From Recognition to Adaptation: How does Forecasting relate to International Aid Funding in Food Security?

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Abstract
The importance of early adaptation to reduce the impact of recognized risks has been underlined in recent years as featured aspect of the Sustainable Development Goals and the Sendai Framework for Action. The aim of this study is to analyze the relationship between forecasted food insecurity levels and allocated funding directed at food security. The dataset was built by combining quantitative data on food insecurity forecasts (FEWS NET), international aid funding addressing food insecurity (UN OCHA) and population distribution (NASA) as well as by the use of GIS analyzing tools. The statistical analysis of the dataset shows that there is a strong positive correlation between forecast and funding streams in the 27 analyzed countries over the analyzed period from 2011 and 2018. There has been an increase in the strength of this relationship from the year 2012, indicating a greater response to forecasts and learning to reduce the risk of food insecurity. Further, the analysis indicates that the country characteristics: population size (negative) and density (negative), the Human Development Index (negative), the year of independence (positive) as well as whether a country has an UNISDR National Platform (negative) weakly correlate to the funding per person per forecasted food insecurity level. The discussion reflects on the high complexity of the system and the potential for strengthening the relationship between recognition and adaptation for improving early warning systems, forecast-based early action and disaster risk reduction.

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Sincerely,
Þórarinn and Matthias

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Abbreviations

DRC	Democratic Republic of the Congo
DRR	Disaster Risk Reduction
EWS	Early Warning System
FAM	Famine Action Mechanism
FAO	Food and Agriculture Organization
FbA	Forecast-based Early Action
FEWS NET	Famine Early Warning Systems Network
FSIN	Food Security Information Network
FTS	Funding Tracking Service
GDP	Gross Domestic Product
GIS	Geographical Information Systems
HDI	Human Development Index
ICRC	International Committee of the Red Cross
IFRC	International Federation of the Red Cross and Red Crescent Societies
IPC	Integrated Food Security Phase Classification
ODI	Overseas Development Institute
SDG	Sustainable Development Goals
UN	United Nations
UNISDR	United Nations Office for Disaster Risk Reduction (formerly known as United Nations International Strategy for Disaster Reduction)
UN OCHA	United Nations Office for the Coordination of Humanitarian Affairs
USAID	United States Agency for International Development
WFP	World Food Programme

1 Introduction

Food insecurity and the negative consequences related to it has been of high relevance throughout history. The Torah, the Bible and the Quran tell the story of the prophet Joseph *forecasting* an extensive famine seven years in advance and telling the Pharaoh of Egypt to take proactive measures to prevent, mitigate and prepare for it. The fear of food insecurity has proven relevant ever since then, with famines being the deadliest disasters, even in the twentieth century (Eshghi and Larson, 2008, p. 80). Although there was a global trend towards fewer people living with hunger in the last decades (FAO, IFAD, UNICEF, WFP, & WHO, 2018; von Grebmer et al., 2018), the opposite is true in recent years as there has been an increase in both total number and global proportion of undernourished people as seen in ***Figure 1***.

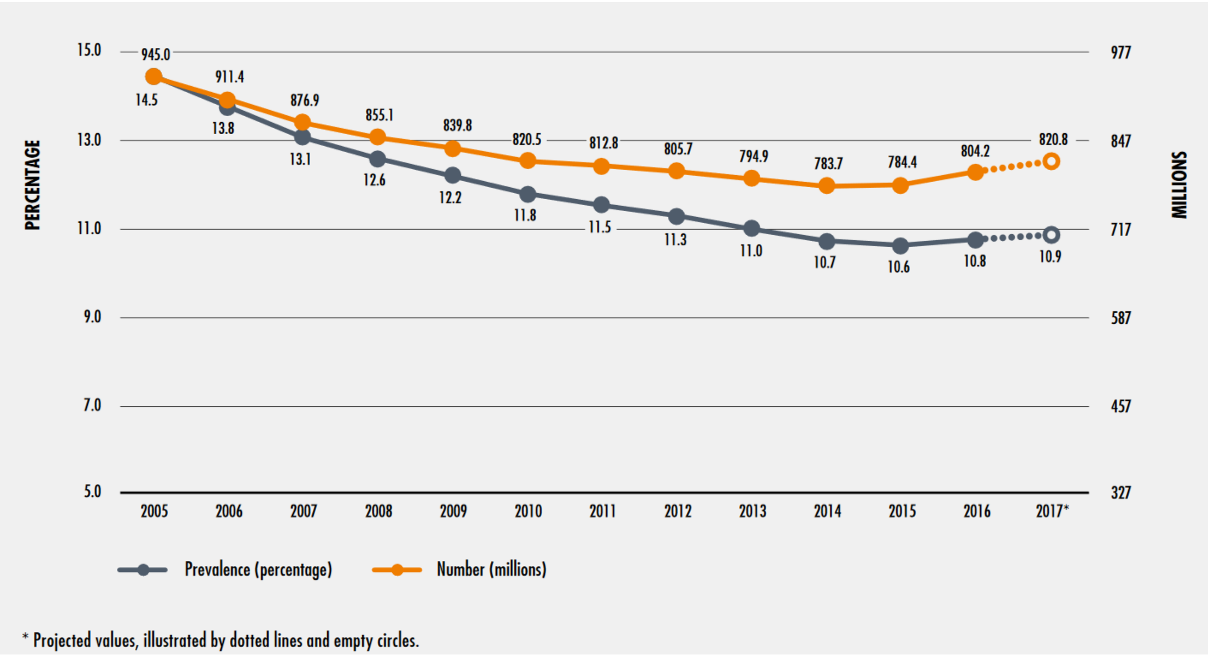

Figure 1: Number of Undernourished People in the World (FAO et al., 2018, p. 3)

Regardless of the reasons for this recent change in trend, which are explored on in the theoretical foundation below, food security is high on the global agenda. The second of the United Nations (UN) Sustainable Development Goals (SDG) states the ambition to ”End hunger, achieve food security and improved nutrition and promote sustainable agriculture” (UN, 2015, p. 17), committing the international community to lower the number of affected people. Food insecurity and famines have “an inherent complexity of the social, economic, political, and environmental dynamics involved,” making it challenging to find and take appropriate actions to reduce such risks and create resilient societies (Howe, 2018, p. 144).

Becker (2014, pp. 154–162) suggests that resilience is an emergent property to develop on the preferred trajectory, which depends on society's ability to perform four key functions, stressing the importance of the links between them:

1. *Anticipation* describes the ability to see, which deviations can potentially happen in the future
2. *Recognition* describes the ability to see, what is happening in the present before or after a deviation
3. *Adaptation* describes the ability to take measures in order to reduce the probability or the magnitude before or after a deviation
4. *Learning* describes the ability to develop and practice new concepts based on former deviations and other experiences

It is, in other words, not enough for the international community to have the ability to forecast food insecurity and the ability to mobilize significant resources, if there is a weak link between these two factors. For instance, large areas of Somalia, suffered from a famine in 2011 and 2012. The situation was officially declared a famine on the 20th of July in 2011 (Maxwell, Haan, Gelsdorf, & Dawe, 2012, p. 1), but spread throughout East Africa and proved to be the most serious case of food insecurity to strike the continent of Africa in 20 years. There were many contributing factors that lead to this situation, such as late and inadequate rainy season and crop failures in the previous years (NASA Earth Observatory, 2011). The famine was forecasted 11 months in advance (Lautze, Bell, Alinovi, & Russo, 2012, p. 43). Hillbruner & Moloney (2012, p. 20) emphasize that "these early warnings were notable in terms of the timeliness, quantity and quality of the warning provided", but the response to the forecasts where nevertheless neither appropriate, nor sufficient (Hillbruner & Moloney, 2012; Lautze et al., 2012; Maxwell, Haan, Gelsdorf, & Dawe, 2012).

The international community is attempting to address these issues. Recently, the Famine Action Mechanism (FAM) was launched by the Secretary-General of the UN with the words that this new tool: "... will help to predict and therefore prevent food insecurity and famine before they have a chance to take hold" (UN, 2018). At its core you find food insecurity forecasting and timely allocation of appropriate funding (UN OCHA, 2018a). However, the relationship between two has not been thoroughly researched.

Based on the occurrence of disaster risk reduction (DRR) failures and the development of new approaches, the goal of the thesis is to analyze the current system and its responsiveness to reduce the risks and the impact of food insecurity. The focus is put on the link between the two resilience functions *recognition* in the form of forecasting food insecurity and *adaptation* with providing international aid funding that targets increased food security. The anticipation of the risk of food insecurity is considered as the first step of forecasting, while learning is explored by looking at the changes of the system over time. That focus leads to the following research aim:

The aim of this research is to analyze the relation between forecasted levels of food insecurity and international aid funding for food security.

The achievement of this aim is based on answering the two research questions:

- *A* *What is the relationship between the forecasted levels of food insecurity and the amount of international aid funding to address food insecurity?*
- *B* *How has the relationship between forecasted levels of food insecurity and the amount of international aid to reduce food insecurity changed over time?*

The following theoretical chapter builds the foundation for the study and puts the focus on literature exploring the topics of food insecurity, forecasting and the international aid funding. Afterwards the research methodology is described and includes the data collection and analysis as well as a short discussion of the research assumptions and limitations. Next, the findings from the data analysis are presented and thereafter the results and the methodology are discussed in more detail. The last chapter concludes this thesis.

2 Theoretical Foundation

This chapter provides a literature review to construct the study's context. The theoretical foundation with definitions, concepts and explanations is presented for the research topics including food insecurity, forecasting, international aid funding and its combination in forecast-based funding. These topics are introduced based on the questions of how they are defined and described in recent literature. This will give the reader a better understanding of the theoretical viewpoint and achieve a common understanding for the description of the research methodology.

2.1 Food Insecurity and Famine

The topic food insecurity in general and famines as extreme cases are introduced in the following section by first providing the definitions. Afterwards different perspectives from the scientific literature regarding the complexity of the topic is presented, before the standard classification method of food insecurity is explained.

2.1.1 Definitions

As pointed by Pinstrup-Andersen (2009, p. 5), the term *food insecurity* has received different meanings and the original understanding of food insecurity was "whether a country had access to enough food" to cover its needs. The Food and Agriculture Organization of the United Nations (FAO, 1996) came up with their own definition at the World Food Summit in 1996. In their Plan of Action, it is stated that: "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life." In contrast to that, the definition for food insecurity is: "A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life" (Napoli, 2011, p. 9). The latter definition of food insecurity is used in this study.

For the term *famine*, a variety of definitions are available. Most of the definitions are "ex-post*"* and do not allow for preventative measures (Rubin & Dahlberg, 2017). The selected definition for this paper comes from the Integrated Food Security Phase Classification (IPC), who describe a famine as an extreme shortage or collapse of food availability in a specific area or an excess in mortality due to starvation. But more technically, the IPC's (2012b, p. 1) used also three thresholds that all need to be met to define a famine. These thresholds are:

- Crude mortality rates exceed 2/10,000/day
- A global acute malnutrition rate (wasting) for more than 30 per cent of the population
- A gap between the level of food consumption required to meet nutrition need and actual food consumption for more than 20 per cent of the population.

2.1.2 A Complex Disaster

In his book on the "Principle of Population" first published in 1798, the British political economist Thomas Robert Malthus describes that the global population will grow faster than the production of food and that human population growth will be stopped naturally by the limited resources available resulting in a "gigantic inevitable famine" (Malthus, 1798, p. 44). In reality, the population has increased tremendously since publication, but there has been no general, long term trend towards higher food insecurity. In fact there has been a stark decrease in food insecurity (De Waal, 2018), as shown in ***Figure 2***. Alfani and Ó Gráda (2018, pp. 283-284) discovered that natural limitations and hazards were the biggest contributing factors of high food insecurity from 1250 until 1710. Since then it has been distribution of food not the production. These findings should however not lead to the conclusion that resources are not limited today or will be in the coming decades (Cole, Augustin, Robertson, & Manners, 2018).

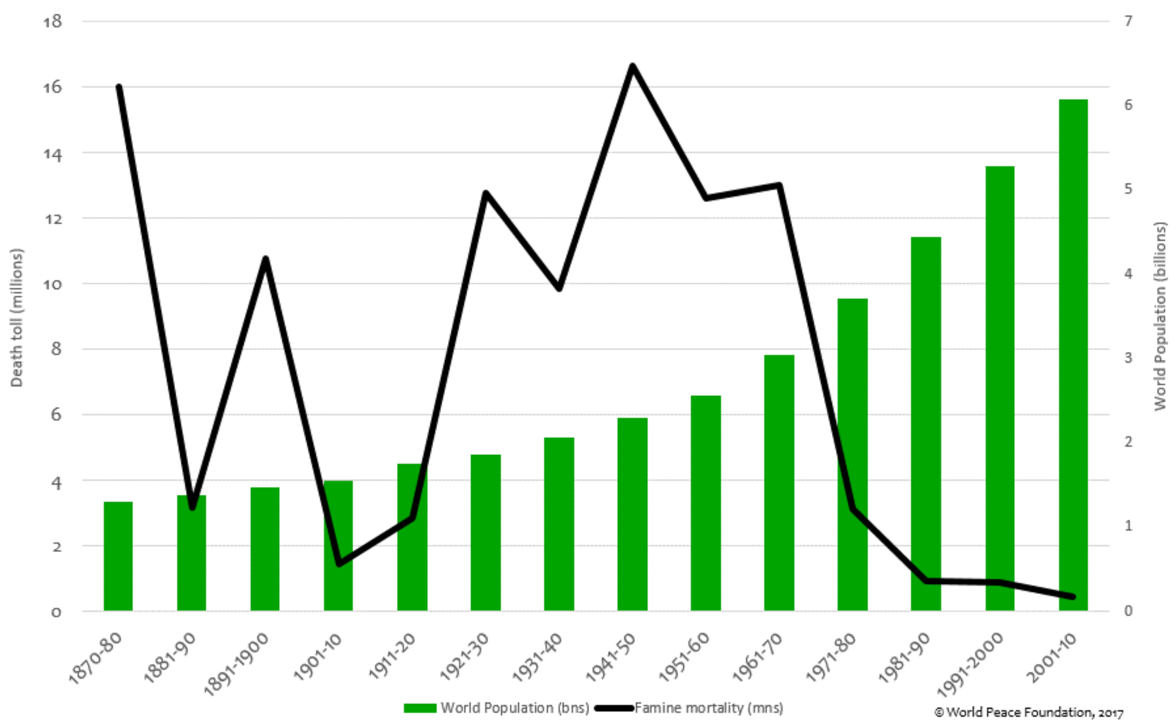

Figure 2: World Population Growth and Death Toll from Great Famines: 1870-2010 (World Peace Foundation, 2018)

There is still an on-going debate on natural and man-made causes of food insecurity. The understanding on the difference between production and distribution of food and its relevance for food security has developed recently. One of the pioneers in the field is the Nobel Prize Laureate Amartya Kumar Sen. Sen (1981) wrote his theory on entitlement and deprivation in relation to poverty and famines. This theory challenged the common understanding that famines are sudden occurring events, where food shortage and scarcity lead to malnutrition and fatalities (Dando, 1980). Devereux (2006) further expands on Sen's theory and targets the human "wrong-doing" and states that: "Contemporary famines are either caused deliberately (acts of commission) or they are not prevented when possible and should have been (acts of omission).” On the other side of the argument is Nolan (1993), who criticizes the work of Sen, by stating that additional causes need to be considered more carefully in order to avoid famines. This is underlined by the International Federation of the Red Cross and Red Crescent Societies (IFRC, 2008), who describe emergencies related to food security as “complex disasters with multiple root causes”.

Due to this complexity, various causes of food insecurity are considered in literature. Newer research has further developed on the perspective that famines are a long-term processes, which is influenced by a number of different factors (Walker, 2009). This implies that there is a general consensus that food insecurity and famines are slow onset disasters. The IFRC (2008) names these possible root causes: drought, conflict, poverty, debt crisis, economic situation at the household level, pandemics, mismanagement and abuse of water resources. The latest global report on food crisis, highlights conflict and insecurity, climate shocks and economic turbulences as three root causes, which continue to erode livelihoods and destroy lives in food crisis (FSIN, 2019, pp. 20–28). In contrast to these perspectives, Bohle, Downing, & Watts (1994) see the crucial role that climate change plays in increasing social vulnerability, a key aspect of food insecurity. This view is shared by the report on food security and nutrition (FAO et al., 2018, pp. 37–113), which puts an emphasis on climate variability and extremes, as the origins for recent developments in food security globally.

2.1.3 Food Insecurity Classification

In order to create a common language on different levels of food insecurity, the IPC was developed by a multi-agency initiative consisting of Non-Governmental Organizations as well as UN Agencies. The IPC “is a set of analytical tools, and processes, to analyze and classify the severity of acute and chronic food insecurity situation according to scientific international standards” (IPC Global Partners, 2018, p. 1). It is one of the most widely known and used standards when it comes to food insecurity and is already used to forecast projected food insecurity levels several months in advance. The IPC (2012a, p. 18) makes a distinction between acute and chronic food insecurity:

1. “Acute food insecurity is a snapshot of the current or projected severity of the situation, regardless of the causes, context or duration.
2. Chronic food insecurity is the prevalence of persistent food insecurity – i.e. levels of food insecurity that continue even in the absence of hazards/shocks or high frequency of years with acute food insecurity.”

In this paper, the focus is put on acute food insecurity as it has a higher relevance in relation to forecasting. Acute food insecurity is divided into five levels of severity, as shown in ***Figure 3***. The classification is based on a standardized analyzing process, which is described in the Technical Manual (IPC Global Partners, 2012a).

