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Research article

Household Drought Risk Index (HDRI): Social-ecological assessment of drought risk in the Cuvelai-Basin

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Abstract

Droughts threaten many regions worldwide, in particular semi-arid environments of sub-Saharan Africa such as the Cuvelai-Basin in Angola and Namibia, as the population depends on critical water-related ecosystem services. Since droughts are multi-layered phenomena, risk assessment tools that capture the societal relations to nature and identify those individuals that are most threatened are required. This study presents the integrated Household Drought Risk Index (HDRI) that builds upon empirical data from the study area to provide insights into drought hazard and vulnerability conditions of households in different socio-economic and environmental settings. The composite indicator integrates environmental measures of drought (frequency, severity, duration) from multiple remote sensing products (precipitation, soil moisture, vegetation) and the vulnerability of households (sensitivity, coping capacity) obtained from a structured survey that comprised 461 households. The results reveal that the Angolan population shows higher levels of risk, particularly caused by less developed infrastructural systems, weaker institutional capabilities and less coping capacities. Overall, urban dwellers follow less drought-sensitive livelihood strategies, but are still connected to drought conditions in rural areas due to family relations with obligations and benefits. The study results provide knowledge for decision-makers to respond to drought in the short and long-term. The latter may build upon the extension of centralized and decentralized water and food supply/production systems as well as the support of households via targeted educational and community-building measures. Specific HDRI components may be included in census surveys to receive continuous drought risk data.

1. Introduction

Drought events threaten many regions worldwide in both developed and developing countries [1]. Sub-Saharan Africa is at particular risk since 70 % of the population lives in rural settings [2] and is hence strongly dependent on water-related ecosystem services to ensure water and food security. Water scarce periods, as recently triggered by El Niño [3], [4], impair the ecosystems' ability to provide fundamental services to society, which results in impaired human well-being [5] and a precarious situation of poverty persistence and humanitarian disasters [6]. As droughts are multi-layered and slowly creeping phenomena [7], [8] that impact on both the natural environment and society in a multitude of ways, risk assessment tools that capture the complex relations between the social and ecological domains are required [9], [10].

The Cuvelai-Basin in northern Namibia and southern Angola was chosen as a case study to conduct a social-ecological drought risk assessment, since extensive research into qualitative and quantitative aspects of drought impact is available [9], [11], [12]. As a semi-arid environment with a population that mainly practices subsistence agriculture of rain-fed grain farming and livestock herding [13], the basin can be regarded as representative of many regions in sub-Saharan Africa. It is periodically dealing with droughts that challenge the population and regularly result in food and water insecure conditions [14]. Governmental and non-governmental, short- and long-term relief measures are frequently required for large shares of the population [15]–[17]. It is essential, in this regard, to understand the causes and consequences of drought events, how these impact on society directly and indirectly via the environment. Decision-making requires adequate instruments to identify those people who are most at risk [18] by following an integrative approach.

On one hand, strictly environmental assessments neglect the role of societal capacities while approaches that exclusively focus on societal actors neglect the fundamental role of environmental conditions, on the other. Recently, the African member states of the United Nations Convention to Combat Desertification (UNCCD) compiled the Windhoek Declaration and highlighted the necessity to "reduce underlying factors of drought risk" and carry out "drought vulnerability and impact assessments" to enhance the resilience of African states to drought events [19].

The scholarly discourse in the field of risk and vulnerability research shows a pronounced shift towards integrated approaches during the past decades [20]–[24]. On one hand, risk-hazard approaches focus on the environmental parameters of an event, assuming that all valued objects in the vicinity of this event are particularly threatened. On the other hand, earlier vulnerability studies took a constructivist position, assuming that all disasters primarily occur as a result of negative pre-dispositions of the affected society [23], [24]. This original differentiation between natural and social science perspectives on disaster risks and hazard, as well as vulnerability in particular was weakened in favour of combined perspectives in which both schools of thought are regarded as indispensable

components. Even though, the Intergovernmental Panel on Climate Change (IPCC) defined disaster risk as a product of hazard, exposure and vulnerability, rather recently [25], the basic idea of combining parameters of societal vulnerability and environmental hazards can be traced back to earlier studies [20]–[22], [26]. Therein, the vulnerability concept encompassed the physical hazard component and was frequently defined as a function of hazard, sensitivity and coping or adaptive capacity. This study follows the aforementioned IPCC definition of risk by assuming that household drought risk can be understood as a function of hazard and vulnerability.

In the target area of this study, the Cuvelai-Basin, drought as a spatio-temporal water scarcity situation was already assessed from an environmental perspective. The Blended Drought Index (BDI) was developed to incorporate precipitation, evapotranspiration, soil moisture and vegetation conditions to holistically represent a drought's impact on water and food resources in the basin [11]. To guarantee an integrated drought risk assessment, however, information on the population's vulnerability has to be collected and combined with the BDI-results. This study builds upon previous research from the study area, in particular a qualitative pilot study on drought risk and vulnerability [9], quantitative estimates of drought hazard [11] and measures of household drought sensitivity [27]. These provide valuable insights into specific components of drought risk and are thus taken up and combined with quantitative measures of coping capacity to populate a composite indicator, the Household Drought Risk Index (HDRI). The study hence seeks to contribute to the challenges identified in the Windhoek Declaration and enable the population, administrative bodies and non-governmental organizations to design and carry out efficient short-term emergency responses and long-term adaptation strategies.

The paper is organized as follows: Section 2 briefly describes the study area and the material and methods used for data assessment and analysis as well as the HDRI construction. Section 3 introduces descriptive statistics on the assessed data, followed by the hazard and vulnerability results, acknowledging for uncertainty effects due to weighting schemes in the aggregation process. The section is finalized by a regression analysis to transfer the HDRI sample results to the spatial scale of the Cuvelai-Basin. Section 4 critically reflects upon the results and the methodology of constructing and populating the composite indicator. Finally, the transferability of the approach is discussed against the background of the water-energy-food (WEF) nexus debate.

2. Materials and Methods

This section serves three major purposes. First, the construction of the HDRI and the selection of variables and indicators are outlined against the background of data availability and research project constraints. Second, the primary assessment tool of the socio-economic data, the structured household questionnaire, is presented, in detail. Third, the statistical analysis and data processing techniques are described.

2.1. Study area

The Cuvelai-Basin is an endorheic watershed that drains the southern Angolan highlands into central-northern Namibia and covers about 172,000 km² at an average elevation of more than 1,000 masl (Figure 1). The environmental conditions are primarily determined by the hydro-climatic system that shows high annual and inter-annual variability. The rainy season lasts from November to April, while no precipitation occurs between May and October. Average annual rainfall increases from the south-west to the north-east, making the south particularly semi-arid [11]. As a consequence, the hydrological system is complex with many ephemeral rivers, locally called *lishana* (sing. *Oshana*) that carry water during the rainy season and regularly lead to flood events. These floods replenish the soil moisture and keep the pastures fertile that are essential for livestock herding in the basin [13], [28].

The majority of the basin's population of approximately 1.8 million people [29, p. 7], [30, p. 89] lives in rural settings, following livelihood strategies that focus on subsistence agriculture and livestock herding [9], [13]. Nevertheless, new lifestyles emerge with accelerated urbanization processes, new economic activities and trading opportunities, in particular between Angola and Namibia [28], [31].

The dependence of the population on local hydro-climatic conditions for livelihood maintenance and the strong variability of environmental conditions resulted in severe drought impacts in the 1980s, 1990s and 2012, 2015 and 2016 [32]. While the Namibian side of the basin is well endowed with tap water infrastructure, even in remote villages, the Angolan part is less well developed and only offers tap water in major agglomerations. Therefore, traditional water sources such

as wells, rivers and rainwater still play an important role in people's everyday lives. The same is true for food consumption that builds upon locally produced food items from pearl-millet grain, fruit trees and livestock products [9].

2.2. Composite indicator

As introduced in section 1, this study adapts a risk definition that incorporates measures of hazard and vulnerability. This pseudo equation was already operationalized by a number of studies that specifically addressed the challenge of assessing drought risk and drought vulnerability by constructing quantitative tools that mainly build on a certain set of indicators. In this regard, Plummer *et al.* [33] conducted a systematic review on water vulnerability assessment tools as preparation of a project that attempted to investigate water vulnerability of three indigenous communities in Canada. They found 55 studies that consider vulnerability from an integrative perspective and derive 50 different ways to define water vulnerability in terms of instruments, indices and collections of indicators. Thus, heterogeneity of available approaches is still high and confusing. Shiao and Hsiao [34] applied an index-based approach to quantify drought risk based on the assessment of hazard, exposure and vulnerability. They utilized one indicator for each of the three dimensions and applied them to the municipal scale in Taiwan. Each indicator was rescaled to a value between 0 and 1 and subsequently combined to generate the drought risk index (DRI). Shahid and Behrawan [35] developed another drought risk index that determined risk as the product of hazard and vulnerability. They described the drought hazard in terms of spatial extent, severity and frequency by calculating a Standardized Precipitation Index (SPI).

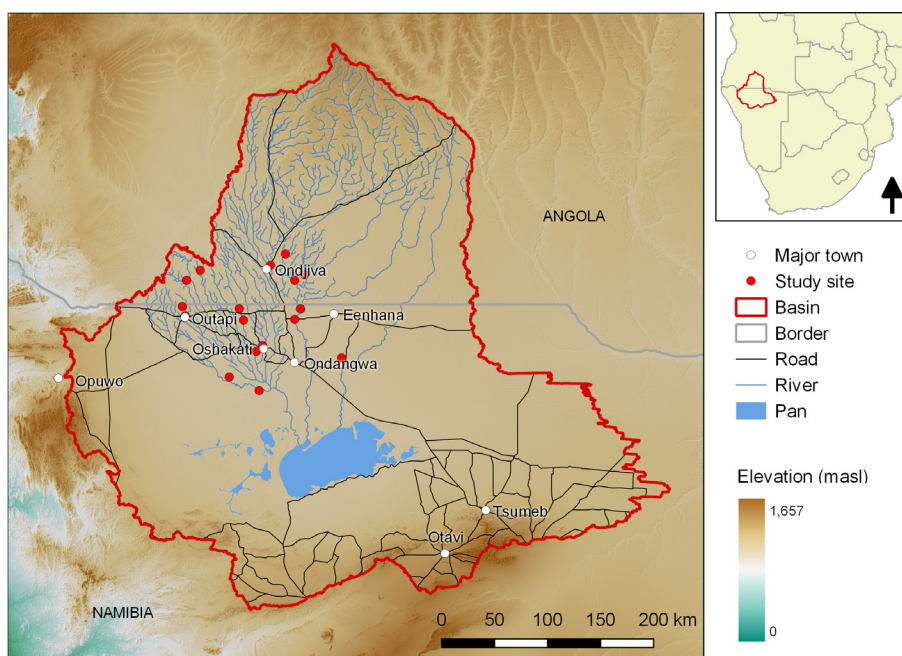


Figure 1: Geographical setting of the Cuvelai-Basin in northern Namibia and southern Angola. The study sites of the structured household survey are depicted, alongside major urban agglomerations.

