## Willenbockel (2011),no.5

CGE (GLOBE) prediction for 2010,2020,2040. Four different scenarios including the baseline.

Wheat, Maize and Rice

19 regions (developing regions selected by OXFAM)

**1. Baseline scenario:**

East Africa is and will be a net importer of all 3 crops analysed here (rice, wheat, maize)

Food consumption per capita generally increases (into the selected poor regions) into 2030, because although the food prices rise, the real income also rises.

But **the food price increase relative to other commodities**, hence, the share of income that household spend on food remains higher than it would be in absence of price increase

**2. Climate change scenario:** with high sensitivity of crops to warming and CO2 fertilization effect at the lower end.

Declines in total factor crop productivity (comparison to baseline scenario)

* Significant further increase in food market prices
* Gross output in 2030 with climate change lower than in 2030 baseline but mostly above the 2010 corresponding levels

**3. Optimistic agricultural productivity growth scenario:**

Assumes that as a result of increased R&D efforts, and so on.. total factor productivity growth rates are 50 percent higher across all regions and agricultural sectors than in the baseline scenario

* Export food price increases smaller than in basic 2030 scenario, but still strong

**4. Scenario, which assumes successful adaption in sub-Saharan regions:**

A set of externally funded adaption measures returns productivity growth in crop and livestock back to the baseline path in SSA regions but in the other region, the impacts of Climate change same as in the Scenario 2.

* Adaption measures that succeed in reversing adverse climate impact in agricultural yields in sub-saharan region would make the prices in SSA to be closer to the baseline scenario, even if in presence of climate –change induced price increase in all other world region

### APPENDIX:

*quite important/what I was wondering about effect of food prices:*

Net exporters will benefit from price surge

Net importers adversely affected: for a particular crop bigger adverse effect on those with higher share of import on total domestic crop demand and higher share of crop demand of total domestic crop demand

**Index of exposure to import price surges** = (import share in domestic demand) \* (share of crop in total crop demand)^(0.5)

## Ochieng, Kirimi and Mathenge (2016), no. 10

Kenya adversely affected by climatic variability and change because it is dependent on rain-fed agriculture

TEGEMEO PANEL DATA SET covered 107 villages

Crop production measured as a value of yields per acre in farm household

**Tea = important cash crop in Kenya**

**Maize = major staple in Kenya**

Impact on gross maize and tea revenue separately.

**Estimating strategy:**

Augmented production function to model effects of climate change on revenue from all crops but also on maize and tea revenues separately

**Production function framework** can control for economic variables but does not take farmers adjustments into account

Revenue is a function of factors of production, farmer’s personal attributes and climate variability and change factors

After estimation also use rainfall and temperature predictions >> simulations of effects of climate change

**Results and discussion:**

Effects of climate variability and change on agriculture

Long term effects of climate change (temperature) larger than short term

Temperature negative effect on crops and maize revenues but positive effect on tea

Rainfall positive effect on crops and maize revenues but negative effect on tea

Temperature more important factor of climate change than rainfall (with respect to agriculture)

Crop diversification negative and significant effects of revenue from all crops

Larger size of land>>lower revenue from all crops grown

But land size effects positively maize and tea revenue

**Tea production strongly depends on stable rainfall and temperature compared to other crops including maize**

Predicted climate change and simulation results

Rainfall will increase between 2020 and 2040

Consistent result with Kabubo-Mariara and Karanja: Ranfall increase in Kenya will have positive and significant effect on crop and maize revenue but negatively affect tea revenue by 2020

**Conclusions and policy implications:**

Kenyan tea sector the most endangered by climate change

## Brown and Kshirsagar (2015), no. 9

In competitive efficient food markets, local weather shocks should have no influence on local prices (Samuelson, 1965)…*but they do have effects because the assumptions are unrealistic *

If local production is affected by weather disturbances, do international commodity prices matter more to local market prices?