	Phase 1 Minimal	Phase 2 Stressed	Phase 3 Crisis	Phase 4 Emergency	Phase 5 Famine
Phase Name and Description	*More than four in five households (HHs) are able to meet essential food and non-food needs without engaging in atypical, unsustainable strategies to access food and income, including any reliance on humanitarian assistance*	*Even with any humanitarian assistance at least one in five HHs in the area have the following or worse:* *Minimally adequate food consumption but are unable to afford some essential non food expenditures without engaging in irreversible coping strategies.*	*Even with any humanitarian assistance at least one in five HHs in the area have the following or worse:* *Food consumption gaps with high or above usual acute malnutrition* ***OR*** *Are marginally able to meet minimum food needs only with accelerated depletion of livelihood assets that will lead to food consumption gaps.*	*Even with any humanitarian assistance at least one in five HHs in the area have the following or worse:* *Large food consumption gaps resulting in very high acute malnutrition and excess mortality* ***OR*** *Extreme loss of livelihood assets that will lead to food consumption gaps in the short term.*	*Even with any humanitarian assistance at least one in five HHs in the area have an extreme lack of food and other basic needs where starvation, death, and destitution are evident.* *(Evidence for all three criteria of food consumption, wasting, and CDR is required to classify Famine.)*

Figure 3: IPC Acute Food Insecurity Reference Table for Area Classification (IPC Global Partners, 2012a, p. 32)

2.2 Forecasting

In this sub-chapter the topic of forecasting is developed through the presentation of disaster risk reduction and early warning systems (EWS). After this wider context is introduced, forecasting in relation to food insecurity is described with a concrete example in the last section.

2.2.1 Disaster Risk Reduction

The UN General Assembly (1989) declared 1990-1999 the International Decade for Natural Disaster Reduction. This led to the foundation of the office for the United Nations Office for Disaster Risk Reduction (UNISDR) in 1999 (UN General Assembly, 1999). The office has held three World Conferences on disaster reduction since then: Yokohama (1994), Hyogo (2005) (UNISDR, 2007) and Sendai (2015). The Sendai Framework for Action was developed during the last conference and highlighted the need for DRR for the international community (UNISDR, 2018) and defined four priorities for action:

1. Understanding disaster risk
2. Strengthening disaster risk governance to manage disaster risk
3. Investing in DRR for resilience
4. Enhancing disaster preparedness for effective response and to “Build Back Better” in recovery, rehabilitation and reconstruction

To support these priorities, the UNISDR (2017, pp. 21 & 23) has created two forms of national DRR implementations and defined them in their “Words into Action Guideline”*:*

- a National Focal Point for DRR is “a national governmental body and entry point responsible for the implementation, review and reporting of the Sendai Framework.”

- a National Platform for DRR is: “a nationally owned and led coordination mechanism or committee of multiple stakeholders with strong foundation in national institutional frameworks.”

DRR integrates the functions of societal resilience, presented in the introduction. Anticipation and recognition of disaster risk makes targeted adaption with prevention, mitigation or preparedness for food insecurity or a famine possible (Becker, 2014), preventing loss of lives, livelihoods, health, economical, physical, social, cultural and environmental assets of persons, businesses, communities and countries as described in the expected outcome of the Sendai Framework (UNISDR, 2015).

2.2.2 Forecasting in Early Warning Systems

In an EWS, the resilience functions from forecasting to proactive adaptation are included in all steps. An EWS consist of four elements (Villagran de León, Bogardi, Dannenmann, & Basher, 2006, p. 25):

1. Risk knowledge, which requires knowledge about the hazards and the susceptible vulnerabilities to it
2. Monitoring and warning service, which requires capacity to forecast hazard evolution and identify critical levels
3. Dissemination and communication, which requires sharing of warnings
4. Response capability, which requires plans and capacities for appropriate actions

These elements must be interlinked with each other. If one element is not working, the EWS might fail when needed. Apart from these four technical aspects, it is important to put a “strong focus on the people exposed to risk”, as pointed out by Basher (2006, p. 2167) this facilitates appropriate adaptation as well as an opportunity to learn.

In the scientific literature it is possible to find reports that approach the research topic similarly, although from different perspectives than this study. Early on a focus was put on the precautionary principle and giving early warning (Gee & Vaz, 2001). This approach developed into EWS, as it includes the necessary activities that follow a warning (Suarez & Tall, 2010) and are based within communities (Villagran de León, Bogardi, Dannenmann, & Basher, 2006). The biggest share of research focused on the problems within these relationships, whether it is the delay (Bailey, 2012), too many warnings (Dow & Cutter, 1998) or the lack in political will (Schmeidl & Jenkins, 1998). Closer to the topic of this thesis is a paper with the provocative title: “Who can eat information” by Vogel and O’Brien (2006), which explores the possibility that information from forecast do not provide any assistance to people suffering from food insecurity. In their research, they investigate the context of Southern Africa, how seasonal climate forecasts influences the risk management and if it is effective.

Rubin & Dahlberg (2017) define forecasting broadly as: “The process of predicting or estimating future events.” Further, they write that depending on the context, it can be used synonymously with predicting and differentiate between qualitative and quantitative forecasting. In this study, the focus is put on the quantitative approach, which they describe as using: “…numerical models developed from past data about recurring events and patterns that are believed to be valid for the future also.” They state as well that forecasts depend highly on the notion of uncertainty, which should be attached in the communication about any forecasts. Lastly, they point out that they are particular useful for risks for floods or heavy rainfalls, but the application is also useful for other forms of extreme events.

Based on the understanding of EWS, forecasting is part of their second element, with strong links to the first and third element. Forecasts have become a big part of everyday life, be it listening to the weather forecast during breakfast or reading the market forecasts on the train. Weather and climate information, including seasonal climate forecasts, has been heralded as a promising tool for early-warning systems and agricultural risk management, but the fear persists that it is not being used to its full potential according to Vogel & O’Brien (2006). Regarding the El Nino weather pattern, Tozier de la Poterie et al. (2018) found that organizations and governments generally put a lot of trust in forecasts, but find it difficult to interoperate depending on presentation. The World Bank gives an overview of the different aspects that are monitored in EWS. It published an assessment report of several national and regional food security EWS in South Africa (Braimoh, Manyena, Obuya, & Muraya, 2018). Apart from the seasonal climate and weather, crop and yields can be forecasted, and attention is given to vulnerability and assessments of societal capacity to deal with food insecurity. Lastly, the report points out the importance of economical indices, which are markets, cross-border trade and policies, prices and different commodities. Each EWS has some specifications depending on who they are monitoring and forecasting.

The forecasting of food insecurity has developed recently. Tapscott (1997, p. 19) says that: “…, the more accurately we are able to predict short- and long-term changes in climate (and weather) the more likely we are to be able to manage the impact of these changes of food security, …” This means that there was a strong focus on the climate and therefore on the “natural determinants of famines” (p. 23). Tapscott (1997, p. 22) identifies one reason for this focus that “Early warnings tend to treat symptoms than causes.” As Broad & Agrawala (2000) discuss, that climate forecasts have limits that reduce their usefulness. Climate modelling has improved and become more precise and reliable due to technological developments. But this has not been the important improvement in forecasting food insecurity, as more aspects are included, which consider the findings from Sen and that food insecurity is complex and has various causes.

2.2.3 Famine Early Warning Systems Network

The Famine Early Warning Systems Network (FEWS NET), a food security EWS, is of a vital interest to this study. The reasons for selection of FEWS NET is that it provides forecasts for different global regions and are an internationally renowned and established organization dealing with food security. This is due to their relatively long history, in which the network has continued to improve their forecasts. FEWS Net was created in 1985 by United States Agency for International Development (USAID) in response to the 1984 famines in East and West Africa. They describe themselves as an organization that: "provides objective, evidence-based analysis to help government decision-makers and relief agencies plan for and respond to humanitarian crises" (FEWS NET, 2019a).

To reduce complexity and identify the "most likely scenario" in forecasting future food insecurity, FEWS NET uses the methodology called "scenario development". This approach is described by FEWS NET (2018) as an eight step process (***Figure 4)*** which: "... involves an assessment of the current situation, the creation of specific, informed assumptions about the future, analysis of expected impacts on food and income sources, and the likely responses of various actors. The areas, for which scenarios are developed are based on the criteria that "food security outcomes are likely to be most severe" (FEWS NET, 2018, p. 2). Based on a convergence of evidence, analysts describe the most likely scenario and classify the expected levels of food insecurity using the Integrated Food Security Phase Classification (IPC).

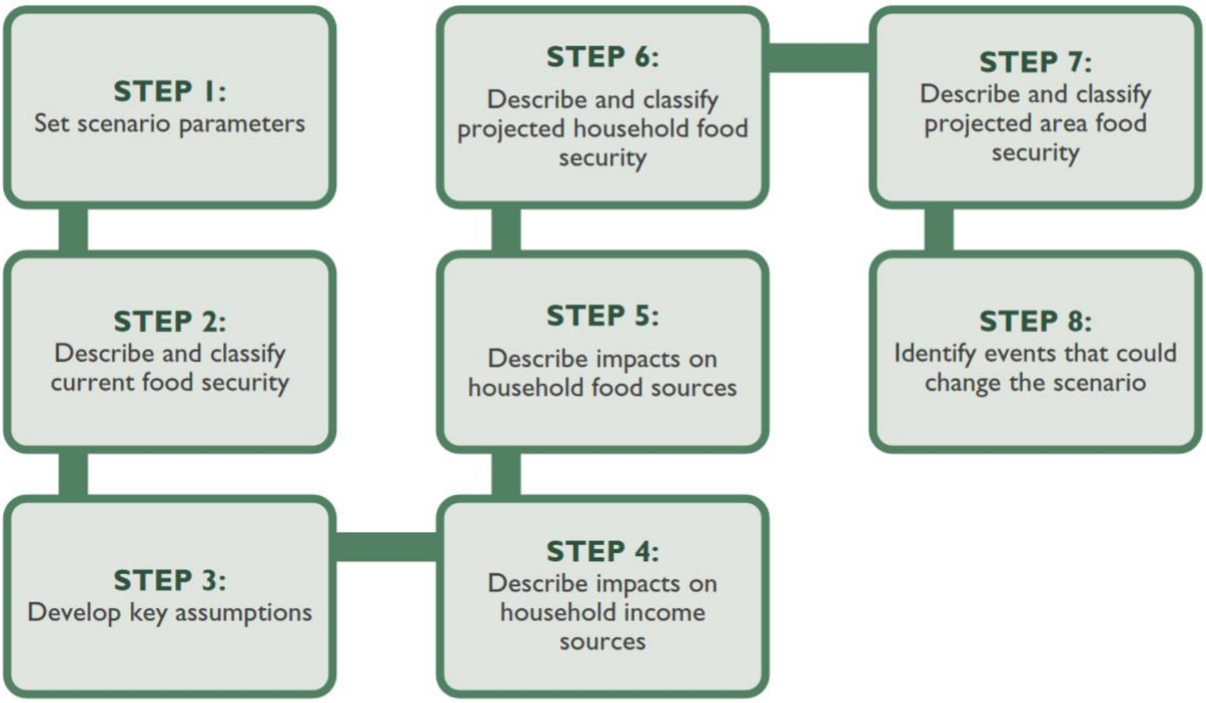

Figure 4: FEWS NET's 8-Steps Process to Scenario Development (FEWS NET, 2018, p. 1)

For scenario building FEWS NET uses a wide range of relevant indicators from different sources. According to the World Bank assessment report, the following indicators are integrated: terms of trade, satellite rainfall estimates, Normalized Difference Vegetation Index, price data, nutrition indices, monthly price data of staple foods, livestock and livelihood commodities such as firewood, charcoal and wage labor are all considered (Braimoh et al., 2018, p. 71). External sources which provide FEWS NET with the latest data for these indicators include actors like the World Food Program (WFP) for market prices or the European Centre for Medium Range Weather Forecasts for rainfall estimates.

FEWS NET forecasts have some specifications in accord to the general theoretical foundation of EWS, which should be mentioned. Firstly, they rely on data collected mainly by third party actors. Secondly, the dissemination of the warning targets decision makers, who might have the power and capacity to lower the risk of a higher food insecurity level. This makes the use of the IPC classification appropriate, as it requires prior understanding for interpretation. In relation to the communication factor of the EWS element, presented in the form of maps, uncertainty of the forecasts is not included. However, events that can change the most likely scenario are identified in the last step of the scenario development. it is important to note that FEWS NET does not include the last element of an ideal-typical EWS as they do not make recommendations on how to act appropriately in cases of high food insecurity but instead rely on other actors.

2.3 International Aid Funding

At first, different perspectives from literature on the system of international aid funding are presented, before an overview to the current development in Forecast-based Early Action (FbA) is provided.

2.3.1 Funding for Food Security

There are innumerable ways to adapt to a recognized disaster risk (Coppola, 2016, pp. 209–303), making it challenging to measure the value of adaptation in relation to risk. An indicator which quantifies adaptation and is comparable between cases was needed for this study. The most appropriate indicator identified by the authors is the amount of funds spent on adaptation. This indicator has different limitations. For example, it does not show how well the adaption is made to address the risk or how sustainable an investment in adaptation is. Despite these limitations, funds spent on food insecurity is used as the indicator for adaptation in this paper.

Limitation of local capacities in an area contribute to risk of food insecurity, there are usually not enough local resources available to adapt in a sustainable way (“providers of first resort”). Therefore, external help is often necessary to provide funding. This aid comes from a source that has the necessary capacities and willingness to support, like the national government. If the national capacities are not able to cover the, cross-boundary or international aid funding can be provided ("providers of last resort") (Lautze et al., 2012, pp. 47–48). International funding can originate from private donors or national and supranational governments and is transferred into the area through different actors. In the field of food security, the Food and Agricultural Organization (FAO), an UN agency, and the WFP, an intergovernmental organization take a leading role due to their position in the cluster system (Inter-Agency Standing Committee, 2015). The cross-boundary funding brings additional challenges in relation to the goal of local ownership and community-driven adaptation.

The countries of the world are pledging more money now than ever to humanitarian action, but the gap between what is asked for and what is received is still growing. This is called the "Humanitarian Aid Gap". There are two ways to look at the gap. One way would be to see the share of what has been funded. This perspective shows that the aid gap has been quite steady over the last few years only varying a few percentages. The other way of looking at it is that the absolute needs of the humanitarian field have been steadily growing as well. So even if the same share is being funded with more money than ever the gap in absolute monetary value is increasing (UN OCHA, 2018b). According to the Financial Tracking Service (FTS) more than six billion USD were donated to the food security sector in 2018 (UN OCHA, 2019a).

The funding system has many different channels, which involves many actors and channels that abide to a different set of rules. This makes the system complex and will not be described in detail. But one important aspect that needs to be emphasized is the general split between funding that is directed towards the development and humanitarian aid sector dividing donors and aid providers. This division of funds has made it difficult to proactively adapt to recognized risk, because it is unclear, whether it should be considered as developmental or humanitarian aid and who is responsible for the funding and aid provision. This is a particular challenge for slow-onset disasters like food insecurity and famines. Urgency plays a vital role, it's easier to ask for help after a disaster has struck. Few organizations focus on the benefit of early action (Tozier de la Poterie et al., 2018).

2.3.2 Forecast-based Early Action

Moving a step closer in relation to linking recognition and adaptation, the concepts of "Forecast-based Early Action" and "Forecast-based Funding" have received some attention over the last few years. Their approach has the potential to overcome the split between development and humanitarian aid funding. In the Overseas Development Institute (ODI) report on FbA (Wilkinson et al., 2018, pp. 7–8) describe a typology of FbA, which consists of the following steps:

1. Forecasting and decision-making
2. Timing and planning early actions
3. Financing
4. Delivery

The new and crucial aspect appears to be step two, which includes that: “FbA mechanisms are designed to trigger and inform action across multiple time-scales before a disaster occurs” as stated in aforementioned report by Wilkinson et al. (2018, p. 7). This describes an automated process of adaptation after forecasts are approved. This requires a better and more detailed planning but allows for faster and more appropriate actions, even before the disaster occurs.

There are different actors in the sector who are pushing this approach with high hopes that it succeeds. According to the IFRC (2018) it is: “A new era in disaster management.” This contrasts the perspective from Tozier de la Poterie et al. (2018), who state that stakeholders often look towards past events to plan and prepare for upcoming disasters and the most common action is just to update contingency plans, but not to put any resources into the field, when a disaster is forecasted. This is mostly because of fear that the resources will not be used and therefore contribute to sunken costs. Those resources that are put into the field are most often “no regret” actions to reduce sunken costs. Only a handful of organizations go into the field beforehand because of strict spending limitation and static budgets. Therefore, Forecast-based financing is an approach for catalyzing humanitarian action based on extreme weather and climate forecasts (Coughlan de Perez et al., 2015).

Not only are there expectations for FbA to decrease suffering but the UNDP (2012) stated that: “Investing 1$ in disaster preparedness, saves 7$ later disaster recovery.” A statement that has been challenged by Res, Goldschmidt, & Kumar (2017, p. 1), who write that there is no “significance reduction on the cost of emergency response”, when researching investments in disaster preparation and preparedness.

FAM has the appearance of a FbA concept in the field of food insecurity, as their goal that it will work through three pivotal promises (UN OCHA, 2018a):

- State-of-art technology, data and analytics
- Much faster financing
- A joint response system

FAM is a co-owned project of the UN and the World Bank. The World Bank (2018d) calls it an “unprecedented global partnership”, as collaborators involve, including the two owners, the International Committee of the Red Cross (ICRC), Amazon Web Services, Google and Microsoft Web Corporations.

3 Research Methodology

To develop answers to the research questions a specific methodology was applied, which is presented in this chapter. At first, the general research design is explained, before the data and analysis used are described. In the last two sub-sections, the assumptions made in the research process and limitations of the research methodology are introduced.

