Lund University GEM thesis series nr 16

Modelling maize *(Zea Mays L.)* phenology using seasonal climate forecasts

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2015
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by

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Thesis submitted to the department of Physical Geography and Ecosystem Science, Lund University, in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation for Environmental Modelling and Management

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Course title: Geo-information Science and Earth Observation for Environmental Modelling and Management (GEM)

Level: Master of Science (MSc)

Course duration: January 2016 until June 2016

Consortium partners:

The GEM master program is a cooperation of departments at 5 different universities:
University of Twente, ITC (The Netherlands)
University of Lund (Sweden)
University of Southampton (UK)
University of Warsaw (Poland)
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Abstract

Agriculture is an essential economic activity which sustains the livelihood of millions of people around the world. Maize is one of the most grown, consumed and traded cereals in the world mostly because of its adaptability to varied environmental conditions. Maize farming depends on climatic factors like temperature, rainfall and radiation to thrive but this also means that it is very susceptible to variabilities in climatic conditions. Farmers every season are vulnerable to the risk of losing their crops and in turn losing their income. In order to reduce the impact of climate variability on crop production, there is need to make use of available climate forecast information to anticipate, plan for and cope with the related seasonal climate risks. In this study the potential use of ensemble seasonal climate forecasts from the new The European Centre for Medium-Range Weather Forecasts (ECMWF) System 4 coupled ocean-atmosphere general circulation model is evaluated for predicting maize (*Zea mays* L.) phenology, particularly the date of silking and the date of maturity in Zimbabwe, Spain and Sweden. Linear-scaling approach was used as a bias correction method to improve the prediction skill of the ensemble forecasts, whilst a temperature driven growing degree days (GDD) model was developed to simulate the development of early and late maize varieties. Verification of the model results was done using Brier skill scores. Results indicate very low skill scores by the model, showing that contrary to the initial study hypothesis, the ECMWF System 4 ensemble data cannot successfully be used to determine the day of silking and day of maturity for both the early and late varieties of maize. Interpretation of results attained in this study have to take into account a number of limitations, which can also be subjects of further research, such as observed and ensemble forecast data uncertainties as well use of more comprehensive bias correction methods like quantile mapping.

Acknowledgements

I would like to first of all thank the European Commission and Erasmus Mundus Program for selecting and allowing me the opportunity to be part of the GEM 2014-2016 program by granting me such a prestigious scholarship. This has been an adventure of a lifetime, not only allowing me to advance my education but also giving me a chance to experience so many different cultures and places. Thank you very much.

Special thanks to my thesis supervisor Anna Maria Jönsson for never getting tired of assisting me with brilliant suggestions and advice on direction to take as well as the time she put in. I am forever grateful for your support in helping me become a researcher. I want to also thank the course coordinators Drs Raymond Nijmeijer (ITC) and Dr Petter Pilesjö (Lund University) and the course secretary Laura Windig for all the administrative assistance, student support as well as support with settling in at the respective institutions.

Thanks to my classmates in the ITC and Lund University who let me into their lives and allowed me to learn about their cultures. From each and everyone of you guys I have made a lifelong friend and you have taught me unforgettable life lessons. I look forward to seeing you one day in Zimbabwe!

Finally, I want to thank my family who stood by me since day one, supporting, encouraging and loving me tirelessly. I made it mummy!

This work is dedicated to my brother, Ashton, who passed during my thesis process. I have done it Kule, I have finished that program!
Continue to fly high with the angels in heaven…

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1.0 Introduction

Agriculture has been part of civilization from as far back as 12 000 years ago, providing food, raw materials as well as playing an essential role in the world's economic activities (Riehl et al. 2013). Agriculture provides employment within the sector as well as opportunities for trade in agricultural products which in turn sustain the livelihoods of millions of people around the globe. Agriculture encompasses a lot of activities from crop farming, dairy farming to beef farming, and cereal production is one of the most prominent practices worldwide. Maize is one of the most grown, consumed and traded cereals in the world mostly because of its adaptability to different environmental conditions (Abbassian 2003). It is grown from areas at sea level to areas that are 4000 meters above sea level, from semi-arid areas where it is grown under irrigation conditions to the tropics where it rains all year round (FAO Water Development and Management Unit 2015).

The agricultural industry depends on climatic factors like temperature, rainfall and radiation to thrive and this also means that it is susceptible to variabilities in climatic conditions (Sivakumar 2006). The year-to-year climate variability is mainly caused by the El Niño Southern Oscillation (ENSO) which affects most countries in the southern hemisphere (Tudhope et al. 2001). This is a climate phenomenon that causes fluctuations in weather conditions leading to floods and droughts and it can have massive negative effects for crop production as well as food shortages in the tropics and the subtropics (Cantelaube and Terres 2005).

Over the years there have been improvements in the understanding of the interactions of the atmosphere with the sea and land surfaces, resulting in meteorologists developing state-of-the-art forecast systems that allow for seasonal climate predictions which are useful in agriculture (Hansen and Indeje 2004). Integrating seasonal climate forecast data in crop models has been used in previous studies where crop yield for the upcoming season was predicted (Guillermo A. Baigorria , James W. Jones, 2002, Peiris, Hansen, & Zubair, 2007 & Mishra et al., 2008). However, with the availability of new and improved versions of seasonal forecast models that possess the capacity for the provision of more ensemble members, higher resolution forecasts, and a larger forecast dataset, there is a need to explore such data to see if it can provide skilful predictions that can prove useful to farmers and help mitigate production risks. Ensembles are a collection of forecast climate model simulations that give multiple realizations based on the different initial conditions and model formulations applied to each member. There is a need to assess the skill of these ensemble data from the seasonal forecast models and explore the need for bias correction for the data before application in impact studies.