Use **of satellite derived vegetation index** that integrates rainfall and temperature impacts on biomass and enables comparison across countries and ecosystems

From the sample, more market influenced by weather shocks than by international food price shocks

food=staple, hence shifts in food demand large and increase in local prices indicates shortages

**FOOD PRICES = INDICATORS OF FOOD INSECURITY**

Model assumptions and structure:

Under certain conditions (including rational expectations and behaviour), the series of prices would behave as random walk

Hypothesis:

Given the market inefficiencies mentioned above, it is possible that lagged weather and world price shocks will influence local food price dynamics

**Data:**They use the vegetation index measure derived from remote sensing observations as a proxy for yield changes (which has long been used)

NDVI= normalised difference vegetation index – proxy for measuring yields from crop cereals

…

…measurements aggregated across time to a monthly time scale and across space to four domestic clusters (k-means clustering algorithm)

Food prices: 60 months 2008 to 2012 from FAO and World Food Programme (WFP)with 554 unique commodity–locations pairs

**Methods:**

KALMAN FILTER

To select model for each commodity-location pair: AICc lower than seasonal random walk and other specifications,. The estim,ated coefficient has expected sign and p-value lower than 0.05

The model uses satellite estimated NDVI as well as shocks from international commodity prices and their interactions

Model description:

Ft = food demand, proportional to food scarcity and price

There are latent factors associated with changing expectations that influence local food price dynamics

…

**Weather disturbance influence:**

NDVI acts as a shock to the price dynamical system and may amplify the (normal) seasonal effects. We would expect Beta NDVI to be negative

Beta NDVI expected to be closer to zero if food market better connected to the outside world. According to the World Bank study, the poorest regions tenuously connected with outside market

**International price influence:**

Bwprice is assumed to be positive.

Four processes. They assume, that each price series is best modelled by one of the 4 processes

..pak popisuji jak a troche proc se odhaduje Kalman filter nmodel…

**Estimation results using synthetic data:**

Fabrikovana data, porovnavaji vysledky state space modelu a dynamic OLS (standard regression with lagged dependent var as explanatory)

**State space methodology: less biased and more efficient estimates in all cases**

Also with false positive and false negative error rates state space model very robust and much better than dynamic OLS

**Results:**

For most of the developing world, much larger impact of weather than of international prices on local food prices *(v knize ‘Food security, food prices and climate variability’, 2014 od Molly E. Brown rika ze je to naopak?? Vetsi vliv maji mezinarodni ceny nez weather??)*

Rice: the markets affected by local weather disturbances nearly all in regions that grow rice locally

**Discussion**:

Do not identify major driver for 377 out of 544 markets. They give reasons for this here…:

* Only capturing short run impacts
* Government interventions can mitigate some impact??
* Markets may be oligopolistics with few market intermediaries

Unable to capture policies

Only focused on short run impacts, but prices – make take longer..

Markets not representative for national level

*Shrnuti myma slovama:*

*Mely 544 casovych rad, jen 90 pozorovani pro kazdou. Pro kazdou vybrali, ktera ze 4 specifikaci state space modelu je nejlepsi, jeslti obsahuje slozku pocasi nebo mezinarodni ceny. Pak spocetli pro kolik z nich byli ceny nebo pocasi signifikantni, coz prezentuji jako souhrne vysledky..*

*V jedne casti trochu popisuji I state space modely. Delaji simulace- pouzivaji state space model I dynamic OLS na suimulovana data a state space je vzdy lepsi po vsech strankach *

## Molly E. Brown (2014, *book*), no. 6

**Ch 1: Introduction:**

**Unusually or prohibitively high local food prices are primary cause of food insecurity in the world**

Local food prices can provide information on whether markets are good functioning, weather (climate??) related production shortfalls.

