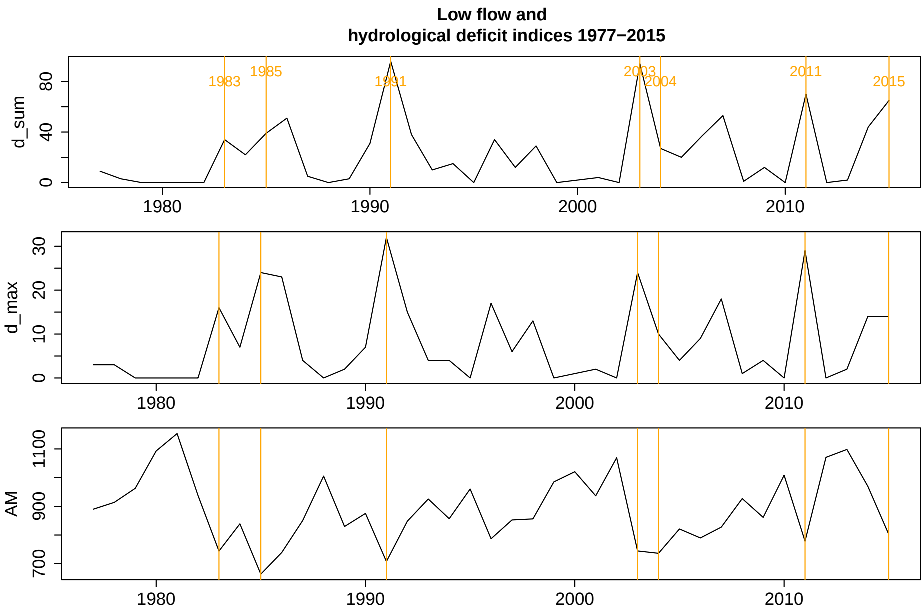


Figure 5.2: Time series hydrological low flow indices for the Danube gauge Hainburg. Top: Total number of days under RNQ_{2010} (d_{sum}). Middle: Maximum consecutive days under RNQ_{2010} (d_{max}). Bottom: Annual minimum (AM). Orange lines represent years with peaks or lows. Data source: HZB, 2016.

5.2.1 Drought and heat forest damage

Fig 5.3 displays an overview of the correlations of drought indices. SPEI, SPI and precipitation are shown (left), as well as their different accumulation periods (middle) and calculation metrics (right).

Results show that SPEI is higher correlated to d&h forest damage than SPI (which was expected, as damage represents drought and heat damage and SPEI is better suited for vegetational calculations than SPI). Precipitation values show lowest correlations. The low performance of precipitation sums as an index could be due to the seasonal patterns in precipitation, which are not corrected for in this approach, as the threshold ($40mm$) is set constant for all months and areas (a relative precipitation index is already presented with the SPI). Correlating precipitation sums for longer aggregation periods results in higher correlations, especially considering "deficit area" index (r_R are between 0.19–0.27 and 0.12–0.17 respectively) than in shorter aggregation periods (1–3 months, $r_R < 0.17$).

An interesting difference is indicated between different aggregation periods. 3 and 6 months of aggregation period seem to correlate stronger than the shorter or longer aggregation periods of 1, 8 and 12 months. Thus, the situation in the main vegetational periods of summer (June–August) and spring&summer (March–August) have a stronger effect on this impact. Considering that the impact data combines heat and drought impact data and does not represent only drought data, the higher weight of the summer period seems plausible. Despite of the importance of the pre-conditions of the water balance in autumn, winter and spring for the vegetation (i.e. soil humidity and water storage), the effects of high temperatures in summer on impact observation in forests is dominating in the empirical data.

Area and duration indices show in their maximum r_R at $a = 3$ and $a = 6$ higher results than the intensity and mean. However, mean and intensity calculations are quite similar in their results across SPEI and SPI, while duration and area are comparably high in SPEI and low in SPI.

Fig. 5.4 shows an overview of all correlations across impact categories in a heatmap. Comparably high correlations (represented in red) are calculated for the category d&h forest damage. Maxima are the $SPEI_3$-area index ($0.371 < r_R = 0.373 < 0.376$) and the $SPEI_3$-duration index ($0.362 < r_R = 0.365 < 0.368$), which indicate overall intermediate correlation (intervals are 95%-confidence-intervals). Wild fire occurrence and burned area lead to very similar correlation results. The two spruce bark beetle damage categories which were included as indirect impact indicators do not show noteworthy correlation to the drought indices. r_R showed results between -0.1 and 0.1 for correlation to the here considered meteorological drought indices.

5.2.2 Wild fires

Fig 5.5 shows an overview of the correlations of drought indices to burned area. SPEI, SPI and precipitation are shown (left), as well as their accumulation periods (middle) and calculation metrics (right).

The difference between SPEI and SPI in the case of wild fires is less obvious than in the d&h forest damage analysis. Correlation of SPEI is slightly higher than of SPI, and precipitation values are lower. Longer accumulation periods (6–12 months) reach higher values than the shorter periods (1–3 months). However, 8–12 months accumulation periods in the area and duration index are less comparable to the other indices. Many BFIs do not have any grid point measurements below threshold in the observation period, consequently, a constant time series of 0 areas or months under threshold leads to standard deviation of 0 and no r_R is computable. Correlation is highest for the regional aggregation of intensity, thus taking the areal minimum value. The mean reaches similar correlation values, all other metric calculations are lower.

SPEI intensity and mean indices show the highest r_R. In particular, $SPEI_6$ intensity shows the highest results ($r_R = 0.23$); the $SPEI_6$ mean index is with a r_R of 0.20 high as well. The maximum correlation of approximately 0.2 (significant at the $\alpha = 0.95$ level, due to a high $n = 1311$) is still low (indicating explained error variance of 4%). There is no interpretable difference between impact occurrence and burned area (only at a level of differences 0.001–0.009 of r_R).

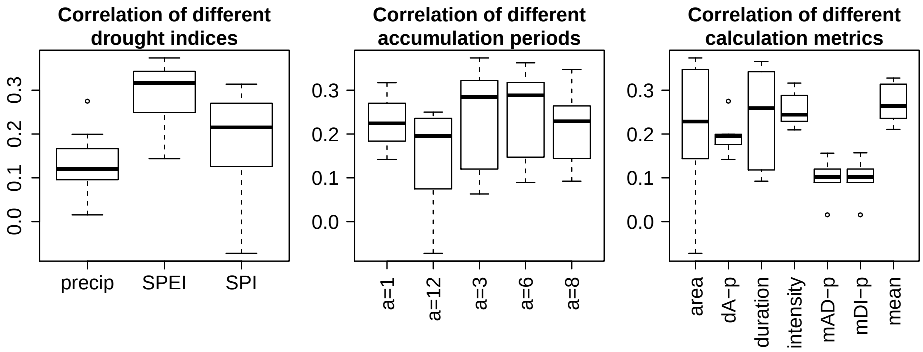


Figure 5.3: Correlation between drought index and d&h forest damage, grouped by drought index characteristics. The panel on the right shows the effects of mean, area, intensity and duration in SPEI and SPI, and the effects of $dA - p$ (deficit area), $mAD - p$ (maximum areal deficit), and $mDI - p$ (maximum deficit intensity) in precipitation.

For further calculations, the mean $SPEI_6$ has been taken, due to its relatively high scores, its continuous variable scale and its robustness compared to the intensity index.

5.2.3 Danube transport

Pearson correlation ($\rho = 0.49$) and Spearman correlation ($r_R = 0.47$) between transport volume v and the AM indicate the expected positive relationship. Furthermore, possibly due to a low record length of the time series ($n = 20$), the 95%-confidence interval (CI) of ρ ($0.15 < \rho = 0.49 < 0.83$) includes negative values and therefore uncertainty is high. Despite high CI ranges ($0.38 < r_R = 0.47 < 0.56$), r_R is positive at a probability of 95%. Correlation coefficients lie above the those resulting from d_{max} ($r_R = -0.37$ and $\rho = -0.23$).