Drought vulnerability is defined as an index (DVI) composed of seven socio-economic and physical/infrastructural indicators. The combined DRI gives insights into the spatial distribution of drought risk on the district level in western Bangladesh. Pandey *et al.* [36] created a spatially explicit drought vulnerability index by combining seven indicators (including water utilization) to quantify the vulnerability to drought in Madhya Pradesh, India. They constructed a DVI-map and verified their estimations by conducting a two-month survey. Unfortunately, they gave no information on how residents were asked about their "real vulnerability to drought" which was the benchmark to verify their model results. Babel *et al.* [37] developed a more balanced representation of vulnerability by creating a vulnerability index composed of a water stress index and an adaptive capacity index. The sub-indices consist of eight parameters that create the overall vulnerability index after weighting. They applied their model to the Bagmati River Basin in the Kathmandu valley, Nepal. By comparing different time steps (1991 and 2001) the authors uncovered that although the water stress level increased, the level of vulnerability did not change significantly due to the simultaneous enhancement of adaptive capacity. Sullivan [38] developed the Water Poverty Index (WPI), where five key components (resources, access, capacity, use and environment) describe the water scarcity situation and contribute to set priorities of water management and planning as well as monitoring. Later, Sullivan [39] combined the water system vulnerability (supply side) and water user vulnerability (demand side) and created an integrated water vulnerability index (WVI). She applied the index to the South African part of the Orange River Basin and compared the municipalities in their total water vulnerability. Brown *et al.* [40] defined drought vulnerability as a function of exposure, sensitivity and adaptive capacity within a socioecological framework. They used indicators from the socio-economic and environmental domain to assess drought vulnerability in a rangeland system of New Mexico, USA. On a larger scale that considers the entire African continent, Naumann *et al.* [41] explored drought vulnerability on the country level and combined 17 variables from natural resources, economics, human resources and infrastructure and technology to create a composite indicator. They used readily available data from national and international databases and applied different weighting schemes to explore the uncertainty in the drought vulnerability scores. Similarly, Carrão *et al.* [42] collected and combined a range of indicators from the economic, social and infrastructural domains to assess drought risk on the national and sub-national scale. Among other things, they found that drought vulnerability is strong on the African continent but the resulting drought risk is smaller compared to Central Asia, when taking into account the hazard component. Overall, Fang *et al.* [43] provide a comprehensive review of household vulnerability studies.

The approaches described above can all be attributed to an integrative perspective on vulnerability and risk, as each study includes some kind of biophysical and social variables. However, one key problem remains, in particular for those studies that are conducted on larger scales. The indicator sets often lack adequate foundation as local legitimacy is not assessed. Plummer *et al.* [33] uncovered that 40 % of all the instruments included in their review did not build upon empirical data but were rather purely conceptual in nature. This

challenges the reliability of a large number of approaches and again highlights the importance of exploring the research topic in the respective area of interest.

2.3. HDRI construction

The HDRI dimensions of hazard, sensitivity and coping capacity are operationalized with a set of indicators that were found to be relevant to determine household drought risk in the Cuvelai-Basin. These insights stem from a qualitative socio-empirical pilot survey that assessed the causal linkages within the social-ecological system, the key determinants of vulnerability and the second-order effects drought events result in [9]. The indicators take up variables that make use of remote sensing products, secondary spatial socio-economic data and primary empirical data from a household survey [44]. Table 1 gives an overview on the HDRI's structure, its constituting dimensions, indicators and variables, as well as the sources, data are obtained from. Against the overall background of limited data availability in the study area, the following sub-sections provide a detailed description of each indicator's configuration and reasoning.

2.3.1. Drought hazard

The hazard dimension is populated with indicators from the Blended Drought Index (BDI) that builds upon multiple remote sensing products to capture a drought's impact on blue and green water availability [11]. The BDI was explicitly constructed for the Cuvelai-Basin and combines the common drought metrics Standardized Precipitation Evapotranspiration Index (SPEI), Standardized Soil Moisture Index (SSI) and Standardized Vegetation Index (VCI) that were constructed as six-months running averages [7]. This time interval was chosen to capture the seasonal, hydro-climatic conditions of the basin with particular interest in the April values as the rainy seasons' aggregates. The BDI is a single standardized index that uses a copula function to maintain the characteristics of the individual metrics' signals and establishes the threshold of -1 for drought event identification. The HDRI makes use of three key characteristics of the BDI that are relevant to the population in the Cuvelai-Basin in the light of subsistence economy and reliance on traditional water supply systems. Though,, some information is given on the calculation procedure below, the interested reader is referred to the respective publication for more details [11].

Overall, the BDI measures the conditions of precipitation, evapotranspiration, soil moisture and vegetation at the end of the rainy season and applies the -1 threshold to determine if a drought is prevalent. This identification of drought events specifically represents the environmental conditions of the rainy season that are essential for the living conditions in the basin. In order to determine *IND1 frequency of drought occurrence*, the BDI counts the number of years in which the index value falls below the -1 threshold during the available time period of 29 years (1982–2010). *IND2 drought severity* is likewise measured as the cumulative sum of BDI index values below -1 and *IND3 drought duration* is the number of consecutive years in which the index value falls below -1. These three characteristics are

Table 1: Construction of the Household Drought Risk Index, depicting variables, indicators and dimensions as well as the sources of data.

Dimension	Indicator	Variable	Source
Hazard	IND1: Frequency		
	IND2: Severity	BDI [11]: SPEI*, SSI**, SVI***	CHIRPS [45], CRU-TS [46], GLDAS [47], NDVI3g [48]
	IND3: Duration		
Sensitivity	IND4: Water and food demand	Household size Age & gender composition	Survey [27], [44] Survey [27]
	IND5: Water source dependence	Source type reliability Source utilization	Survey [27], [44]
	IND6: Food source dependence	Source type reliability Source utilization	Survey [27], [44]
Coping Capacity	IND7: Infrastructural endowment	Distance to road network Distance to tap water	OpenStreetMap [49], [50] Spatial data [28]
	IND8: Institutional endowment	Dist. to community centres Population density	Spatial data [28] Census data [29], [30]
	IND9: Social capital	Neighborhood Relatives	Survey [44]
	IND10: Human capital	Education Workforce	Survey [44]
	IND11: Financial capital	Income Expenditure	Survey [44]
	IND12: Physical capital	Assets Housing quality	Survey [44]
	IND13: Natural capital	Livestock Property	Survey [44] Google, Digital Globe 2015 [51]

*SPEI: Standardized Precipitation Evapotranspiration Index, **SSI: Standardized Soil Moisture Index, ***SVI: Standardized Vegetation Index

important to determine the overall impact of drought and are hence combined in the HDRI hazard dimension.

2.3.2. Sensitivity

The qualitative insights into drought impact in the study area reveal that blue and green water scarce periods predominantly affect food and water availability on the household level that lead to second-order effects of mental and physical illness as well as social conflicts/crime (e.g. theft of food products between and within communities), among others [9]. Therefore, the indicators chosen to populate the sensitivity dimension focus on these two compartments and consider the total demand for food and water, on one hand, and the respective source types, water and food are withdrawn from, on the other. The empirical assessment of water and food consumption patterns was conducted using a seasonal ranking scheme in questions 1, 2, 11 and 12 of the structured questionnaire [44]. The sensitivity results are published and taken up in this study for further processing. Though, some information is given on the assessment procedure below, the interested reader is referred to the respective publication for more details [27].

IND4: Water and food demand

During a drought situation, households are challenged to provide adequate quantities and qualities of food and water to meet the household member's dietary demands. Hence, the more members a household has, the more food and water is required and therefore, the more sensitive it is to droughts. Although, larger households may

have more capacities to cope with drought situations (e.g. higher human capital via more workforce and better education), they are more affected by water scarce periods in the first place, as they are forced to acquire more quantities of food and water than smaller households. Therefore, *IND4 water and food demand* considers a household's size, age and gender composition in order to estimate the amount of food and water required. The indicator utilizes common metrics for food and water requirements [52], [53].

IND5: Water source dependence

Since the amounts of water and food alone are not sufficient for being highly sensitive to drought, two more indicators are considered. Both deal with the types of sources the households utilize to meet their water and food demands. This builds upon the assumption that source types of water and food differ in terms of their reliability in drought periods. Assuming that two households have an equal member structure, they will have the same value for the *IND4 water and food demand* indicator. However, the types of sources from which they obtain their water might differ tremendously. While the first household might utilize traditional water sources such as shallow wells and open waters, the second household might rely on tap water. The latter source is less sensitive to local water availability conditions and hence more reliable under dry conditions.

Thus, households that strongly depend on unreliable, often traditional water sources show a higher water source dependence and hence a higher drought sensitivity. For a more in-depth description of the seasonal ranking scheme and the sensitivity results, see [27].

IND6: Food source dependence

The same mechanism described in the previous paragraph is applicable to *IND5 food source dependence*. While traditional, subsistence food systems such as rain-fed grain farming, fruit trees and wild-food collection often rely on local green water availability, food systems such as local markets and supermarkets are based on a larger network of suppliers and hence less sensitive to local water conditions. Though price fluctuations occur in times of water scarcity, the results from the sensitivity analysis clearly show that supra-regional supply systems as well as food relief via the extended family network tend to be more reliable than traditional, subsistence-based food systems [27].

2.3.3. Coping capacity

As part of the vulnerability concept, coping capacity seeks to capture the capabilities of an affected societal entity to overcome a threatening situation. Multiple studies operationalized vulnerability and coping capacity in particular, often via secondary data on larger spatial scales [35], [41]–[43], [54] and less often in combination with primary empirical data on a finer scale [37], [55]. This study builds upon the indicators selected in previous studies and sub-divides the coping capacity dimension into an external and internal sub-dimension. While the first sub-dimension characterizes an area in terms of the coping-opportunities it offers to households, the second sub-dimension considers a household's internal capital endowment. The latter explicitly adopts Amrita Sen's insights into entitlement and deprivation [56], captured in the sustainable livelihoods approach [57], which was frequently taken up and adopted, particularly by developing organizations such as Oxfam [58] and the Asian Development Bank [59].

IND7: Infrastructural endowment

Infrastructure generally serves multiple purposes, e.g. to provide an area with energy, water, mobility and communication, among others. In the case of a drought situation, infrastructure is one key for a household to meet basic needs of water and food but also to generate income and receive support in health and security issues. Against the background of limited spatial data availability in the study area, two variables are chosen to represent the infrastructural endowment.

First, the distance of a household to the nearest tap water system is calculated to explicitly cover the aspect of reliable water provision as a backup resource. Second, the distance of a household to the nearest road is regarded as an important proxy, as mobility is essential for the population to meet basic needs, in particular via local market and supermarkets and governmental drought relief programs [60]. Both variables narrow down their perspective on the spatial availability of infrastructural components. They deliberately leave aspects of access out of the focus, as these, such as financial resources, are incorporated into the capital indicators that characterize the internal constitution of a household.

