Chapter 5

Financing agricultural drought risk through ex-ante cash transfers

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Abstract

Despite advances in drought early warning systems, forecast information is rarely used for triggering and financing early actions, such as cash transfer. Scaling up cash transfer pay-outs, and overcoming the barriers to actions based on forecasts, requires an understanding of costs resulting from False Alarms, and the potential benefits associated with appropriate early interventions. On this study, we evaluate the potential cost-effectiveness of cash transfer responses, comparing the relative costs of ex-ante cash transfers during the maize growing season to ex-post cash transfers after harvesting in Kenya. For that, we developed a forecast model using Fast-and Frugal Trees that unravels early warning relationships between climate variability, vegetation coverage, and maize yields at multiple lead times. Results indicate that our models correctly forecast low maize yield events 85% of the time across the districts studied, some already six months before harvesting. The models’ performance improves towards the end of the growing season driven by a decrease of 39% in the probability of False Alarms. Overall, we show that timely cash transfers ex-ante to a disaster can often be more cost-effective than investing in ex-post expenditures. Our findings suggest that early response can yield significant cost savings, and can potentially increase the effectiveness of existing cash transfer systems.
5.1 Introduction

In February 2018 the government of Kenya declared a national drought emergency, identifying 2.7 million people as food insecure (ReliefWeb, 2018). This emergency occurred due to a prolonged drought, leading to a cascade of events that affected the access to, and consumption of, food (FEWS NET, 2018b; ReliefWeb, 2018). Droughts can have high socio-economic impacts in Kenya, such as crop failures (Omoyo, Wakhungu, & Oteng’i, 2015; ReliefWeb, 2018), high food prices and inflation (The World Bank, 2009), and increased levels of malnutrition (Alinovi et al., 2010). One of the most vulnerable groups is smallholder farmers, who rely on rainfall for the cultivation of staple crops, and on maize production for income generation (D’Alessandro et al., 2015). Among important crops, maize is considered the main staple food of the Kenyan diet, accounting for about 65% of total staple food calorific intake (Mohajan, 2014). Therefore, increasing maize productivity and climate resilience of smallholder farming systems, and enabling them to better prepare for climate extremes, is an important issue. This critical challenge will largely determine whether Kenya succeeds in achieving the Kenya Vision 2030 development agenda (Harvey et al., 2014), and the Sendai Framework goal of substantially reducing disaster risk.

A potential way to compensate smallholder farmers’ production losses and increase their climate resilience is through weather index insurance programs, which correlate crop losses with weather parameters (Dick et al., 2011). While there has been an increased interest in such insurance products, most of these programs have failed to reach significant scale in Kenya (World Bank, 2015). Humanitarian assistance, such as the distribution of goods, food vouchers, and cash transfer (Bailey, 2012), is still an important instrument for enabling the poorest to achieve short-term goals of drought preparedness and recovery. Recently, there has been an increasing debate as to whether aid should be given to people directly in the form of cash as an alternative to traditional in-kind food aid and food vouchers (Harvey, 2007). Such cash transfers are typically less expensive to administer, and have the advantage of transferring the purchasing power to the recipients. They can therefore be effective for disaster risk financing (Kenya Red Cross, 2017; UNDP, 2015).

Among the numerous cash transfer programmes (Garcia & Moore, 2012), only a handful focus on transfers before an event occurs (ex-ante); the majority focus on transfers after an event occurs (ex-post). Therefore, cash transfer programmes for drought responses are typically based on observations after an event has taken place (Pulwarty & Sivakumar, 2014), which may result in the assistance not being in place in a timely manner. An example of ex-post cash transfers is the Kenya Hunger Safety Net Programme, which releases cash
based on an observed Vegetation Condition Index that serves as a rough proxy for drought conditions (National Drought Management Authority, 2016).

Over the past decades, new drought forecasting systems have emerged, which could pave the way towards ex-ante cash transfers. Examples are the Africa Flood and Drought Monitor (Sheffield et al., 2014), and the Famine Early Warning System (FEWS NET). Recently, there has been an emerging literature on ways to automatically trigger action based on early warning systems (Coughlan De Perez et al., 2016; Stephens et al., 2015; Suarez & Tall, 2010). For instance in 2015, based on an El Niño forecast, funds were released through the World Food Program’s Food Security Climate Resilience Facility for Zimbabwe and Guatemala (World Food Programme, 2016) to help both countries to face its consequent droughts. Despite these advances, associated uncertainties in forecast systems remain large, and the vast majority of forecast information is not routinely used as a basis for financing early action for drought risk reduction (Kellett & Caravani, 2013). Improving the understanding between the full costs of ex-ante and ex-post assistance associated with uncertainties of forecast information may influence more cost-effective ex-ante humanitarian aid. Furthermore, since agriculture employs the majority of the population in Kenya, adopting forecasting information into farmers’ decision-making may result in better forecast-based monetary policies (Anand et al., 2011), since agricultural production, prices and rainfall play an important role on inflation (Durevall, Loening, & Ayalew, 2013; Mawejje et al., 2016).

Timely finance prior to a disaster can be more cost-effective than investing in post-disaster expenditures (The World Bank, 2016a). However, assessments of the cost-effectiveness of ex-ante and ex-post cash transfers are still missing. Creating better guides to cash transfer pay-outs, while overcoming the challenges to actions based on forecasts, greatly relies on a comprehensive understanding of the costs of ‘acting in vain’ due to false alarms and model uncertainty. The overall objective of this research is therefore to compare the potential cost-effectiveness of forecast-based ex-ante cash transfers during the maize growing cycle with ex-post cash transfers made after harvesting. To the best of our knowledge, no previous studies have examined the cost-effectiveness of ex-ante and ex-post cash transfers. By doing this, we provide novel early warning information that can be useful for reducing cost and increasing the effectiveness of existing cash transfer programmes. We do this with a case study for five districts in Kenya. First, we set a forecast model using Fast-and Frugal Tree (FFT) that unravels early warning relationships between climate variability, vegetation coverage, and maize yields at multiple lead times before the maize harvesting. We then evaluate the cost-effectiveness of ex-ante...
cash transfers during the growing season prompted by the expected probabilities of low maize yield that are obtained from the FFT models, and compare these with the costs of ex-post cash transfers after harvesting.