For the loading rate l, the results show a higher correlation ($r_R = 0.87$, $\rho = 0.78$) than for v. Correlating d_{max} ($r_R = -0.62$, $\rho = -0.5$) indicates a relationship as well, however it is less clear. Despite comparably high correlations, results have to be interpreted cautiously, considering the

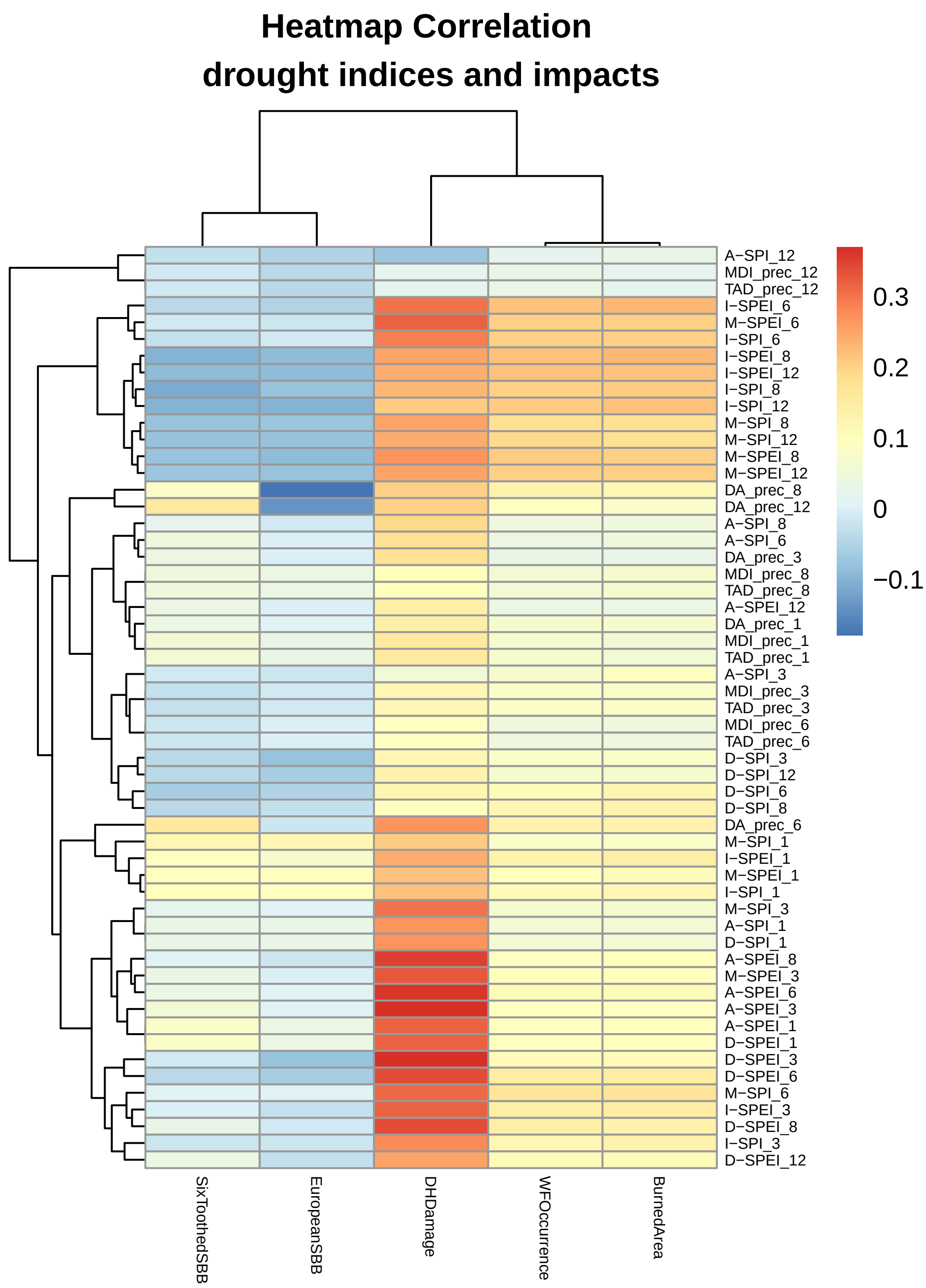


Figure 5.4: Heat map of correlations between drought indices and drought damage in forests.

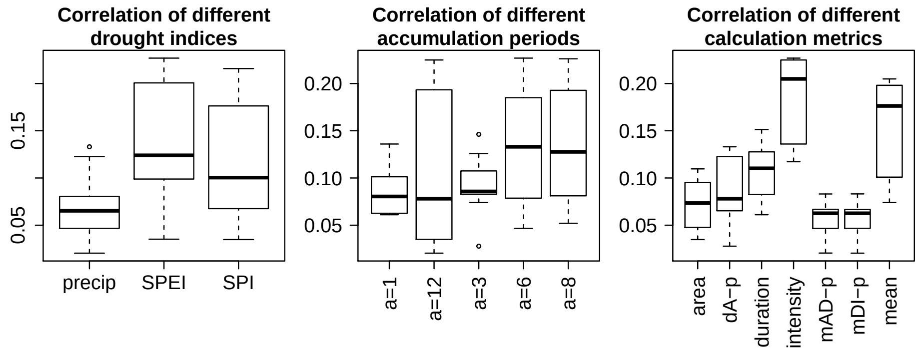


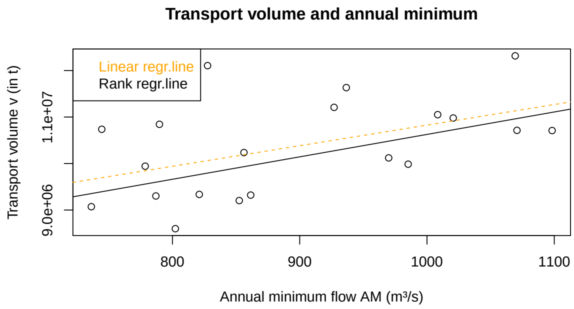
Figure 5.5: Correlation between drought index and burned area, grouped by drought index characteristics. The panel on the right shows the effects of mean, area, intensity and duration effects in SPEI and SPI, and the effects of $dA - p$ (deficit area), $mAD - p$ (maximum areal deficit), and $mDI - p$ (maximum deficit intensity) in precipitation.

small number of years of observed data in the loading rate ($n = 9$). 95%-confidence intervals for the AM are at $0.78 < r_R = 0.87 < 0.96$.

The regression lines in the scatterplot in Fig. 5.6 provide more evidence on a linear relationship, and also show a high remaining rest-variation. The regression lines will be investigated more profound in the following analysis in the next section.

5.3 Regression analysis

Regression analysis is performed for all three impact categories forest damage, wild fires and Danube transport to quantify the effects of drought. The LIO model, the likelihood of impact occurrence, describes the (raising) probability of drought impacts happening as the drought event gets more extreme. A linear rank regression model describes the development of the intensity of these events, however, it is restricted in its interpretation because model assumptions are not satisfied. Moreover, a quantile regression model is tested for the category of forest damage. For Danube transport a linear regression model of transport volume and loading rate is built.



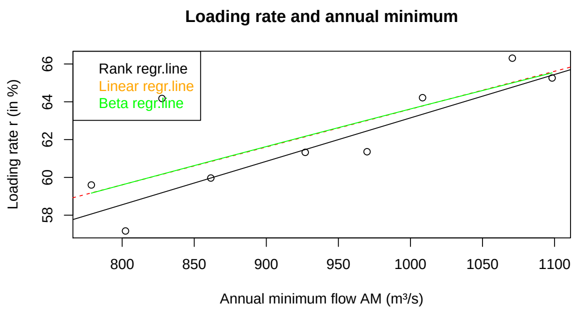


Figure 5.6: Correlation of Danube transport and AM. Top: Transport volume v, bottom: Loading rate l. Low flow index = annual minimum AM. Lines present linear, linear rank and beta regression lines. Data source: HZB, 2016.

5.3.1 Drought and heat forest damage

The LIO function (logistic regression on the likelihood-of-impact-occurrence) and the linear rank correlation regression on the affected area are presented here.

Likelihood of impact occurrence LIO

(i) Theoretical model:

$$log(\frac{LIO_{i,BFI}}{1 - LIO_{i,BFI}}) = \beta_0 + \beta_{SPEI} * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + \epsilon_{i,BFI} \quad (5.3)$$

where: $i = years$

(ii) Fitted model:

$$log(\frac{\widehat{LIO}_{i,BFI}}{1 - LIO_{i,BFI}}) = 0.29 - 0.81 * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + e_{i,\hat{B}FI} \quad (5.4)$$

where: $i = years$

Equ. 5.3 shows the theoretical model and Equ. 5.4 the estimated model parameters. Coefficients result in 0.29 for β_0 and -0.81 for β_{SPEI} (significant at the level 0.1 and 0.001, respectively). β_{SPEI}, the estimator for the effect of $SPEI_6$ is highly significant and shows a decrease in damage of more than 50% each increase of 1 unit of SPEI ($exp(-0.81) = 0.44$). Fig. 5.7 shows the model predictions vs. $SPEI_6$. The control variable β_{BFI} (as a dummy variable, being set to 1 for the BFI in which observations occur, and 0 for all the others) includes the regional component in the model, allowing deviations from the mean for single BFIs. BFIs with significant deviation from the mean curve ($\alpha = 0.1$) are represented as individual curves. The parameters β_{BFI} were calculated in contrast to the BFI Zwettl, which corresponds to the mean in impacts regarding d&h forest damage. Furthermore, the BFI has a larger effect on damage occurrence than the meteorological index. It can be seen that the likelihood of forest damage increases with drought magnitude (lower $SPEI_6$-values), but deviations across single BFIs are still higher. Around an $SPEI_6$ of 0 or higher (average meteorological or wet situations) low damages are still reported. As the mean $SPEI_6$ decreases to its extreme, LIO increases by more than 0.3 up to values at approximately 0.8.