3.1 Research Design

Lindell (2013, pp. 812–813) writes in his paper on "Disaster Studies": "The field will progress if research continues to be done both inductively, beginning with data and working toward theory, and deductively, beginning with theory and making predictions about data." For this research a deductive approach has been selected due to two main reasons. Firstly, there are theories about the potential of forecasts for early action with implication for the practice as described in the last chapter. By testing this theoretical perspective, it was possible to contribute to its development. Secondly, there is numerical data available, that is largely untested by the scientific community, and can be used for quantitative analysis as part of a deductive approach (Muijs, 2010, p. 1). Based on the research questions two Null-Hypotheses (H_0) and Alternative-Hypotheses (H_1) have been developed, which are tested and falsified, if the results are significant (Greasley, 2008, p. 87).

For the first research question about the correlation these two hypotheses (A) were formulated:

- *H_{A0}: There is no relation between the food security forecast and the funding per affected capita for food security, which flows before and during the forecasted periods.*
- *H_{A1}: There is a relation between the food security forecast and the funding per affected capita for food security, which flows before and during the forecasted periods.*

The two hypotheses for the second question (B) on the change over time are:

- *H_{B0}: There is no change over time in the relation between the medium-term food security forecast and the funding per affected capita for food security, which flows before and during the forecasted periods.*
- *H_{B1}: There is a change over time in the relation between the medium-term food security forecast and the funding per affected capita for food security, which flows before and during the forecasted periods.*

The reason that the Null-Hypothesis for both questions describe the negative scenario is due to the need for falsifiability of the tests. It is not possible to test any relation or change over time in one test.

For testing the hypothesis key variables providing information about the forecast and funding were needed. These key variables are described in ***Table 1***.

Table 1: Overview of the Key Variables

Key Variables	**Description**	**Unit**
Average IPC Level	The average IPC level in a country at an estimation date for a forecasted period.	IPC Classification
Funding per Affected Capita	The funding amount that is monthly available per person in a country at an estimation date for a forecasted period.	Dollar per Person
Funding per Affected Capita per IPC Level	The funding amount that is monthly available per person in a country at an estimation date for a forecasted period per average IPC level in a country at an estimation time for a forecasted period.	Dollar per Person per IPC Classification

It is very important to note that these three variables are always location, time and period bound. This means that all data points belong to a specific country (location bound) and to a specific estimation date, when the forecast was made (time bound). Strongly linked with the time aspect, is that the three variables must always relate to a specific forecast period (period bound). For a better illustration of these three aspects, an example from the dataset is provided, which states: The calculated average IPC level in *Afghanistan* forecasted in *April 2011* for the period between *July to September 2011* is 1.6. This means that the average household in Afghanistan is located between minimal and stressed levels of food insecurity on the IPC scale. In more relative terms this means that most households are able to meet essential food and none food needs without assistance, however up too one in five households are not able to do so (IPC Global Partners, 2012a, p. 32).

In order to further develop the answers to the research questions, more variables were used, which allowed for clustering of countries according to some specifications, which are:

- Area Size
- Population Size
- Population Density
- Gross Domestic Product (GDP)
- GDP per Capita
- Human Development Index (HDI)
- Last Colonial Power
- Year of Independence from Colonial Power
- Sendai National Focal Point
- UNISDR National Platform

The dataset for the analysis integrated the key as well as the country variables. The dataset originated from different sources and are introduced in the next sub-chapter. The country variables were collected using a brainstorming method and selected based on their potential relevance to the forecasting and adaptation system.

3.2 Data Collection

This section explains the applied criteria for the data collection and which data sources were used, before the data sample is presented.

3.2.1 Data Sources

For the selection of the data sources, several inclusion criteria were defined to satisfy scientific standards (Salkind, 2010). The criteria were based on the paper by Cai & Zhu (2015) about data quality and were selected according to the context of this study. The first criterion was availability and accessibility of data, which means that it is possible to get hold of the data and that it is not copyrighted, which would make the use illegal. Secondly, the reliability of the source as well as the documentation of the data origins and data creation process, which were evaluated by the authors and therefore, to a certain degree subjective. The last requirements were on the completeness, the accuracy and the level of detail in the data. This means that the dataset selected should had close to no gaps and should have been as detailed as possible as long it can be processed with the available resources. As stated above, all the data also needed to fulfill the characteristics of being time and location bound in order to guarantee the compatibility. Therefore, the sampling was limited to the criteria defined for the data selection. All the data was used in the selected sources, where there was compatibility between them in time and space.

With the application of the defined criteria, the data sources and formats presented in ***Table 2*** were selected.

Table 2: Data collected for Building the Database.

Data	Source	Datatype	Format
Food Insecurity Forecast	Food Security Classification Data (FEWS NET, 2019c)	Geospatial	Shapefile
International Funding for Food Security	Financial Tracking System (UN OCHA, 2019b)	Numerical	Spreadsheet
Administrative Boundaries from 2019	FEWS NET (2019a)	Geospatial	Shapefile
Population Distribution from 2015	NASA's Earth Observing System Data and Information System (CIESIN, 2018)	Geospatial	Rasterfile
Annual Country Population	World Bank (2018b)	Numerical	Spreadsheet
GDP from 2017	World Bank (2018a)	Numerical	Spreadsheet
HDI from 2017	UNDP (2018)	Numerical	Spreadsheet
Last Colonial Power	Colonial History Data, University of North Texas (Hersel, 2018)	String	Spreadsheet

Year of Independence from Colonial Power	Colonial History Data, University of North Texas (Hersel, 2018)	Numerical	Spreadsheet
Sendai National Focal Point	UNISDR (2019)	String	HTML
UNISDR National Platform	UNISDR (2019)	String	HTML

The decision was made to focus on one food insecurity classification type provided with hegemonic data that did not have to be harmonized for the analysis. FEWS NET (2019c) adopted the afore mentioned IPC classification system in March 2011, and it was thus possible to analyze the data before or after that break without harmonizing the data. As this study's interest is in more recent developments, the first forecast integrated into the analysis is April 2011. The time periods for the FEWS NET forecasts varies as well over time. Before October 2015 the forecasts were for a three-month period and afterwards for four-months. At the time of the data collection, the latest estimation month, which fulfills the criteria of compatibility with the funding data was June 2018. This leads to 27 time periods, which were analyzed.

For the data on the Food Insecurity Forecast it is important to point out that FEWS NET provides forecasts for two different time periods:

- *Near-term*: This forecast provides an estimation for the period, which starts at the estimation date. The relevant period of time for these forecasts is either 3-months (before September 2015) or 4-months (after September 2015).
- *Medium-term:* This forecast provides an estimation for the period, which starts after the Near-Term forecasts ends and has the same duration. The relevant period of time for these forecasts is either for the following months 4 to 6 (before September 2015) or 5 to 8 (after September 2015) after the estimation date.

It is important to be aware of the differences between these two forecasting periods for a better understanding of the calculated variables and therefore, the presented and discussed results. ***Table 3*** is provided to illustrate the differences.

Table 3: Examples Presenting the Differences in Forecasted Periods

Estimation Date	Near-Term Forecast Period	Medium-Term Forecast Period
January 2012	January - March 2012	April - June 2012
January 2018	January - April 2018	May – August 2018

Regarding the geographical scale, the limiting factor was the funding data, as the geographical information describing the targeted area was not as detailed as the forecast information. It included the targeted country but not specific areas within a country. Therefore, the analysis was done on a country level. The data on the funding amounts by FTS used US Dollars as the currency. Therefore, throughout this study, the unit for monetary values is US$. FEWS NET had provided estimation for more than 40 countries, since it was established. However, during the analyzed time period some countries had no forecasting data available or had a different IPC scale. Suitable data for the analysis was available for 27 countries.

Numerous resolutions were available for population distribution. What was selected for the analysis was the second most detailed resolution found with a resolution of 2.5 arc minutes. This means that the data points for the population count were pulled from grids that span 5 kilometers in diameter (around the equator). The most detailed dataset found was not selected due to difficulties with the available software and computers, as they were not powerful enough to handle the highest resolution data sets. This is likely to have little to no effects on the analysis.

The raster file and the shapefile format mentioned can be envisioned in the form of maps, as they contain information that is bound to a specific point in space. These files can be analyzed and processed by the usage of Geographical Information Systems (GIS). Such geospatial information is often captured through remote sensing and applied in disaster research as pointed out by Andersson, Kennedy, & Ressler (2007, pp. 83–86).

The annual country population from the World Bank was only available until the end of 2017. Therefore, the year 2018 was extrapolated based on the population growth in percent between the year 2016 and 2017.

3.2.2 Data Sample

The variety of the 27 countries analyzed was based on the available forecasting data during the analyzed time period. As shown in the map in ***Figure 5*** and in ***Table 4***, most of the countries that were analyzed are located on the African continent with a concentration around the equator. FEWS NET has made a distinction between five global regions. Afghanistan was the only country in Central Asia, whereas Haiti and Guatemala are the two countries in Central America and the Caribbean that received an Acute IPC classification forecast during the analyzed period. Yemen has been considered to be part of the East African analysis according to FEWS NET. This case selection provided an ample data for the analysis, with variability between countries in terms of size, economy and culture.

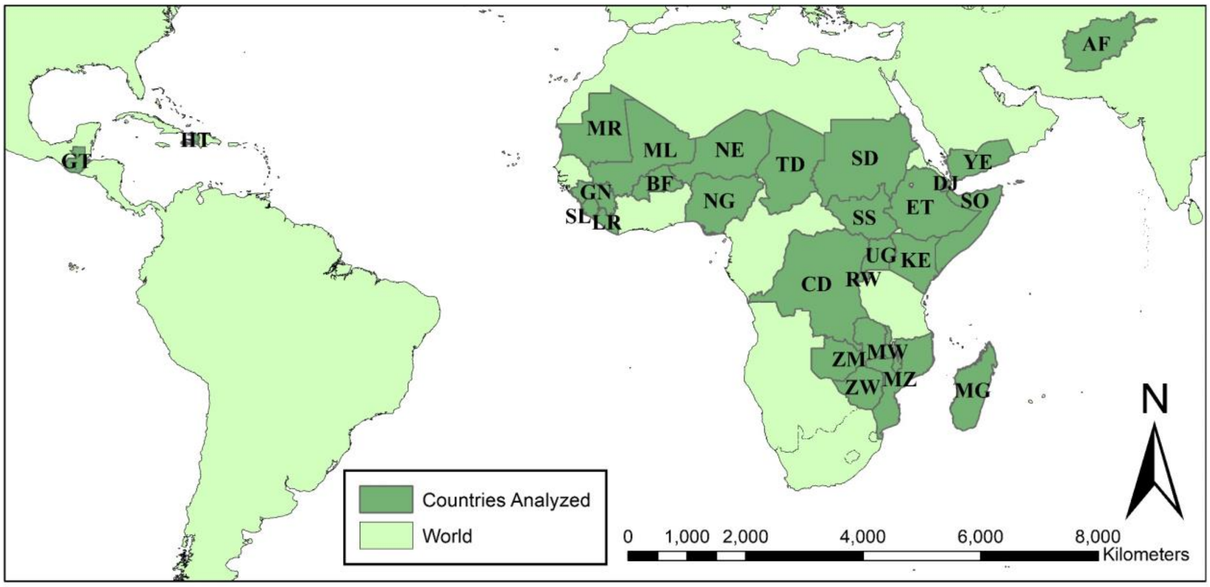

Figure 5: World Map with Countries Analyzed

Table 4: Name of Countries Analyzed

Country Code	Country Name	Country Code	Country Name	Country Code	Country Name
AF	Afghanistan	KE	Kenya	RW	Rwanda
BF	Burkina Faso	LR	Liberia	SL	Sierra Leone
TD	Chad	MG	Madagascar	SO	Somalia
CD	Democratic Republic of the Congo (DRC)	MW	Malawi	SS	South Sudan
DJ	Djibouti	ML	Mali	SD	Sudan
ET	Ethiopia	MR	Mauritania	UG	Uganda
GT	Guatemala	MZ	Mozambique	YE	Yemen
GN	Guinea	NE	Niger	ZM	Zambia
HT	Haiti	NG	Nigeria	ZW	Zimbabwe

For each of the 27 countries in the dataset, there were 27 different data points produced due to the three to four IPC forecasts made annually. This resulted in a total of 729 data points collected for the dataset.

3.3 Data Analysis

The data analysis consisted of three steps, the analysis of the geographical information, the calculation of the variables and the statistical analysis. Each of this step is presented in the following sections. Further, the complete methodology is discussed in relation to the scientific quality in the last part of this sub-chapter.

3.3.1 GIS Analysis

The goal of the first analysis was to calculate the number of people living in an area with a specific IPC level. The data was different for all 27 estimation dates in the analyzed period.

The forecasting data has been available in maps, which consists of numerous polygons, each with an associated IPC level, as shown in ***Figure 6***.

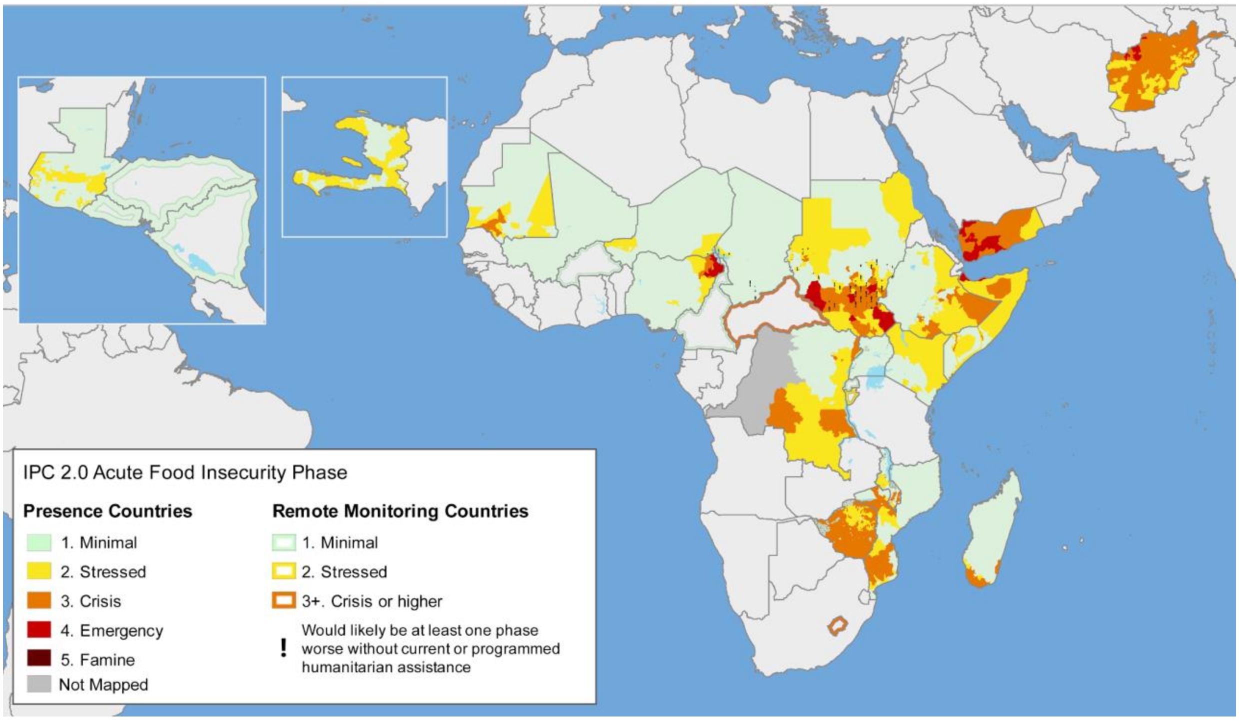

Figure 6: Medium Term Forecast of IPC Acute Food Insecurity from June 2018 (FEWS NET, 2019c)

To estimate the number of people living in these areas, with different IPC levels, for each country with a forecast, the program ArcGIS was used. In this analysis several steps were taken for each estimation date as well as estimation period (near-term & medium-term forecasting). ***Figure 7*** gives an overview to the steps taken in the GIS analysis:

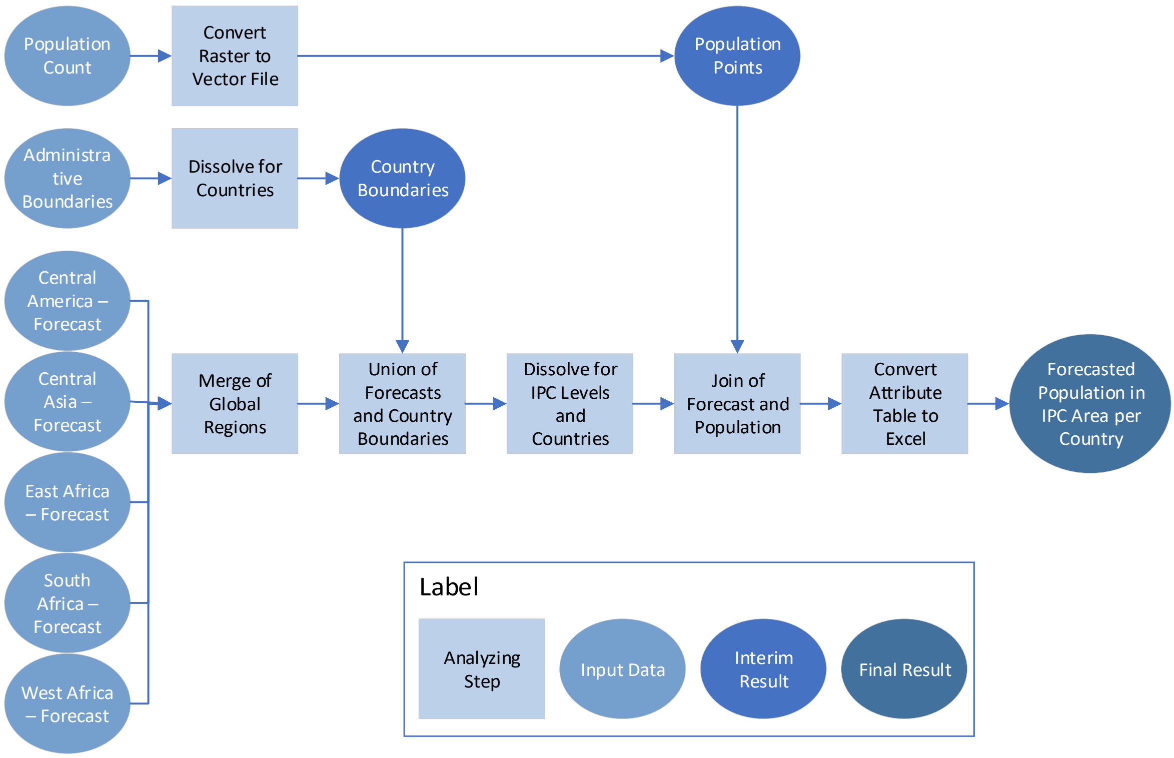

Figure 7: Overview of the GIS Analysis Process

The GIS analysis process involved the geospatial input data, shown on the left side, which was run through three separate analyzing steps to start with. The interim results from the first two analysis, were integrated into the third analyzing process. The analyzing steps taken in ArcGIS involve converting, dissolving, merging, uniting and joining data, which led to the final results on the forecasted population size living in specific areas with a certain IPC classification for each country analyzed. These steps were repeated for the 27 estimation times and for each forecasted period (near-term & medium-term). A manual describing this process in more detail, can be found in ***Appendix 1: Manual for ArcGIS Analysis***.