IND8: Institutional endowment

Institutions are understood as societal rules and norms. These can take the shape of formal physical institutions of governmental agencies or security bodies or informal community and/or traditional rules that shape people's daily lives [61], as in the specific case of local water management [12]. Institutions are relevant in times of drought on both the formal and informal level. For the purpose of quantifying this aspect of formal and informal institutions in the current study, two variables are selected. First, as the official governmental drought relief program is organized via regional and local office structures [60], the distance of a household to the nearest community center was regarded as an important proxy. The second variable considers the overall population density, assuming that more densely populated areas provide a household the opportunity to maintain a social network which provides support in situations of crisis. Households that live isolated in rural areas do have limited opportunities to receive support from neighbors, relatives and governmental relief programs.

IND9: Social capital

The capacity of households to deal with drought situations builds upon multiple kinds of capital. Therein, social capital is a contested approach with a variety of conceptual meanings. It basically assumes that people are embedded into a social environment/network of mutual trust, reputation and reciprocity. These interpersonal relationships of bonding and bridging ties enable people/households to withstand crisis situations [62], [63]. While institutional indicators, such as the number of civil society organizations, are often used as indicators for larger scale assessments, in the study area, social capital is primarily characterized by local support from neighbors and relatives [9]. Neighborly support is common in both urban and rural communities and helps to receive support (e.g. in kind). Though, this type of assistance cannot be overstrained since donors and receivers find themselves in a similar situation, it is a common social norm that is based on mutual respect and trust. In order to incorporate this factor, the first variable covers the relationship of a household with its neighbors, assuming that people who are better integrated into the local social environment are more likely to receive assistance. Likewise, the second variable assesses the support from relatives, as kinship relations are stronger and more reliable than relations with neighbors and friends. Both variables were assessed using questions 35–38 of the structured questionnaire with categories of answers arranged on an ordinal scale [44].

IND10: Human capital

While social capital is context specific, particularly the way it is measured, there are established metrics for measuring human capital that capture the "productive wealth embodied in labor, skills and knowledge" [64], [65]. The educational level is most often used as a proxy [66]. In this study, this perspective is expanded by using both the educational level and the household workforce. The first variable focuses on the workforce available to a household and hence its

physical ability to act. In this regard, the proportion of members able to work between 15 and 59 years old compared to those members that require care, under 14 and over 60 years old was calculated. The more workforce is available, the better a household's human capital. The second variable considers the highest level of education. In this respect, the highest educational level among all household members was assessed rather than the education level of a household's head. Kinship relations are strong traditional components of the Namibian and Angolan society and hence, well-educated children and relatives with higher incomes support the family.

IND11: Financial capital

Financial means are essential for a household to deal with a drought situation. It enables them to purchase necessary amounts of food and water and have access to transportation and health services. Since measuring income or wealth in amounts of money is a difficult task [67], the financial situation of a household was assessed in two complementing ways. First, essential fields of expenditures are identified, and second, the dependence on drought-sensitive income sources is assessed. For both purposes, the seasonal ranking scheme from [27] was adopted in questions 15–19 of the structured questionnaire [44]. The seasonal change of expenditures from the rainy to the dry season reveals, for which purposes a household spends its limited amount of money. Those fields of expenditure that are even served under stress situations in dry periods are regarded as essential (e.g. hygiene, basic consumption items). However, if households are not able to fulfill these essential needs, their financial capital is regarded as limited. In order to support this first measure of financial capital, the income source types are classified according to their reliability in dry periods, again assessed through the seasonal change pattern. Households that depend on unreliable income sources (e.g. salary from agricultural sector, selling own agricultural products), only have limited financial means available in crisis situations. Both metrics are combined to provide a more comprehensive measure of financial capital.

IND12: Physical capital

The fourth kind of capital regarded as important in this study is the physical capital as a measure of wealth that is less quickly available than *IND11 financial capital*. Again, two variables are selected, being the availability of specific assets and the housing quality. With regard to the asset ownership of a household, a standardized list of asset items was adopted from the Namibian census survey [68] in question 47 of the structured questionnaire [44]. Based on the sample itself, high-value assets were identified, as they are only owned by a small number of households. From this frequency distribution, a level of wealth could be estimated for each household.

The second variable of interest was assessed using questions 41–43 in the structured questionnaire [44]. Several housing quality standards, such as the material of walls, roofs and floors were assessed. Households with higher quality materials used for construction are regarded as wealthier and hence have more physical capital available.

IND13: Natural capital

The population of the Cuvelai-Basin is strongly linked to its natural environment. Natural capital a household possesses is thus an important sign of wealth. Two variables are chosen in this regard, which are the type and number of livestock a household owns and the property size. Livestock is essential for a large share of the population in financial, in kind and traditional perspectives. Thus, the livestock characteristics were assessed as large stock units (LSU) [69] using question 48 of the structured questionnaire [44]. The more LSU a household owns, the wealthier it is. As a second variable, the property size a household is entitled to use (customary right granted by traditional authorities) was selected, assuming that the larger a property, the more potential a household has to use the ecosystem components located on the pasture. The property size was assessed both through question 44 of the structured questionnaire [44] and satellite imagery, as land property is normally fenced off by the households and hence visible on spatial images [51].

2.4. Structured household survey

The data requirements to populate the HDRI, in particular the sensitivity and coping capacity dimensions cannot be obtained with existing primary information. Therefore, data for the respective indicators was collected by means of a structured household survey. The following sub-sections will present the process of preparing and conducting the field work in both countries.

2.4.1. Questionnaire design and pre-test

The structured questionnaire [44] is the primary tool to assess the required socio-economic information and was set up, based on (i) the indicators' data requirements, (ii) a desired overlap with census information to perform subsequent regression analysis and (iii) time limitations for each interview. Overall, the questionnaire is composed of different assessment tools. Among standard questions on structural parameters (e.g. household size, age, gender) and descriptive aspects (e.g. housing quality, sanitation conditions, energy utilization), several questions assessed perspectives on e.g. drought impact and the relations with neighbors. As an important component, seasonal ranking schemes were included on water and food consumption patterns as well as income sources and fields of expenditures. For further details on the seasonal ranking scheme, see [27].

If possible, the question was phrased in accordance with the recent census surveys in both countries to ensure comparability of results. Furthermore, several questionnaire items were cross-validated, using multiple, differently phrased questions for the same purpose.

The initial questionnaire was pre-tested among 6 households in Oshikango constituency, close to the Angolan border. After the interviews were done, the respondents gave brief information on the understandability of the questions. This information was used to update the questionnaire. The final version was translated from English into Portuguese for application in Angola and is available online [44].

2.4.2. Sampling and field work

The total statistical population of about 350,000 households [29, p. 16-20]; [30, p. 159] comprises every single household located within the boundaries of the hydrological watershed of the Cuvelai-Basin at the time of the surveys. Due to this high number, a sample of households was selected to carry out a structured household survey. Against the background of a maximum Relative Standard Error (RSE) of 0.1, as often envisaged in comparable demographic surveys [70], a desired sample size of about 500 households was targeted. A multi-staged sampling methodology was identified as the most suitable tool. At the first stage, 10 administrative units all over the basin were selected (communes and constituencies). Due to the fact that some administrative units only have a small population share, the *probability proportional to size* (PPS) sampling method was applied. Herein, administrative units that show a higher number of households had a higher probability of being included in the sample. Compared to a simple cluster sample design, the probability of each household to become part of the sample was more equal in the PPS scheme [71]. The PPS sampling methodology fulfilled the requirements of a random sample design. At the second stage, villages were selected via expert consultations. Experts of the respective administrative units were supposed to pick two communities in their unit that were accessible within a few hours using 4x4 vehicles so that the community could be surveyed in a day including a return journey. At the third stage, households were selected by the interviewers via random walk methodology. After the survey team introduced themselves and the research purpose to the community headman or headwoman, the interviewers started their walk by picking every household in a certain direction. The interviewers were supposed to ask the household's head or his or her life partner. If a household was unavailable or refrained from answering, the interviewers proceeded to the next one. The aim was to survey all the households of the respective community.

2.4.3. Interviewer training and quality control

The household survey was conducted with the help of seven interviewers. It was necessary to hire them due to (i) the envisaged sample size of about 500 households, (ii) limited travel funds and associated time constraints, as well as (iii) language barriers, in particular for the rural population that rather speaks Oshiwambo in Namibia and/or Portuguese in Angola. Because of this, interviewers that could prove experience in the conduction of empirical surveys were hired. In this regard, three Namibian university students, two female and one male, were chosen, while in Angola, four official employees from the Civil Protection Agency in Ondjiva were hired. The interviewers were trained in conducting the structured questionnaire. Both the Namibian and the Angolan team were trained in a half-day session on the intention of the survey, the scientific background and the specific questions. For clarification, in-depth queries of the interviewers were dealt with and additional photo material was discussed to provide a precise understanding of key terms such as the range of water and food source types.

The entire household survey in both countries required a four-staged

research permission procedure. On the first stage, research visa were acquired for both countries, while on the second level, official permit applications were addressed towards the regional (Namibia) and provincial (Angola) governments. As soon as these permits were granted, the respective lower levels of constituencies (Namibia) and communes (Angola) were approached in a similar way, according to the sample design. Before approaching the households individually, the entire interviewer team and the supervisor (lead author) spoke to the headman/headwoman of every single community to introduce the purpose of the survey and guarantee data privacy regulations.

2.4.4. Validation of coping capacity scores

Household surveys that try to measure societal phenomena such as vulnerability, sensitivity or coping capacity necessarily only measure proxies, which are assumed to be relevant to describe the phenomenon. Validating the results of respective assessments is the focus of ongoing research but yet, no satisfactory solutions were found.

One approach is to conduct a media analysis on reported drought crisis in a particular area and to compare the events found with the vulnerability scores calculated by means of a specific methodology [72]. However, this approach is only applicable if vulnerability metrics are available for a longer period of time. As the focus of this study is to provide a snapshot in drought vulnerability, the approach cannot be followed.

Another promising approach was presented by Notenbeart *et al.* [73]. They conducted vulnerability assessments using standard socio-economic indicators to derive an overall vulnerability score. Simultaneously, they asked the households to compare themselves with their neighbors with respect to their personal ability to cope with hazard situations. From this, they derived a rather "objective measure" of how households view themselves, relative to their neighbors. Notenbeart *et al.* [73] compared these estimates on the community level with conventional vulnerability indicators and found that only 9 out of 26 indicators they tested fitted the self-evaluation of the households. This approach was incorporated into this study in the form of validation questions 22–24 that were part of the structured questionnaire [44]. The households were asked to say to which extent drought events affect them compared to their neighbors and whether they required food or water aid during the last drought situation. The respective answers were used as benchmarks to determine whether the estimated coping capacity scores are reliable on the community level.

2.5. Data analysis and interpretation

The collected data from the remote sensing products and the empirical surveys were processed before entering the composite indicator. The following sub-sections provide information on the imputation of missing data, the normalization and aggregation scheme, the uncertainty analysis and the transfer of the sample results to administrative units via regression analysis.