Interaction terms of $SPEI_6$ and BFI have not been included in any of the models, as the number of BFIs is already high (above 60) and additional variables would have led to modelling limitations. Overall model significance is given at the α = 0.001 level, and MacFadden $R - squared$ indicates an explained error variance of 0.23. ANOVA test and Wald test (for independent variable significance) are significant at $\alpha = 0.001$.

There is evidence for non-linearity (Box-Tidwell test is significant) of the regression parameter β_{SPEI}. Replacing the SPEI index by its square does not improve the model but worsens its significance. Therefore, evidence for further non-linearity remains in the model at this point, and will be discussed below.

The Receiver Operating Characteristics Curve (ROC-curve) in Fig. 5.8 shows the predictive performance of the model (Fawcett, 2006). Sensitivity corresponds to the true positive rate, the rate at which occurring events are identified correctly, the "benefit" of the model. Specificity corresponds to the true negative rate, the rate at which non occurring events are correctly identified. Usually, it is possible to raise the sensitivity rate at the cost of lowering the specificity. The graph in Fig. 5.8 shows the ratio at which this is possible in the LIO-model. At a sensitivity of approximately 0.8, the specificity is at 0.6. This means that at a rate of correctly identifying occurring events of 80%, non-occurring events are identified correctly with 60%. Raising one of the rates will lower the other, following the curve.

Moreover, the area under the curve A_{ROC} is an indicator of overall model performance, where values above 0.5 are a sign of intermediate predictive performance, and values above 0.8 of good predictive performance. The ROC-curve in Fig. 5.8 shows an A_{ROC} of 0.805.

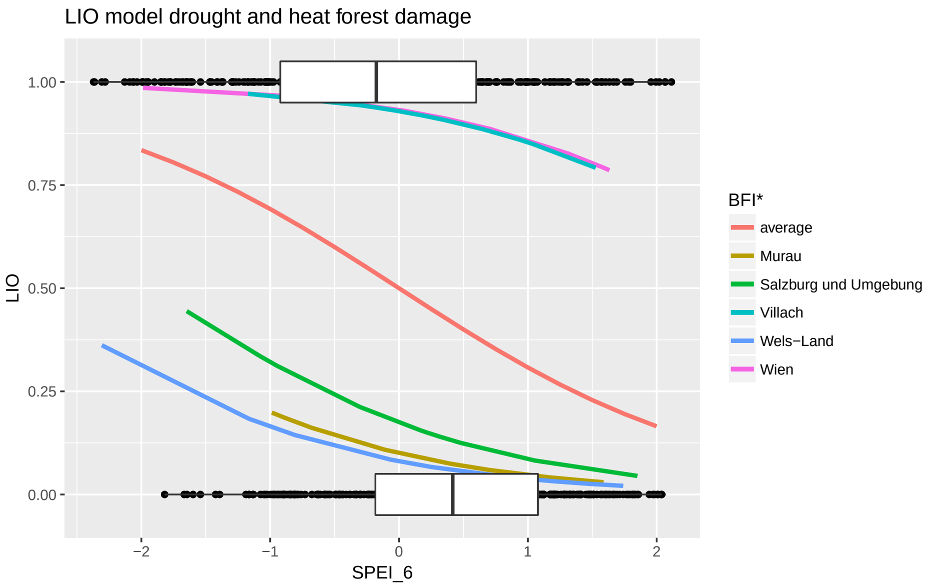


Figure 5.7: The LIO-model of Equ. 5.4. Effects of $SPEI_6$ and BFI on d&h forest damage occurrence are shown. BFIs are presented if the dummy β_{BFI} is significant ($\alpha = 0.1$), $n_{year} = 10$. The boxplots represent observed events.

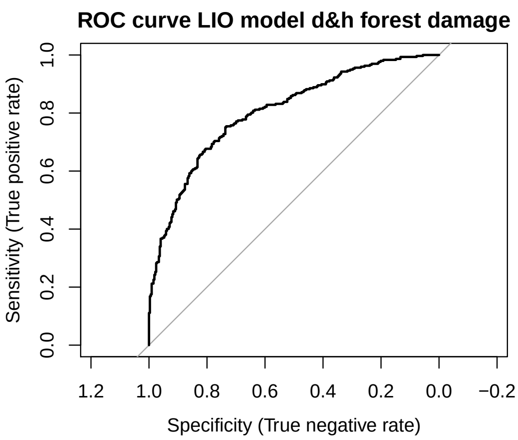


Figure 5.8: ROC-curve for the *LIO* model of *d&h* forest damage. $A_{ROC} = 0.805$.

Linear rank regression

(i) Theoretical model:

$$log(affectedArea_{i,BFI}) = \beta_0 + \beta_{SPEI} * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + \epsilon_{i,BFI} \tag{5.5}$$

where: $i = years$

(ii) Fitted model:

$$log(\widehat{affected}Area_{i,BFI}) = -2.15 - 0.77 * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + e_{i,\hat{B}FI} \tag{5.6}$$

where: $i = years$

Model parameters are displayed in Fig. 5.9. The model parameter β_{SPEI} is at -0.77. Thus, a change in affected area at +50% in damage is estimated at every 1 unit decrease of $SPEI_6$ ($exp(-0.77) = 0.46$) Fig. 5.10 as visualisation of the model shows a similar picture as in the LIO model - a higher variation across BFIs than within a BFI. The average in the graph indicates, depending on $SPEI_6$, an increase of up to 1.5ha across the $SPEI_6$ feature space. In more vulnerable BFIs this can go up to an increase as 3 or even 5ha/1000ha forest. The model implies a considerable increase in affected area as the $SPEI_6$ values decrease, depending on the BFI.

Model fit evaluations show a robust R-squared value of 0.40, the robust ANOVA equivalent test for rank based regression models (raov in {Rfit} in R) shows a significance of the $SPEI_6$ as effect on damage and the drop in dispersion test indicates an overall significance ($p - value < 0.001$). There is evidence for remaining non-linearity (Box-Tidwell test is significant) of the regression parameter β_{SPEI}. Replacing the $SPEI_6$ with its square does not improve the model, and neither does the logarithm. The single terms are kept for proceeding, and transformations are dropped.

The observed vs. predicted diagram (Fig. 5.11, left) shows the high remaining rest variation. The residuals vs. fitted (Fig. 5.11, right) is considered to verify the necessary characteristics of the error term ϵ. As it can be seen from the plots, the mean of the error term is uncorrelated to damage, but ϵ_is are not supporting their identical variance for all values of damage (some heteroskedasticity is indicated). The neither Normal Q-Q plot indicates normal distribution (see Fig. 5.11, middle).

```
Coefficients:
                       Estimate  Std.Error t.value p.value
(Intercept)           -2.151046   0.240031 -8.9616 < 2.2e-16 ***
SPEIInd               -0.765638   0.115924 -6.6046 2.235e-10 ***
Amstetten              0.322150   0.680289  0.4735 0.6362188
Bregenz               -2.257685   0.852104 -2.6495 0.0085538 **
Bruck-Mürzzuschlag     0.981261   0.930164  1.0549 0.2924352
Burgenland Nord        1.989125   0.746250  2.6655 0.0081688 **
Burgenland Süd         2.514631   0.793098  3.1706 0.0017033 **
Deutschlandsberg      -3.618155   1.030530 -3.5110 0.0005262 ***
Feldkirchen            0.026762   1.031121  0.0260 0.9793139
Freistadt              1.098599   0.927165  1.1849 0.2371380
Grieskirchen           1.590578   1.030488  1.5435 0.1239211
Hermagor              -2.153598   0.851645 -2.5287 0.0120392 *
Horn                   1.036155   0.851998  1.2161 0.2250320
Imst                  -1.458042   0.928112 -1.5710 0.1174042
Innsbruck             -2.576269   0.928026 -2.7761 0.0059019 **
Klagenfurt             3.155863   0.852386  3.7024 0.0002608 ***
Krems                 -0.650131   0.928067 -0.7005 0.4842285
Kufstein              -1.891290   0.936119 -2.0204 0.0443722 *
Leibnitz               1.928216   0.677148  2.8476 0.0047575 **
Leoben                 0.920320   0.930548  0.9890 0.3235783
Osttirol              -1.283111   0.708361 -1.8114 0.0712362 .
Perg                   1.123503   0.750134  1.4977 0.1354151
Scheibbs              -0.298153   0.853137 -0.3495 0.7270133
Spittal/Drau          -1.337097   0.748094 -1.7873 0.0750474 .
St. Johann im Pongau -1.945384   1.030470 -1.8879 0.0601582 .
St.Veit/Glan           2.002952   0.752899  2.6603 0.0082919 **
Steinach              -2.330057   0.851395 -2.7368 0.0066328 **
Südoststeiermark       1.323178   0.793596  1.6673 0.0966551 .
Villach               -0.587052   0.713101 -0.8232 0.4111274
Vöcklabruck           -0.804922   0.851465 -0.9453 0.3453643
Voitsberg             -1.530106   0.929679 -1.6458 0.1010041
Völkermarkt           -0.541662   0.794421 -0.6818 0.4959519
Waidhofen/Thaya        0.351364   0.928176  0.3786 0.7053284
Wien                   1.778465   0.710112  2.5045 0.0128758 *
Wien-Umgebung          1.823875   1.182616  1.5422 0.1242321
Wiener Neustadt        0.603829   0.793917  0.7606 0.4476029
Zwettl                 0.375475   0.927585  0.4048 0.6859663
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Multiple R-squared (Robust): 0.3995701
Reduction in Dispersion Test: 4.8062 p-value: 0
```