3.3.2 Calculation of Variables

For the next step in the data analysis process, key variables were calculated based on the output from the GIS analysis and the FTS dataset. For the calculation of the variables Microsoft Excel was used.

The IPC levels as introduced are categorical in nature and even though they follow a scale they proved problematic for the analysis. To remedy this, an average was calculated for countries so that a common denominator was in place for the funding data, this also means that the data was now neatly presented in a scale that benefited the analysis.

The calculation of the data for key variable *Average IPC Level* was done by multiplying the IPC levels and Population in an area with each other. These products needed to be summed up, before divided through the sum of the population. This calculation was done considering the specific country, estimation month and forecasted period. Based on this calculation, there were two variables created, which were used in the statistical analysis:

- *Near-Term Average IPC Level*
- *Medium-Term Average IPC Level*

The data for the key variable *Funding per Affected Capita* was calculated by summing up all the funding amounts flowing into a country during the forecasted period. This interim result was then divided by the affected population in the country to get the funding amount per affected capita. In order to get a comparable value over time, the funding per affected capita was divided by the number of months in the forecasting period, due to the varying length of the forecasted periods. This calculation was done considering the specific country, estimation month and forecasted period. Due to this calculation, two new variables were created, which were used in the statistical analysis:

- *Near-Term Funding per Affected Capita*
- *Medium-Term Funding per Affected Capita*

The last key variable *Funding per Affected Capita per IPC Level* provides data based on a calculation including the last two variables. The *Funding per Affected Capita* was divided by the *Average IPC Level.* This calculation allowed for four combinations between the near-/medium-term aspect of the forecasted and the funding period:

- Near-Term Funding per Affected Capita per Near-Term Average IPC Level
- Near-Term Funding per Affected Capita per Medium-Term Average IPC Level
- Medium-Term Funding per Affected Capita per Near-Term Average IPC Level
- Medium-Term Funding per Affected Capita per Medium-Term Average IPC Level

In order to reduce complexity of the analysis and to put the focus on the early funding to the forecasts only the following variable was used in the statistical analysis:

- *Near-Term Funding per Affected Capita per Medium-Term Average IPC Level*

The variables that provided country information, were not in need of additional calculations for the statistical analysis, which is why they are not further described here.

3.3.3 Database Analysis

The step of the data analysis consists of the inspection and clearing of the dataset, before it could be used for the relationship analysis.

At first, the dataset was inspected using descriptive statistics:

- Frequency analysis
- Descriptive analysis

The goal of this inspection was to identify data errors and statistical outliers. Errors in the data were corrected, if possible. If the identified data-points could not be rectified they were later deselected for the analysis. There are also rules on how to deal with the identified outliers in different variables, which are less clear. Therefore, where strong outliers were identified, the underlying data was inspected more in detail and if there was a legitimate reason to assume that there is an unreasonable anomaly in the underlying data, these outliers were also excluded. This decision was made in order to keep a higher scientific validity of the results.

The following step was to test the two null-hypothesis. To get the significance values for the analysis, inferential statistics was used, which included the following methods:

- Pearson's Correlation
- Linear Regression
- Independent T-Test

The dataset was analyzed in the program SPSS. For the visualizations of the findings, apart from the SPSS output, ArcGIS, Excel and Power Point were used.

3.3.4 Scientific Quality

Alexander Himme (2009) describes three criteria for the assessment of the scientific quality of empirical methods, which are: Reliability (p. 376-380), Validity (p. 380-386), and Generalizability (p. 386-389). These three criteria are assessed and discussed in relation to the used research methods for data collection and analysis in the following paragraphs.

The results of the study are reproducible, in particular since secondary quantitative data is used and the analyzing method is clear in the GIS analysis, the variable calculations and the established statistical analysis. This indicates a high quality in regards of reliability. But this needs to be challenged by the data collection method, because it is possible that other researchers might set the priorities within the applied selection criteria different, as a limited degree of subjectivity is included in the decisions.

With regards to the validity, the question could be raised, whether the most appropriate variables were used in the analysis to develop the answers to the research questions. This is difficult to judge from an internal perspective, and external critique of this study is welcome. The methods seem to be very exact, but there was an error in the GIS analysis, where two data-points needed to be excluded from the statistical analysis. Further, it could be argued that specific outliers in the dataset should have been additionally excluded.

Lastly, it is difficult to make a statement on the generalizability, apart from the analyzed countries, there are no other countries that have a FEWS NET forecast about the acute food insecurity during the analyzed period. Thinking further outside, the generalizability can be seen as limited since each data type relies only on one source. For example, the food insecurity forecasts stem only from FEWS NET and no other provider. But still, it would be stated that there is a medium generalizability for other (more regional) food insecurity EWS and their relation to funding to address the risk. Looking at EWS that consider other risks, the findings might have limited value, depending of the similarity to the specific characteristics (like the slow-onset and complexity of the food insecurity risk). This means that the findings might be more generalizable to a drought EWS than a flooding EWS.

3.4 Research Assumptions

This sub-chapter gives an overview of the assumptions made in relation to the data used and the analysis of said data.

The first assumption is that the IPC classification fulfills the criteria for continuous variables that the distances between the different scores are the same (Lewis-Beck, Bryman, & Futing Liao, 2004). This means that the increase in the level of food insecurity is assumed to be the same for example between IPC level 1 and 2 and between IPC level 2.5 and 4.5. Thus, implying that the variables are not an example of an exponential exacerbation of the situation. This was assumed although the introduced IPC classification does not necessarily fulfill the criteria for an objective perspective, it is difficult to state that the distances between the different scores are everywhere the same. In the paper from Rhemtulla, Brosseau-Liard, & Savalei (2012), the question was asked: "When can categorical variables be treated as continuous?" and different methods compared. They concluded that for the use of an ordinal variable with 5 to 7 categories, both analysis performed acceptably (Rhemtulla et al., 2012, p. 371). This statement provides a justification for the assumption, that the use of the IPC classification as a continuous data does not affect the findings. Further, it is assumed that the calculated average forecasts in the data points follow normal distribution. Therefore, the Pearson correlation is used to analyze the data.

It is not specified in the funding data when, or for which disaster phase (proactive or reactive) the funding is used. In order to analyze the correlation between forecasting and funding without this information, the assumption is made that the flowing date of the funding in the dataset corresponds with the usage of the funding in the estimation period, whether it is before or during a forecasted event. Since the usage of the funding is likely to be equally distributed in reality, this assumption should not affect the general findings.

It was further assumed that inflation and purchasing power do not have a strong enough effect on the results from the data analysis that it warrants being taken into account. Different countries have different purchasing power, which changes gradually and the global inflation rate for consumer goods was annually between 1.4 and 4.8 per cent between the years 2011 and 2017 according to the World Bank (2018b). As the values are depending on the specific country and the time, it is difficult to integrate these aspects into the calculation. Therefore, these two assumptions were made to reduce the level of intricacy in the data analyzed. But it can be pointed out the purchasing power is considered by FEWS NET (2019d) in their forecasts as a factor for the social vulnerability by considering the general livelihood of the populations.

Regarding the GIS Analysis, it is assumed that the population distribution and the country boundaries were stable between 2011 and 2018. The population data used for the GIS analysis is dated back to 2015 (Center for International Earth Science Information Network, 2018). This alignment of the populations for the analyzed period is likely to overstate the population in older datasets as well as underestimate population in newer datasets. Geospatial data for population density is updated every five years which means that there was data available from 2010 and an estimation for 2020. With some clever geodetics it would have been possible to interpolate population for the periods in between ultimately making the analysis more concrete. The same is true for the boundaries of the countries. In the GIS analysis the latest updated geographical information about the administrative boundaries from 2019, this dataset was provided by FEWS NET (2019b). With building an appropriate database of country boundaries, it might have been possible to consider changes in country areas. In the building of the dataset, the population distribution is anchored at 2015 levels and the latest country boundaries used, it is assumed that these factors will have no significant impact on the results.

Assumptions where made about the statistical significance, which relates to the discussion in the research design sub-chapter about the appropriateness of significance testing in statistical testing. To achieve a higher credibility to claims, Benjamin et al. (2018) proposed that the statistical significance should be set to be below 0.005 instead of the standard 0.05. In this study, the significance level is kept at $p<0.05$, as according to the literature it appears to still be the conventional level in social sciences. But this approach requires more critical reflection of the results than the use of lower significance level to support a claim (Kennedy-Shaffer, 2019).

3.5 Research Limitations

The main limitations identified in the above described research methodology are discussed in more details in the following sub-chapter.

The data selection is biased by the limitations in personal resources. In order to deal with this limitation, the data criteria were defined. But the usefulness was in some cases limited and decisions needed to be made, which were influenced by the subjective perspective. For example, the decision was made that not the most detailed population distribution was selected due to time constraints. This constraint also led to the limitation in the collection of other country factors that would have been interesting. Furthermore, the assumptions made about the purchasing power and inflation could have been addressed with more resources. The country variables where especially sensitive to personal biases of the authors, it is therefore safe to assume that some interesting variables where not identified by the authors.

For the data sourced from the Funding Tracking Service (FTS) from the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA), the question is raised if there are any specific funding streams that are not tracked or overlapping and could therefore affect the overarching picture displayed in this study. It could be interesting to look at different datasets on funding, which might collect different streams. But so far, the authors have not found any other that fulfills all the necessary criteria. Meanwhile, there is also a potential for FTS to provide more specification for the data. For example, getting geotagged aid data would open the opportunity to make the same analysis on a regional scale rather than on a country level as the IPC classification does not strictly adhere to administrative boundaries and which further opens the possibility for a more detailed analysis. Information on the time horizon of spending, as well as the phase of disaster management it is used, would add to the quality. But awareness is required that it is not easy to categorize and put all the information into a specific box, as reality is far more complex.

There is also the potential for improvement regarding the forecasting data. FEWS NET is not the only organization out there that functions as an EWS for food insecurity, gathering data from additional sources that use the IPC standards or harmonizing data from sources that use a different standard could bolster the database and further strengthen the findings of this report or alter them. For the forecasting data provided by FEWS NET, there might also be potential for improvement. Instead of just stating the predicted IPC classification for the areas, it might helpful for decision makers to provide them with a forecast of the impact of the food insecurity. As done in this analysis, the affected population of an IPC level was estimated with the use of GIS analysis. Such an addition might make the communication slightly more complicated, but it could add a crucial information to plan for the necessary adaptation.

Considering this study as part of disaster research Rodríguez et al. (2007, p. 77) write that: “The ethical issues of disaster research are no different from those associated with the social sciences in general.” From the perspective of the authors, scientific research should include the humanitarian principles of independence and neutrality as described in the Core Humanitarian Standards (CHS Alliance, 2014) and keep the minimal requirements of “Do no harm”. In relation to this study, it is true that the research and in particular the data collection, was done very remotely from the people suffering. This distance is a limitation of this study, as it does not discuss the aspect of vulnerability and what the results mean for the individuals affected of food insecurity. Further, there might be the expectation and hope of the authors to identify in the analysis a trend towards more proactive measures over time, which might affect the selection of the methods and the selected findings.

This thesis deals with food insecurity and famines. Meanwhile, the perspective selected in this thesis is very distant and the research is mainly based on numerical data. The authors want to emphasize that this approach can remove the reader away from the terrible suffering of individuals and entire societies, which make up these statistics. Therefore, it is important that our readers try to be aware of the context this research is taking place. The motivation of the authors to work on this important topic is to get a better understanding and identify potential for changes, which can improve the situations for the most vulnerable.

4 Results

The results from the statistical analysis are presented in this chapter. At first, the selected cases are described, before the results from the analysis are provided in relation to the two hypotheses.

4.1 Data Overview

This sub-chapter provides information about errors and outliers in the dataset first, while characteristics of the used dataset are described in some detail afterwards.

4.1.1 Data Points Selection

From the total of 729 data points in the dataset, 162 were identified as not suitable for the analysis. These data points where deemed inappropriate because of an error in cataloguing. A few of the counties analyzed by FEWS NET are relatively new to the operation and some have reached a level where the organization no longer considers a need to monitor them. This led to the identification of 160 data-points where no forecasting data is recorded. However, instead of marking it as “no data” the GIS analysis produced data points with an IPC level of 0 and therefore the *Average IPC Level* in these data points is 0. These data points were thus omitted from the analysis as they were considered as errors in the data and of no significance to the study. Leaving 567 data points to be analyzed, in other words N = 567.

Additionally, there were two errors found in the geospatial part of the analysis. In these cases, FEWS NET did neither provide any forecasts for this time period. However, the GIS analysis produced data-points where there was a small affected population. After being found, these two data-points were unselected from the analysis, as they did not represent the actual situation and were therefore not suitable for the analysis.

4.1.2 Data Description

In this section, the different variables in the data set are presented in more detail by providing results from descriptive statistics. First, the variables on the forecasted IPC Levels is introduced before the variables that are related to the funding are presented. These variables are described considering the main characteristics, a histogram and their distribution between the analyzed countries, shown in a box plot. Lastly, the country variables are described.

Table 5: Descriptive Statistics on the Average IPC Level

Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Near-Term Average IPC Level	567	.927	4.153	1.392	.522
Medium-Term Average IPC Level	567	.927	4.153	1.382	.534

Based on the selected cases (N=567), ***Table 5*** provides information about the Near- and the Medium-Term Average IPC Level. Both forecasts show very similar characteristics; the Minimum and Maximum Value are the same, while the Mean and the Standard Deviation of the two variables vary minimally. The Mean value for the forecasted IPC level is 1.382 and indicates that a big share of the data-points is close to IPC level 1, as the minimum value is at 0.927. This is underlined with the histogram presenting the Medium-Term Average IPC Level, which is shown in ***Figure 8***. It also shows that data-points with an average IPC level higher than 3 in a country is very uncommon. Further, the histogram indicates that, if an area in a country is forecasted with minimal food insecurity (IPC level 1), only small areas have an IPC level of 0. This is why the values between IPC level 0 and 1 are close to 1.