2.5.1. Missing data imputation

Missing data is a common feature of household surveys due to a variety of reasons (e.g. response denial, false value, illegibility) [74]. Deleting entire sample cases due to selective missing values reduces the sample size and hence weakens the survey's representativeness. Thus, missing data positions need to be filled with appropriate information taken from the remaining cases that show structural similarities. For this purpose, several methods are available [74], [75]. This study applies the unconditional mean imputation procedure. Therein, the sample mean/median of a variable, depending on the scale of measurement, is used as information to fill the data gaps in the sample. The following equation was used [75]:

$$X_i = \frac{1}{m_q} \sum \text{recorded } X_{i,s} \quad (1)$$

where x_i being a variable, while $x_{i,s}$ is the observed value of x_i for case s with $s = 1, \dots, M$. Let m be the number of available values on x_i and $M - m_i$ the number of missing values. Thus, equation 1 gives the unconditional mean or median value to be entered in every data gap of x in sample I [75]. In the case of data that is available on an ordinal scale, the median value of the sample was used for imputing data gaps.

2.5.2. Aggregation and normalization

The variables selected in Table 1 have different measuring units as they represent specific environmental and socio-economic characteristics of drought risk on the household level. However, the HDRI requires a common unit to combine the individual variables, indicators and components, respectively. Therefore, a certain normalization and aggregation scheme is required. First, each parameter is calculated for all sample households, for example the human capital variable "education". This variable is measured on an ordinal scale from 1 (no education) to 4 (university degree). Hence, each household will receive a value from 1 to 4, while the human capital variable "workforce" has an interval measuring scale from 0 (no workforce) to 1 (all household members are able to work). The first step for combining these two variables is a normalization procedure. Several normalization techniques are available such as z-transformation and Min-Max normalization, among others [75]. The linear Min-Max transformation procedure is widely applied in composite indicator construction and particularly in environmental risk assessments [41], [75]. Therefore, each variable was normalized on a common scale from 0 to 1 with values close to 0 indicating bad/unfavorable conditions and values close to 1 pointing to good/favorable conditions. The transformation was conducted following the equation [75]:

$$V_s = \frac{(X_s - X_{min})}{(X_{max} - X_{min})} \quad (2)$$

where V_s is the normalized variable, X_s is the original value of variable x , X_{min} is the minimum value of x and X_{max} represents the maximum value of x . This normalization technique offers the opportunity to combine

the variables in an additive way. The results are again normalized and combined on the next level from variables to indicators and dimension up to the final HDRI. If required, data transformation is performed to better fit the assessed data to the Gaussian normal distribution. Here, several techniques are applied, such as logarithmic, exponential, inverse sine or square root transformations, based on the respective skewness of the distribution ranges.

2.5.3. Weighting and uncertainty

The normalization and aggregation procedure outlined above implicitly assumes an equal weighting scheme of the final dimensions hazard, sensitivity and coping capacity when combining them to the $HDRI_{equal}$ irrespective of any underlying properties of the data. However, the number of indicators and the statistical characteristics of each dimension should be represented in the final HDRI. In order to account for these data properties, two more weighting schemes are applied.

First, the dimensions are combined, proportional to the number of indicators they entail. This means that the normalized dimensional scores are weighted with the number of indicators they are composed of, following the equation:

$$HDRI_{prop} = h * w_1 + s * w_2 + c * w_3 \quad (3)$$

with $HDRI_{prop}$ being the HDRI-score from proportional weighting, h , s and c being the hazard, sensitivity and coping capacity scores and w_1 to w_3 are the weights applied to the dimensions. The $HDRI_{prop}$ is subsequently normalized according to equation 2.

Going one step further and not just accounting for the number of indicators within each dimension, a weighting scheme is applied that takes into account the statistical properties of the data. For this purpose, a Principal Component Analysis (PCA) was applied on the indicator level. Since the PCA is essentially a technique to reduce the number of indicators, it will identify underlying principal components that capture most of the initial indicators' variances. The number of principal components is determined by their respective eigenvalues with components being selected if their eigenvalues are larger than 1. The indicators are grouped into these components on the basis of their specific loadings [75]. The resulting $HDRI_{pca}$ -score is subsequently calculated similar to equation 3, where the components' weights are the amount of variance they explain, following the equation:

$$HDRI_{pca} = p_1 * v_1 + p_2 * v_2 + \dots + p_n * v_n \quad (4)$$

with $HDRI_{pca}$ being the HDRI-score from PCA weighting, p_1 being the first principal component that is multiplied by the aggregated variance v_1 it explains. As a result, every sample household receives an HDRI-score from equal, proportional and PCA weighting with values ranging from 0 (bad/unfavourable conditions) to 1 (good/favourable conditions).

The different weighting schemes now allow the analysis of uncertainty in the final HDRI-scores. For this purpose, the arithmetic mean of the

three HDRI-scores is taken and set into reference to the minimum and maximum values of the three weighting schemes. The range of uncertainty is attributable to the aggregation scheme and provides insights into the robustness of the theoretically derived composition of the HDRI.

Besides this uncertainty among the final HDRI scores, their statistical sensitivities to the underlying indicators is an important benchmark, in particular when influential control parameters that should be altered to reduce overall drought risk should be identified. Among the diverse range of analysis techniques [76], variance-based sensitivity analyses are commonly used in the context of composite indicators [75], [77]. The method developed by Ilya Meyerovich Sobol and the derivatives that emerged subsequently assess the explanatory power of input variables with respect to a specific output variable. In this regard, the first order effect can be assessed as the explained variance by single input variables, while the total effect acknowledges interactions among the diverse variables included in a respective model to explain the variance of an output variable. The first order effect S_i of a particular input variable X_i can be formally written as,

$$S_i = \frac{V_{x_i}(E_{x-i}(HDRI|X_i))}{V(HDRI)} \quad (5)$$

where V_i is the conditional variance and $V(HDRI)$ being the unconditional variance of the HDRI as the output variable. Likewise, second and higher order effects can be calculated to account for the interactions among the variables. Adding up these first and higher order effects reveals the total effect S_{π} that is formally written as,

$$S_{\pi} = \frac{E_{x-i}(V_{x_i}(HDRI|X_i))}{V(HDRI)} \quad (6)$$

2.5.3. Spatial drought risk

The knowledge on drought risk on the household level is important to structurally identify vulnerable people. It helps answering the question on "why" people are at risk of drought. However, the subsequent question of "where" people at risk live remains. Decision-makers require information on both, "why" and "where" in order to efficiently design short-term emergency responses and carry out long-term adaptation strategies in the most important areas among the most vulnerable people. Hence, the HDRI sample results are projected onto the administrative units within the Cuvelai-Basin in Angola and Namibia to receive a first approximation of spatial drought risk hot-spots.

Spatial data is available for part of the HDRI indicators. The hazard dimension builds upon remote sensing data to calculate the BDI and its key characteristics. Each administrative unit hence receives a hazard score as the spatial average of BDI frequency, severity and duration. Likewise the indicators *IND7 infrastructural endowment* and *IND8 institutional endowment* build upon spatial socio-economic parameters. Again, the values were averaged for the administrative units for the variables distance to road network, distance to tap

network, distance to community centers and population density. Only the dimension sensitivity and the capital indicators within the coping capacity dimension do not primarily build upon readily spatially available data. Therefore, a transfer of results to the spatial scale is required. Estimating statistical characteristics of certain areas or societal groups is one of the central motivations in quantitative social sciences. Sample surveys are commonly designed to reveal estimates for the entire statistical population, targeted. Thus, the results are only valid on this level. For the purpose of estimating statistical characteristics of areas or domains smaller than the targeted ones, large standard errors occur due to small or even non-existent sample sizes in the sub-entities [78]. For this reason, methodologies were developed, already in the 11th century in England and in the 17th century in Canada, to make reliable estimates on small areas and domains [79]. The methods can be grouped together under the term of Small Area Estimation (SAE) [78]. According to Noble, several sub-groups of SAE can be distinguished [80].

The results of sample surveys borrow the strength of similar or related surveys (i.e. census) to reduce the sampling error. Auxiliary data plays a critical role, since this data is used to interpolate sample results [80]. In this study, the questionnaire contained a number of variables that overlap with available census information. These overlapping variables were used to predict the sensitivity and the aggregated capital indicators for the administrative units on the constituency/communal level. The basic assumption herein is that the patterns surveyed in the sample are applicable in the other areas. The multiple linear regression models follow the equation:

$$\hat{d}_a = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \dots + \hat{\beta}_n x_n + \epsilon \quad (7)$$

Herein, \hat{d}_a is the estimated value of the dimension sensitivity or the aggregated capital indicators in the administrative unit a , $\hat{\beta}_0$ is the intercept and $\hat{\beta}_n$ the slope coefficients of the n -th variable x and ϵ is the error term [81]. The results for each administrative unit from both direct spatial measurements and the regression analysis were combined based on the normalization scheme outlined above.

Since the census data from Angola, even the micro dataset [82] were not available on the communal level as compared to Namibia, only the provincial results could be used [83]. These values were projected onto the communes under the assumptions that conditions are equal. This is a drawback for the interpretation of the spatial results. As soon as the census results become available on the communal level, data can be updated to reveal more detailed results.

3 Results

The study results are presented in the following sub-sections. First, key sample variables are shown and compared to available census information. Second, the drought risk results are illustrated with special emphasis on the disaggregated dimensions. Third, the effect of different weighting schemes and the uncertainty analysis is presented and fourth, the spatial drought risk estimates are shown.

3.1. Descriptive statistics

The entire statistical population in the Cuvelai-Basin is approximately about 350,000 households [29, p. 16-20]; [30, p. 159] of which 461 were selected in the survey sample. Against the background of the envisaged sample size to undercut a certain relative standard error and against the project constraints (time, funds and accessibility), this sample size is regarded as reasonable to represent the living conditions of a large share of the population. In this regard, **Table 2** shows key socio-economic variables of the households, distinguished into groups according to nationality and settlement type. The values are measured against overlapping census variables, obtained from census micro-datasets [82], [84] to compare the statistical means of metric variables and proportions of nominal/ordinal values. The comparison of sample and census values reveals heterogeneous results. While significant deviations are observable among certain variables, some group estimates such as the household size of urban Namibians, the number of household members between the ages 15 to 59 and the gender ratios show a good fit. Likewise, the discrete variables of marital status, energy utilization, sanitation and ethnic groups and in particular the relative proportions between the groups are, again,

well reproduced. Only the energy utilization in urban Namibian and urban Angolan areas overestimates the utilization of firewood as an energy source for cooking. In general, the sample shows low shares of missing values per variable of about 4 % on average and a low non-response rate (households rejecting to participate) of less than 5 %. Overall, the sample is regarded as adequate for further processing and the intended purpose of approximating the HDRI indicator values.

The variables served to populate the 13 indicators of the HDRI for each household of the sample, based on their specific location (hazard, infrastructural and institutional indicators) and assessed socio-economic setting (survey data). **Figure 2** shows histograms of the indicators, after their skewed distributions were transformed, using exponential, inverse sine and square root transformations, based on the direction and intensity of prior skewness. Though not perfect, the transformations enhanced the fit to the Gaussian normal distribution, as quantitatively indicated by the test statistics of the Shapiro-Wilk test [85] and the W/S normality test [86] as well as the visual comparison with the hypothetical normal distribution (red line, **Figure 2**).

Table 2: Descriptive statistics for key variables obtained from the socio-economic household survey. Comparison of sample (n = 461) and sampled census mean values (two-sided t-test) and proportions. All values are compared based on groups of nationality and settlement type.