Climate variability defined as seasonal, annual, inter-annual or several years-long variability in temperature and precipitation around an average condition defined over several decades

Expensive and inadequate rural transportation infrastructure and inadequate legal framework>>low level of partitioning ion market by subsistence farmers. Then also when bad weather>> low yields>> it is hardly possible to buy food on market from different region

The book explains connection between climate variability, international markets and food security

Developing a production-price model will allow early estimation of effects of droughts on food prices and their geographic impact

**Objectives:**

Which food markets most vulnerable to weather related shocks?

Can nutritional outcomes be linked to climate variability and food price volatility?

**Income and food prices:**

Households, that growth food for their own consumption can have substantial assets such as land or farm equipment, but they cannot purchase food within in a time of crisis as it requires cash

**Food systems and vulnerability:**

Food systems defined as processes and infrastructure that are involved in meeting population’s food requirements

Some studies agree that international prices affect local food prices a lot, other agree that the international prices do not affect the local food prices too much

Because not enough cash in poor regions>> not enough purchase power, which does not attract suppliers even through higher prices there

In this book, **household survey data examined** to understand the likely dual effects of food prices and climate variability on nutritional outcomes.

**Chapter 3 Climate variability, agriculture and remote sensing**

*Jen tak nahlizim do tehle kapitoly, prectu asi jen prvni stranku..*

Climate variability how it can be measured using remote sensing information…

Remote sensing of vegetation as an alternative to precipitation datasets (to ensure comparability and reliability)

**Climate, climate variability and climate change**

Climate = average weather over decades

Climate variability and change here using in different meaning

**Chapter 7 Modelling the impact variability on local food prices**

Food prices are the best short-term indicator of food availability as they are easily observable and immediately analysed unlike household food consumption or household income

If unusually high prices in data, it is important to distinguish if it is artifact of the data, an individual incident, or a larger broader crisis emerging due to lack of access

Many households restrict participation in the market because of high transaction costs

Because of volatile markets, households try to be self-sufficient and not to participate. Because they do not participate>>markets not properly functioning>>cycle…

Traders may avoid paying transporting cost of grain transport into these areas as they are afraid of not finding enough buyers.

**Modelling food price dynamics:**

Models that incorporates international prices time series and climate variability time series (NDVI) as inputs and local prices as outputs

Extension of the model developed with Kshingar – but more extensive use of satellite data

Generation of out-of-sample forecasts

To capture a significant change in direction of direction from increasing to decreasing prices over an area would be of great use

87 out of 179 locations influenced by local weather anomalies during the 2003-2012

**Price NDVI model conceptual framework:**

IN EQUILIBRIUM differences in prices will reflect differences in transport costs. Can fail for example because: ad hoc policies>>unpredictable. Or credit constrains

The ability to store grains will help to mitigate adverse effects of large local surplus caused by favourable weather conditions

Weather shocks will influence the local price at isolated markets. For connected food markets, weather shocks have much smaller effect *(implied by the figures*

Model should provide guidance to areas which are most likely to benefit from marketing/supply chain interventions or food aid

**Empirical methodology**

STATE SPACE APPROACH

*Popisuji, jak tu Kalman vec delaji, rozkladaji time series…*

Weakness: omitting transport cost

Different models estimated with different NDVI signals and length of lags and the best is chosen based on out-of-sample performance over three years. optimal model can differ per locations..

**Maps of NDVI time series correlated with price changes**

Improvement over using only the NDVI around each market

Pak jsou tu mapy, kde jsou vyznacena mista, ktere maji korelovane ceny s jednim urcitym mestem (napr. Njamena, nebo Nampula, Mozambique)

**Comparison of model predictions:**

..seasonality is the main element of not only local food production but also for food prices in many regions where food security is a problem and food market do not function well.