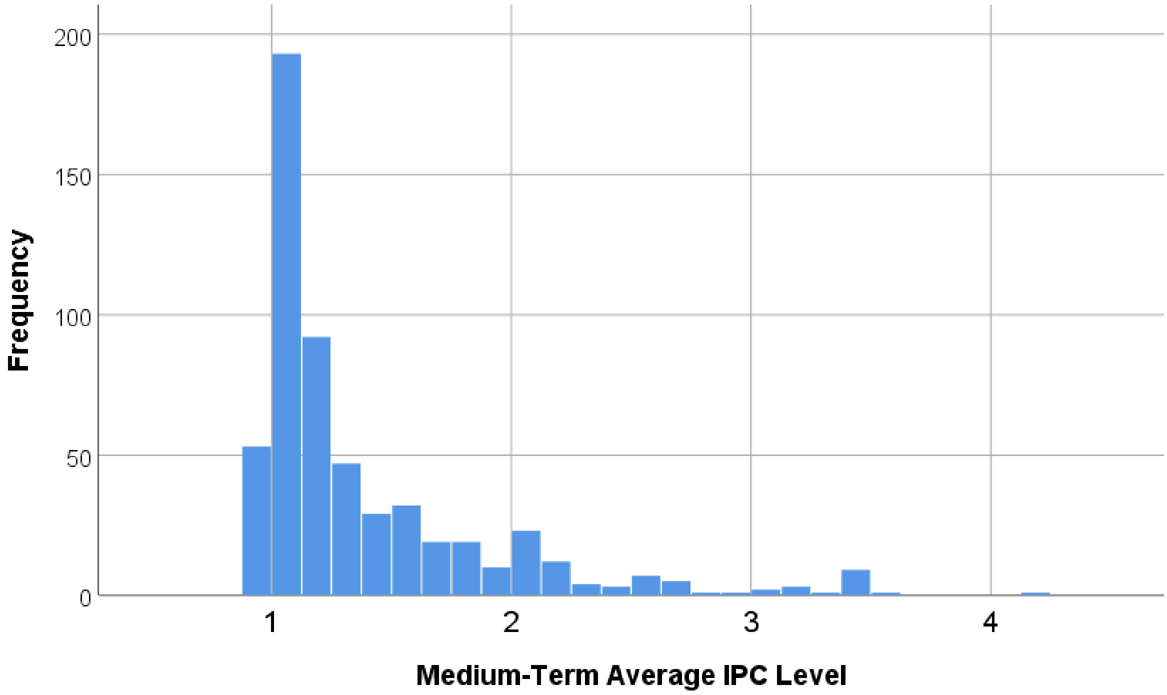

Figure 8: Histogram on the Medium-Term Average IPC Level

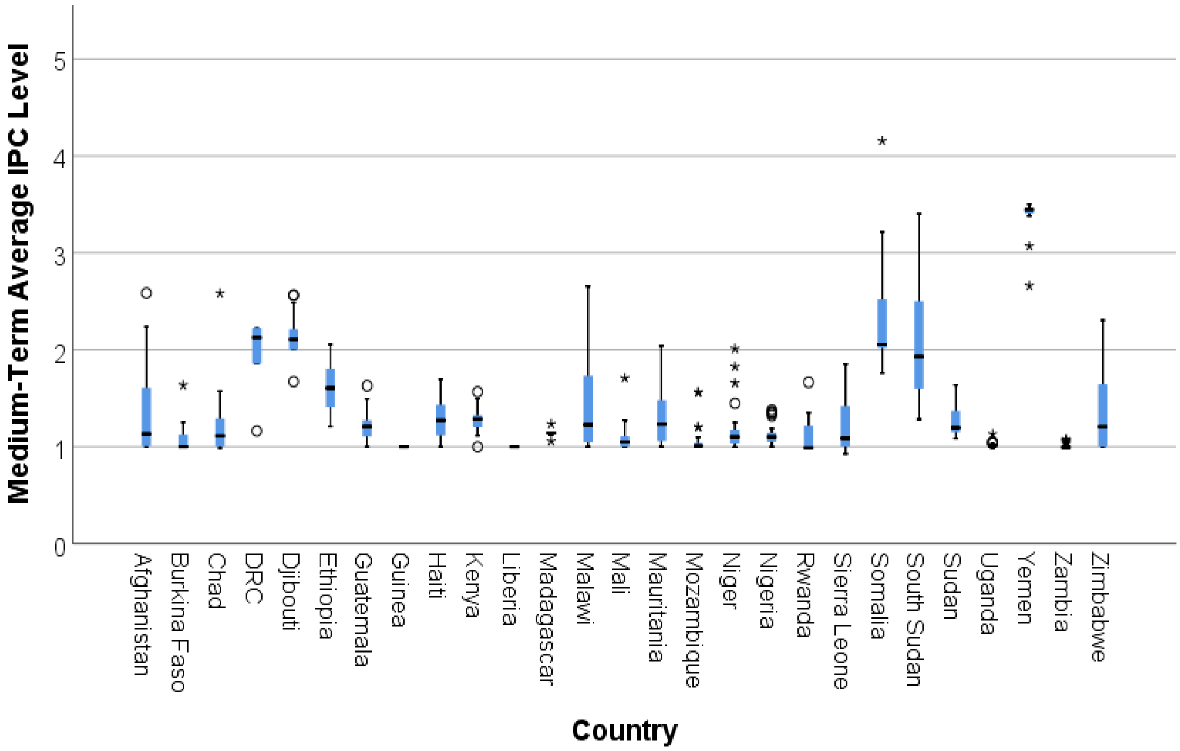

Figure 9: Boxplot of Medium-Term Average IPC Level sorted by Country

The boxplot presented in ***Figure 9***, shows a considerable variation between the countries analyzed in regard to the average IPC level in the medium-term forecast. The graph shows that Yemen has the largest average IPC Level with little variation, which might be caused by the fact that FEWS NET started their forecasting in October 2014, when the food insecurity was already severe. Other countries with high mean forecasted IPC values are DRC, Djibouti and Somalia. South Sudan has the largest variation of any analyzed country. On the opposite end of the spectrum are the forecasts for Guinea, Liberia, Mozambique, Uganda and Zambia, which have little to none variation and are very close to a minimal food insecure situation throughout the analyzing period. Often it is the case that countries jump from no data to IPC level 1 or the other way around.

Table 6: Descriptive Statistics on Funding Variables

Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Near-Term Funding per Affected Capita	567	.000	12.840	.453	1.106
Medium-Term Funding per Affected Capita	567	.000	13.231	.468	1.152
Near-Term Funding per Affected Capita per Medium-Term Average IPC Level	567	.000	6.732	.267	.529

Table 6 presents some characteristics of the funding variables. In relation to the *Funding per Affected Capita* variables the maximum values are all related to one country and year, South Sudan in 2014. South Sudan was the recipient of four relatively large donations (over 250 million USD) over the time that the analysis covers. This is well above average and could have been interpreted as outlying data points. It was concluded however that these data-points represent reality even though they are extreme and therefore kept in the dataset. Since the data used for the Near-Term and Medium-Term Funding is the same, the Mean Values are very similar. The difference is related to the deselection of certain data-points due to lacking FEWS NET forecasts. It is important to point out that the Means of 0.452 and 0.468 respectively show the average funding a person receives monthly in the analyzed time period and countries. All funding related variables share the characteristic that their Mean values are smaller than their Standard Deviations, which shows a high variation of the funding data. In one period, a lot of funding can stream into a country, while during others there is no funding provided that addresses food insecurity. A large share of the data-points is close to 0 for the Near-Term Funding per Affected Capita, as shown in ***Figure 10***. The same is true for the other two funding-related variables.

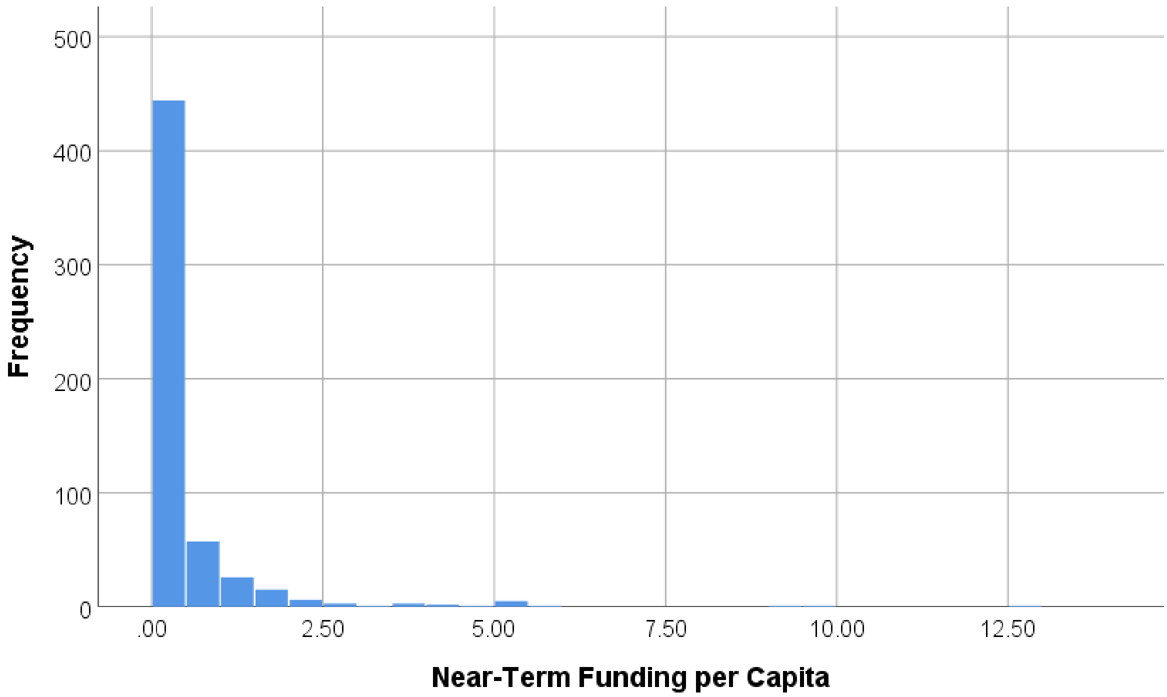

Figure 10: Histogram on the Near-Term Funding per Affected Capita

Figure 11 shows how near-term funding per affected capita is distributed in the countries represented in the analysis. There are a few recipient countries that receive far more funding compared to other countries, which are Yemen, Djibouti, South Sudan and Somalia. These countries have also a higher mean value of the monthly short-term funding per affected capita.

The comparison of the two boxplots in ***Figure 9*** and ***Figure 11*** indicates that countries with a high average IPC Level are likely to have a high Funding per affected capita over the analyzed time period. The other way around, it is more difficult to make a statement, as the low averages and distributions are close to 0.

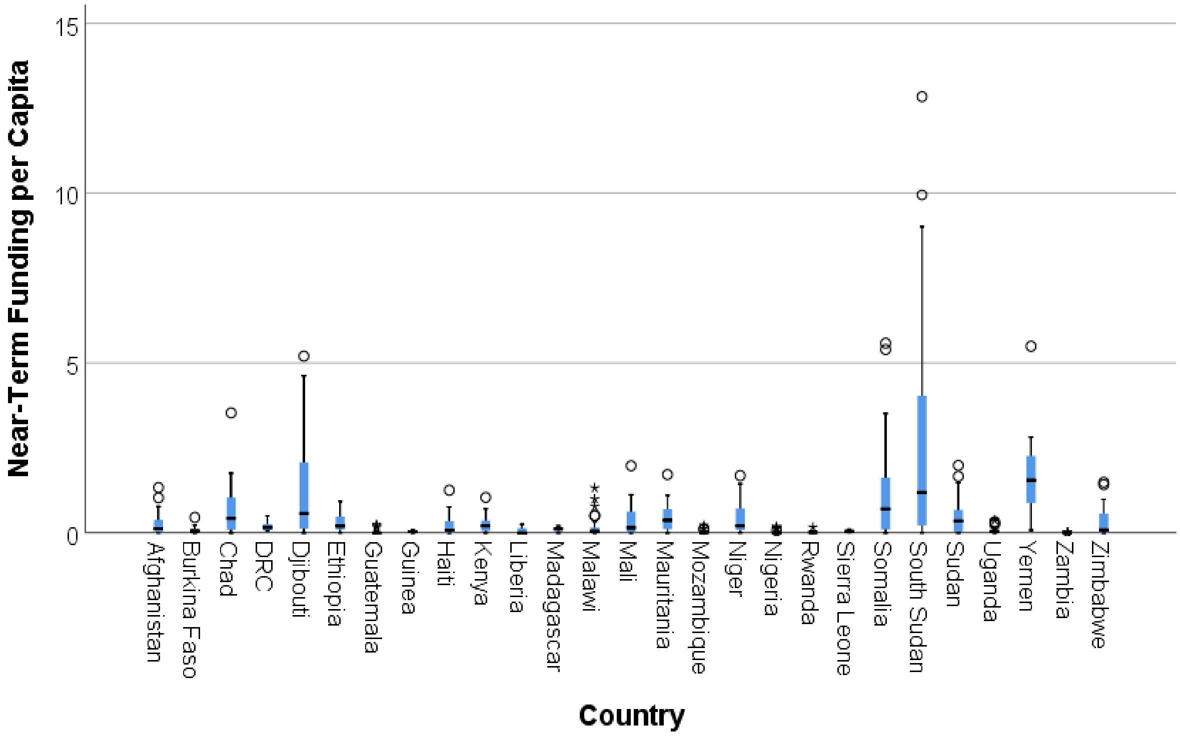

Figure 11: Boxplot for Near-Term Funding per Affected Capita sorted by Country

In relation to the country variables, which provide relevant results, ***Table 7*** presents the descriptive statistics. At first, it shows that there is a big variety, between the most and least populated country as well as for their population density. Considering the global HDI ranking, the maximum value in the dataset of 0.650 which is relatively low and indicates that all countries analyzed are developing. Further, the range of the country Independence starts in year 1804 with Haiti being the first one in the sample getting their independence. The youngest country is South Sudan, which got its independence from Sudan in 2011.

Table 7: Descriptive Statistics on Country Variables

Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Population Size	567	956985	190886311	34064497	41372657
Population Density	567	3.7	483.7	89.5	108.2
HDI	541	.350	.650	.488	.071
Year of Independence from Colonial Power	567	1804	2011	1944	49

4.2 Results in Relation to Hypotheses A

The results concerning the first hypotheses are presented in this sub-chapter. The test results show the correlations between the medium-term forecasts for the average IPC Level and the funding per affected capita that is allocated in the period before the forecasting period as well as during the forecasting period. Adding on that are the results, which consider the correlation between the country variables and the funding per affected capita per IPC level.

4.2.1 Correlations between Forecasted IPC levels and Funding per Affected Capita

The statistical analysis using the Pearson Correlation method is presented in ***Table 8***. The correlations between *Near-Term IPC Country Average* and *Medium-Term IPC Country Average* (independent variable) with *Near-Term Funding per Affected Capita* as well as *Medium-Term Funding per Affected Capita* (dependent variables). All four correlations are statistically significant with a significance value of *p<.001*. The different correlations are very similar between the variables with values ranging between *r=.454* and *r=.478.* This result is further illustrated with the scatterplot in ***Figure 12***. The scatter plot shows the distribution of the data-points with the variables (*Medium-Term Average IPC Country* and *Near-Term Funding per Affected Capita*) and their respective correlation. Although there is high variance in the distribution, the fit line shows a clear positive trend.

Table 8: Pearson Correlations of Average IPC Levels and Funding per Affected Capita

		Near-Term Funding per Affected Capita	Medium-Term Funding per Affected Capita
Near-Term Average IPC Level	Pearson Correlation	.478	.454
	Sig. (2-tailed)	.000	.000
	N	567	567
Medium-Term Average IPC Level	Pearson Correlation	.472	.474
	Sig. (2-tailed)	.000	.000
	N	567	567

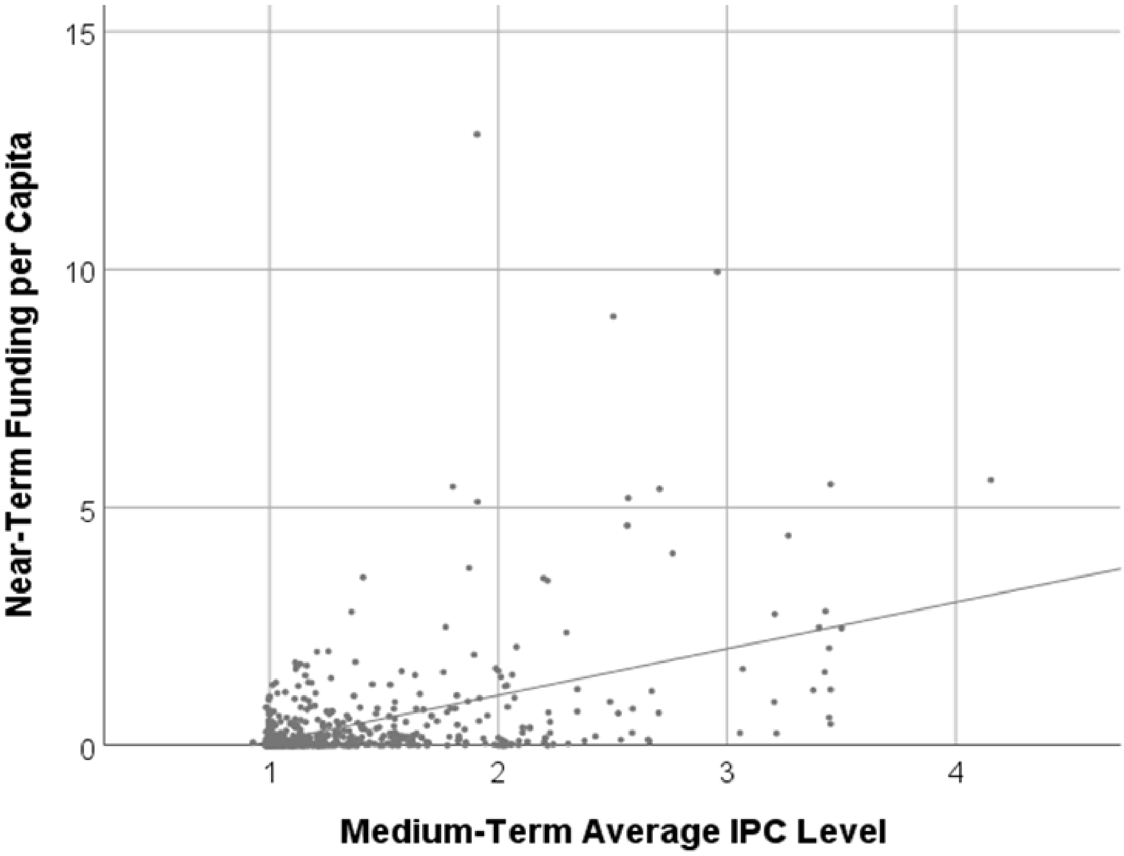

Figure 12: Scatterplot with Fit Line of Medium-Term Average IPC Country and Near-Term Funding per Affected Capita

4.2.2 Correlations of Country Variables with Funding per Affected Capita per IPC level

In this part of the chapter, the main findings are summarized with regards to the analysis of potential affects that country characteristics might have on the dependent variable *Near-Term Funding per Affected Capita per Medium-Term Average IPC Level.* The effect of the country variables where analyzed with different statistical methods:

- Pearson Correlation for continuous variables
- Independent T-Tests for dichotomous variables

The following variables have a statistically significant negative influence on the dependent variable, according to the Pearson Correlation analysis: *Total Population* (*r*= -.140, *p*=<.001), *Population Density* (*r= -.195, p*=<.001) and the *HDI* (*r*= -.265, *p*=<.001). These results mean that people living in a country with a bigger population, a higher population density, and a higher HDI are likely to receive on average less funding per IPC Level they are affected by.