Variables	Namibia				Angola			
	Urban [98]		Rural [212]		Urban [67]		Rural [84]	
	Sample	Census	Sample	Census	Sample	Census	Sample	Census
Household size	4.82 (3.27)	4.42 (8.67)	***8.00 (4.36)	5.49 (4.22)	***7.04 (4.33)	4.97 (3.27)	***10.44 (5.36)	5.60 (3.40)
No. of household members < 14	***1.48 (1.63)	2.39 (1.74)	*2.70 (1.97)	3.03 (1.95)	3.02 (2.45)	3.06 (1.86)	***4.56 (2.55)	3.18 (1.93)
No. of household members 15 – 59	3.29 (2.22)	2.95 (8.06)	***4.73 (3.12)	2.53 (2.52)	***3.95 (2.89)	2.54 (1.64)	***5.32 (4.19)	2.52 (1.75)
No. of household members > 60	***0.05 (0.26)	1.74 (1.26)	***0.62 (0.72)	1.95 (0.84)	***0.12 (0.37)	1.15 (0.39)	***0.43 (0.61)	1.27 (0.53)
Household gender ratio Males/Females]	0.82 (0.84)	0.85 (1.73)	1.02 (0.86)	0.99 (0.96)	1.06 (0.96)	1.14 (1.03)	1.08 (0.99)	1.10 (1.00)
Marital status: Head married [%]	29.60	31.24	50.33	46.49	50.97	52.83	48.25	54.17
Energy: Wood for cooking [%]	70.50	34.66	94.74	88.68	53.59	18.13	100.00	96.92
Sanitation: No toilet [%]	34.61	33.56	86.06	78.39	92.81	82.25	100.00	99.36
Ethnic group: Kwanhama [%]	58.21	---	30.30	---	53.72	32.80	79.87	58.55

Significance levels for deviations in sample mean from sampled census mean (*p < 0.1, **p < 0.01, ***p < 0.001). Squared brackets indicate the sample sizes, while standard deviations of the means are given in round brackets. "---" indicates that no data is available in the census micro-dataset. The census parameters were obtained from official census micro-datasets [82], [84]. The relative standard error (RSE) of the given metric variables is on average 12 %.

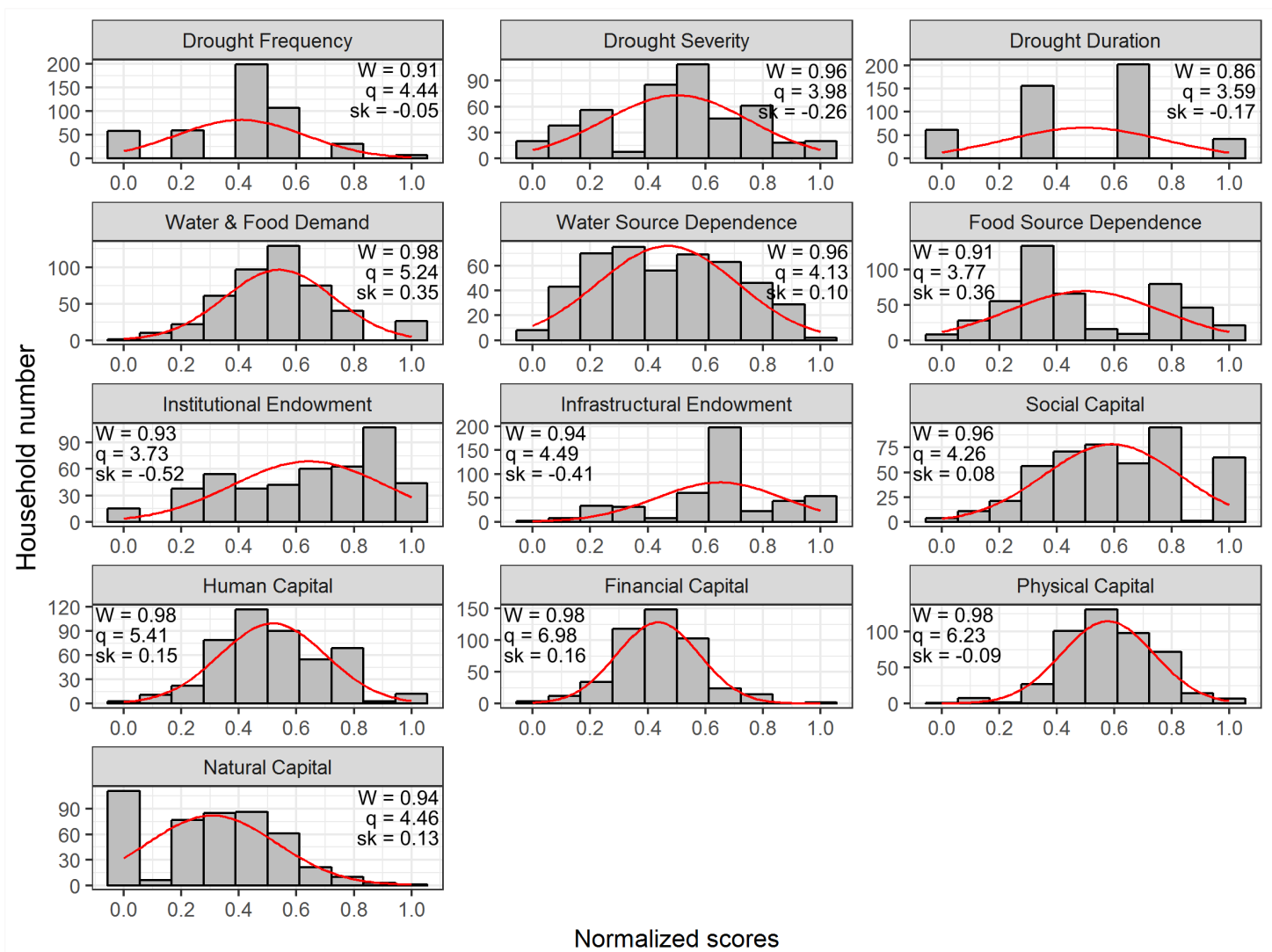


Figure 2: Histograms of HDRI-indicators and targeted normal distributions ($n = 461$). Data of indicators was transformed prior to further processing (exponential function, square root and inverse sine transformation) to better fit the Gaussian normal distribution. Red line indicates the Gaussian normal distribution, if the mean and standard deviation of the respective data is used. "W" = Shapiro Wilk test statistic, "q" = W/S normality test (quotient of data range and standard deviation), "sk" = Skewness of distribution.

3.2. Household drought risk

As the previous section found the assessed variables and the derived indicators were suitable for further processing, this section elaborates on the signals that the individual indicators and the aggregated dimensions show. **Figure 3** shows radar charts that depict the average indicator scores and the final HDRI scores of rural and urban households in Angola and Namibia. Therein, smaller sectors represent smaller score values and hence indicate unfavorable conditions, while larger sectors show rather better conditions. Differences are observable especially between rural Angolan and urban Namibian households. Here, the orange sector, representing the average HDRI scores, is significantly larger among urban Namibian inhabitants which

is primarily attributable to less sensitivity (blue sectors) and better infrastructural and institutional endowment (light green sectors). In terms of social, human and financial capital, both groups are rather equal, while differences are apparent when considering the physical capital (e.g. assets) and natural capital (property, livestock). While urban Namibians have a higher physical capital stock, their natural capital is rather non-existent. Here, the Angolan rural population can fall back on larger properties and in particular higher numbers of livestock. Nevertheless, urban dwellers are still connected to the conditions in rural settings, as they maintain kinship relations and provide financial resources to their relatives and/or receive in-kind support from the villages.

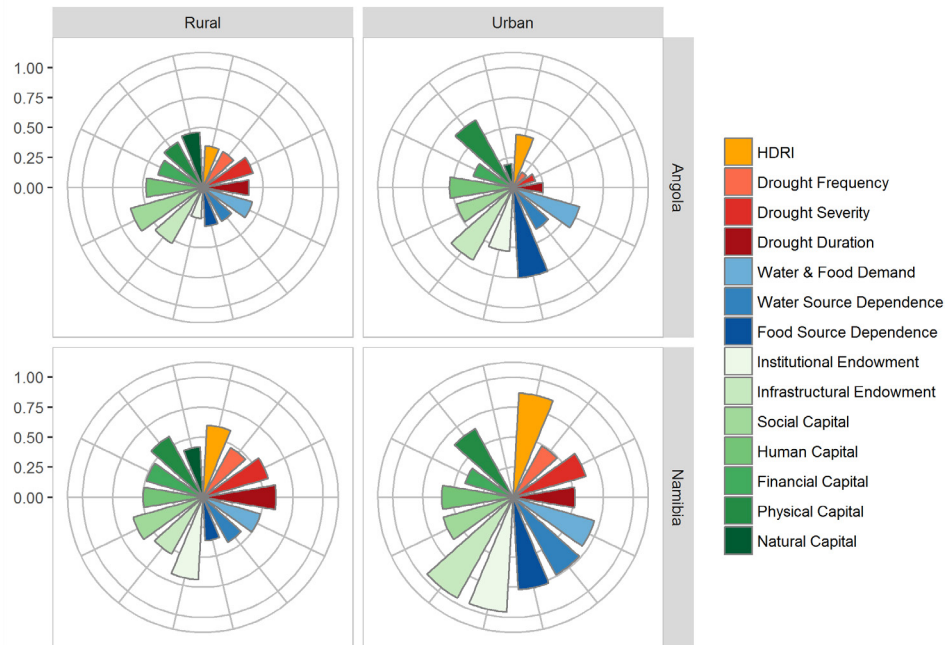


Figure 3: Indicator scores of rural and urban households in Angola and Namibia ($n = 461$). The scores range from 0 (bad/unfavourable conditions) to 1 (good/favourable conditions). The HDRI score is added to the radar charts.

Urban dwellers have better sensitivity conditions, in general, as they can access more reliable water and food source types. This is true for both countries, while in Angola, only major urban agglomerations show a good coverage with tap water, for instance. Another obvious difference exists in the hazard conditions when comparing Angola to Namibia. Especially the urban Angolan households experience rather unfavourable environmental conditions, while these are more favourable in rural areas, particularly in Namibia.

Analysing the indicators among different groups gives detailed insights into the drought risk conditions for specific households, in particular when considering their socio-economic setup. As implied by the colours in the previous figure, the indicators can be grouped into the dimensions proposed by the HDRI structure: hazard, sensitivity and coping capacity. This offers the opportunity to evaluate the indicators' combined signals and retrieve an aggregated measure of drought risk.

Figure 4 shows how the dimensions correlate with one another and with the final HDRI value. On one hand, it is important to note that the hazard dimension does not correlate with the socio-economic dimensions of sensitivity and coping capacity. This is an important asset, as it confirms their statistical independence and indicates that they indeed measure different aspects of drought risk. On the other hand, sensitivity and coping capacity show a medium strength correlation to one another. This is reasonable, as the socio-economic conditions in people's consumption patterns (sensitivity) and their internal constitution (coping capacity) is necessarily linked. When combining only the latter two dimensions, a measure of vulnerability

is available, which also shows a clear distinction to the hazard dimension.