5.2 Methods
The methodological framework used in this study involves three main steps (Figure 5.1). First, we extract monthly indicators of climate variability and vegetation coverage, to be used as predictors; and annual indicators of maize yield, to be used as predictands. The two indicators used to represent climate variability are: Net Precipitation (Np) and Oceanic Niño Index (ONI). Vegetation coverage is represented by the Normalized Difference Vegetation Index (NDVI). These three indices are obtained for each month of the maize growing season during the long-rain season (March to August). For Np, we use the cumulative sum over the growing period (one to six months prior to harvest) and for NDVI we use cumulative mean of the monthly NDVI maximum through the same period. Maize yields are obtained from an annual database produced by the Kenyan Ministry of Agriculture, Livestock and Fisheries for the period 1983-2014 (Figure 5.1, Step 1). Second, we apply the Fast-and-Frugal Tree Machine Learning algorithm (Phillips et al., 2017) to predict high/low maize yield events for each month within the growing season. FFT uses the predictors (in this case the indices of climate variability and vegetation coverage) to establish a classification between high or low values of the predictands (in this case high and low yield years) (Figure 5.1, Step 2). In summary, FFT models adopt non-compensatory algorithms that apply simple rules for making decisions based on few pieces of information (Gigerenzer et al., 1999), and offer transparent guides for practical decision problems (Phillips et al., 2017) as a competitive alternative for more complex Machine Learning methods. Third, we evaluate the cost-effectiveness of ex-ante cash transfers during the growing season prompted by the expected probabilities of low maize yield that are obtained from the FFT models, and compare these with the costs of ex-post cash transfers after harvesting (Figure 5.1, Step 3). The study area, datasets, and methods are described in more detail in the following subsections.

5.2.1 Step 1: Extract indicators from datasets

5.2.1.1 Maize yield data and study area

Annual historical maize yields (in ton/hectare) from 1983 to 2014 are based on collated reports from the Kenyan Ministry of Agriculture, Livestock and Fisheries. These yield data have been used in prior studies examining agricultural drought simulations (Davenport, Husak, & Jayanthi, 2015) and climate/development scenarios (Davenport, Funk, & Galu, 2018).
Figure 5.1 Flowchart of the methodological framework applied in this study, handled in three steps: (1) extraction of monthly indicators of climate variability, vegetation coverage and annual indicators of maize yield; (2) predictions of low maize yield years for each month within the growing season and district using Fast-and-Frugal Tree; (3) evaluation of the cost-effectiveness of ex-ante cash transfers at each month of the growing season compared with ex-post cash transfer after harvesting. Ex-ante cash transfers are considered to be more cost-effective than ex-post cash transfers in months when CBHₘ < CAH.

In this paper we focus on five districts (Figure 5.2), where the primary growing season occurs during the long-rains season, therefore planting generally occurs in early March and harvest in September (FEWS NET, 2017). In addition, these
areas are chosen because critically low annual maize yields events are often observed, as displayed in appendix Figure D1. While harvests occur in September, peak rains typically occur much earlier, in April.

From the annual data, we derive six percentiles of annual yield ($Y$), namely $Y_{15\%}$ representing the lowest 15% of annual maize yields, and $Y_{20\%}$, $Y_{25\%}$, $Y_{30\%}$, $Y_{35\%}$ and $Y_{40\%}$. For each percentile, we classify annual maize yields as “below yield threshold” (when they are below the defined percentile) and “above yield threshold” (when they are above the defined percentile). An overview of the annual maize yields and the six percentiles per district is shown in appendix Figure D1.

![Figure 5.2 Map of Kenya and districts examined in this study.](image)

5.2.1.2 Climate variability and vegetation coverage indicators

In this study, we represent climate variability using ONI and cumulative Np indicators, and vegetation coverage using NDVI.

5.2.1.2.1 El Niño Southern Oscillation

We use the Oceanic Niño Index (ONI) from 1983–2014 (NOAA, 2017a) to represent the El Niño Southern Oscillation (ENSO). ONI is a three-month running mean of sea surface temperature anomalies in the Niño 3.4 region using centred 30-year base periods updated every 5 years. This index is calculated based on a moving average of three-months. The ONI record in March, for instance, is the mean value observed in February, March and April.
While some authors have suggested weak links between Kenyan boreal spring rains and ENSO (Lyon, 2014), FEWS NET studies have shown that a predictable La Niña drought impact has arisen due to human induced warming in the Western Pacific (Funk et al., 2014; Funk et al., 2018; Shukla, Funk, & Hoell, 2014).

5.2.1.2.2 Cumulative Net Precipitation

We use the difference between monthly precipitation (P) estimates from the Climate Hazards group Infrared Precipitation with Stations (CHIRPS), and the reference evapotranspiration (E) to calculate the Net Precipitation (Np) indicator for 1983-2014. CHIRPS is a quasi-global (50°S-50°N), high resolution (0.05°), daily, pentad (five-day rainfall), and monthly precipitation dataset, which was created to support the drought early warning system FEWS NET (Funk et al., 2015). The CHIRPS dataset is freely available online at the CHIRPS website. The reference evapotranspiration product is a multi-scalar measure of anomalous atmospheric evaporative demand, which captures signals of water stress (in mm) at weekly to monthly timescales. This product can be used as a tool for preparedness planning for both flash droughts and ongoing. The cumulative Np indicator (Equation 5.1) is calculated at the district level d, and within each month of the maize growing season m (from March to August):

\[
Np_{i,m,d} = \sum_{i=1}^{6} P_{i,m,d} - \sum_{i=1}^{6} E_{i,m,d}
\]

Equation 5.1

where \( i \) represents a time window accumulation that varies from 1 to 6 months. For instance, an \( Np_{6,August,Laikipia} \) represents the 6 month cumulative Net Precipitation observed from March until August at the district of Laikipia.