The results show the opposite for the *Year of Independence* variable. People living in a country that reached independence more recently are on average more likely to receive additional funding per forecasted average IPC level in the country. The Pearson Correlation for the variable is presented as *r= .200*, *p*=<.001. This would mean that for example, that an average population that has the same medium-term forecasted IPC level in Haiti that got independent in 1804 receives less funding than in South Sudan, which got its independence in 2011. A similar conclusion can be drawn from the boxplot in ***Figure 13***, although the changes in the Mean values are changing just to a limited degree.

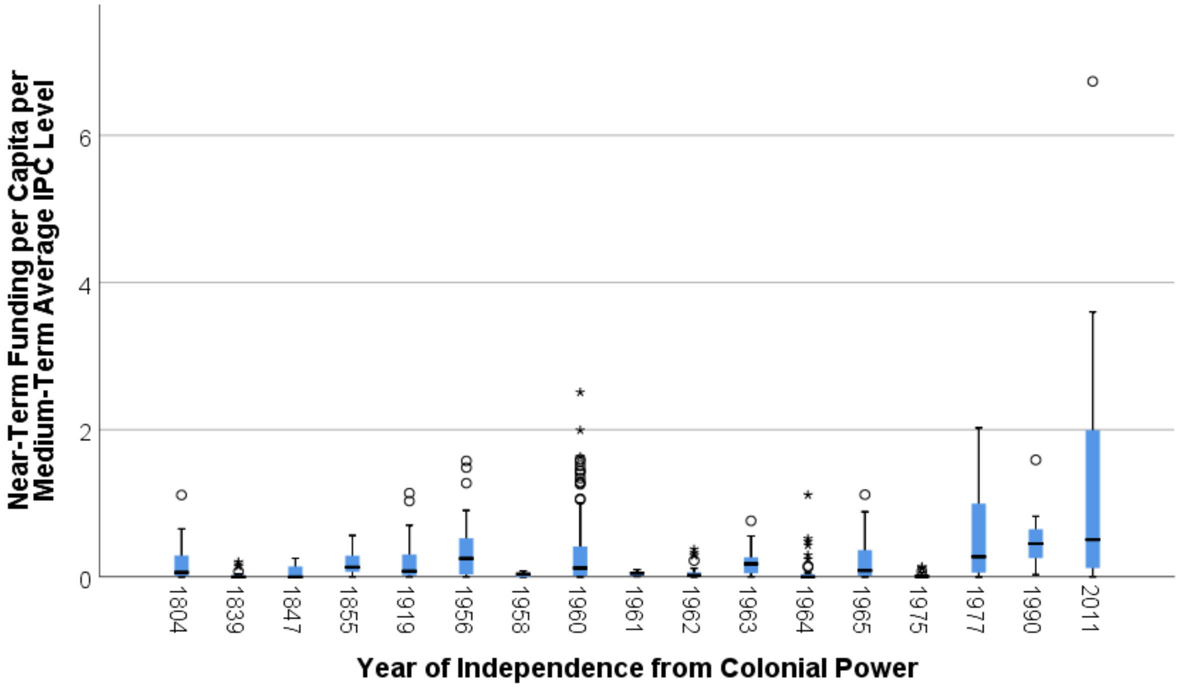

Figure 13: Pearson Correlation between Year of Independence and Near-Term Funding per Affected Capita per Medium-Term Average IPC Level

The independent T-Test *(t(262) = 4.007, p<0.001)* showed that countries, which have a UNISDR National Platform receive less *Near-Term Funding per Affected Capita per Medium-Term Average IPC Level* than those countries without this platform. The result is presented in ***Table 9***, which shows the different Mean value for the two groups of countries. Although the countries that have *a Sendai focal point* have a Mean value that is more than half as high than those that do not have it, no statement about the relation can be made, as the result from the T-Test is not statistically significant *(p=0.06)* As the implementation of these variables took place after the Sendai Conference, the analyzed data-points were limited to data-points after the year 2014.

Table 9: Independent T-Test on UNISDR National Platform and Sendai Focal Point

	UNISDR National Platform	N	Mean	Std. Deviation	Sendai Focal Point	N	Mean	Std. Deviation
Near-Term Funding per Affected Capita per Medium-Term Average IPC Level	No	157	0.355	0.576	No	203	0.230	0.476
	Yes	107	0.121	0.209	Yes	61	0.361	0.471

For the country variables: *Area Size, GDP, GDP per Capita* and *the Last Colonial Power*, no correlation was found, which is of statistical significance.

4.3 Results in Relation to Hypotheses B

This part gives an overview to the results of correlations in relation to time aspects, which are analyzed in order to test the second hypothesis. At first, the change over time of some key variables is presented, before the development of correlations over the year is considered.

4.3.1 Correlations of Time with Forecasts and Funding

The first time-related analysis investigated the correlation between *Estimation Date of the IPC Forecasts* (independent variable) with the three dependent variables *Near-Term Average IPC Level, Medium-Term Average IPC Level, Near-Term Funding per Affected Capita, Medium-Term Funding per Affected Capita.*

The data indicates that there is a slight trend for the variable *IPC Country Average* towards a higher food insecurity globally. For the Pearson Correlation analysis, the results of the near-term forecasts are $r=.093$, $p=.027$ and for the medium-term $r=.103$, $p=.014$. Meaning that on average that there is higher food insecurity forecasted in the monitored countries at the end of the analysis than there was at the start. Although this trend is weak it is statistically significant.

On the other hand, there is no indication that there is a trend over the time of the analysis towards more or less *Funding per Affected Capita* neither during the near-term ($r=.035$, $p=.409$) nor for the medium-term ($r=.018$, $p=.669$) of the forecasted food insecurity period.

4.3.2 Correlations between Forecasted IPC levels and Funding per Affected Capita over time

In order to investigate the development over time, the correlation is analyzed between *Medium-Term Average IPC Country* (independent variable) with *Near-Term and Medium-Term Funding per Affected Capita* (dependent variables) and split by year of the forecasting time. The result of the Pearson Correlation, the 2-tailed statistical significance and the number of cases (N) is provided in ***Table 10***. Apart from the correlation between the *Medium-Term Average IPC Country* and the *Medium-Term Funding per Affected Capita* in year 2013, all results are statistically significant with $p<0.05$.

Table 10: Change over Years between the Correlations of Forecasting and Funding per Affected Capita

			Near-Term Funding per Affected Capita	Medium-Term Funding per Affected Capita
Medium-Term Average IPC Level	2011	Pearson Correlation	0.704	0.623
		Sig. (2-tailed)	<0.001	<0.001
		N	62	62
	2012	Pearson Correlation	0.362	0.279
		Sig. (2-tailed)	0.001	0.013
		N	78	78
	2013	Pearson Correlation	0.387	0.189
		Sig. (2-tailed)	<0.001	0.091
		N	81	81
	2014	Pearson Correlation	0.361	0.289
		Sig. (2-tailed)	0.001	0.008
		N	82	82
	2015	Pearson Correlation	0.432	0.493
		Sig. (2-tailed)	<0.001	<0.001
		N	84	84
	2016	Pearson Correlation	0.347	0.547
		Sig. (2-tailed)	0.003	<0.001
		N	73	73
	2017	Pearson Correlation	0.489	0.689
		Sig. (2-tailed)	<0.001	<0.001
		N	67	67
	2018	Pearson Correlation	0.830	0.764
		Sig. (2-tailed)	<0.001	<0.001
		N	40	40

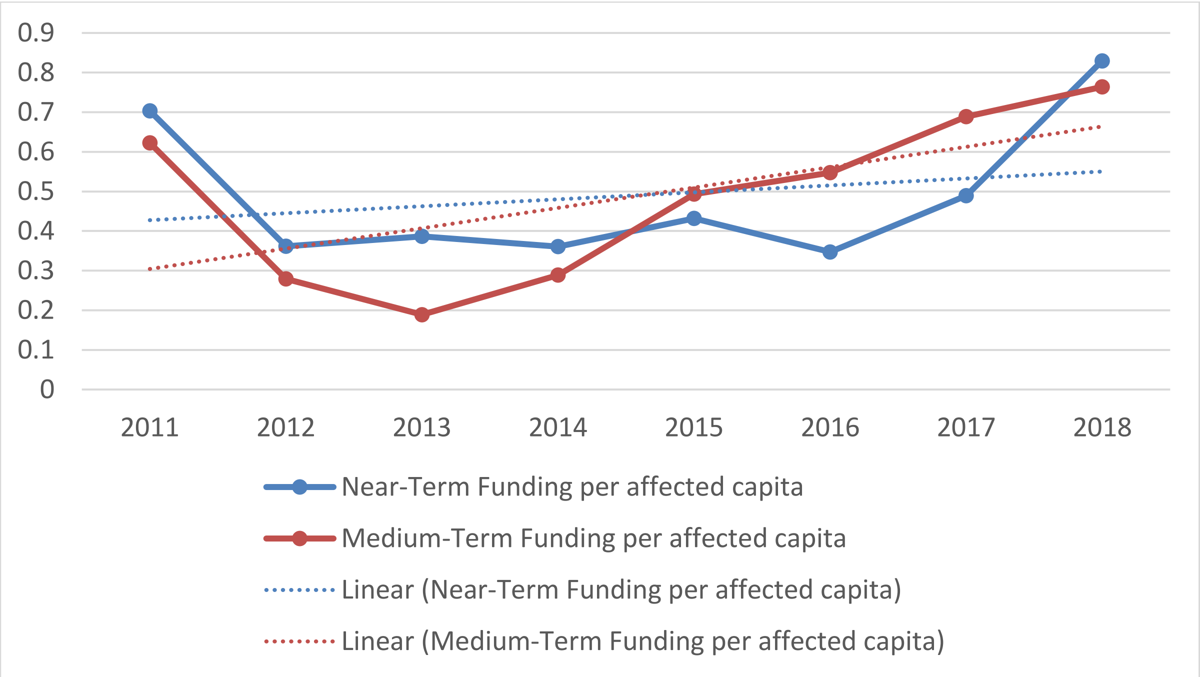

Figure 14: Change over Years between the Correlations of Forecasting and Funding per Affected Capita

After 2011 there is a considerable drop in correlation for the next two consecutive years before an increase occurs in the last five years of the analysis as presented in ***Figure 14.*** Further, it shows that there seems to be a considerable increase in correlation between the forecasted IPC levels and funding per affected capita over the recent years. Neither line appear to be constantly a better indicator of funding as the strength of the correlations changes from year to year. This means that for some of the cases the medium-term forecast proved to be more appropriate indicator for funding in the near-term, while for others it is the funding in the medium-term. Even so, a change in correlations is shown, where the correlation between the forecasts and the near-term funding per Affected Capita is stronger, while after 2014 there is a switch and then again in 2018.

When considering year 2011 as an outlier, as it was the only year with a high population affected by a famine, according to the FEWS NET forecasts. Both models show low variance and that the trajectory indicates that the international community is adapting more to proactive measures. The linear regression method shows a strong correlation, with $r= .719$ for the *Near-Term Funding per Affected Capita* and $r= .954$ for the *Medium-Term Funding per Affected Capita* (where the year 2013 is included as well). But the first correlation is not statistically significant with $p=0,069$, why the claim that there is a development over time needs to be rejected. But the picture looks different for the linear regression between the *Year* and the *Correlation of the medium-term forecast with the medium-term funding*, where $r^2= .910$ with $p=.001$. This indicates a stark change over the years 2012-2018 in the correlation, which means that time increases the correlation between forecasting and funding.

5 Discussion

In this chapter the results of the analysis are discussed and a reflection from different perspectives provided for the findings based on the two research questions:

A Is there a correlation between the forecasted levels of food insecurity and the amount of international aid funding to reduce food insecurity?

B And if so, does this correlation between forecasted levels of food insecurity and the amount of international aid to reduce food insecurity change over time?

5.1 Discussion of the Results

This sub-chapter discusses the hypotheses and the related results. For each research question, the answer to the posed hypothesis is presented, before the results are discussed in more detail.

5.1.1 Discussion on the Results in Relation to Research Question A

The results from the data analysis indicate that the Null Hypothesis A (H_{A0}) can be refuted with considerable confidence. Therefore, the Alternative Hypothesis H_{A1} is accepted, which states that: *There is a relation between the medium-term food security forecasts and the funding per Affected Capita for food security, which flows before and during the forecasted periods.*

The results from the Pearson Correlations in ***Table 7*** show that there is a strong and statistically significant relationship between the average severity of predicted food insecurity and of international aid funding per affected capita being administered to these effected areas. This is the case for all analyzed correlations between the forecasting and funding, no matter whether the food insecurity forecast was made for the near-term or medium-term period and the funding per affected capita flowed during the near-term or medium-term period. The reasons for this similarity in the correlation strength can be manifold. One important aspect could be that food insecurity is a slow-onset disaster and the (forecasted) magnitudes change slowly as well. Therefore, it is often the case that the forecasts for the near-term as well as the medium-term food insecurity are the same or at least very similar. Related to that is the second explanation, which considers the funding data. The data on the funding streams does not provide information about the targeted food insecure period. Therefore, the data used for the near-term and medium-term funding per affected capita is the same, it is just related to a different estimation date.

Despite the similarity of the correlation for these variables, a closer look at the differences provides us with interesting information. The biggest differences in correlation is between the Near-Term Forecast with the Near-Term Funding (*$r=.478$)* on the one hand and between the Near-Term Forecast with the Medium-Term Funding(*$r=.454$)*. Surprisingly, the correlation is bigger between the forecast with the funding per affected capita flowing into the country during the near-term period than the amount of funding after this period. This finding could indicate that reactions from the international community to provide funding are more likely to come earlier during the disaster than later according to the used data.

The two correlating key variables: Average IPC Level and Funding per Affected Capita in relation to the near-term and medium-term period were presented in the first analysis. As shown, integrating all these variables does not provide big differences in the results. Meanwhile, using all these similar variables in an analysis can be confusing. This is the reason why in the analysis, which followed, not all key variables are presented. The focus is put on the Medium-Term Average IPC Level and the Near-Term Funding per Affected Capita. The causes for this selection are two-fold. The first reason is the assumption that after the forecasts are published, some time is required to adapt and to transfer the funding. Secondly, the study takes place in the field of DRR, which has an interest in early action, why the focus is set on the funding between the estimation date and the start of the food insecure situation.

This focus is already shown in the scatterplot in ***Figure 12***. The data are widely distributed, making it difficult to give a good prediction for the funding following a forecast for the average IPC level in a country. Further, the graph shows that there is a big collection of data around IPC level 1. Although there are no extreme outliers in the near-term funding per affected capita, there is still a big variety. Areas that are affected by an IPC level 1 have often been in that stage for a long time and there might be less urgency to address the food insecurity issues. Therefore, other factors can have a larger impact on the aid being distributed than food insecurity forecasts in cases with a lower IPC level. Such factors could be long-term development work or refugee camps, which can also create a demand for food security funding. Low food insecurity would also be *easier* for individual countries to mitigate as the “providers of first resort” (Lautze et al., 2012, pp. 47–48), since fewer local capacities are required to deal with it.

A sort of clustering was done in the second analysis to give more validity to the answer of the first research question. This led to the identification of different variables, that correlated significantly to the funding streams. Total population, population density as well as the score on the HDI, have all a weak negative correlation to the funding per affected capita per forecasted IPC level. A reason that a higher total population and a higher population density results in general in less money spent per capita per forecasted food insecurity, could be related to the economies of scale. This means that the costs are lower, since less administrative work per person is necessary and logistics is simpler, if more people are reached within a shorter distance. Meanwhile, city dwellers that are often the result of development rely more on markets than subsistence and self-reliance like is common with agrarian communities, where the population distribution is less dense.

That a higher HDI has the same effect on funding might be because this index integrates the income per capita, which allows the population to use their own capacities to better deal with food insecurity and are less dependent on international funding than countries with a lower position on the HDI. But this explanation contradicts another part of the analysis, which looked at the variable GDP per Capita and did not show a significant correlation to the funding per affected capita per IPC level. The HDI includes an education component, which could describe a society with less vulnerability, since better educated people can provide more capacity to deal with food insecurity.

Although a weak positive correlation was found regarding the year of independence (in contrast to the three variables in the last paragraph), similar arguments could be used, stating that countries that have been independent for a longer time, are more developed. A Pearson Correlation between the year of independence and the HDI of a country shows that there is a negative and significant correlation underlines this perspective. But this correlation is a research field on its own. The question could be raised, what role do extreme cases play in this analysis with Year of Independence? The four most *extreme* cases are Haiti in 1804, Guatemala in 1839, Yemen in 1990 and South Sudan in 2011. The latter two cases are also extreme cases in relation to funding. Therefore, it is possible that excluding those data-points would diminish the correlation.

That countries with a UNISDR national platform receive less money per capita per forecasted food insecurity might appear to be surprising at first sight. But if looking closer at the underlying data of the countries, it appears that the platforms are not placed in countries with the highest risk of food insecurity according to recent history. Based on the results discussed about the correlation between forecasts and funding, it seems likely that in these countries the funding is lower because they have less food insecurity and not because they have platforms. Further, it could have been expected that in countries that have a Sendai Focal Point, the funding before the forecasted period is higher, as such focal points could be used as example cases on how DRR could be implemented. But probably, the relevance of such focal points is too small (yet) to make a difference in the adaptation.