Figure 5.9: Table of estimated coefficients of the linear rank regression model of *d&h* forest damage in Equ. 5.6.

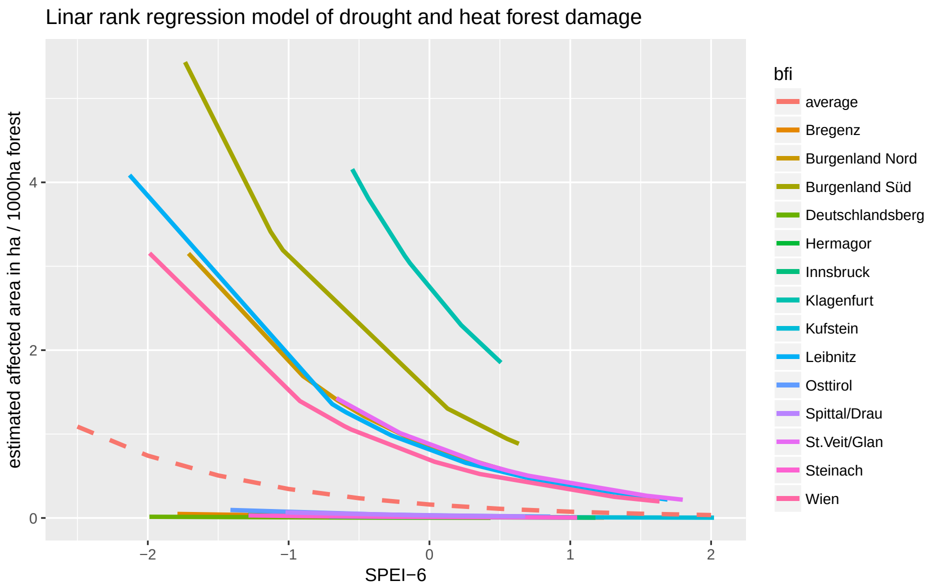


Figure 5.10: Linear rank regression model of d&h damage of Equ. 5.6. It shows the effect of $SPEI_6$ on affected hectares of $d\&h$ forest damage in ha/1000ha forest. BFIs are included when β_{BFI} is significant at the level $\alpha = 0.05$. BFIs with small numbers of n are not modelled individually.

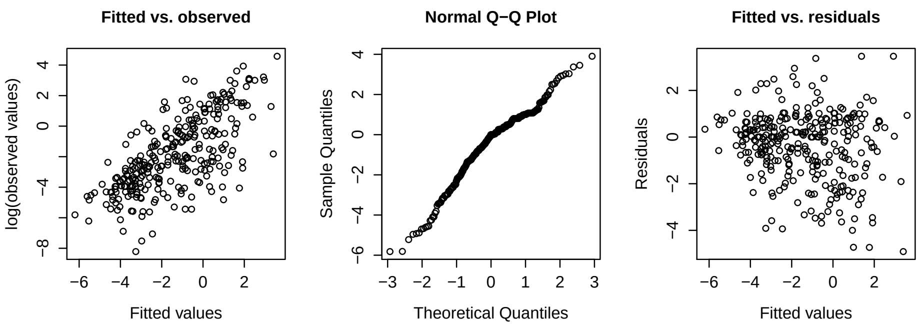


Figure 5.11: Diagnostic plots for the the linear rank regression model of d&h forest damage in Equ. 5.6.

Quantile Regression

The variation in the intercept and the β_{SPEI} across the distribution of affected area (in %) in d&h forest damage are shown in Fig. 5.12. While an increase in SPEI has a decreasing effect on damage, the intercept shows a positive mean damage ($exp(-2.15) = 0.12$). Thus, both shows an increasing effect on damage at the higher range of quantiles, where the estimate increases as well as the variance increases. This effect is stronger, however, for the intercept than for the SPEI, while the latter also shows some decrease of effect at the very high end of the distribution.

The two graphs in Fig. 5.13 show the regression lines across the observed data points (left: on a log scale of the % of area damaged). The slope has less effect than the location of the quantile. It is visible, however, that the effect of SPEI increases at higher ranges of damage (higher quantiles$>$ $Q50$).

5.3.2 Wild fires

An LIO-model of the likelihood of impact occurrence, and a rank regression model of the burned area are presented.

Likelihood of impact occurrence LIO

(i) Theoretical model:

$$log(\frac{LIO_{i,BFI}}{1 - LIO_{i,BFI}}) = \beta_0 + \beta_{SPEI} * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + \epsilon_{i,BFI} \quad (5.7)$$

where: $i = years$

(ii) Fitted model:

$$log(\frac{\widehat{LIO}_{i,BFI}}{1 - LIO_{i,BFI}}) = -1.11 - 0.59 * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + e_{i,\hat{B}FI} \quad (5.8)$$

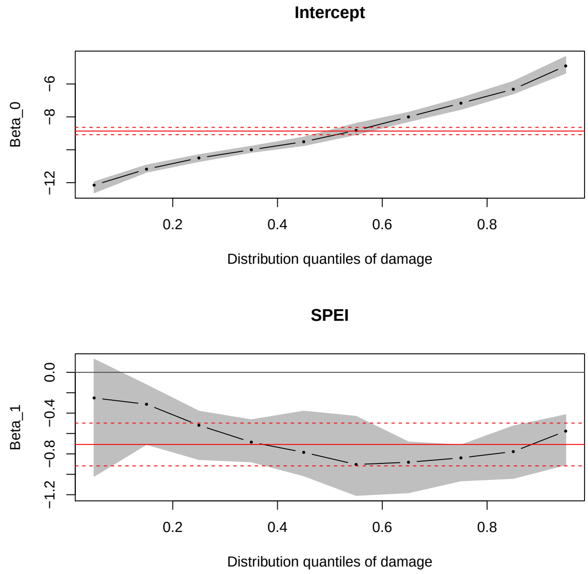


Figure 5.12: Effects of intercept and SPEI across quantiles of damage distribution of d&h forest damage of Equ. 4.13.