5.2.1.2.3 Cumulative Normalized Difference Vegetation Index (NDVI)

For the same period (1983-2014), we use cumulative mean of NDVI maximum values over the growing season (Equation 5.2), as a proxy to measure the physiologically functioning surface greenness level of a region (Myneni et al., 1995). The NDVI dataset generated from NOAA’s Advanced Very High Resolution Radiometer has an 8 kilometre resolution, and can be used to monitor vegetation changes at different spatial scales (Pinzon, Jorge E and Tucker, 2014). We use the version termed NDVI3g, and obtained data from https://ecocast.arc.nasa.gov/data/pub/gimms/.
\[
\sum_{i=1}^{6} NDVI_{i,m,d}
\]

Equation 5.2

The monthly mean of NDVI maximum indicator is accumulated at the district level \(d\), within each month of the maize growing season \(m\), where \(i\) represents a time window applied for accumulation, similarly as described for the Np indicator.

5.2.2 Step 2: Fit Fast-and-Frugal Tree (FFT) for a month \(m\) and obtain probabilities

FFT model is a simple algorithm that establish rules for making efficient and accurate decisions based on limited information (Gigerenzer et al., 1999; Phillips et al., 2017). Such models seldom over-fit data (Phillips et al., 2017), and are easier to interpret and psychologically more plausible to internalise (Keller et al., 2010) than other Machine Learning methods (Luan, Schooler, & Gigerenzer, 2011). We use FFT to predict classes of maize yields as a function of the indices of climate variability and vegetation coverage (Np, ONI, NDVI described in ‘Climate variability and vegetation coverage indicators’ section). In heuristic decision-making, FFT is a supervised learning algorithm that is used for classifying cases (e.g. maize yield) into two classes (in this case below or above yield threshold) based on particular predictors.

As displayed in appendix Figure D2, the structure of an FFT model determines the exact number and sequence of predictors that are applied to reach a final classification (Gigerenzer et al., 1999; Gigerenzer & Todd, 1999). FFT uses a maximum of five cues, meaning that a five-cue decision tree is based on the best five performing indices out of the total number of climate variability and vegetation coverage indicators accumulated for each respective month, as displayed in Table 5.1. The selection of the five best performing indices for each particular month, district and maize yield percentile is based on their marginal weighted accuracy (WACC), which is further described in the paragraph below. Therefore, FFT uses non-compensatory algorithms, which include only a limited subset of all predictors for establishing a binary decision. Non-compensatory algorithms are designed to ignore information, because once a decision is completed based on the selected predictors, no additional predictors can change the decision (Phillips et al., 2017). This characteristic is considered to have both practical and statistical advantages over compensatory algorithms, such as regression models. First, given that FFT models use a subset of predictors, the decision trees can perform better in predicting unseen data,
thus they tend to be robust against overfitting. Second, FFT algorithms use information in specific and sequential order, which can guide decision makers in collecting information and assist in decision tasks (Phillips et al., 2017).

The FFT algorithm is designed to learn from, and make predictions on, data. FFT is fitted to a training dataset, which is used to derive the parameters of the model. The FFT algorithm is constructed as follows: a) select predictors; b) determine a decision threshold for each predictor; c) determine the order of predictors; and d) determine the exit for each predictor, which by definition, FFT must have either a negative or a positive exit (or both in the case of the final decision node) (Phillips et al., 2017). The FFT models are then tested using an independent testing dataset. In order to select trees that identify “below yield threshold” rather than “above yield threshold” cases, we set the Sensitivity Weighting Parameter \( w \) to \( w=0.75 \), using the `ifan` algorithm, which is described in detail by Phillips et al. (2017). Sensitivity Weighting Parameter determines the overall value of WACC of the FFT, and the WACC measures how well the algorithm balances correct decisions. In summary, the `ifan` decision algorithm tests several different thresholds of the predictors to identify the one that maximizes the predictor’s accuracy. Consequently, once the set of FFT is created, `ifan` selects the tree with the highest weighted accuracy. For clarification, it is important to notice that the value of \( w \) parameter does not change how the set of FFT is constructed, but rather, it changes which specific tree in the set of FFT is selected (Phillips et al., 2017). We performed an additional sensitivity analysis on the WACC index by assigning similar weight when identifying below yield threshold and above yield threshold cases, thus setting \( w=0.5 \).

We analyse the performance of the FFT models to predict classes of “below yield threshold” and “above yield threshold” using Receiver Operating Characteristic (ROC) (Metz, 1978). ROC is a graphical plot (appendix Figure D3) that illustrates the performance of a binary classifier system (Zweig & Campbell, 1993). The ROC index varies between 0 and 1, where perfect and random predictions have values of \( \text{ROC}=1.0 \) and \( \text{ROC}=0.5 \), respectively (Hamill & Juras, 2006). We calculate the ROC index using the trapezoidal rule, and test the predictive skill of the FFT models using leave-one out cross validation, further described in appendix D4. We use this cross validation method since: a) it is highly recommended for small sets of training data; and b) it can be used with any kind of predictive modelling, including discriminant analysis such as decision trees (James et al., 2013).
Table 5.1 Description of accumulation periods for each variable and total number of predictors considered in each month. From April onwards, we included predictors of current and previous months. Therefore, FFT models in April take information from March if any predictor registered in the latter had a higher marginal weighted accuracy WACC value than predictors observed in April. FFTs use a maximum of five predictors.