4 types of models compared for all regions:

* Previous month or Markov price analysis alone
* Previous month and seasonality
* Previous month and seasonality and NDVI
* Previous month and seasonality and NDVI and world prices

Totally 42 models for 42 locations: (viz table 7.1)

7 - the best is just markov

21 – seasonality improve prediction

4 – NDVI improve the prediction

10 - NDVI and world prices additional improvement

**Local market response to shocks:**

Niger: prices in the biggest market are signals for the prices in smaller markets. In years following weather related production shocks, the prices are more tightly in tandem than in other years

Essam (reference, uses NDVI data as well) in good years market less integrated, in bad years markets more integrated (integration measured as a degree of price transition)

Impact of weather and global food price shocks:

Kenya has two types of areas:

1.affected by international prices and not affected by weather shocks

2. affected by weather shocks and not affected by international food prices

Kenya can be classified as high-intervention country. But this can cause higher local price variability because unpredictability

***Now description of features of types of markets summarised in Table 7.2, i.e. affected by neither weather shock and international prices, by one of them and by both***

Garissa, Kenya is an example affected by weather shocks but not international prices, because quite isolated. Probably consumes less per capita (not extreme surplus of production). There is also extreme price seasonality….

Rice dominant commodity that appears to reflect changes in world prices. Higher value to weight ratio>>profitable to import rice

**Implications for policy and response:**

….The model analysis would also provide improved baseline for poverty assessment

Measuring consumption by aggregating at national level does not have sense if heterogenous response to shocks these markets show..

## Extreme weather, extreme prices (OXFAM) no. 4

Prices of staple food could double by 2030, half of it due to changes in average temperature and rainfall patterns

drought: USA 2012, Russia 2010. Also political instability and export bans

...July 2012 was the 328th consecutive month with a global temperature above 20th century average

**Food price volatility hits poor people hardest**

Sudden price hikes can be more devastating than consequent slow rise (to which they can adjust). But combination of short term and long term price increase the most devastating

Food price increase bad to farmers: they are usually net food consumers. They do not have credit so they cannot take advantages of the price increase and expand production

Double jeopardy: when food prices go up and purchasing power goes down

weather event>sudden price increase and damage of assets

**some factors not taken into account, so the adverse effects estimated for 2030 may be underestimated**

***North America could remain the largest maize and wheat exporter by 2030, so shocks there would have hard impact on import dependent countries***

**SHOCKS IN SUB-SAHARAN AFRICA:**

a drought in east Africa similar to that in 1995 could cause rise in consumer price of maize and other coarse grain by around 50 percent

The extreme weather events are likely to be more devastating for local food prices in Sub-Saharan Africa than price spikes on global markets (because the most of the food consumption is from local sources)

because most of the rice is assumed to come from South East Asia and India by 2030, shocks there would have huge impacts on rice price. Domestic rice price in Sub-Saharan Africa could increase by 6-43 percent (hardest hit Nigeria)

**BUILDING A RESILIENT FOOD SYSTEMS:**

presented scenarios not inevitable

The simulation results set out in this issue briefing are based on the

research report ‘Extreme Weather Events and Crop Price Spikes in a

Changing Climate: Illustrative Global Simulation Scenarios’ by Dirk

Willenbockel of the Institute of Development Studies, UK. The full report

can be downloaded from Oxfam’s website:

## Nicholson (2017), no. 11

*Celkove: hodne literature review, popis pocasdi, podnebi, meteorology, vetry, smer jejich, srazky a jak to souvisi se suchem, zaplavami. Vliv ENSO, klima nad Indickym oceanem?? IOZM, ruzne typi vetru a cykli kde kdy jsou. Minulost popsana, vykyvy, anomalie*

***All about Eastern Africa***

**1. Introduction:**

*Some of the highlights:*

* The paradigm of two rainy seasons inadequate
* The ‘long seasons’ should not be treated as a single season
* Factors governing the short rains are nonstationary
* Atmospheric variables provide more reliable forecast than those traditionally considered

Projections of consequences of climate change quite diverse for this region

2 sectors of east Africa:

1. **Equatorial rainfall sector (southern):** bimodal rainfall regime, peaks in boreal spring and autumn.
   1. Uganda, Tanzania, Kenya, Somalia
2. **Summer rainfall region (northern):** rainfall peaks in boreal summer.
   1. The rest of Greater Horn of Africa = Ethiopia (65-95% of the rainfall in the northern Ethiopia happens during boreal summer rains), Eritrea, Djibouti, South Sudan, Rwanda and Burundi

**2. Climatic Controls and Regionalization:**

Rainfall higher over highlands, lower over northeastern Kenya and Somalia

Complexity of the precipitation regime>>attempts have been made to regionalise the precipitation regimes of eastern Africa for purpose of prediction, agriculture or analysis of interannual variability

Most studies have **utilized PRINCIPAL COMPONENT ANALYSIS, CLUSTERING TECHNIQUES, linear correlation**

Various studies then divided eastern Africa into various regions. (for example using the PCA..). Regions that frequently stand out include**: the Lake Victoria Region, the Highlands, the Coastal plain**

Nichols et al. delineated seven rainfall regions within the equatorial rainfall regime. These are highly intercorrelated ☺ (str.6)

**3. The Rainy Seasons:**

**Most of East Africa two rainy seasons: March to May (MAM) and October to November (ON)**

But western highlands and coastal regions get also loads of rainfall in boreal summer (July to September). Inland regions in central and southern Tanzania most rainfall in boreal winter

**MAM Rains:**

Usually called the ***long rains***, the heavier and longer of the two seasons. More reliable

**ON Rains:**

Usually called the *short rains.* **Most interannual variability associated with the short rains** and it receives less rainfall on average.

Some authors different seasons: two long rains and two short rain seasons.

### 3.1.

The Classical explanation of the seasonal cycle = INTERTROPICAL CONVERGENCE ZONE (ITCZ). But closer examination>>this is not justified

### 3.2.

The spatial coherence of rainfall much greater during the short rains than during the long rains. It is highest at the peak of short rains

### 3.3

Spatial rainfall anomaly pattern similar in March and April but different in may>>May shoul be considered separately when analysing atmospheric dynamics

Various differences among the months of the long season

**>>Each month of the long season should be considered separately**

### 3.4

### 3.5

Definition of rainy season and rain event somehow arbitrary

Kenya: average start and end of rainy season: 25 March and 21 May, but sd 14.5 days for start and 10.3 days for end. Average start and end of the short rain 23 October and 26 December. Sd is 24.7 and 20.4 day respectively.

**4. Intraseasonal variability:**

Wet and dry periods within the rainy season

In East Africa, generally 3 to 4 wet spell of roughly 5 to 10 duration comprise the rainy season

### 4.1

The most spatially coherent variable = frequency of rain days, then seasonal total

Greatest spatial coherence: peak of the short rains

For both long and short rains, seasonal total correlated strongly with the onset

For the short rains – the leading mode of intraseasonal variability is covariability of ENSO and the Indian Ocean Dipole

### 4.2 Zonal Winds

All 3 rainy seasons:

Some link between westerly/easterly wind events and wet/dry spells. Valid for coastal regions, but opposite for western highlights of Kenya??? IT IS WRING< SOME NONSENSUS IN THE PAPER HERE

The heaviest rain events depend on: the intensity of the land/sea breeze, strong easterly to south-easterly wind anomalies and sea surface temperatures higher than air temperatures

…uh…

### 4.3 Relationship to the MJO (Madden-Julian oscillation)

Eastern Africa- intraseasonal variability, rainfall strongly coherent with MJO amplitude on this time-scale (time scale 20-80 days). MJO probably the strongest factor controlling intraseasonal variability over East Africa during both the long and short rains.

Wet condition- first half of the MJO cycle along the coast and second half of the cycle in the highlands.