The HDRI scores and the underlying dimensional and indicator level results can be explored further with respect to group specific features. **Figure 5** shows several group variables that were assessed during the structured household survey in addition to the variables required for the indicator construction. The Figure shows the differences between the arithmetic mean vulnerability scores of households when grouped according to settlement type, sanitation conditions, nationality, marital status, household size, ethnic group and energy use for cooking. Of particular interest is the question whether the mean values differ significantly from one another. This is true for all but one of the investigated groups. While no significant difference can be found when Kwanhama households were compared to other ethnic groups, there were strong differences when considering the settlement type and the sanitation conditions. Some of the groupings are also available in the census surveys in both countries and hence, they will serve the purpose of constructing linear multiple regression models to derive spatial drought risk estimates in the following section.

3.3. Uncertainty of HDRI scores

The final HDRI scores are the result of aggregating the three dimensions hazard, sensitivity and coping capacity. The uncertainty attached to these HDRI scores is made explicit by applying different weighting schemes when aggregating the dimensions. While the primary method implicitly assumes an equal weighting of the dimensions, two more schemes on the dimensional level are considered being

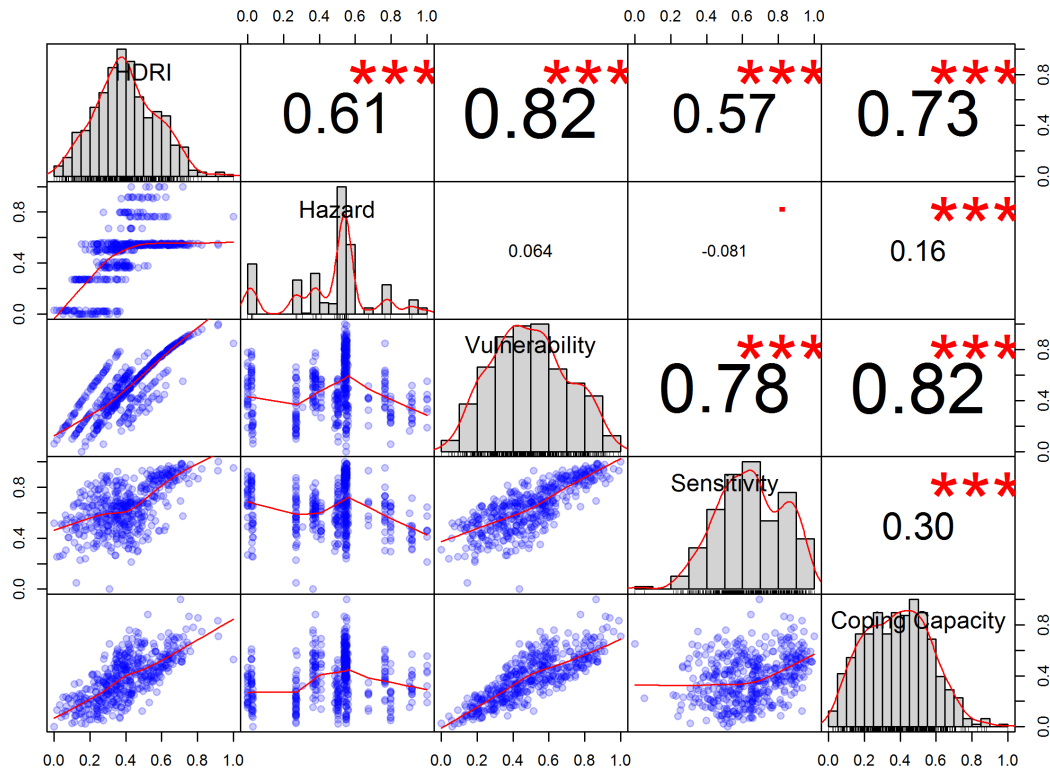


Figure 4:Correlations among the HDRI and its dimensions for the entire household sample (n = 461). The lower panel shows the individual scatter plots between two individual dimensions, the diagonal plots show the dimensions' histograms and the upper panel shows the Pearson correlation coefficients with their statistical significance levels (*p < 0.1, **p < 0.01, ***p < 0.001).



Figure 5:Comparison between vulnerability scores of selected socio-economic groups. Differences among the groups are statistically significant at levels of *p < 0.1, **p < 0.01, ***p < 0.001.

proportional (weights according to the number of indicators the dimensions entail) and PCA weighting (weights obtained from principal component analysis).

Figure 6 shows the households' HDRI scores as the arithmetic mean of the three weighting schemes with values closer to 0 representing unfavorable/bad conditions and values closer to 1 indicating good/favorable conditions. The respective minimum and maximum scores that derive from the other weighting schemes are depicted as error bars. The individual plots show the distribution of HDRI scores in the countries as well as the settlement types rural and urban, respectively. The sequence of full-colored points gives an impression of how drought risk is distributed among households of different groups. For instance, most of the urban Namibian households show HDRI

scores of above 0.75 while all of their Angolan counterparts score below this threshold. Similar patterns are observable among rural households. Rural Namibian households are generally worse-off than their urban neighbors, but better-off in comparison to their Angolan counterparts. Combining these two settlement types gives the aggregated picture for Angola and Namibia. Therein, Namibian citizens have lower drought risk levels (higher HDRI scores) than Angolan citizens. When considering the error bars among the full-colored points in **Figure 6**, it becomes apparent that the weighting schemes have a limited influence on the final results. Therefore, the primary method of aggregating the dimensions with equal weights is regarded as a statistically robust estimation of drought risk levels in the present case.

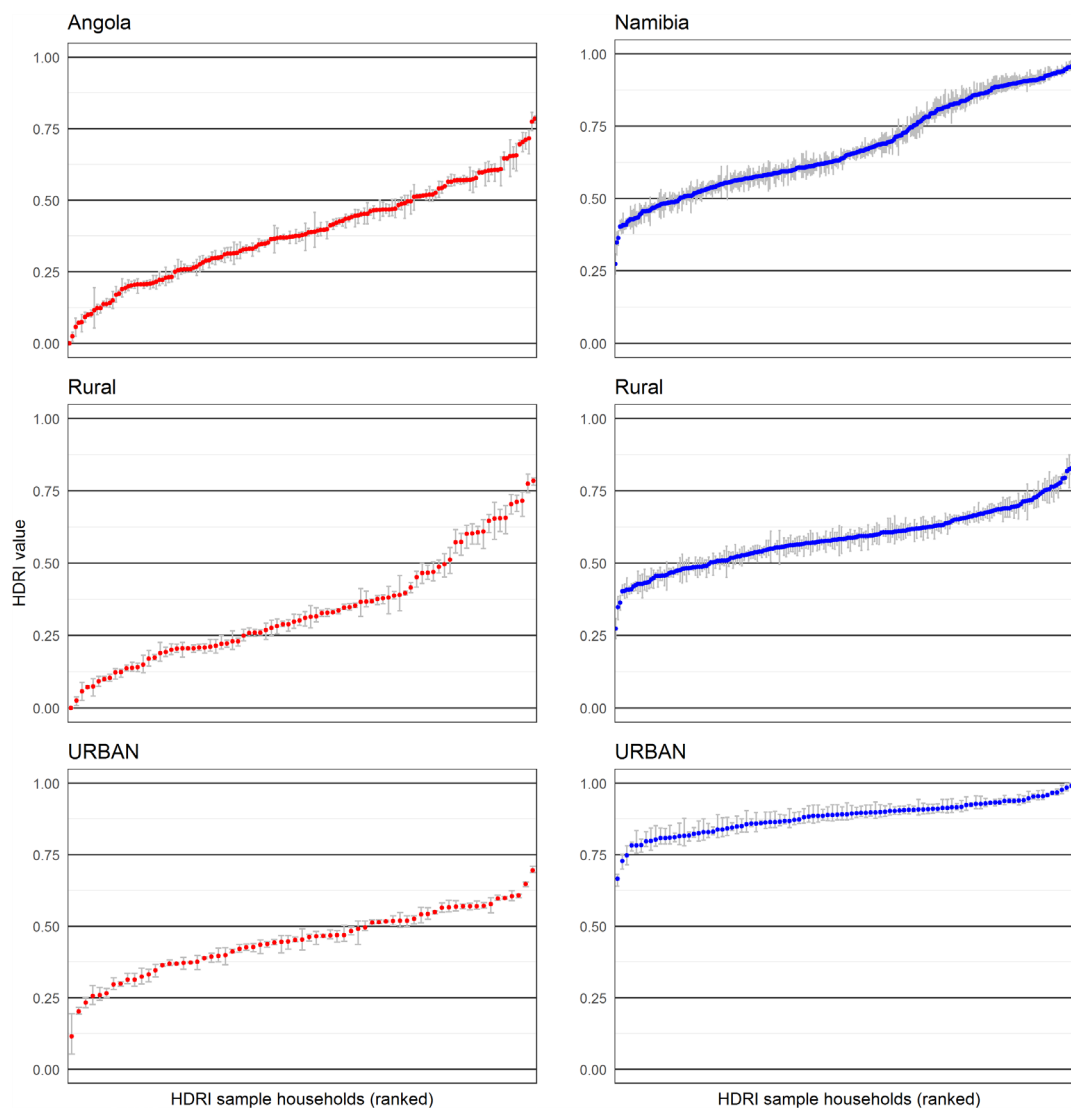


Figure 6: HDRI score comparison and variation among households in different groups ($n = 461$). Three weighting schemes are applied prior to aggregation being equal, proportional and PCA weighting. The full-coloured points indicate the mean scores from the weighting schemes and the error bars show the minimum and maximum scores. Households are afterwards ranked from lowest (bad conditions) to highest (good conditions) mean HDRI scores

The importance of individual indicators for the final HDRI scores can be analyzed via a variance-based sensitivity analysis. Table 3 shows the results of the Sobol global sensitivity analysis that reveals both first order (S_i) and total effect (ST_i) of the indicators on the HDRI scores. When the explanatory power of the individual indicators is considered with respect to their ability to explain the variance in the target value, indicator 4 (Water and food demand) and indicator 5 (Water source dependence) have the largest first order effects. The sum of variance over all indicators adds up to about 40 %. Hence, the remaining 60 % of variance is explained by interactions among the indicators. With regard to the indicators' total effects that incorporate the interactions among them, in particular the sensitivity indicators still show the strongest signal. In addition, human capital and financial capital as well as infrastructural endowment gain importance, compared to their respective first order effects.

Table 3: Sensitivity results for the HDRI scores based on Sobol's sensitivity analysis. First order and main effects are presented for the thirteen indicators.