<table>
<thead>
<tr>
<th>Month</th>
<th>March</th>
<th>April</th>
<th>May</th>
<th>June</th>
<th>July</th>
<th>August</th>
</tr>
</thead>
<tbody>
<tr>
<td>Np₁</td>
<td>M</td>
<td>A</td>
<td>M</td>
<td>J</td>
<td>J</td>
<td>A</td>
</tr>
<tr>
<td>Np₂</td>
<td>FM</td>
<td>MA</td>
<td>AM</td>
<td>MJ</td>
<td>JJ</td>
<td>JA</td>
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<tr>
<td>Np₃</td>
<td>JFM</td>
<td>FMA</td>
<td>MAM</td>
<td>AMJ</td>
<td>MJJ</td>
<td>JJA</td>
</tr>
<tr>
<td>Np₄</td>
<td>DJFM</td>
<td>JFMA</td>
<td>FMAM</td>
<td>MAMJ</td>
<td>AMJJ</td>
<td>MJJA</td>
</tr>
<tr>
<td>Np₅</td>
<td>NDJFM</td>
<td>DJFMA</td>
<td>JFMAM</td>
<td>FMAMJ</td>
<td>MAMJJ</td>
<td>AMJJA</td>
</tr>
<tr>
<td>Np₆</td>
<td>ONDJFM</td>
<td>NDJFMA</td>
<td>DJFMAM</td>
<td>JFMAMJ</td>
<td>FMAMJJ</td>
<td>MAMJJJA</td>
</tr>
<tr>
<td>NDVI₁</td>
<td>M</td>
<td>A</td>
<td>M</td>
<td>J</td>
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<td>A</td>
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<tr>
<td>NDVI₂</td>
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<td>MA</td>
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<tr>
<td>NDVI₅</td>
<td>NDJFM</td>
<td>DJFMA</td>
<td>JFMAM</td>
<td>FMAMJ</td>
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<td>AMJJA</td>
</tr>
<tr>
<td>NDVI₆</td>
<td>ONDJFM</td>
<td>NDJFMA</td>
<td>DJFMAM</td>
<td>JFMAMJ</td>
<td>FMAMJJ</td>
<td>MAMJJJA</td>
</tr>
<tr>
<td>ONI</td>
<td>FMA</td>
<td>MAM</td>
<td>AMJ</td>
<td>MJJ</td>
<td>JJA</td>
<td>JAS</td>
</tr>
<tr>
<td>Total number of predictors</td>
<td>13</td>
<td>26</td>
<td>39</td>
<td>52</td>
<td>65</td>
<td>78</td>
</tr>
</tbody>
</table>

For each FFT model where the ROC is higher than 0.5, we analyse standard classification statistics such as probabilities of Hits (H), False Alarms (FA), Correct Rejections (CR), and Misses (MS). Their definitions and formulae are given in appendix Table D5. In summary, we obtain FFT model for each particular month within the growing season, each district, and each percentile level of annual yield, through the following steps:

1. Ranking and selecting 5 best predictors based on their marginal WACC, for each district, maize yield percentile, and month;
2. Pruning decision trees by cross-validating the FFT model using leave-one out cross validation, further described in appendix D4;
3. Calculation of the ROC index;
4. Analysis of the performance of the cross-validated FFT model by calculating standard classification statistics, as displayed in appendix Table D5.

From April onwards, we include maize predictors of the current and previous months. For instance, when fitting FFT model in April, information from March was also taken into consideration if any predictor registered in March had a higher marginal WACC value than predictors observed in April. After following these steps, we build a new FFT using all the dataset and adopting the pruning parameter that maximizes the WACC index. Hence, this procedure enables us to suggest the set of predictors which are most important for each district, lead time and yield percentile.

5.2.3 Step 3: Cost-effectiveness analysis

We use a simple methodology to assess the cost-effectiveness of cash transfers. In humanitarian response, early action aims to provide short-term resources for emergency situations. Therefore, the aim of this cash transfers is to prevent populations from becoming undernourished, from slipping below the limit of the mean Human Energy Requirement (HER) in seasons with low yields. HER is defined as “the amount of food energy needed to balance energy expenditure in order to maintain body size, body composition and a level of necessary and desirable physical activity consistent with long-term good health”(Pacetti, Caporali, & Cristina, 2017). The HER depends on individual characteristics such as age, sex, body weight and lifestyle, and according to FAO a mean HER is approximately 3,000 kcal/cap/day (Pacetti et al., 2017; World Health Organization, 2004).

We define a household energy loss value by the difference between the predicted low maize yield transformed into calories, and the HER mean per capita. Therefore, the expected cost of cash transfer (hereafter ECT) is defined by the amount of calories (multiplied by price levels, see Figure 5.1 step 3 and appendix Figure D1) needed to supply a household calorific deficit in comparison to the HER mean threshold. The expected total cost of cash transfer determines the least costly (hence most cost-effective) month for initiating cash transfer. The expected cost of cash transfer before harvesting (hereafter CBH\textsubscript{m}) takes into account the probability of Hits and False Alarms in a month \textit{m} (equation 5.3), while the expected cost of cash transfer after harvesting (hereafter CAH) considers 100% and 0% probabilities of Hits and False Alarms, respectively (equation 5.4). Therefore, CAH is defined as the total expected cost
of the cash transfers only. A cash transfer is considered to be cost-effective before harvesting in months when $\text{CBH}_m < \text{CAH}$.

\[
\text{CBH}_m = P(\text{Hits}_m) \times \text{ECT}_m + P(\text{False Alarms}_m) \times \text{ECT}_m \quad \text{Equation 5.3}
\]

\[
\text{CAH} = \text{ECT} \quad \text{Equation 5.4}
\]