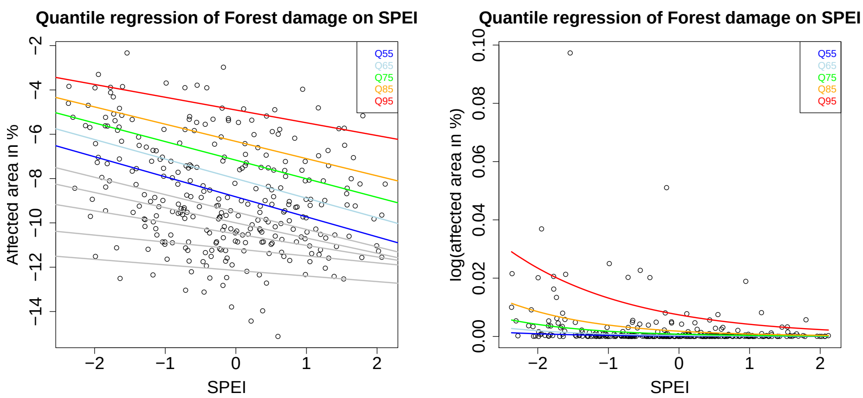


Figure 5.13: SPEI vs. affected area (in %) of drought and heat damage including regression lines Q050 – Q95. Left: Affected area in % on a log-scale. Right: Affected area in %.

where: $i = years$

Equ. 5.7 shows the theoretical model and Equ. 5.8 the estimated model parameters. Coefficient of $SPEI_6$, and therefore the estimated effect on the logit is at $\beta_{SPEI} = -0.59$ ($\alpha = 0.001$). Thus, the estimated effect is at -45% each increased unit of SPEI ($exp(-0.59) = 0.55$), and less strong than for $d\&h$ damage. The control variable β_{BFI} (as a dummy variable, being set to 1 for the BFI in which observations occur, and 0 for the others) includes the regional component in the model, allowing deviations from the mean for single BFIs. The influence of BFIs is represented in Fig. 5.14. BFIs with significant deviation from the mean curve ($\alpha = 0.1$) are represented as individual curves. The parameters β_{BFI} were calculated in contrast to the BFI Zwettl, which corresponds to the mean in impacts. Furthermore, an average is shown for the effect of $SPEI_6$ ("average"). The LIO increases with drought magnitude by a change of up to $+0.6$. The graph also shows, that BFI variation across areas has a stronger influence on the logit of LIO than the drought index $SPEI_6$. The boxplots at $LIO = 0$ and $LIO = 1$ show the distribution of the observed event occurrence data.

As in model 5.4, model fit was assessed in various steps. The model including the interaction term of $\beta_{BFI-SPEI_6} * BFI * SPEI_6$ results in higher pseudo R-squared and in higher error reduction. However, the BFI Amstetten in this case gains high leverage (with hat-values above 0.8). There is no obvious reason to exclude Amstetten, therefore the model without interaction terms was kept. Another issue including the interaction term would be raising the already high number of variables which would lead to more difficulties in parameter estimations. Overall model significance is given at the α = 0.001 level, MacFadden pseudo R-squared is at 0.22, which improved considerably compared to 0.03 for the model without considering the BFI but only SPEI-values. Error reduction values from ANOVA analysis is higher for the parameter β_{BFI} than for β_{SPEI} (286.41 and 51.35, respectively).

Accounting for the different influences of the independent variables, it can be seen that variation in LIO resulting from BFI is partly bigger than variances resulting from variation in SPEI. The difference between BFIs is quite high, some BFIs are experiencing hardly any occurrences of wild fires where others have a minimum of wild fire occurrence of over 0.25.

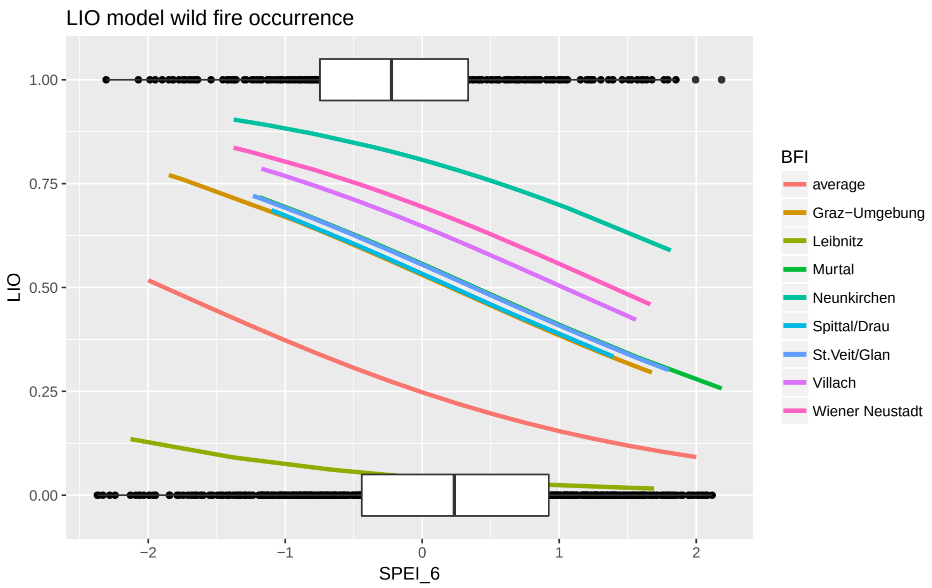


Figure 5.14: Visualisation of the LIO-model in Equ. 5.8. Effects of $SPEI_6$ and BFI on wild fire occurrence is shown. BFIs are presented when β_{BFI} is significant at $\alpha = 0.1$ ($n_{year} = 19$). The boxplots represent the observed events.

Most BFIs experience a continuous decrease in wild fire occurrence as $SPEI_6$ increases.

The ROC-curve is displayed in Fig. 5.15 and shows an A_{ROC} of 0.809, which is approximately the same as for the forest damage model and stands for reasonable predictability.

Linear rank regression

(i) Theoretical model:

$$log(burnedArea_{i,BFI}) = \beta_0 + \beta_{SPEI_6} * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + \epsilon_{i,BFI} \quad (5.9)$$

where: $i = years$

(ii) Fitted model:

$$log(\widehat{burnedArea}_{i,BFI}) = 5.53 - 0.31 * SPEI_{6,i,BFI} + \beta_{BFI} * BFI + e_{i,\hat{BFI}} \quad (5.10)$$

where: $i = years$

Model parameters are displayed in Fig. 5.16. The model parameter β_{SPEI} is at -0.31 (Equ. 5.10), indicating a change in burned area at -27% at a raise of 1 unit of $SPEI_6$ ($exp(-0.31) = 0.73$). The characteristics of the model are similar as in Fig. 5.9 of d&h forest damage. A higher variation across BFIs can be seen than within a single BFI (and the effect of $SPEI_6$ on damage). The model implies an increase in affected area as the $SPEI_6$ values decrease with a wide variety in location. The average here indicates, depending on the level of $SPEI_6$, an influence of up to 400m² burned Area each 1000ha forest.

Model fit evaluations show a robust R-squared value of 0.20. The robust ANOVA equivalent test for rank based regression models (raov in Rfit in R) shows significance of the $SPEI_6$ as effect on damage ($p - value = 0.003$) and the drop in dispersion test indicates an overall model significance ($p - value < 0.001$).

Model limitations are similar compared to Fig. 5.9. A test of replacing the $SPEI_6$ with its square does not improve the model, and neither does the

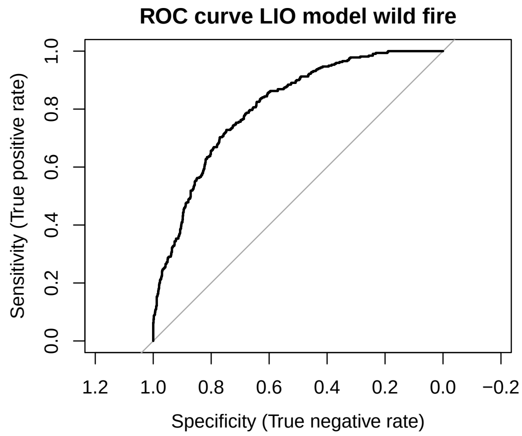


Figure 5.15: ROC-curve of LIO model of wild fire occurrence. $A_{ROC} = 0.809$.

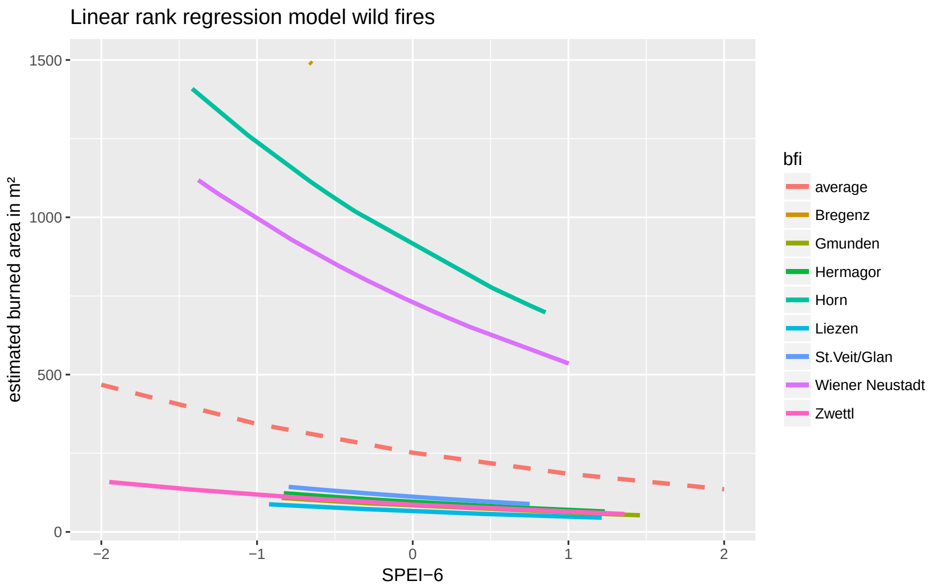


Figure 5.16: Linear rank regression model of wild fires (burned area) of Equ. 5.10. It shows the effect of $SPEI_6$ on burned area (m^2). BFIs are included when β_{BFI} is significant at the level $\alpha = 0.1$. BFIs with small numbers of n were ot modelled individually.

logarithm. Non-linearities therefore remain. The observed vs. predicted diagram (Fig. 5.17, left) shows the high remaining rest variation. The residuals vs. fitted (Fig. 5.17, right) is considered to verify normal distribution of the error term and the identical variance across all fitted values. As it can be seen from the plots, the ϵ_is are not supporting homoscedasticity.