Pohl and Camberlin (2006a) also shows that MJO modulates interannual variability of the long rains season and extreme daily events within the season

**When MJO very strong, the rainy season commence sooner, rainfall enhanced**. In April the influence of MJO shifts from western highlands to coasts. Hence, at coast, the influence of MJO is close to zero during the entire long rains (based on some study, bit different based on other study…

Several studies found that influence of MJO modulated by ENSO… (results of studies somewhat differ..)

**5. Interannual variability:**

ENSO primary driver of interannual rainfall variability in eastern Africa, El Nino resulting in wet and La Nina in dry conditions. Primarily affecting short rains.

Zonal circulation over the Indian ocean has a critical role in transmitting the ENSO’s signal

* Indian Ocean Zonal Mode

Much of recent literature: Relative importance of Pacific vs. Indian ocean in driving Interannual Variability, the relationship between ENSO and the Indian Ocean Zonal Mode and changes over time in these roles and relationships. These issues are all reviewed in this section…

### 5.1 The long rains of March to May

**Long Rains produce more rainfall than short rains and less variable**

**Studies: LONG RAINS HAVE BEEN DECLINING DRAMATICALLY**

Long rains have been declining over years*. Not so sure based on figure 12*

A strong influence of Madden-Julian Oscilation (MJO) on Interannual variability and seasonal extremes was found

Some study about Northern Tanzania: Interannual variability in March and April linked to factors different from those affecting Interannual variability in March

### 5.2 June through September: The Boreal Summer

= dominant rainy season in western Kenya. (and parts of some other counbtries)

A strong relationship between summer rainfall and Indian monsoon and strong relationship with ENSO and the Pacific Walker cell.

### 5.3 The short rains of the Boreal Autumn

In contrary to long rain, the short rain has been increasing in the equatorial rainfall period. Since 1980 rainfall seldom far below long term average.

The short rains strongly coupled to a zonal vertical circulation cell in the central equatorial Indian Ocean (Walker cell or Walker type circulation)

High OND rainfall associated with increase in upper level easterlies and decrease in midlevel easterlies across the equatorial belt as well as increase in low level westerlies (flow out of the Congo basin??)

### 5.4 The role of ENSO and the Indian Ocean in the Interannual variability of the Short Rains

October-December rains seem to be markedly enhanced during El-Nino years and reduced during La-Nina years. But the link with ENSO was not always so strong. It varies depending on time scale and on regional basis.

Controversy over main driver of the short rains, because evidence of influence of Indian Ocean, Atlantic and Pacific

Studies comparing influence: Indian Ocean has more control than Pacific on Eastern Africa’s short rains on both interannual and interdecadadal time scale..

### 5.5 Changes in the relationships among the short rains, ENSO, IOZM and Zonal Winds

Disparity among the various studies partially explained by the fact, that relationship non-stationary

Study of winds and rainfall between 1983 and 1993: 3 major regime shifts (1918,1961, 1983,1994-1997) in tropics, coincide with extremely positive IOZM event and high ON rainfall. Las t 2 coincide with El Nino event. Prior to 1918, the ON rainfall was generally below average

1918-1960 rainfall dropped markedly and remained very low. Also coupling between rainfall and other variables markedly lower. Coupling between zonal winds and ENSO and IOZM markedly weak during this period as well. ENSO dominant factor in rainfall activity

1961-1997 shift in dominance between ENSO to IOZM. Rainfall correlation and winds and IOZM increased abruptly.

The regime shifts in 1982 and 1997 were not so abrupt or pronounced

1983 onwards rainfall higher correlation with the two zonal wind indices than with ENSO or IOZM

FAILURA RATE OF DROUGHT INDICATOR (Nicholson 2015):

* Strong negative anomalies in Nino 3.4
* Strong positive anomalies in the IOZM
* Strong westerly winds over the central equatorial Indian Ocean
* Strong easterly winds above them in 200mbar.