In more detail, we set the cash transfers as the total costs involved in compensating low maize yields (in monetary values) to fulfill the calorific deficit of a group of smallholder farmers (equation 5.5). In this study, the total costs of the cash transfer depend on: a) total number of households that the cash transfer aims to support ($\text{NH}$); b) total amount of maize per household needed to reach the HER mean threshold ($\text{NM}$); and c) monthly maize price ($\text{MP}_m$). For simplicity, we do not take into consideration administrative costs of ex-ante and ex-post cash transfers. Occasionally funding can be spent to “act in vain”, as the result of a false alarm. To compute the total expected costs of this action, cash transfers are considered to be irreversible once disbursed, and therefore the costs associated with False Alarms are equal to those associated with Hits.

\[
\text{ECT}_m = \text{NH} \times \text{NM} \times \text{MP}_m \quad \text{Equation 5.5}
\]

We use wholesale monthly price records from Nairobi between 2000 and 2017 from the FEWS NET data warehouse to calculate monthly mean maize prices between March and August. Prices are deflated to February 2009 values using a consumer price index generated by the Kenyan National Bank. We fit a linear model between deflated annual Nairobi prices in September and annual maize yields. When this relationship is significant ($p$-value$<0.05$), we use this model to determine maize prices based on yields. When not significant, we assume that prices in September ($P_s$ or $\text{MP}_9$) vary proportionally to the low maize yield percentile ($Y_p$) being investigated (appendix Figure D6.2) and described in equation 5.6. Lastly, we consider that maize prices within the growing season ($P_i$) follow their observed respective monthly mean ($\bar{P}_i$), as described in equation 5.7

\[
P_s = -1 \times Y_p + 100 \quad \text{Equation 5.6}
\]

\[
\bar{P}_i = \frac{\sum P_i}{N} \quad \text{Equation 5.7}
\]

Where $i$ represent months 3 (March or $\text{MP}_3$) to 8 (August or $\text{MP}_8$), and $N$ represents the length of the price time series in years. In addition, we assess the sensitivity of the cost-effectiveness analysis by adopting four different rates of variations in September prices for the districts where prices at harvesting are assumed to be conditioned to maize supply (appendix D7).
In order to calculate the amount of calories available per household per year, we consider that: 100g of maize has 365 kcal (United States Department of Agriculture, 2016); the mean size of a household in the Rift Valley in Kenya is 4.6 persons (Munene, 2003); each household owns one hectare of land for farming; and the total number of households granted with cash transfer is 1000 per district. Therefore, for each of the six investigated percentiles of maize yield, we transform tonnes/hectare/year into kcal/household/year. In addition, we also assume that cash transfers do not create a disincentive to work, and beneficiaries do not cease maize production. This assumption was previously suggested by the Food and Agriculture Organization of the United Nations, where an investigation (Food and Agriculture Organization, 2016) concluded that cash transfer programmes were linked to increased livelihood activities of farmers. An illustration of the cost-effectiveness analysis is found in Figure 5.1 (step 3).

5.3 Results

5.3.1 Obtaining probabilities using FFT models

In Figure 5.3, we present the performance of the tested FFT models in predicting true low maize yield events (Hits probabilities are highlighted in blue), and false low maize yield events (False Alarms probabilities are highlighted in yellow) per district, for the six low maize yield percentiles and the different lead times before harvesting. We predict high/low maize yield events for each month within the growing season (March to August), which represent six lead times. The spatial distribution of the probabilities of Hits and False Alarms are available in appendix D8. Overall, the performance of the FFT models improve with shorter lead times as a result of reduced probability of False Alarms, and consequently increased probability of Correct Rejections. The FFT models have skill (ROC>0.5) in predicting annual high/low maize yield in all districts. For most models some skill already exists six months before the harvesting season (on average ROC=0.63) despite the high probabilities of False Alarms at this lead time. The WACC index, which measures how well the algorithm balances correct decisions, exhibits the highest value among districts and yield percentile levels in July (lead time 2 months), and the lowest in March (lead time 6 months). Among all models with predictive skill, lead times, and yield percentiles, the district of West Pokot has, on average, the highest WACC and ROC (0.81 and 0.73, respectively) driven specially by the high probabilities of Hits in this district; and on average the district of Nyandarua has the lowest WACC (0.72), as shown in appendix Figure D9. Across different yield percentiles, districts, and lead times, the mean probability of Hits is 85%. Results of the sensitivity analysis are available in appendix Figure D10.1. When adopting a
different weight parameter (w=0.5 instead of w=0.75), the performance of the FFT models improves with shorter lead times as a result of reduced probability of False Alarms. Among lead times, percentiles and districts, the probability of Hits is, on average, 66%. Overall, the probabilities of False Alarms and Hits are, on average, lower compared to those obtained when w=0.75. The best performing predictors of maize yield per district, and their respective thresholds, are shown in the appendix Table D11.

In March and April, six and five months before the maize harvesting season in Kenya, the FFT models have predictive skill (ROC>0.5) for most districts and yield percentiles (Y). Exceptions are for percentiles $Y_{15\%}$ and $Y_{25\%}$ in Baringo, $Y_{20\%}$ in Narok, and $Y_{40\%}$ in Nyandarua during lead time 6, and for $Y_{20\%}$ in Baringo, $Y_{30\%}$ and $Y_{35\%}$ in Nyandarua during lead time 5 (Figure 5.3). On average, the probability of Hits for the different maize yield percentiles is 84% and 86% for lead times of 6 and 5 months, respectively, while the probability of False Alarms is 56% for both of these lead times. The mean probability of Misses for the different maize yield percentiles is 16% and 14% for lead times of 6 and 5 months respectively, while the mean probability of Correct Rejection is 44% for both of these lead times. The most important predictor for FFT models in these two lead times is Net Precipitation five in March ($N_{p5,March}$). In other words, the FFT models mostly use the difference between cumulative five months precipitation and reference evapotranspiration observed in months previous to sowing (March) for classifying between above and below yield threshold. Such results demonstrate that initial soil conditions play an important role during the emergence and establishment of maize growth, and in the vegetative development (approximately 60 days after sowing (Barron et al., 2003)), when higher moisture levels benefit yields (FAO, 2017; Mati, 2000).