Indicator / Dimension	First order (S_i)	Total effect (ST_i)	$ST_i - S_i$
IND01: Drought frequency	0.01	0.09	0.08
IND02: Drought severity	0.02	0.10	0.08
IND03: Drought duration	0.01	0.07	0.06
IND04: Water and food demand	0.08	0.19	0.11
IND05: Water source dependence	0.08	0.18	0.11
IND06: Food source dependence	0.05	0.16	0.11
IND07: Infrastructural endowment	0.02	0.15	0.13
IND08: Institutional endowment	0.01	0.09	0.08
IND09: Social capital	0.02	0.10	0.08
IND10: Human capital	0.04	0.14	0.10
IND11: Financial capital	0.03	0.14	0.11
IND12: Physical capital	0.02	0.10	0.09
IND13: Natural capital	0.01	0.08	0.07
Indicator sum	0.40	1.60	1.20

3.4. Validation of vulnerability scores

The validation of the coping capacity scores is performed using three questions of the structured questionnaire. Two of them encouraged the respondents to self-reflect upon their performance within the last drought period. They stated whether they would have been able to endure the last drought period with or without food or water aid/donations. Table 4 shows the results when comparing the households' answers to the calculated scores of the coping capacity dimension. The validation only considers the coping capacity dimension, as this specifically reflects the capability of a household to act during a crisis situation. Table 4 indicates that positive correlations are apparent for the presented sub groups of rural and urban settlements in Namibia and Angola. In particular, the urban Namibian citizens and the urban Angolan citizens show stronger positive correlation, while the other groups only present weak correlations between the calculated scores and their self-reported ability. The fit between the scores to the water aid/donations people obtained is weaker than when considering the

use of food relief.

Table 4: Spearman correlation coefficients for self-evaluation. Coefficients between the coping capacity scores and the households' self-reported ability to cope with or without food or water aid.

Group	Sub-group	Food aid	Water aid	Cases
Namibia	Rural	*0.13	0.00	212
	Urban	**0.48	-0.08	98
Angola	Rural	0.11	-0.12	84
	Urban	**0.42	***0.45	67

Significance levels: *p < 0.1, **p < 0.01, ***p < 0.001.

The third question asked the respondents to self-evaluate their performance in the last drought period in comparison to their friends and neighbors in the same community. They stated whether they performed best, better, equal, less good or worse in the community. This metric was again compared to the calculated coping capacity scores of each household, relative to the other households within the community. Table 5 shows the results of the comparison by showing the spearman correlation coefficients on the community level. The results show positive correlations of varying strengths. While strongly positive and statistically significant correlations are apparent in Namibian communities such as Etayi, Oponona, Oshandja and Outapi, only weak correlations are recorded in the Angolan communities, except Oshitumba.

Table 5: Spearman correlation coefficient of self-evaluation. Coefficients are depicted between community-level self-evaluation of households' relative performance in drought periods compared to their neighbours.

Country	Community	r	Cases
Angola	Chiede	0.03	41
	Ehoko	NA	6
	Ohamukuyo	-0.10	40
	Okadweya	NA	15
	Ombala Sede	0.00	20
	Onepolo	0.00	14
	Oshitumba	0.23	15
Namibia	Etayi	*0.36	28
	Ikelo	0.12	9
	Ohamaala	0.28	19
	Olukekete	0.04	25
	Omanghwi	0.08	24
	Onaushe	0.21	28
	Oponona	*0.26	23
	Oshandja	*0.36	30
	Oshimumu	-0.10	26
	Oshoopala	0.11	54
Outapi	*0.41	44	

Significance levels: *p < 0.1; NA: no data.

Nevertheless, most communities show positive correlations between the calculated scores and their self-evaluation. However, the results on the community-level have to be interpreted with caution, as the individual sample sizes are partly small.

Overall, the validation questions provide the opportunity to evaluate the performance of the calculated scores against an independent measure of the respondents' self-reflection. Though the correlation coefficients are heterogeneous and often weak, the results of questions one and two confirm the calculated scores, in particular when comparing these results with other studies in the field [73]. Question three also shows heterogeneous results, specifically in the difference between Angola and Namibia. When only considering the Namibian results, the coping capacity scores confirm the self-evaluation, though on a low level of weak to medium correlation strength. The reason for the poorer fit in Angola is speculative, but maybe attributable to differences in perception of the question or translation problems.

3.5. Spatial drought risk hot-spots

While it is important to understand the causes and effects of drought risk on the household level, it is essential for authorities and non-governmental actors to identify spatial hot-spots. To provide a first approximation of the spatial patterns of drought risk, the sample results are made spatially explicit using both primary spatial data and

regression model estimates.

Figure 7 depicts the spatial HDRI scores on a scale from 0 (bad conditions/high risk) to 1 (good conditions/low risk) and shows the spatial configuration of the underlying dimensions. The highest HDRI risk levels are found in the southern part of central-northern Namibia and along the Kunene River in the west of the Angolan part. These regions are characterized by stronger hazard impacts and higher levels of sensitivity, particularly in Namibia. Although the coping capacity is regarded as good in Namibia, it cannot compensate the negative influences of the first two dimensions. The areas of lowest drought risk are found in the south and south-east of the basin and the central administrative units that are rather urbanized. Though hazard levels are still high, households located in these constituencies have better coping capacities and less sensitive consumption patterns. Considering the underlying dimensions in more detail, it becomes obvious that the spatial patterns vary from dimension to dimension. While the hazard is found to be most severe in the central and north-western administrative units, sensitivity shows a rather heterogeneous pattern with rural constituencies in Namibia having the highest sensitivity, due to critical water and food consumption patterns. Coping capacities are rather good in the central areas of northern Namibia, where water and food infrastructures are well available. In Angola, coping capacities are lower, as the entire area is less developed and households obtain less capital endowment.

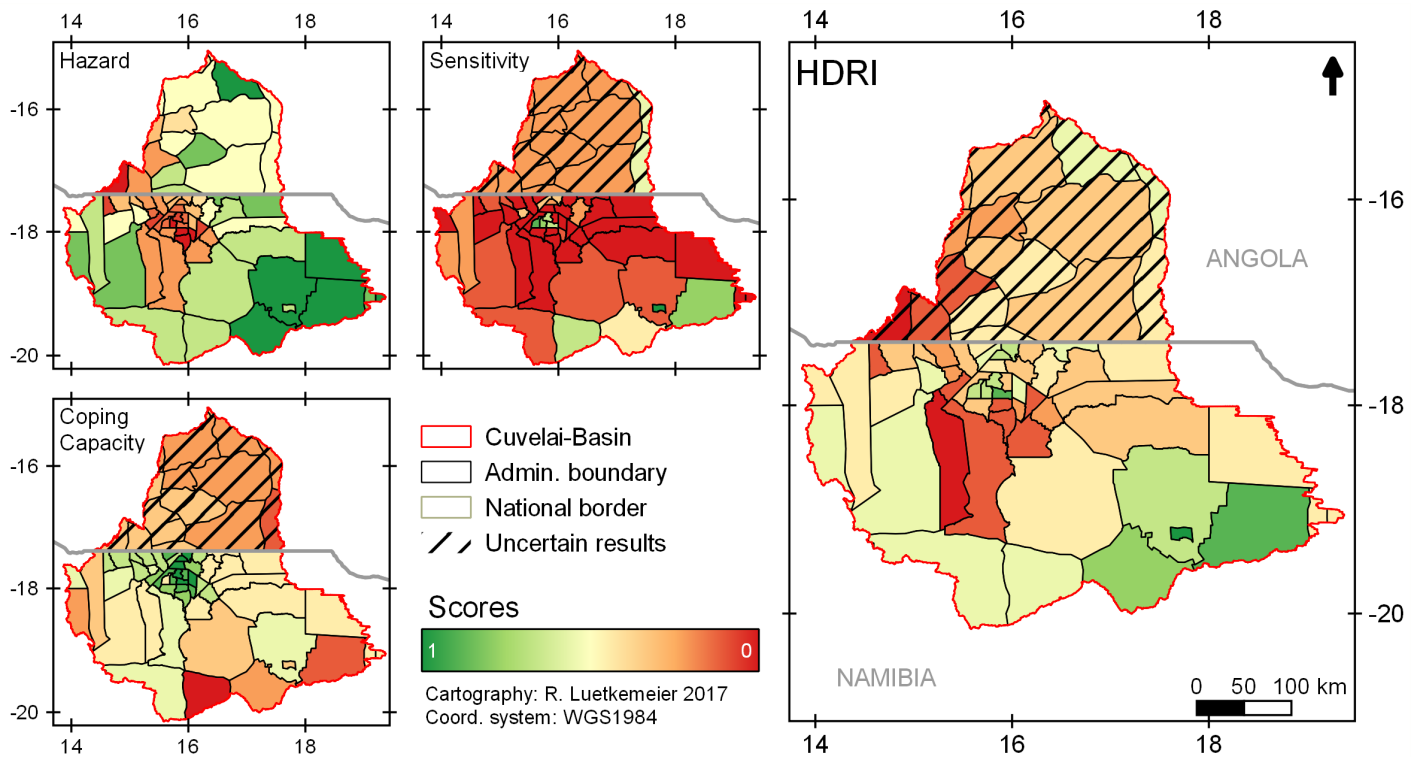


Figure 7: Spatial estimates of drought risk and the underlying dimensions. The depicted maps build upon primary spatial data and regression model results. The hatched areas indicate uncertain results due to low resolution census data in Angola.

Overall, the spatial drought risk estimates can only be regarded as a first approximation, as the sensitivity and coping capacity dimensions partly build upon regression estimates. In this regard, linear multiple regression models were constructed to populate the capital-indicators of the coping capacity dimension and the entire sensitivity dimension, as these variables are not readily available from census surveys. Therefore, overlapping variables between the sample and the census are used to construct regression models and estimate the required parameters. Several variables were tested for suitability in the regression models as they were found to reveal significant differences between HDRI scores (Figure 6). As a result, the best-performing model to estimate sensitivity is composed of the parameters settlement type, marital status of the household's head and sanitation conditions which provides an explanatory power of 52 % (R^2 : 0.52). With respect to the aggregated capital indicators, the best-performing model included settlement type, sanitation conditions, marital status and energy type used for cooking and is able to explain about 14 % (R^2 : 0.14) of the data's variance.

The results for sensitivity and coping capacity are less detailed for the Angolan administrative units, since census information to perform the regression analysis is only available on the provincial level. Results on the communal level are linearly interpolated and hence they do not show (sensitivity) or they only show slight (coping capacity) deviations.

4. Discussion

The discussion section will shed light on three major areas of interest. First, the results will be critically reflected with regard to the advantage of an integrated perspective on drought risk. Second, the methodology in terms of indicator selection and construction as well as validation and regression analysis will be discussed. Third, the potential to transfer the study design to other areas of interest is considered in the last sub-section.

4.1. Reflection on results

The consideration of societal and environmental aspects to describe and analyze drought risk on the household level is essential. If only the hazard dimension had been considered to identify people at risk, different areas/households would have come into the focus, compared to a purely sociological perspective. On one hand, if the hazard dimension is narrowed down to low precipitation alone, Namibian inhabitants would be regarded as most affected by drought since mean precipitation conditions improve from south to north. On the other hand, if a broad vulnerability perspective that considers the overall development status had been taken, most Angolan households would have been found at risk. Bringing these perspectives together reveals new insights into drought risk and helps understanding specific options for adaptation.

Figure 8 shows a boxplot diagram to compare the aggregated HDRI scores with the dimensional scores of hazard and vulnerability (combined sensitivity and coping capacity). Both the median values

and the distributional ranges of each score show that considering either the environmental hazard side or the sociological vulnerability side in isolation reveals different results. The HDRI accounts for both perspectives but also offers the opportunity to review the individual dimensional results and even the underlying indicator scores to explore the reasons for drought risk levels of specific groups.