5.3.3 Danube transport

The fitted linear model for transport volume:

$$\hat{v}_i = 6399103 + 4428 * AM_i + \hat{e}_i \tag{5.11}$$

$$\begin{aligned} \text{where:} \quad v &= \text{transport volume} \\ AM &= \text{annual minimum} \\ i &= \text{years} \end{aligned}$$

Transport volume v and loading rate l are modelled on the AM, as correlation analysis provided enough evidence of linearity. Considering the high correlation between AM, d_{max} and d_{sum}, only the AM was selected here as independent variable. It has also advantages due to its continuous scale, contrarily to the integer d_{sum} and d_{max}.

Considering the fitted model in Equ. 5.11, p-Values of the coefficients show levels of significance of $\alpha = 0.05$ for both of those (0.0012 and 0.0272 for parameters β_0 and β_1, respectively). Interpreting the coefficients, at a decreased annual minimum of $1m^3/s$, mean effects would be at $-4427.53t$ in absolute transport volume on average, according to this model. However, standard deviation and remaining error variance stay high. The range of transported goods moves from approximately 9 million t to 12 million t, giving a range of $\pm$ 1.5 million t. Below $850m^3/s$, v is expected to fall below 10 million t. For a graphical illustration of the relation see also Fig. 5.6, the rank based model shows a similar fitted curve. Parameters of the rank based distribution are at $\beta_0 = 5801529$, $\beta_1 = 4825.2$ and $p - values < 0.05$.

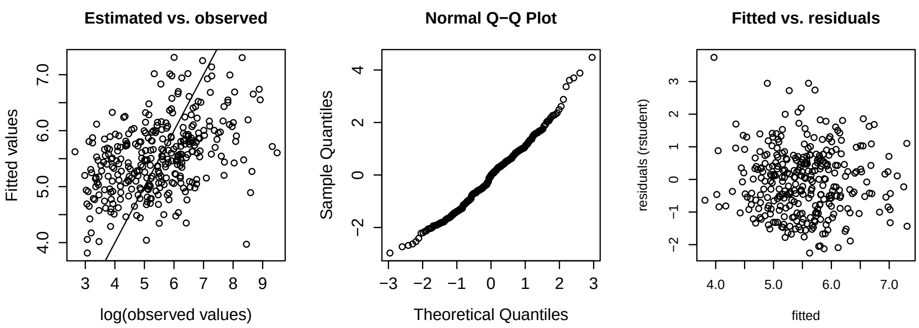


Figure 5.17: Diagnostic plots for the linear rank regression model of burned area in Equ. 5.10.

The "Residual vs fitted"-plot in Fig. 5.18 (top left) indicates acceptable levels of linearity of the error-term. The "Normal Q-Q"-plot in might indicate a step-wise distribution, but does not give enough evidence. The leverage plot (bottom right) shows that leverage effects of the year 2007 are low enough for keeping the data point included in the model. Thus, no indications for a need to adapt the model are derived.

The two model performance characteristics the p-value of the F-statistic for the overall model is at 0.03 (and therefore also significant at the level $\alpha = 0.05$), and the adjusted R-squared value of 0.2 shows an explained error variance of approximately 20%. This is expectingly close to the squared Pearson correlation coefficient $0.49^2 = 0.2401$. The rank based model has a robust R-squared of 0.27 and thus shows similar properties to the linear model. The outlier in 2007 has less influence in the rank based model than the OLS regression. Model evaluation show furthermore very similar Residual vs. Fitted and Normal Q-Q plots compared to the OLS regression.

The fitted linear model for loading rate:

$$\hat{l}_i = 43.59 + 0.02 * AM_i + \hat{e}_i \qquad (5.12)$$

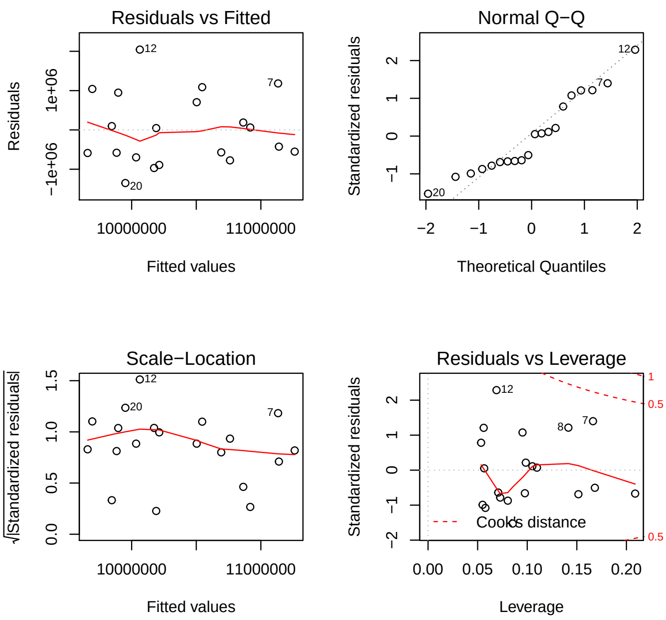


Figure 5.18: Diagnostic plots for the linear regression $\hat{v}_i = 6399103 + 4428 * AM_i + \hat{e}_i$.

$$\text{where: } l = \text{loading rate}$$
$$AM = \text{annual minimum}$$
$$i = \text{years}$$

The coefficients show that l drops 0.02 points with every m^3/s less of AM. Below the flow of $820m^3/s$, expected average l falls below 60%. The significance of the model is valid only at the $\alpha = 0.05$ level, which is negligible in this context due to the low n ($n = 9$).

Fig. 5.6 shows the linear, the linear rank and the beta regression. Beta-regression models are often used for rates as dependent variables. It is added here as a comparison. The regression line in the curve is almost identical to the OLS-line. Parameters are $\beta_0 = 0.29$, $\beta_1 = 0.00085$ and $\phi = 739.2$ (with p-values for β_0 and $\beta_1 < 0.05$). Parameters for the rank regression are $\beta_0 = 40.19$ and $\beta_1 = 0.023$, with p-values for both parameters < 0.05.

The diagnostic plots in 5.19 shows some irregularities. The Q-Q-plot (top right) does not support a high level of linearity, and the Residuals vs. fitted plot (top left) as well as the Scale-Location (bottom left) plot might indicate non-linearity of the error-term. Considering the short time scale, this might be only the effect pf the short observation period. For comparison, the linear rank-correlation and the beta-regression line are calculated and plotted in Fig. 5.6 and show similar form and location. Furthermore, the leverage plot (bottom right) shows acceptable leverage values for the years 2002 and 2007 (data points 7 and 12 in the plot)

The adjusted R-squared of 0.55 is high, compared to the other models presented in this master thesis. Robust R-squared for the linear rank regression model is 0.60, and pseudo R-squared for the Beta-Regression model is 0.61. Further interpretations would need a longer time-series for analysis.

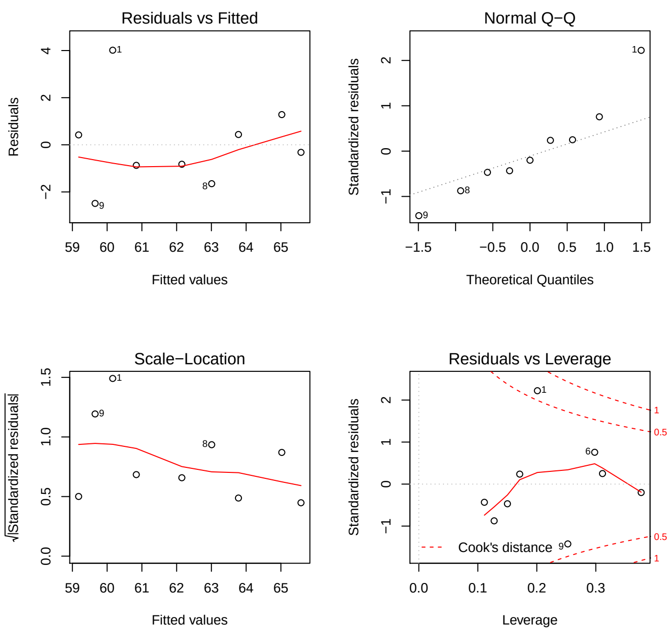


Figure 5.19: Diagnostic plots for the linear regression $\hat{l}_i = 43.59 + 0.02 * AM_i + \hat{e}_i$.