In May and June, four and three months before the maize harvesting season in Kenya, the FFT models also have predictive skill for most districts and percentiles. Exceptions are for $Y_{30\%}$, $Y_{35\%}$ and $Y_{40\%}$ in Narok, $Y_{30\%}$ and $Y_{35\%}$ in Nyandarua during lead time 4, for $Y_{30\%}$ in Laikipia, and $Y_{15\%}$ in Narok during lead time 3 (Figure 5.3). Compared to the two antecedent months (March and April), the probability of False Alarms remains high on average in May (56%), and lower in June (47%). The probability of Hits, on average, remains high (86% and 83%) in May and June, respectively. In May and June, the FFT models predict maize percentiles $Y_{15\%}$, $Y_{20\%}$ and $Y_{25\%}$ using the Net Precipitation variability accumulated from previous and post maize planting date, such as $N_{p5,March}$, $N_{p6,April}$, and $N_{p4,May}$. Other predictor that is often used is the Normalized Difference Vegetation Index (NDVI) such as NDVI$_{3,April}$ and NDVI$_{5,June}$. Next to the climatic predictors of maize yield also suggested by others (Estes et al., 2014;
Funk & Verdin, 2010; Shi & Tao, 2014), the NDVI index was also found to be a predictor for maize yields in previous studies (Lewis, Rowland, & Nadeau, 1998; Rojas, 2007). For predicting below yield threshold/above yield threshold maize percentiles $Y_{30\%}$, $Y_{35\%}$ and $Y_{40\%}$, FFT models mostly used $Np_{5,March}$ in combination with other intra-seasonal indices of climate variability and vegetation coverage, such as the Oceanic Niño Index (ONI) in April and NDVI$_{5,June}$. Both El Niño and NDVI indicators have also been highlighted as predictors of maize yield in other studies (Amissah-Arthur, Jagtap, & Rosenzweig, 2002; Lewis et al., 1998; Rojas, 2007). The most damaging crop water deficits arise during these lead times (maize reproductive stage), when the cereal plants switch from growing leaves to growing grains (Funk & Verdin, 2010), and midseason water deficits can drastically reduce maize yields (Senay & Verdin, 2003). Even though the climatological conditions during the vegetative growth period are relevant, conditions during the reproductive growth period influence yields more directly (Iizumi, Yokozawa, et al., 2014). This may explain the improved performance of FFT models during lead time 3 months (maize reproductive growth stage), which uses intra-seasonal information of indices of climate variability and vegetation coverage observed in June to predict maize yield percentiles.

In July and August, the FFT models have predictive skill in all districts and percentiles, except for $Y_{15\%}$ in Narok (Figure 5.3, lead time 2). Compared to the previous two months of May and June, the performance of the FFT models improves slightly. On average, the mean probability of False Alarms is lower (44% and 40% in July and August, respectively), and Hits, on average, remains high (87% and 83%). For predicting below yield threshold/above yield threshold maize percentiles $Y_{15\%}$, $Y_{20\%}$ and $Y_{25\%}$, the FFT models mostly use indicators that include observations from June and July such as NDVI$_{5,June}$ and $Np_{2,July}$ and $Np_{6,July}$, while FFT models mostly predict below yield threshold/above yield threshold maize percentiles $Y_{30\%}$, $Y_{35\%}$ and $Y_{40\%}$, using $Np_{5,March}$, NDVI$_{5,June}$ and $Np_{2,July}$. At these lead times, maize reaches its grain filling and drying stages (Barron et al., 2003), and late season soil water deficits after the grain biomass accumulation is complete may lead to higher yields (Funk & Verdin, 2010). Very high accumulated levels of precipitation in June and July may cause maize yields to decline due to the high likelihood of diseases, insects, and mould infestation, which are favourable when such conditions are observed (Funk & Verdin, 2010). Furthermore, maize yield in the investigated districts is linked to other seasonal indices of climate variability and vegetation coverage and to accumulated rainfall and soil moisture conditions prior to the maize-planting season.
3.2 Cost-effectiveness of cash transfers

3.2.1 Cost-effectiveness of cash transfer assuming a perfect forecast

In Figure 5.4, we display the cost-effectiveness analysis of cash transfers assuming a perfect forecast skill within the growing season from March to August. Therefore, for this analysis we assume that the probability of Hits and False Alarms is 100% and 0%, respectively. (H=100% and FA=0%). Thus, in this case the cost-effectiveness is solely based on maize price variations. We only carried out a cost-effectiveness analysis for districts and maize yield percentiles.
for which the calories/household/year fall below the Human Energy Requirement mean threshold (section Methods section and appendix Figure D1) (boxes in Figure 5.4 that are not blank). For all of the 17 cases for which this is the case, we find that cash transfers assuming a perfect forecast skill are most cost-effective at a lead time of 6 months. This is due to lower mean maize price in March compared to September. In the appendix Figure D6.1 and D6.2, we display the pricing models used in the districts for the month of September, and average monthly maize prices adopted for months between March and August. This shows that during the growing season, mean prices are relatively low in March, and highest in June.

3.2.2 Cost-effectiveness of cash transfer using probabilities from FFT models

In Figure 5.5, we present the results of the cost-effectiveness analysis using the probabilities of Hits and False Alarms obtained from the FFT models per district, lead time, and maize yield percentile. These probabilities are available in Figure 5.3. Overall, in 11 out of the 17 cases tested, cash transfers are cost-effective (CBH < CAH) for at least one of the lead times before harvesting.