The failure rate = percentage, when the indicator suggest drought, but instead the ON rainfall is above average. Prior 1982 the failure rate was much smaller

After 1982 reduction in rainfall and in the variance of all parameters except Nino 3.4

…the post-1982 increase in the Indian Ocean Walker cell consistent with the infrequent occurrence of very wet years after 1982. But inconsistent with near absence of drought after the time

### 5.6 Nonlinearity of Relationships

The most important factors associated with the interannual variability of the short rains of eastern Africa ANSO, IOZM, upper level zonal winds over the central equatorial Indian Ocean**. Several studies suggested that the relationships are nonlinear**. Most studies use simple linear correlation, although the relationship differs for wet and dry years. Wet years: three or four factors involved. Dry years usually one or two factors contributed (some cases none, so additional must be sought)

**6. Recent Trends and Extreme Events:**

### 6.1 Flood events

*To me tolik nezajima ☺*

Eastern Africa both extreme floods and extreme droughts

All flood events occurred during the short rains (1896, 1982, 1997, 2006, 2011)

### 6.2 Recent Trends

In more recent years, droughts bigger concern than floods

Again, decline in the long rains…

Decline both in equatorial and summer rainfall regions, the trend weaker in the latter

4 major droughts (in the summer rainfall region I think): 1978/79, 1984/85, 1994/95, 2003/04, but these were not evident in the summer region as a whole??

ON season: weak upward trend in rainfall.

MAM season: downward trend. In both seasons the strongest trends in the central and southern portions of the Horn (north-eastern Kenya and south-eastern Ethiopia) and in the Lake Turkana basin (north-western Kenya)

JJAS season: decline similar to boreal spring (particularly summer rainfall region)

Trends in annual precipitation in greater horn of Africa between 1960 mixed and generally insignificant.

Lake Naivasha Basin (Kenya): reduction in Lake levels and River flow, but commensurate trends in rainfall could not be found

OND rainfall in the Mount Kenya region: trends generally insignificant and spatially diverse

### 6.3 Large-Scale Factors Associated with the Trends

**Funk et al. (2008)** linked decline of the long rains to warming in the south central Indian Ocean. Global warming on eastern Africa manifested through disruption of moisture patterns, which is provoked by increased precipitation over the warm anomalies in the Indian Ocean

Williams and Funk (2011): midtropospheric diabatic heating associated with increased precipitation over the Indian Ocean == major cause of decline of the long rain

Rowell et al. concluded that Anthropogenic radiative forcing played role in long rain declines. Lyon (2014) contrary view…**The question of Anthropogenic effects open**..

Other factors that may play role in long rains decline suggested: enhanced east-west SST gradient, enhanced upper level westerlies over the central Pacific and increased upper level easterlies over the western Pacific and Indian Oceans

### 6.4 Recent Droughts

Decline in long rains>> series of disastrous droughts from 2005. Eastern Africa>>drought widespread in every year since 2008. Particularly severe droughts in 2009, 2010, 2011 in both the summer and equatorial rainfall regions

The 2010/2011 drought the most intense in Kenya, southern Somalia and Southern Ethiopia. High rainfall in November 2009 and Jan 2010>> floods

Persistence of droughts over several rainy seasons. Similarity in both equatorial and summer rainfall regions (this is surprising given different trends in interannual variability)

### 6.5 Large Scale Factors Associated with Flood and Droughts Events

Important factor = equatorial westerlies over the central Indian Ocean

Weak westerlies associated with floods in 1961,1997,2006

Association between stronger/weaker westerlies in the boreal autumn and drought/wet conditions explains shift from flood to drought in November 2010 and 2011. Other factor(s)

Contrast between drought and wet years:

4 potential causes examined in both cases:

* + Surface and 200 mbar zonal winds over equatorial Indian Ocean
  + SST in Nino 3.4
  + IOZM

The wet years generally associated with 3 or 4 of the factors, dry year with one or two or none

In wet years: linear relationship of rainfall and each of the factor.