6 Discussion

The aim of this master thesis was to summarise drought impacts and test options for drought modelling. For Austria no previous studies have been found, and approaches to drought investigation are relatively new. Therefore, results in this master thesis raise more questions than they answer, and they also underlie various restrictions. However, they also allow interpretations on the specific context and the general framework.

6.1 Data for drought impacts in Austria

Drought impacts and their monitoring in Austria show a high variance in data availability across different categories and are characterised by high levels of uncertainty and complex processes causing drought conditions. This leads to difficulties in impact monitoring, which likely remain imperfect, even when specifying individual reporting criteria.

On a general level, the term "drought impact" as a negative drought damage is a subjective interpretation. Drought damage can only be considered in respect to a benefit of a standard situation and is highly centred around the functioning of human societies. Thompson and Calkin, 2011 raise similar questions in referring to the ecological value and benefits of wild fire events and formulate questions about the nature of "damage".

In this master thesis, documented drought and heat forest damage, wild fire events and effects on Danube transport are considered. Mostly highlighted in the data used are the years 2003 and 2015 as years of intense drought events, which corresponds to general expectations. Moreover, other years in between this time frame appear in the impact data (2007, 2011, 2013). The years 2007 and 2011 were visible in the forest damage data.

2013 showed noticeable effects in forest damage and in water supply but shows low effects in low flow indices (a very low number of days under threshold). Reason for this is a very wet spring in 2013 (BFW, 2013a), filling up the hydrological storages, followed by a very dry and warm summer, leading to consequences in ecology but not in hydrology. The years 2003 and 2015 were visible in the Danube discharge data, and the year 2003 was also visible in the SPEI data set, and forest and wild fire impacts showed a peak as well. SPEI data was not available for 2015, therefore it is not compared here. Danube transport did show a low for the year 2015, but average levels of transport in 2003.

However, firstly these documented impacts are not only caused by drought but also by other factors, and secondly the drought impact measured represents only a small part of occurring drought effects in general. This is also mentioned in detail in the previous chapters where the data was introduced and used. These data sets include observational biases and under-representation of impact categories which are harder to monitor, as well as short time series. These circumstances have to be considered when interpreting the results of this thesis.

Moreover, drought as a widespread and complex phenomenon very likely has more aspects and impacts than mentioned here. One aspect that is not considered is the effect of droughts in the context of climate change. This requires estimations about changing frequencies and thus changing impact and is beyond the scope of this study. Other authors did refer to these developments before, and for conclusions Austrian Panel on Climate Change, 2014, Laaha et al., 2016 or ZAMG and TU Wien, 2011 can be taken into consideration. Thus, the data, even though not covering drought effects or features in detail, do show some important characteristics.

6.2 Correlation analysis and drought index selection

Testing possible drought indices as suitable measures for impact occurrence was focused on different characteristics. These include on the meteorological level the indices of SPEI, SPI and precipitation sums and methods of regionalisation, and on the hydrological level the low flow indices of the annual minimum and the total number of days below threshold.

The SPEI, developed for the specific purpose of including vegetational characteristics of meteorological situations (Vicente-Serrano et al., 2009), shows advantages to SPI and precipitation sums. The difference between SPEI and SPI in the case of wild fires is less obvious than in the forest damage analysis. This suggests an interpretation, where adding the evapotranspiration to the precipitation information improves the model to some extent. Using the regional precipitation regime information, which is an inherent part of SPEI and SPI due to their distributional characteristics, but not included in pure precipitation values, adds valuable information. The less fitting of the direct combination with precipitation in mm suggests a high difference in climate regimes within the data.

One of the main challenges of index selection is the different availability of time scales and regional scales for different data sets. In general, the mean metric showed to be useful, nevertheless the indices with the highest correlation were others. The mean, however, provides useful characteristics in interpretability and its continuous variable scale. Moreover, it showed relatively high results for drought and heat forest damage as well as wild fire events. Interpretability of the results is mainly led by low correlation values in general (around 0.3 and 0.2, respectively). Another interesting result is the possible use of an area-index. A closer look into the composition of this index for regionalisation of data has to be made, which is not done here.

The aggregation period which showed highest correlation is the vegetation period of around six months from March to August. Vegetational drought processes suggest importance of the winter and spring period to create resilient or vulnerable conditions for the vegetation even before the summer period. In the model this was only visible to a low extent and was better visible for wild fires than for drought and heat forest damage. A reason could be the strongly effecting heat damages in the drought and heat forest damage data set. While wild fire danger is usually evaluated on a short and local scale (Altenkirch et al., 2002), it was here assessed on a longer time scale, leading to a seasonal and even yearly view different to a current wild fire danger observation. The indirect drought damage category of bark beetle damage did not show significance. This is possibly caused by difficulties in index selection, but most likely due to more complex influences of the development of this damage category. In hydrological indices annual minima, total number of days below threshold and maximum consecutive days below threshold were compared. There was no interpretable difference between the hydrological drought indices d_{sum} and d_{max} for this purpose. Interesting differences can be seen between AM and d_{sum}. The AM is higher correlated to both the transport volume and the loading rate. This could point out the AM as a good indicator of the restrictive flow situation in a year. The probable reason for this lead is the continuous and variable scale and a distribution more similar to the transport volume and the loading rate. However, this should be visible in the Spearman correlation coefficient and therefore the AM is hypothesised here as a good indicator for restrictive flow situations in the context of Danube transport.

Drought index selection and regionalisation issues to estimate drought impacts have been investigated by various authors recently (Bachmair et al., 2015; Bachmair et al., 2016a; Jain et al., 2015; Potop et al., 2012; Pasho et al., 2011; Stagge et al., 2015). Most studies include SPEI and SPI comparisons. Stagge et al., 2015 find fast responding rates for freshwater ecosystems (1–3 months aggregation periods) and longer responding rates for agriculture (2–12 months). The study is based on the EDII and therefore on an event-reporting-based impact inventory. No study was found investigating inland river transport. Pasho et al., 2011 investigate drought impacts on forests and find a high variability between species, ranging in their reaction time from below 5 months aggregation period of SPI to 9–11 months reaction time. Bachmair et al., 2015 investigated differences in areal aggregation and calculations of drought index metrics (mean, intensity, quantiles, area index), but found negligible effects for Germany. The study also underlines the importance of regional (NUTS1-level) and category-based threshold selection. This result is somewhat comparable to the results of this thesis. Bachmair et al., 2016a find slightly higher correlation of SPEI to drought damages than of SPI to drought damages for Germany, which is comparable to the results of this thesis too, but no differences for the UK. This emphasises the value of the SPEI in intermediate to summer dry climates (Vicente-Serrano et al., 2009).

The analyses performed in this thesis aim for impact estimation on the one hand and for understanding the relationship between drought impact and drought indices on the other. For real-time monitoring and early warning systems specific indices already exist (e.g. wild fire warning or the EDO).

An important conclusion for regression analysis is the already evident high level of remaining unexplained variation. Another observation on index selection is made. While drought and heat forest damage is a direct damage measurement, wild fire occurrence can be interpreted as a direct damage, transport volume and loading rate is an indirect damage, i.e. the impact results in a decrease of v or l. Partly this leads to weaknesses in the interpretation, however, this kind of data is easier to obtain, easier to validate and regression models allow an identification of the specific effect of low flows on these variables. Thus, a combination of direct damage data and easier obtainable indirect damage data might lead to better results of modelling approaches.

6.3 Regression analysis

The quantitative analysis of forest data was performed to detect possible differences between impact occurrence and the intensity of damage, for each of the observed damage category. Main restrictions lie in the low number of observed years for each BFI (which is 10). Moreover, BFI showed a high effect in all models, while it may represent a number of different factors: differing vulnerability due to geological or on-site factors, different management options or different reporting practices (e.g. in d &h forest damage).