In addition, in Figure 5.5, we show that for Y_{15\%} in all districts there is at least one lead time for which the expected cost of ex-ante cash transfers is lower than ex-post cash transfers, while for Y_{20\%} ex-ante cash transfer is more cost effective in 3 out of 4 districts. Ex-ante cash transfers are often cost-effective when the probability of a False Alarms is below 50%, and when prices during the growing season are lower than prices in September. Cash transfer costs ex-ante for Y_{15\%} and Y_{20\%} can be, on average, 29% and 14% lower than ex-post cash transfers in September, respectively.

Ex-ante cash transfers during the growing season are also estimated to be more cost-effective for Y_{25\%} and Y_{30\%}. In Laikipia and Nyandarua districts (Figure 5.5), the expected costs of ex-ante cash transfers are 5% and 2% lower than those associated with ex-post cash transfers, respectively. This is attributed to a combination of low probabilities of False Alarms (below 13%), and low mean prices during the growing season compared to September. However, the number of months with cost-effective ex-ante cash transfers decreases when comparing Y_{25\%} and Y_{30\%} to those found in Y_{15\%} and Y_{20\%}. For Y_{35\%} we found ex-post cash transfers to be more cost-effective than ex-ante. This is because the assumed price of maize in September, when a maize supply of Y_{35\%}, is below the monthly average from May and July (appendix Figure D6.2). Consequently, cost-effective ex-ante cash transfers would only be possible in March, April and August if there is a low probability of a False Alarms. However, the additional
costs driven by high probability of a False Alarms in March, April and August resulted in cash transfers being more cost-effective ex-post.

Figure 5.4 Total expected cost of cash transfer per district, for different lead times and maize yield percentiles, assuming a perfect forecast before harvesting from March to August. Therefore, the probabilities of Hits and False Alarms are 100% and 0%, respectively. Yellow dots show all lead times before harvesting (starts in September) for which expected cost of cash transfer is lower than the expected cost of cash transfer after harvesting (CBH < CAH); black dots show the opposite. The most cost effective lead time is highlighted in grey. Boxes are blank when the maize yield percentile for the specific district is higher than the mean human energy requirement (3,000 kcal/day/person), and therefore no cash transfer is required.
In addition, we assessed the sensitivity of the results using two moderate (Figure 5.6A an 5.6B) and two conservative (Figure 5.6C and 5.6D) scenarios of September prices for the districts where prices at harvesting are assumed to be conditioned to maize supply (Laikipia, Nyandarua, West Pokot). A more detailed illustration is available in appendix Figure D7.1 and D7.2. We show that when adopting price scenarios 1-3, there is at least one lead time for 17 out of the 36 tested cases (boxes that are not blank in Figure 5.6A-5.6C) for which cash transfers are more cost-effective ex-ante. When considering price scenario 4, we still find some lead times for which the ex-ante cash transfers are expected
to have lower costs than ex-post cash transfers. Therefore, despite prices variations, we show that ex-ante cash transfers can often be more cost-effective than ex-post cash transfers, especially for the more extreme yield deficits.

Figure 5.6 Sensitivity analysis of total expected cost of cash transfer testing four rates of change in $P_s$ (price) for change in $Y_p$ (maize yield), per district, lead time, and maize yield percentile. Yellow dots highlight all lead times before harvesting when expected ex-ante costs of cash transfer are lower than the expected ex-post costs of cash transfer ($CBHm < CAH$); black dots show the opposite. The most cost effective lead time is highlighted in grey. Boxes are blank when the maize yield percentile for the specific district is higher than the mean human energy requirement, and therefore cash transfer is not triggered. Results are shown only for models with ROC>0.5.

### 5.4 Discussion

#### 5.4.1 Current practices and challenges of cash transfer operationalization
In our study, we show that despite model uncertainties and prices variations, ex-ante cash transfers can often be more cost-effective than ex-post cash transfers, especially for the more extreme yield deficits. Even though studies on the cost-effectiveness of early action are very limited, some suggest that early response can yield significant cost savings (Venton, 2018; Wilkinson et al., 2018). For instance, in 2015 a FoodSECuRE Cost Benefit Analysis (ex-ante) in Sudan and Niger suggested that early actions based on a forecast mechanism could reduce the cost of emergency response by approximately 50 percent compared to ex-post responses (World Food Programme, 2016).

Our results could potentially increase the efficacy and efficiency of existing cash transfer systems. Currently, the Kenya Hunger Safety Net Programme triggers two types of cash transfers (standard and emergency payments) based on a single satellite vegetation condition index (VCI). Neither of these cash transfer types depend on field assessment, and emergency payments are made monthly in any Sub-County when the VCI hits the scale up threshold (from moderate to extreme drought), and payments are suspended when the threshold is no longer reached for that month (National Drought Management Authority, 2016). The use of a single drought indicator may not provide a comprehensive assessment of drought impact, and can occasionally trigger payments in situations where drought conditions are not evolving (National Drought Management Authority, 2016). The National Drought Management Authority could potentially improve the reliability of cash transfers and anticipate pay-outs by including other drought early warning indicators, such as the ones adopted in this investigation.

Furthermore, when different drought severity levels are observed in pre-selected areas, fixed emergency cash transfers of 2,550 Ksh (approximately 25 US$) are payed in addition to standard payments that are given monthly to households. This emergency payment aims to support the increased needs that households may experience during a drought period. However, establishing a fixed amount of cash in order to respond to different drought severity levels does not fully account for different needs that may arise during a drought, especially the more severe ones. Establishing payments of cash that vary based on forecasts of different agricultural drought levels, such as proposed in this study, may be more efficient in achieving households’ dietary diversity and reducing malnutrition rates.