5.1.2 Discussion on the Results in Relation to Research Question B

The analysis shows that for Hypothesis B the null hypothesis (H_{B0}) can be rejected, if the year 2011 is excluded from the dataset and the funding per affected capita during the forecasted period is analyzed. Therefore, the general finding states with a reduced degree of confidence that H_{B1} is valid: *There is a change over time in the relation between the medium-term food security forecasts and the funding per affected capita for food security, which flows before and during the forecasted periods.* The main reason for this difficulty is whether the correlations in year 2011 should be considered as an outlier or not. The case for excluding 2011 from the dataset is made later in this section.

The first analysis considering the time aspect shows that there is generally a slight increase in forecasted medium-term food insecurity over the study period, whereas the international aid funding showed neither a general upwards nor downwards trend with statistical significance over the same time period.

The reasons for the slight, but still significant increase of the average forecasted medium-term food insecurity in the countries over the analyzed period can be multi-faceted. The first approach could consider trends of increasing complexity, more and larger conflicts in recent years or population growth that can affect the vulnerability or climate change that increases the hazard. This would be very worrying and creates a negative prospect about the ability of the system to improve. Another possible explanation could be changes in the forecasting, due to small modifications in the process (that are not made explicit) to be more accurate or a more reasonable explanation would be that the data sources used have updated their methods, for example by using another technology. It is difficult to say, which of these explanations correspond most with reality or if it is a combination.

There is no clear indication that there is a trend towards more funding to combat food insecurity over the complete time of the analysis. Neither is there a statistical significance to the finding. This comes as a surprise due to two reasons. First, if there is a small but significant increase in the forecasted IPC level, a similar increase could be expected from the funding. Secondly, the exclusion of inflation in the calculations created the expectation that there is an increase in the absolute values of funding to balance out the inflation in real life. So, neither the increase in food insecurity nor the inflation create an in increase in absolute funding. This finding can be troubling and underlines the issue of the increasing funding gap in the humanitarian sector. Ones hope is that the aid being administered is now spent more cautiously and that this trend will reverse in the future.

As shown in ***Figure 14***, there is a drastic drop in correlation between 2011 and 2013, before increasing during the rest of the period being analyzed. Therefore, in 2018 the correlations are slightly higher than at the start in 2011. That being said the pool of data points for this analysis was much smaller, when analyzing the annual correlation between the forecasted funding and the funding per affected capita.

The start of the analyzed period, the year 2011, has some properties that should warrant an exclusion from the dataset. One reason is the declaration of the famine in Somalia. Based on the calculation made with the FEWS NET forecasts, July 2011 was the only case a country had an average forecasted medium-term food insecurity of more than IPC 4. Meanwhile, the famine was declared on a UN level, which puts emphasis on the need for urgent adaptation and more monetary resources to be allocated. Meanwhile, the analyzed period started in April 2011, when the effect of this famine is even stronger. According to the data, several East African countries had a high IPC classification forecast at that time, which could be an explanation for the high correlation during this year. Therefore, this year could be considered as a statistical outlier. But this perspective can be opposed with the consideration that the famine is seen as ongoing until 2012. Further bolstering the case for excluding the year from the dataset is the fact that the data set covers only parts of 2011 as FEWS NET adopted the IPC standard in March. There are other plausible causes that would warrant another analysis altogether, which might influence the annual correlations. One of them might be the Arab spring, which was the political uprising of large populations in Arab states in 2011. It is possible that the wave of protests that swept through neighboring areas could have motivated global decision makers to stabilize the surrounding countries with additional spending on food security. This theory is especially interesting as connections have been made between the unrest in the area and food security (Johnstone & Mazo, 2011). These factors would have to be further analyzed but it does indicate that there is a stronger correlation between funding and forecasting. However, if 2011 is to be considered as an outlier, it would be necessary to look closer into the year 2017, where the UN declared a famine in parts of South Sudan and the year 2018, as the high correlation could be explained by the conflict in Yemen reaching a high, which has led to high food insecurity. This goes to show that the results that relate to Hypotheses B are in some form more ambiguous than for Hypothesis A and this might generate some controversy. But it has been concluded that 2011 is in fact an outlier and warrants an exclusion from the analysis. This might further show that famines, IPC level 5 generates tremendous effort on the part of the international community, but since the dataset cannot verify this that question remains unanswered.

Another special case is the correlation between the medium-term forecasts and the international aid funding per affected capita in the year 2013, as it is the only correlation that is statistically not significant. This finding indicates a high variance in the underlying data used, but the origin of this higher variance is difficult to identify. A simple explanation would be that it is random, but it is likely that there are other underlying reasons, like that the medium-term IPC forecasts are on global level on the lowest averages, which can affect the variance in the correlation, as discussed before.

The next aspect to discuss is the differences in correlations between the different funding periods, near-term and medium-term. Although the annual correlations follow the same general tendencies over the time, there are differences, which might have an underlying cause. During the years 2011-2014, the correlation for the funding before the forecasted period is always higher than the funding during the forecasted period, which changed from the year 2015 onwards. A possible perspective could be that the smaller funding gap in the first years allowed for more funding before a forecasted period, whereas after 2014 the funding was provided later in the food insecurity phase, when the needs became more visible. But this explanation contradicts the result that the correlation between forecasts and funding for the near-term funding has increased considerably after 2015 and surpasses the medium-term funding correlation in 2018. This trend might be possible to explain with the role of the new guidelines adopted in the year 2015, the SDG as well as the Sendai Framework for Action. Guidelines that strongly encourage decision makers to adapt early on. But this explanation cannot be verified with this data.

The last results from this analysis, look at the change over the years 2012-2018 of the correlation between the forecasts and the funding during medium term, provides a similar perspective, as discussed in the last paragraph. Both show a trend over the last years towards higher correlation between the forecasting and the funding. These changes implicate possible improvements in the interplay between the forecasts and the international aid funding before and during a forecasted food insecurity event. Such improvements can have different reasons, like improved forecasts using new technology, better availability of the forecasts for the decision makers or an awareness of the decision-makers to act timely. If these trends and the explanations are true, there would be hope that the system is able to learn, that disaster risks can be reduced, and societies can become more resilient.

5.2 General Reflection on the Findings

The answers to the two research questions could be provided only by considering the two accepted hypotheses H_{A1} and H_{B1}, but there are more perspectives to that. At first, it is important to point out that the findings do not prove any causality between the two aspects forecasting and funding. But identifying the causes appears to be very difficult in this “complex, uncertain, dynamic, and ambiguous world” (Hagelsteen & Becker, 2019). Therefore, this sub-chapter provides broader context to discuss the utility and appropriateness of the study and its findings.

Food Security, Early Warning as well as Funding can be considered as complex systems. The complexity increases even more, when combining these systems. This means that there are countless variables, which are uncertain and can affect the interplay between all these factors. The results show that other variables correlate as well with the funding, although they are not as strong as the forecasts. But on the one side, there was just a limited number of (independent) variables in relation to the countries analyzed. There are many more, which might have a significant correlation. On the other side, there can be many factors, which might be difficult to prove a statistical significance, as they are difficult to identify and quantify. But still they can be crucial and might play in certain cases a more important role than forecasts.

It is also true that there are more variables that influence the ultimate decision of organizations to start an operation or increase funding for a particular area that is facing food insecurity. It would be juvenile to think that the forecasting reports are always being distributed and read by every policy maker and head of operations before deciding to increase funding. However, by looking at the processes used at FEWS NET, you see that their scenario building method takes various variables into considerations and seems to predict the future quite accurately as such (if their own estimation of the current situations is considered as the scale). This could implicate that these predictions are a self-fulfilling prophecy and that would be a valid point. But this would indicate that the aid system is exceptionally responsive and constantly making changes to funding streams to reflect the current situation. Such changes would than affect again the food insecurity in reality.

Politics or media have in all likelihood a major effect on the different variables analyzed. For example, articles can be found stating that there is food insecurity in North Korea and Venezuela, but FEWS NET does not produce forecasts or monitor these countries remotely. A reason for this could be that FEWS NET is funded by the US government and there is tension between these countries, meaning it could be difficult for them to get access to the necessary data. This limited access from the outside however could be said for many other countries as well. The same could be stated about relevance of international relations and the politics in the distribution of funding. Some countries share more similar interests compared to others and therefore, support them more with funding in a crisis. The media can play a crucial role as well. Media coverage can make people spring to action. What comes to mind is the west African drought of 2011 and the ongoing war in Yemen. Both cases were and are covered by the media, although some might argue that the former case got overshadowed by the Arabic spring. There is a probability that the attention from the media has had some effect on how aid has been distributed, which is described in literature as the “CNN Effect” (Jakobsen, 2000). The humanitarian aid requests for the Yemeni situation have been largely addressed and the aid gap discussed earlier is only smaller for the case of Iraq. Humanitarian aid requests in Yemen have been 85.3 per cent funded (UN OCHA, 2018b). Hence, it is important to remember that the analyzed system is complex with many elements contributing.

The findings show not only a correlation between forecasting and funding, but also that there is potential for a stronger relationship, which show opportunities for improvements of EWS in relation to food insecurity. The potential for a stronger relationship means that decision makers could put more emphasis on using the information from forecasts, when deciding on the provision of funding to address food insecurity. Further, they could also make their decisions faster or even have an automated process in place, which initiates the distribution of funding, according to the forecasted food insecurity level. FbA in particular, appears to be on the right track with strengthening the automation of the steps that lead to reduced risk. In relation to the risk of food insecurity, FAM appears to be a promising way with its strong interconnectedness and the use of existing expertise in the field of big data. FAM could develop into a flagship project to improve DRR approaches and create a more resilient humanitarian aid system. But it is crucial to keep in mind that this is all about human beings, which on one side contribute to the creation of needs and act according to power dynamics and on the other side are culturally diverse and suffer in the disasters.

The methodology used to provide answers to the research questions could have been approached differently. But one of the many positive aspects of working with quantitative numerical data is the scope in which the analysis can be conducted in. Looking at differences between 27 countries over a period of eight years with multiple forecasts each year and multiple agencies donating towards the different situations lead to 729 data-points to analyze, although some where omitted later. This kind of analysis in this short amount of time would not be feasible in terms of qualitative data. Tracking down all the different actors that contributed to the missions and operations that made this dataset would require tremendous resources. Institutional memory fades and getting all the people and setting up interviews for a contribution that was made nine years ago could be very difficult. That being said a similar result could have been produced with key informants that have a good overview of the current situation and are well versed in the relationship between funding and aid administered. But the process of getting a large enough sample size using a snowballing effect was thought to be too time consuming to even make preliminary inquiries on the subject. What could bolster the reliability of the findings would be to find subjects that have been in the humanitarian field for a long time that could give their experience regarding the changes in forecasting and the relationship it has had on the field in general. But it is doubtful that this would lead to any conclusion on its own. Regardless, the perspective remains in place that monetary value, although subject to inflation, is a better indicator on the actual change in the system than memories could have in this case.

The collected data, allowed for the creation of a dataset with many data-points and dozens of variables, which were analyzed. A unique feature is the calculated Average IPC Level for the analyzed time period and countries. Although this approach should be challenged by the scientific community to move further, it opens potential for further research. The created dataset can be analyzed more in-depth with additional interesting and significant findings. But the dataset could also be further extended. Using data that goes further back and harmonizing it with the data at hand would of course increase the time scale of the analysis. But through the harmonization, additional limitations would be added. It is also possible to add to the dataset and as new data is constantly being produced by the same organizations that have contributed to this dataset. This would have the same effect as going further back, extending the time frame. This option is slower however as the latest data in the dataset is not even a year old, this has the obvious advantage however that there is no need for harmonization of the data as the IPC standard is still being used. Getting a more exhaustive and tailored database for the funding variables would be ideal as well as it would increase the strength of the findings.

It appears important that the relationship between the resilience function of recognition and adaptation are to be researched increasingly and assumptions taken further. But the focus should not only be on food insecurity related disasters. Other disasters, which are induced by natural hazards that can and are being forecasted should be investigated as well. The correlation between the two functions might be easier to analyze for hazards which are less complex and more sudden onset in nature and therefore open up the potential to identify causal relationships. Flooding is a prime example of this, as there have been scientific papers published on the matter that analyze the interplay between recognition and adaptation using a qualitative approach (Braman et al., 2013; Coughlan de Perez et al., 2016; Plate, 2002; Tall et al., 2012).

6 Conclusion

The research aim of this thesis was to analyze the relation between forecasted levels of food insecurity and international aid funding targeting food security. The aim was achieved using a deductive approach, which used quantitative data on forecasted food insecurity and international aid funding. The study was guided by the two research questions, which lead to the creation of a dataset that includes 27 forecasting periods between 2011 and 2018 for 27 countries.

The first research question investigates the correlations between forecasted food insecurity levels and amount of funding. Based on the results from the analysis, it can be assumed that a higher food insecurity forecast can be related to more funding streaming into the respective country. The strong correlation has a high statistical significance, although it has a limited strength due to variation. Additionally, other variables where identified which influence the correlation. For example, it is shown that more developed countries receive less funding per affected capita.

The second question relies on the same dataset as the first research question. The potential development in trends over time in correlations between the two key variables were researched. The results of this analysis proved to be more ambiguous than the earlier analysis. When the year 2011 is considered as an outlier, a statistically significant trend is found, which shows an improvement in terms of higher correlation between the recognition of food insecurity levels and the funding to adapt.

These results from the study were discussed. It is important to point out that the relationships examined are highly dynamic and the correlation between forecasting and funding should not be confused with the causality that forecasting leads to funding. The analyzed variables are taken from a complex system, where there are too many elements, which interrelate with each other in a dynamic way. When investigating the role of forecasting, it is further important to consider the aspect of a self-fulfilling prophecy. The results showed that there is also high variance in international aid funding, which is why it is difficult to make funding predictions. The results show that there is plenty of hope, that the global community seems to be learning and improvements to reduce the suffering due to food insecurity are possible and increasing.

The selected research methodology has some advantages as well as disadvantages. It appears that the data collection and the first data analyses steps produced a big dataset, which is of high quality and can be used for a variety of analysis. Meanwhile, the GIS analysis is seen as an element which adds a lot to the originality of this study. On the other hand, many assumptions are necessary for the selected quantitative approach, which could be challenged, but this does not automatically reduce the value of the findings. The most crucial assumption is that the IPC classification is assumed to be continuous. Further, inflation is not included in the analysis, and the assumption is made that it has not affected the results to a degree, where they become invalid. Some recommendations can be made for the provider of the data on food security. FEWS NET might make their forecasts more valuable for the decision makers, if they add an impact aspect (e.g. affected population). Additionally, the data from the Financial Tracking Service could be geotagged and displayed with more information about time-period for funding streams.

This study provides a picture of the interplay between two functions of recognition and adaptation. Although the relation of these two aspects is crucial for the success of Disaster Risk Reduction in general, is difficult to measure and evaluate. The results from this study make a contribution to the learning functions in Disaster Risk Reduction, as well as make them more accountable. These findings should encourage donors to increase their consideration of forecasts, when making decisions related to funding. The results further come as a contribution to the development of FbA, as the research provides some information about the current state of practice. This might be particular interesting for FAM, which is focusing on food insecurity and is just about to start the implementation of their automated process connecting recognition and adaptation. It would be interesting to replicate the analysis again in a few years' time, as stronger correlation between forecasts and funding can be expected due to increased use of FbA.

This study raises several additional questions, which require further research. It is crucial to understand better why the correlations between forecasts and funding are higher for certain cases and what are the contributing factors. Such research aims might be better approached using a qualitative approach that focuses on a more specific context and uses expert knowledge. More research could be based to a certain degree on the data collected for this research. For example, it could be of interest to research different clusters of countries. They could be grouped together using population density, geolocation and so forth to see if there is a bias in the system towards different clusters. It would be possible to analyze, whether there is variability between the months of funding or the origin of funding. This could answer whether funding coming from specific donating countries is provided earlier or later with regards to the forecasted food insecure period, or if there are certain time of year where the funding gap for food security is smaller. With the dataset, it is further possible to investigate to a limited degree the quality of the forecasts. Lastly, it would be important to research the interplay between risk recognition and adaptation for other risks that can be forecasted, like droughts, floods or storms.