Overall, urban inhabitants are less affected by drought situations as their coping capacities are higher and sensitivities are lower. This is particularly driven by higher coping capacities, in terms of better infrastructural and institutional endowment as well as less sensitive consumption patterns. When considering the sensitivity of the final HDRI scores to its underlying indicators, from a statistical perspective, it turns out that the infrastructural endowment of a region and human as well as financial capital are of greater importance than the other indicators.

The results in terms of both the socio-economic groups and the spatial approximation of drought risk offer entry points to reduce drought risk on the household level. From a spatial perspective, the densely populated rural areas in both countries are most at risk of drought, as the environment shows signs of degradation and the infrastructural endowment is limited. However, urban centers offer rather favorable conditions to the inhabitants with more reliable water and food source types and better opportunities to enhance the capital endowment.

4.2. Reflection on methodology

This study makes an attempt to quantify the drought risk phenomenon by populating the HDRI's indicator set with measurable variables that are either readily available from remote sensing products, spatial socio-economic data or the conducted structured household survey. Though the qualitative insights put the HDRI on a well-founded basis, the selection and construction of the individual indicators can be subject to improvements. In particular, the accuracy of *IND09 social capital* hat focuses on the fact that support from neighbors and relatives can be enhanced, since the answers only show little variance. Further investigations into people's embeddedness into local level organizations or the responsibilities they take over may be a promising way to go [87], [88]. Nevertheless, the overall approach of selecting targeted variables is regarded as a more feasible approach than relying on generic variables used in other studies (e.g. [89]). In addition, the spatial variables used to populate *IND8 institutional endowment* might be revisited to include relevant aspects of political institutions and traditional authorities as well as the role of churches. However, respective data on this level was not readily available to this study. Furthermore, *IND11 financial capital* used a new methodology of seasonal ranking to estimate the financial means available to a household at a sub-annual level. While the metrics obtained are consistent, they have to be measured against conventional estimates of financial means to explore their suitability.

The task of validating the coping capacity scores is still a challenging task. The technique taken up in this study revealed heterogeneous results but gives a positive overall picture of the estimated scores.

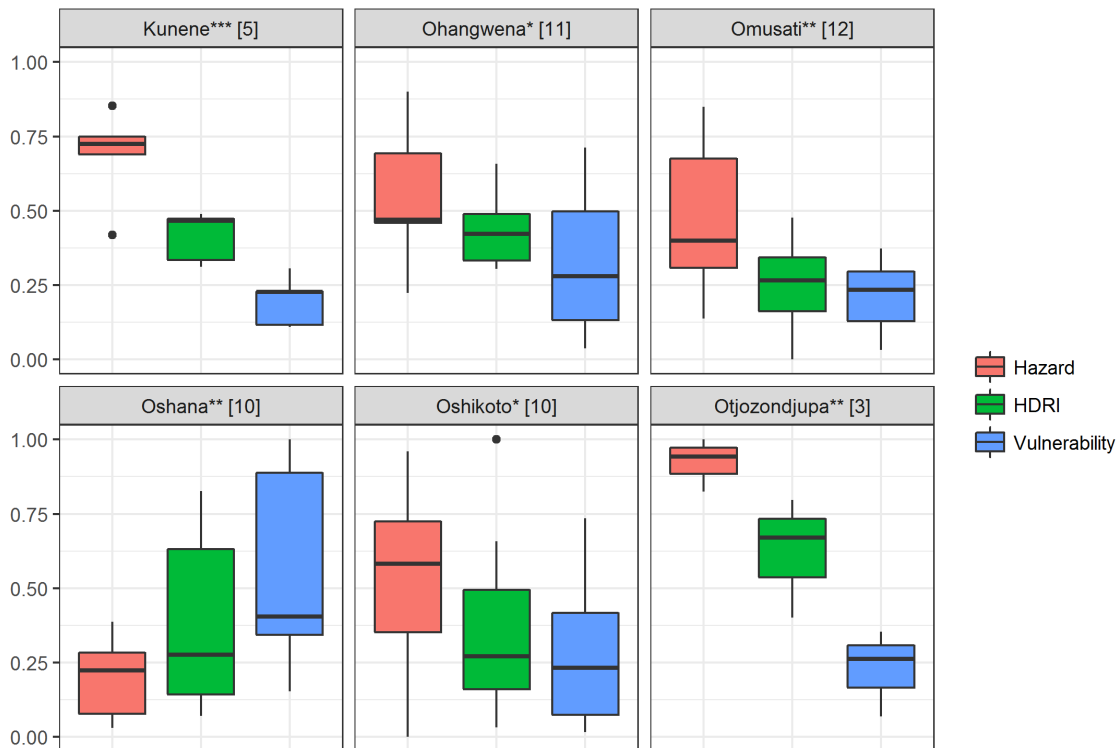


Figure 8: Comparison between HDRI, hazard and vulnerability scores among Namibian regions. Data is based on the spatial estimates of the dimensions on the constituency level. Numbers in brackets indicate the number of constituencies included in the calculation, while the “*” indicates whether the means between the hazard and vulnerability scores are statistically different (* $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$). The Kavango region was excluded as only one constituency falls into the Cuvelai-Basin.

Further research into this way of validating measurements of societal phenomena is required, though. One further option might be a targeted household survey during the next drought period when the population requires food relief items. Those households that obtain food relief at the governmental offices throughout the regions may be surveyed in detail, so that their socio-economic characteristics and the hazard conditions they are subjected to can be assessed.

In general, the use of a composite indicator approach is regarded as reasonable as it is a common tool within development cooperation and research and thus well-known to practitioners and politicians [75]. It offers good opportunities to combine data of different measuring regimes, even from the natural and the social sciences. As a promising alternative, Bayesian Belief Networks (BBN) gained momentum in the recent decades as ready-to-use software tools are available that facilitate their application for instance in a spatially explicit context [90]. While they are applied in many fields, in particular the topics of ecosystem (services) and water management (e.g. [91]–[93]) and recently in the African context with respect to food security and climate-driven migration [94], [95], BBN-based models are capable of handling different types of data, even expert judgments can be incorporated and processed.

The estimation of spatial drought risk within the Cuvelai-Basin borrows strength from the most recent censuses in both countries.

Nevertheless, a regression approach always depends on the suitability of spatial data to reveal valid estimates. In this regard, the low spatial detail of the census data in Angola prohibits a more detailed description of the spatial patterns in capital endowment and the sensitivity dimension. Furthermore, the small number of variables available to perform the regression also limits the overall reliability of the regression models. If more census data becomes available even on finer spatial scales, such as electoral districts, the HDRI estimates may be transferred and reveal better insights into drought risk, especially in the Cunene province.

4.3. Transferability

The HDRI should not be reduced to the final composite indicator value but should rather be regarded as a social-ecological drought risk assessment procedure that includes different stages. Therein, the qualitative exploratory research phase is inevitable to understand the provisioning system and the internal linkages between nature and society. It reveals how spatio-temporal water scarcity impacts on the environment and how this impact is transmitted to society and which second-order effects occur. Subsequently, appropriate quantifiable indicators need to be identified to capture key aspects of both the environmental and societal domain. These have to be assessed, statistically processed and evaluated for their suitability to populate the final composite indicator. If the HDRI is perceived this way, as a

holistic assessment procedure, it is capable of capturing the multifaceted impact of drought in a specific social-ecological system.

The exploratory research phase primarily serves the purpose to gain system knowledge. It is necessary to identify key ecosystem services that decline in times of drought and result in impaired benefits people can obtain from nature and hence reduced human well-being. In this study, water and food provision were found to be critical ecosystem services in the subsistence society of the Cuvelai-Basin. These services are essential to meet basic needs and to support the economic development in this area, but they respond quickly to drought conditions. Nevertheless, other ecosystem services might come into focus in other regions that show a different configuration of the social-ecological system. For instance, cities such as Gaborone in Botswana, where the population's energy supply depends on hydropower [96] or the case of drought prone energy production in Mozambique [97], the qualitative pilot study might rather reveal that the HDRI's indicator set should focus on energy provision rather than on water and food supply. The context-specific setup of the HDRI to capture the characteristics of the social-ecological system under consideration is a key task when performing a holistic drought risk assessment.

Against this background, the HDRI explicitly links to the water energy food nexus debate [98], [99]. In sub-Saharan Africa, water is a fundamental resource that is connected to multiple sectors such as the agricultural and the energy sector. Spatio-temporal reductions in quantity and/or quality of water have impacts in these sectors. Droughts hence manifest themselves in declining food and water resources but also in impaired energy supply or associated services. The HDRI should be seen as a reconfigurable tool to capture the interlinkages between water and other sectors against the background of drought propagation and the specific sensitivities and coping capacities of people in a particular area [100].

5. Conclusion

This study approaches the challenge of drought risk assessment in a semi-arid environment in sub-Saharan Africa, the Cuvelai-Basin and seeks to capture its multifaceted impact on the social-ecological system in a quantitative manner. Against the background of the six principles presented in the Windhoek Declaration, three major conclusions can be drawn from the HDRI study to provide recommendations for drought risk analysis, monitoring and strategic mitigation.

First, from an analytical perspective, the overall HDRI procedure serves the purpose of analyzing drought risk in an integrated way. It offers the opportunity (i) to understand the underlying causes of drought impacts (qualitative pilot study), (ii) to assess household's internal coping capacities and sensitivities, as well as (iii) the spatial hazard conditions. This enables the researchers, practitioners and politicians to perform targeted analyses of key determinants for risk reduction strategies.

Second, for monitoring purposes, part of the HDRI methodology

should be taken up into larger scale surveys to continuously monitor drought risk among the population. In this regard, the seasonal ranking scheme and the assessment of household capital endowment should be focused and applied to even finer spatial scales of the electoral district level, for example.

Third, in terms of short-term emergency responses and long-term adaptation strategies, as requested by the Windhoek Declaration, key recommendations are the following: while the alteration of precipitation conditions is beyond the scope of the Cuvelai-Basin's population, particularly vegetation and soil moisture conditions can be improved, e.g., via targeted ecosystem restoration or reforestation activities and improvements in livestock management [101]. In order to reduce sensitivity, the households have to be enabled to switch their consumption patterns to less drought-sensitive source types. In this regard, the positive experiences in Namibia with regard to the centralized tap water system [12] may serve as a blueprint for the Angolan part, when respective shortcomings in the institutional setup are adequately addressed [102]–[104]. Together with the centralized infrastructure, decentralized solutions of improved wells and boreholes, as well as Rain and Floodwater harvesting techniques (RFWH), can be promising ways to go, in particular when combined with irrigation and gardening activities [105], [106]. Furthermore, infrastructure to enhance mobility among the population and to provide access to local markets has to improve in order to enable people to purchase and sell food items. Coping capacities can be enhanced by fostering local level community-based approaches, in combination with targeted support of households via capacity development measures. Co-knowledge production among rural smallholders and agricultural extension officers [107], the training of young professionals for construction and technical maintenance of RFWH facilities, as well as the empowerment of women to run agricultural businesses [108] are regarded as promising ways forward.

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