Of the built models, the LIO model to show drought and heat damage occurrence is the best in the context of the data presented in this thesis. The SPEI shows a decrease in damage at 50% at an increase in SPEI. Moreover, the data shows a positive mean SPEI for no-drought evens and a negative mean SPEI for drought events. The impact variation between BFIs is higher than the impact variation within single BFIs due to changes in $SPEI_6$. This is also valid for the wild fire analysis, where data is assumed not to underlie observational biases. Thus a high regional difference in vulnerability across Austria is reasonable. In both data sets BFI specific curves had very diverse developments along the $SPEI_6$ feature space, therefore no possible thresholds can be taken from this analysis. The diversity of these curves represents differences in local climate and vegetation, but also differences in local observation habits. In both categories the most affected BFIs lie in the northeastern to southeastern parts of Austria, where most damages are expected to happen due to regional climate. Comparisons of model quality measures for the models used in this thesis show average results. An A_{ROC} value of 0.8 indicates explanative value of the regression model. This supports model validity.

Logistic regression was applied by various authors before. Blauhut et al., 2015 apply the LIO function for different sectors and interpret the results as vulnerability. Research is based on drought impact data of the EDII (event-reported-based data). Their found baseline vulnerability is 0, e.g. for average meteorological conditions, they do not find damage reporting. This result differs to the current study. These differences could arise from the different data used. Correlation rates and AUC (corresponding to A_{ROC}-values here) values are at a similar level (0.70–0.88). Concerning wild fire occurrence, Gudmundsson et al., 2014 apply logistic regression for predicting above normal wild fire activity several months ahead. Predictions are based on the meteorological drought index SPI. Results suggest valuable prediction capacity. This refers to above normal wild fire occurrence, therefore a slightly different approach than found in this thesis was used which has no implications on intensity. Thompson and Calkin, 2011 also review logistic regression for wild fire estimation.

Concerning the linear rank regression models of d&h forest damage and on wild fires, restricted interpretability prevents further considerations. Main restrictions on interpretation and main limitations of the analysis are represented by weaknesses in the modelling: non-linearities and heteroskedasticity. Although those mainly result in weaknesses in inference of the parameters (i.e. confidence-intervals) (Wooldridge, 2009). In the presence of heteroskedasticity in the model estimation, robust inference testing (Bachmair et al., 2015) could be applied. Comparably low effect of the SPEI, high effect of the single BFIs at a small number of observed years each BFI, and a high remaining error variance prevent a strong focus on quantitative result interpretations. However, the logarithmic-like distribution of the impacts are visible. The high effect of BFI in both models, and the stronger reaction of d&h forest damage than wild fires can be concluded (which is also stringent with results from other models and the literature).

Moreover, relatively little can be said about the distributions, these time series of damage follow. They have a logarithmic-like development and are possibly similar to extreme value distributions. In this context, quantile regression has advantages and results show differences in the distribution for higher quantiles. This means, SPEI has a stronger effect when higher damage occurs. However, this effect is still smaller than the effect of the intercept. As cited for quantile regression characteristics from Cade and Noon, 2003, this results from modelling situations in which many explanatory variables remain unobserved due to measuring difficulties. However, also quantile regression analysis results in a high unexplained error variance. It depends upon a high number of observations, which was not available for the variable BFI and therefore was dropped out of the model.

Regression models provide more direct insights in the relationship between Danube transport and Danube low flows and result in explained error variances across the models between 20 and 5%. There remain unexplained outliers in the years 2002 and 2007, which may be normal outliers without external explanation. Danube transport loading rate is apparently stronger affected by low flow than transport volume, which will have to be verified using longer time series.

Restrictions in the model include – apart from the short time series of 7 and 20 years, respectively - modelling Danube transport in Austria on the gauge Hainburg potentially misses out on effects outside Austria. Shallow water sections or channels influence Danube transport. Van Lanen et al., 2016 mention e.g. restrictions on the Rhein-Main-Danube waterway e.g. in Romania and the Netherlands for 2015, which influences the transport possibilities along the whole transport way.

Conclusions will include methodological aspects, and aspects of more specific data requirements.

7 Conclusion

In the first part of this thesis, the state of drought impact monitoring in Austria amongst different sectors was explored, and different drought indicators was used or applied. Most drought impacts in Austria are not monitored on a regular basis, except for drought and heat forest damage in wild fire occurrence. For most impact categories there is not enough evidence yet to clearly identify monitorable impact indices. In particular, ecological impacts on ecosystems and long-term impacts are characterised by complex damage processes and require profound indicator design and testing. Where impact monitoring exists, approaches are different amongst impact categories. For future drought monitoring and early warning systems, it will be crucial to include stakeholder experience as well as individually identified drought impact documentation. Moreover, evidence from those results also suggests conflicts of interest of water use under drought events, i.e. in situations of water supply shortage.

To find suitable drought indices to model drought impact as a function of drought intensity, meteorological data was used to model forest damage and wildfires, and hydrological data to model Danube transport. As this is a data set based on regions, selections of methods for a regionalisation of the meteorological grid data set was necessary.

Analysis for drought and heat forest damage and wild fires showed that the the $SPEI_6$ in August was amongst the indices with the highest correlation (Spearman correlation r_R) to observed drought impacts. The SPEI performed better than the SPI and precipitation. This reflects the indices' more comprehensive properties in capturing vegetational conditions, and becomes also evident in its preferred usage for this purpose in literature.

Furthermore, this firstly supports the preference of a more easily calculated SPEI-mean than more complicated indices. Areal and duration indices may bring additional benefit and are interesting options for further investigation. Secondly, the dominance of the spring and summer periods (March–August and June–August) become visible. Although previous periods will have an influence on vegetation (the winter period will have influence on the general situation of soil and forests, and short-term precipitation and heat conditions on wild fire outbursts), for the observed damage impacts the meteorological summer conditions showed most influential.

Comparing transport volume and loading rate, the latter shows better results, reacting in theory more directly to low flows than the transport volume. However, limited data availability (i.e. less than 10 years) did not favour further analysis and interpretation as a drought damage is less stringent.

The AM as low flow index did show advantages in the analysis, resulting in higher r_R (0.47 for the AM and -0.37 for the d_{max}) to the annual transport volume. This could indicate a more continuous relationship to damage, rather than the existence of a drought identifying threshold. Across all analyses, continuous drought indices have advantages over indices based on thresholds which maybe reflects a more continuous decrease in shippability.

Logistic regression models in the form of a likelihood of impact (LIO) function for $SPEI_6$ on forest drought damage and wild fires showed to be the most suitable model approach. It gives explanatory insights on a gradual development of drought damage, including the BFI area as a control variable. Interesting aspects include the high importance of the BFI area, in terms of error correction higher than of $SPEI_6$ index, and the damage occurrence under normal and humid conditions as well. The effect of $SPEI_6$ increases the damage probability to up to 0.8. The A_{ROC}-value as an indication for model explanation value is at 0.805 and 0.809 respectively, representing intermediate-good model fit. Results suggest a baseline vulnerability, independent of the $SPEI_6$ of the region, and a significant increase of the impact occurrence as well as the affected hectares as $SPEI_6$ decreases.

Regression of transport volume on the AM was significant ($\alpha = 0.05$) and more straightforward than the other models. Like in the other models, these results are accompanied by a high remaining error variance and thus uncertainties (reflected in the explained error variance R-squared of approximately 0.2). The simple version of the model is unsuitable for explaining the influences on transport volume, but was built for another purpose and does suggest an influence identifying low flow impacts.

While it seems practical to have direct measured impact data, at this point another contradicting aspect is underlined. Drought damage in most cases will overlap or collide with stakeholder interests or conflicts of interest, this may lead to reporting or observing biases. More neutrally collected and reported data such as transport volume may be subject to less restrictions. The EDII collects textual information on drought damage reporting, and analyses on this data base have showed promising results for this approach.

The LIO-model offers advantages in the interpretability of results, and less sensitivity to observational biases. While it might be more difficult in observation processes to differentiate and define the size of damage occurred, the occurrence of damage in general is more clearly distinguishable. It is clear, that the complex process of drought damage occurrence is not fully reflected in these models. Despite this restriction, the LIO-models as initial models, contribute to understanding effects on bigger scales and help understanding the type of data needed for further analysis.

However, results also show a need for a better understanding of the underlying distributions of these regional damage time-series, and possibly a development of further specified index or even index-combinations.

Nevertheless, a valuable first approach is made here and questions are raised: 1) How can existing information be made available and standardized for application? 2) Would there be interest biases? 3) And is there interest in establishing more standardised monitoring and documentation processes? It is suggested here, that on the level of impact categories individual indicator definitions and monitoring schemes are necessary. Advantages and disadvantages will mainly lie in their value of drought representation, and in their validity (i.e. bias issues). Interests exist at the level of stakeholders. The main restriction is the difficulty in methodology to connect large scale drought events and complex local and regional characteristics determining the impact vulnerability.

Considering the wide spread effects of drought like in 2003 and 2015, increased data availability and better process understanding would favour the implementation of warning systems as well as mitigation and adaptation strategies and lead to higher resilience.

Appendix

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