Dry years associated with specific signs of the factors, but no correlation

**Extreme events during long rains:** fewer studies. Floods are rare but droughts common..Large number of tropical depressions associated with droughts in Ethiopia..

Influence of Madden-Julian Oscillation on the long rains. Dry conditions associated with weak MJO activity. In these cases, westerly wind anomalies in coastal Kenya

### 6.6 Commonalities in factors influencing the two regions and Three Rainy Seasons

Difficult to explain recent tendency for consecutive drought seasons

As for similar trends in summer and equatorial rainfall regions: greatest similarity in the January to March and in the July to September seasons. Jan to March dry in both regions>>focus here on common factors in the July to September seasons

Promising mechanisms of common factors: (this mechanism can account for July to Sept Anomalies of the same signs in both regions. It cannot account for persistence of anomalies into the boreal autumn season, patterns so different)

* Components of the Indian monsoon system
* ..westerly flows bring moist Congo air into the summer rainfall region…
* The westerly flow is a part of circulation cell over the western Indian Ocean

The above cannot account for persistence of anomalies into the boreal autumn season, patterns so different. Another possibility well documented changes in SST in the Indian and Pacific Oceans

**7. Seasonal Prediction:**

**Short rains relatively predictable, long rains not**

*interesting as in section 3. It says most interannual variability associated with the short rains)*

2 types of forecasts:

- statistical: higher forecast skill than dynamical

- dynamical: poorly predict extreme events, underpredict drought but significant forecast skills for the short rains

Other new forecast approaches considered in literature (e.g. SST dipoles..whatever it is☺)

### 7.1 The Long Rains of the Boreal Spring

Predictability of boreal springs Kenya and Uganda: Camberlina and Philliphon [2002]. Four February indecies. Linear regression and discriminant analysis. Period 1968 to 1997 plus cross validation (v. good cv results).

Other studies: good predictors SST of the Indian Ocean adjacent to East Africa

Some prediction studies for Ethiopia…

Moron et. al: potential predictability from SST higher during the rain weeks in march

Nichollson 2014a,2015b, regression:

atmospheric variables emphasized (SST, sea level pressure..). Atmospheric variables (especially zonal winds) provide higher forecast skills than surface vars such as SST. ENSO and Indian Ocean Dipole provide less forecast skills than variables associated with them.

Predicted and observed rainfall data quite high correlations.. 0.6 or so

MAM season: Nicholson 2015b developed seasonal forecast models for the three individual months

### 7.2 Summer Rainy Season

For this period predictions almost only for Ethiopia

Korecha and Barston (2007): ENSO most significant predictor. Forecast skill only with relatively short time leads..

Description of studies about Ethiopia..

Nicholson 2014a: regression forecast model for eastern Africa (well beyond Ethiopia). Majority of predictors: sea surface temperature and pressure. Good predictions for July to September rainfall, but not so good for equatorial summer region

### 7.3 The Short Rains of the Boreal Autumn

In literature many statistical forecast model, a few numerical forecast models

Most rains October, November. Sometimes considered longer, October November, December, but then less coherent

Mutai et al. 1988 July to Sep SST global pattern correlated with O to Dec seasonal rainfall for a large sector of eastern Africa>> regression forecast model

Philipon et al. 2002: multiple regression to predict OND rainfall in big region including Kenya. Predictors included monsoon index involving NE and SW wind components

Hastenrath et al. experiments to predict ON rains with variable number of predictors

To sum up. Seasonal predictability of short rains is strong with circulation variables providing the strongest skill, especially for short lead time.

The relationship between predictors and predictands may be NONSTATIONARY. Models that do not assume linearity, such as **neural networks** may outperform regressions

Forecast skill greater for October-November than for September to November or October to December

*It seems that some models for ON use May predictors and some use August predictors (see Figure 19 str.36)*