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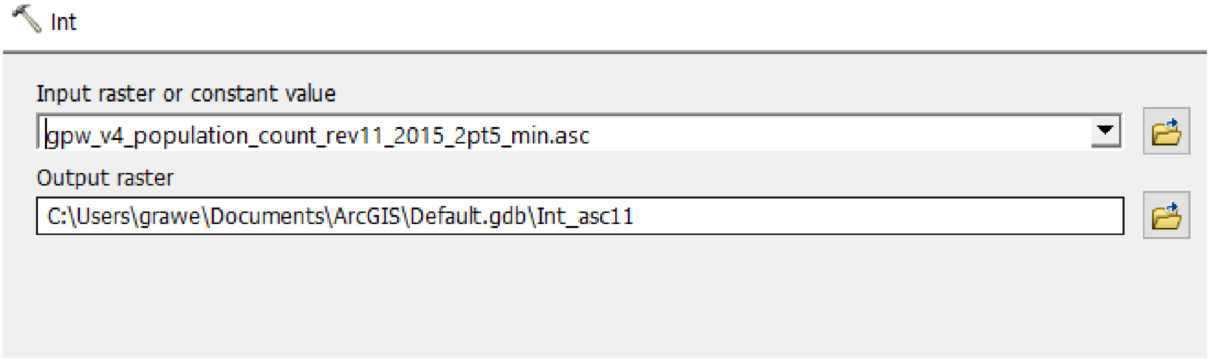
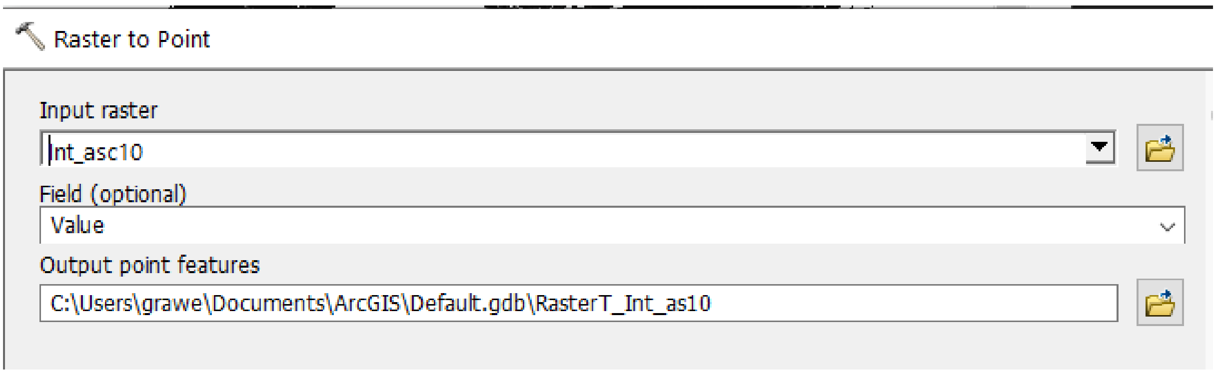
Appendix 1: Manual for ArcGIS Analysis

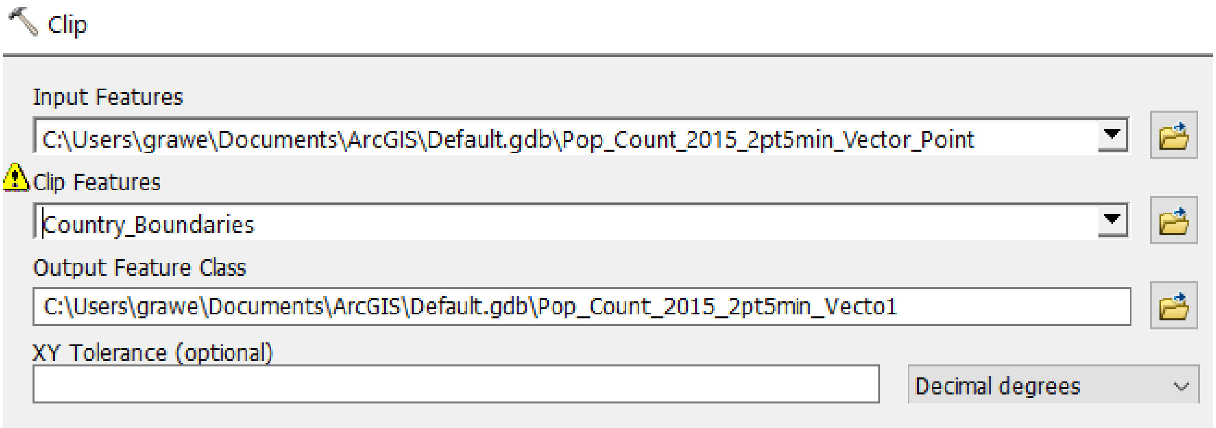
1. Select the Layer for population count 2015 with 2.5min resolution and convert to an integer raster with the tool Spatial Analyst Tools → Math → *Int*



2. Convert the new created raster layer to a point vector layer with the function *Raster to Point*

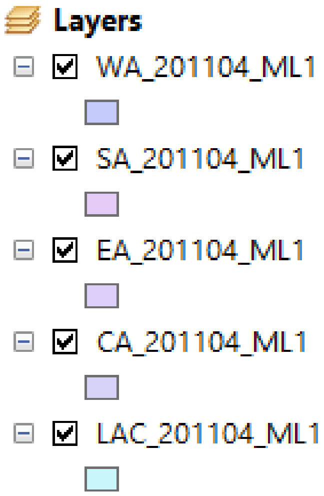


3. *Clip* the newly created layer with the country boundaries layer.

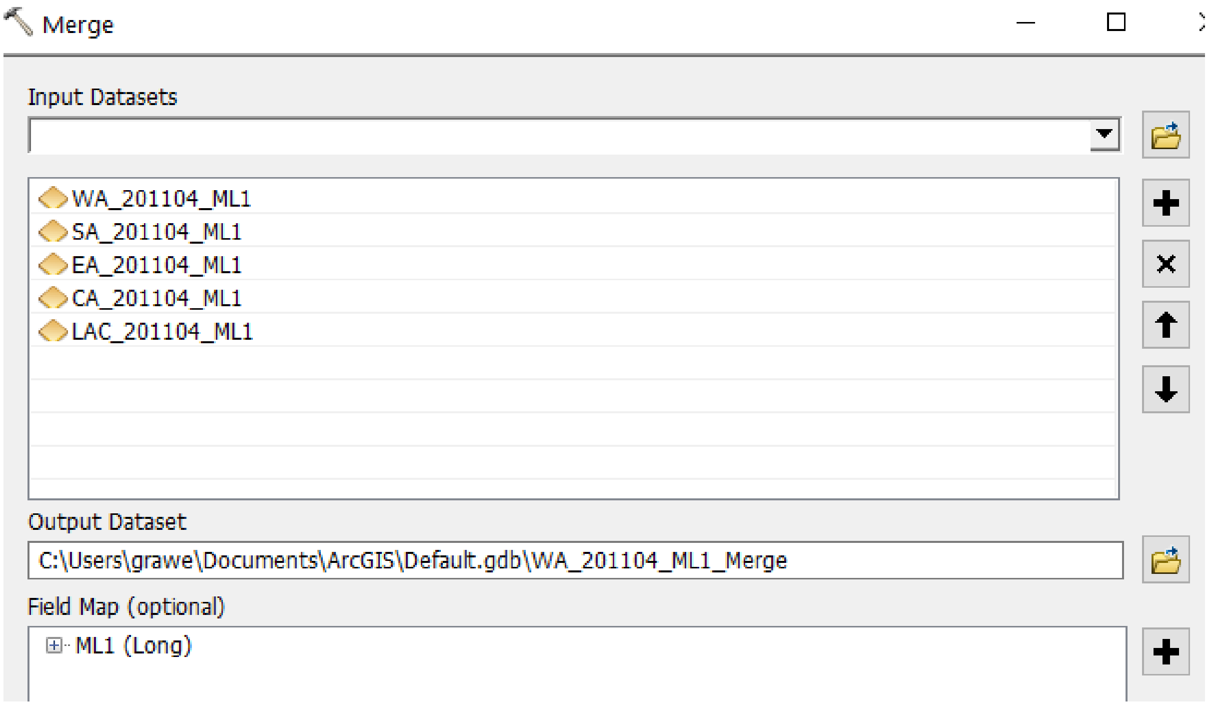


(The first three steps do not need to be repeated.)

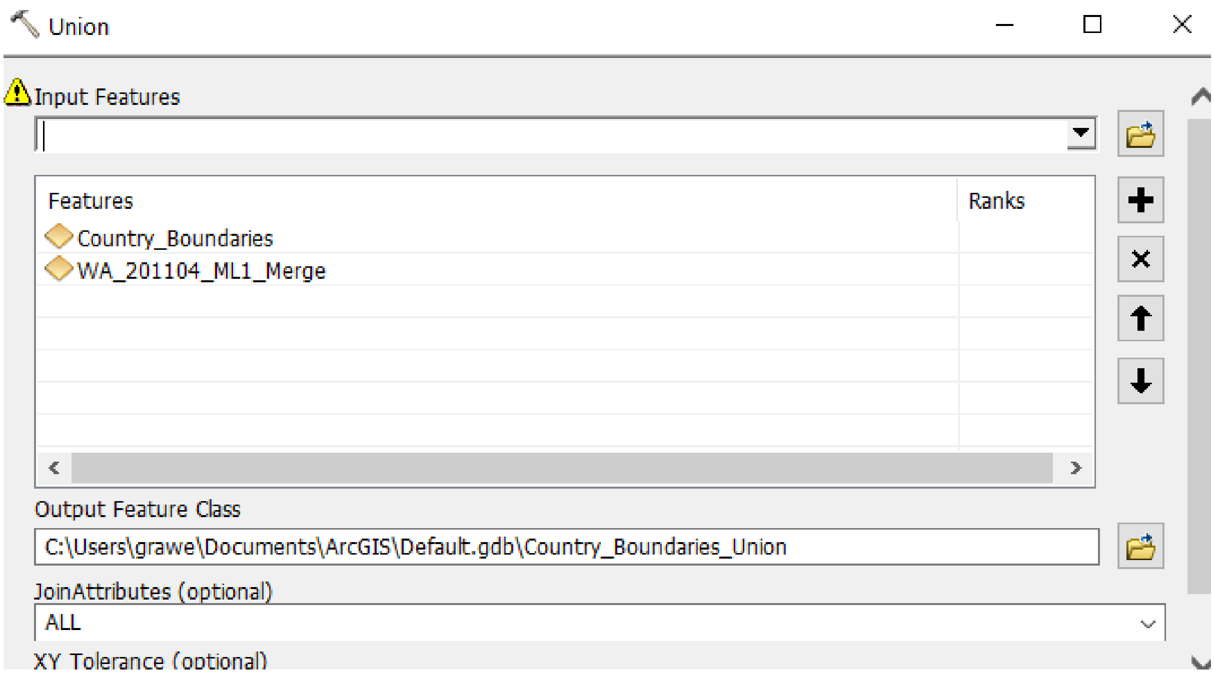
4. *Add* 5 regional layers from the same estimation time and the same time horizon (CS, ML1, ML2).



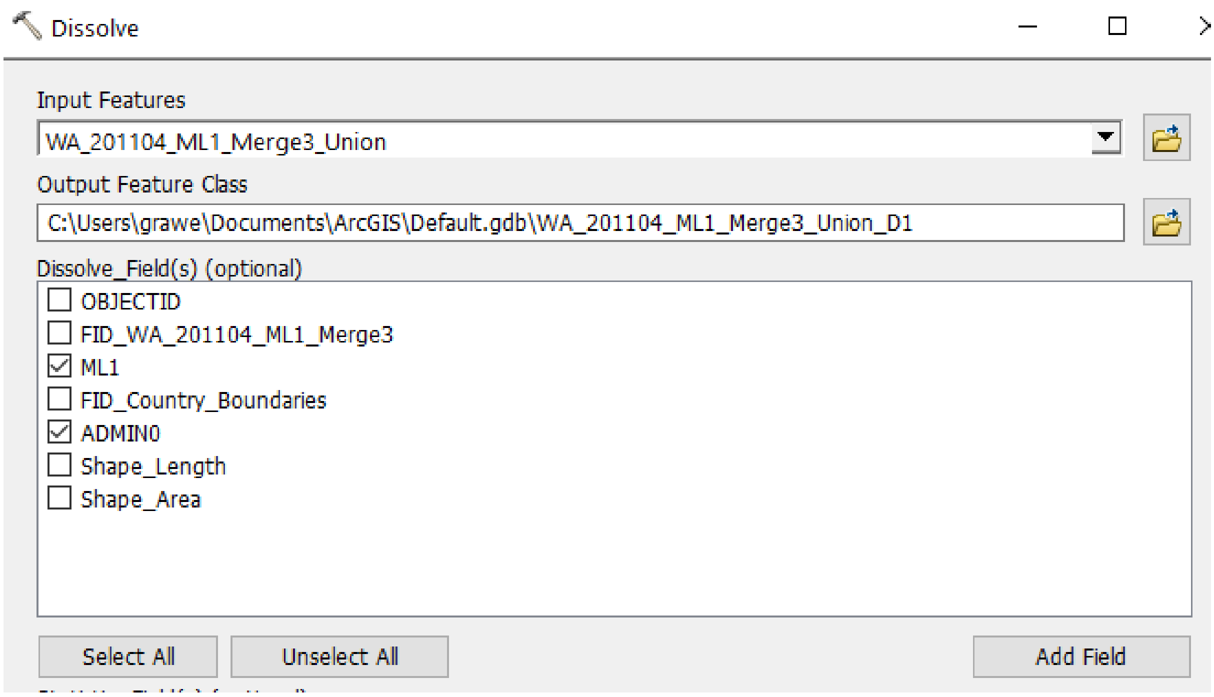
5. *Merge* these 5 layers into one layer



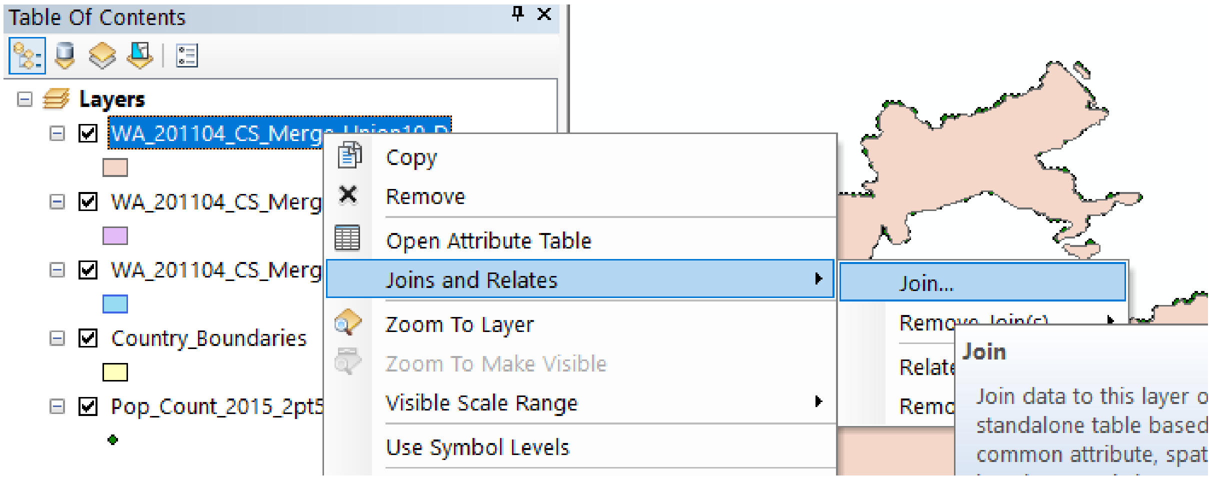
6. Make a *Union* analysis between the new created layer and the country boundaries layer.

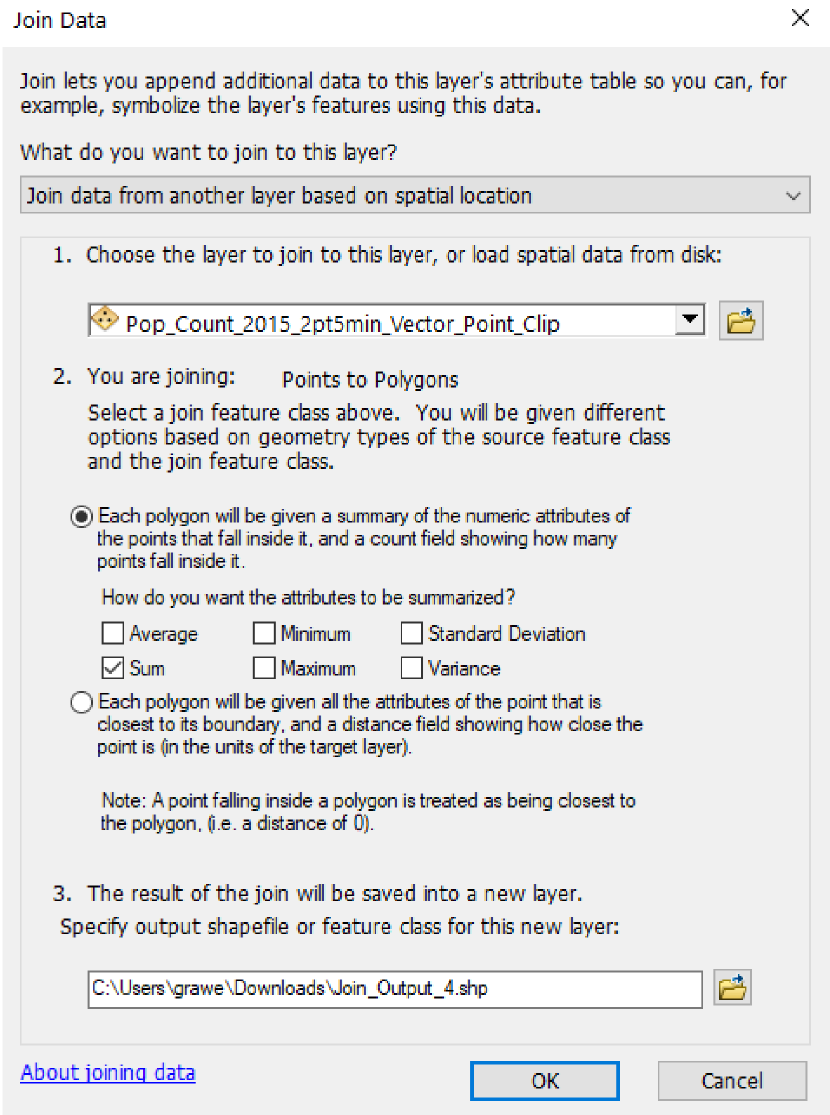


7. *Dissolve* the newly created layer by the attribute data ADMIN0 and the IPC level (CS, ML1 or ML2)



8. *Join Data* to dissolved layer through a right click on the layer and select “join…”, where the option *join form another Layer* should be selected. The other layer is the point layer of the population count, which should be summed up in a new layer, therefore select *Sum.*





9. Export with *Table to Excel* tool and give the name according to the FEWS.net system