In addition, the Kenyan National Drought Management Authority holds the National Drought Contingency Fund (NDCF), which receives contributions from the government of Kenya and multi-donors, with the capacity to disburse funds to drought-prone affected districts in a flexible way (National Drought
Management Authority, 2016). This fund enables fast drought early responses in all districts based on drought early warning information and contingency plans. To enable fast triggering and scalability, efficient budget allocation within lead times while avoiding fund depletions, a set of evidence-based mechanisms should be in place based on drought forecasts. Therefore, impact-based forecast information and cost-effectiveness analysis, such as developed in this study, could support a more timely pooling and distribution of resources, and consequently a more efficient management of the NDCF.

Multiple challenges can be observed for operationalizing cash transfers based on indicators of droughts. Taking actions in response to early warnings of drought risks based on indices requires an in-depth understanding of the potential impact, scale, aid-triggering thresholds, severity and timing of a disaster (Wilkinson et al., 2018). Operationally, cash transfer programs can be unconditional, meaning that they aim to reduce poverty by providing cash independent of the receiver’s actions; or conditional, meaning that receivers must make pre-specified investments.

Most emergency drought response systems use unconditional cash transfers, which often have a lower cost per beneficiary compared to other interventions such as vouchers and in-kind food (Doocy & Tappis, 2017). However, cash transfer is not always a suitable option, especially when the local economy is isolated from other markets, in which case an inflow of cash can increase prices (Cunha, De Giorgi, & Jayachandran, 2019). Furthermore, beneficiaries of the program must be aware of the predicted drought threats in order to spend cash wisely (National Drought Management Authority, 2016). Therefore, cash transfer programs could benefit from information on individual preferences regarding the timing and expenditure of cash transfers when dealing with food insecurity. In addition, establishing a range of early warning drought indicators as triggers for payments may be beneficial since it can remove possible subjective analysis or political influence on decisions to disburse cash transfer (National Drought Management Authority, 2016). Lastly, initiatives that use forecast-based early action, such as cash transfer, have either provided support directly to beneficiaries, or have worked with national governments and partners through state institutions (Wilkinson et al., 2018). As such, a choice between these distribution alternatives must be made based on the capacity and coordination of government actors, on the country-specific context, and on the mandates of agencies promoting forecast-based early action in order to ensure timely aid (Wilkinson et al., 2018).

5.4.2 Limitations and recommendations
The primary limitation of this investigation was that we assumed that prices are solely dependent on the supply of maize, when in reality price is associated with a combination of factors including supply and demand in neighbouring regions and global price shocks (Brinkman et al., 2010). We also assumed that prices during the growing season would follow their mean values, when in practice price levels and volatility can increase under a perceived or actual drought impact. Another important cost component of cash transfers which was not investigated in this study is operational costs. For instance, including transaction costs in the analysis would result in a more realistic estimation of costs. In addition, we considered only indicators of climate variability and vegetation coverage as drivers of maize yield while other aspects such as in-farm level management activities play an important role on yields. Regarding the applied methods, further insights into relationships between climate variability and maize yields can be obtained by applying compensatory models (e.g. Random Forest) since a more complex model can reveal important features that are not captured by a simple model such as the FFT. In addition, the accuracy of the results could potentially improve when testing different decision algorithms, since the ifan algorithm used in this study assumes independence between predictors. Furthermore, historical crop yield databases, such as the one used in this study, are also known to face limitations, such as reporting errors.

Future work could benefit from using other indices of climate variability at different time scales, and from including other aspects such as in-farm level management activities. More accurate results and predictions of maize yields can also be obtained if the threshold of skilfulness of the FFT model (ROC>0.5) is increased. However, this would inhibit large part of the analysis, especially at longer lead times, since the FFT models have, on average, ROC scores between 0.63 and 0.72. In addition, this study would substantially benefit from a more detailed analysis of supply and demand dynamics and drivers of maize price in Kenya. Furthermore, testing the proposed methods using different algorithms, crop databases, crop types, and early actions (such as vouchers or in-kind food aid) would provide further insights in the strengths and limitations of the approach. Lastly, in order to produce a robust economic estimation, which would potentially reflect the actual expected costs of ex-ante and -post cash transfer programmes, other information should be taken into account such as operational costs, the precise number of beneficiaries, and maize yield per household.

Providing timely finance prior to a disaster can be more cost-effective than investing in post-disaster expenditures, and may prevent farmers, especially small-scale ones, from falling into poverty. Increasing the productivity and
climate resilience of smallholder farming systems is a great challenge that will be important in determining whether the world succeeds in achieving the post-2015 development agenda, and the Sendai goal of substantially reducing disaster risk. In Kenya, and East Africa in general, yield growth has remained relatively stagnant as population continues to grow rapidly (Funk & Brown, 2009), as predictable droughts become more frequent (Davenport et al., 2018; Funk et al., 2014). As suggested here, developing more proactive disaster mitigation responses should help buffer the impacts of future crop yield deficits. A secondary, but important benefit of such actions might be the reduction of food price volatility. As seen in 2010/11, and to a smaller degree in 2016/17, these price spikes can affect even more fragile pastoral and marginal agropastoral households.

5.5 Conclusion
Our study developed a forecast model using FFT for multiple lead times for assessing early warnings of low maize yield based on predictors of climate variability and vegetation coverage. Using this model, we focused on assessing the relative costs of ex-ante and ex-post cash transfer in Kenya. This is a primary step towards the adoption and use of climate information in disaster risk financing and humanitarian early action. In this paper we showed that:

- Overall, FFT models have skill to forecast low maize yields in all five districts. In most cases, we identify some model skill already six months before the start of the harvesting season;
- Across different yield percentiles, districts, and lead times, the FFT models correctly forecast “below yield threshold” 85% of the time. On average, the probability of False Alarms is 49%, but this value decrease towards the end of the maize growing season.
- When assuming a perfect forecast (Hits=100% and False Alarms=0%), cash transfers can be most cost-effective ex-ante at a lead time of 6 months (March).
- Despite uncertainties associated with FFT predictions, we show that ex-ante cash transfers can often be more cost-effective than ex-post cash transfers, especially for the more extreme yield deficits.
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