The aim of this study is to investigate the potential use of seasonal climate forecasts from the new The European Centre for Medium-Range Weather Forecasts (ECMWF) System 4 coupled ocean-atmosphere general circulation model for the modelling of the maize (*Zea mays* L.) phenology using a simple linear growing degree days (GDD) crop model, particularly the date of silking and the date of maturity. Silking is the flowering stage where there is emergence of the silks, which are the elongated stigmas of the maize plant whilst maturity is when kernels reach their maximum dry matter weight and it is indicated by the brown or black colouring on the kernel tip. ECMWF System 4 forecast data is used in this study because it provides more ensemble members, higher resolution forecasts, and a larger forecast dataset compared to other forecast models. The study will focus on three geographic areas; South Sweden, Spain and Zimbabwe which are areas with contrasting climate conditions.

The hypotheses for the study are:

1. seasonal climate forecast data can with significant accuracy, predict, maize phenology in the three study countries
2. seasonal maize development will significantly differ among the three countries

2.0 Background

2.1 Agriculture in the world

Agriculture is an essential economic activity which sustains the livelihood of millions of people around the world. 99.7% of food for humans comes from the land (David 2014), which translates to over 4.3 billion tons, with cereal production consisting of maize, rice, wheat, sorghum, barley and rye at 2.1 billion tons being most pronounced in the world (FAO 2009). At the same time, an estimated 873 million tons of fodder feed was produced worldwide from the land in 2011 alone (Global Survey: Feed production 2012). The main categories of fodder grown in the world comprise of root crops, grasses that include cereals which are harvested green, as well as legumes that include pulses which are harvested green as well (FAO: Economic and Social Development Department 2015).

In many developing countries, agriculture contributes significantly to a country's Growth Domestic Product (GDP), provides jobs as well as contributes to the country's foreign exchange earnings through the production and export of cash crops like tobacco, cotton, palm oil, coffee and tea (Cervantes-Godoy and Dewbre 2010). Agriculture in some developing countries is focused on subsistence farming with a lot of smallholder farmers producing enough for their families, and all the surplus is sold off for income (Diao et al. 2010). Crops for human consumption produced from farming contribute less to the GDP of most industrialised countries if compared to developing countries, however, a lot more fodder is produced for use in activities such as dairy farming, beef farming and livestock ranching in developed countries (The World Bank 2016).

2.2 Maize (corn) production

Maize or corn (*Zea mays* L.) is a cereal or grain crop belonging to the *Poaceae* family of grasses. It is an annual plant with high productivity and it can be grown under diverse environmental conditions, which is a significant property that aided its cultivation to spread around the world (Abbassian 2003). That being mentioned, maize production is mostly prominent in the temperate regions of the world, with 70% of maize production coming from United States of America (USA), China, Brazil and Argentina (Ranum et al. 2014). According to the 2012 estimates, production of maize was just over 872 million tons worldwide, with the largest producer, the USA, producing over 30%. 6.5% of total maize production estimates was attributed to Africa and the largest African producer was South Africa followed by Nigeria, both producing over 20 million tons combined in 2012 (FAOSTAT 2013).

The use of maize is different in all producer countries but its most notable use is for human consumption (FAO 1992). In the Mexican cuisine, maize is typically used as cornmeal in food like tortillas and tacos. In Africa, maize is the most prominent staple in most countries, and is used in the form of maize meal to make a thick porridge called mealie pap in South Africa, *sadza* in Zimbabwe, *nshima* and *ugali* in other parts of Africa (Diao et al. 2010). In most African native households this is a daily meal, with other households making a thinner version of the dish as porridge for breakfast as well. The Italians have polenta, Brazilians have *angu* and cornmeal mush of the United States of America are other examples of the cultural food derived from maize in the world. Other food products from maize worldwide include popcorn, corn flakes (breakfast cereal), bread, corn starch, cooking oil or just maize on a cob either roasted or boiled (Nuss and Tanumihardjo 2010). In developed countries, since maize has a greater biomass quantity, it is used mainly as fodder to feed animals after drying or it is sold to feed production industries as is or as raw material for fermentation industries as digestibility and tastiness of the fodder is improved if the maize is ensiled and fermented (Ranum et al. 2014). Other uses of maize include its use for bio-fuel, plastics, adhesives, fabrics and ornaments (Wallington et al. 2012).

Maize production in the world is typically rain fed, however because of limited fresh water resources there are also places where maize is grown under irrigation conditions (Zwart and Bastiaanssen 2004). Irregular rainfall can lead to droughts that ultimately lead to starvation. The occurrence of the El Niño is one factor that causes uncertainty of yields for maize production periodically. The effect of the phenomenon is experienced most in the southern hemisphere where, for example, in Zimbabwe, one of the study areas of this work, prolonged periods of dry conditions often lead to droughts (Tudhope et al. 2001). However in northern Europe, like Sweden, the El Niño Southern Oscillation (ENSO) signal is weak, whilst in southern Europe, for example, Spain experiences higher precipitation and milder winter temperatures than in non-ENSO years (Gimeno et al. 2002). During the 1980-90s El

Niño events, maize production in the South Africa in the southern hemisphere, for example, fell by between 40 to 60% (Ross et al. 1998). However, there are some instances where El Niño events lead to desirable growing conditions, which can then boost production and yields. This can happen when the El Niño event coincides with the tasselling (emergence of tassel-like male flowers) stage of maize. These kinds of positive effects are not prominent but are not uncommon and have been experienced before in the past in USA as well as Argentina, which also happen to be some of the largest producers of maize in the world (Abbassian 2003).

2.3 Climate variability and effects on agriculture

Climate varies over seasons and years instead of daily like weather. This suggests that some summers maybe be colder or warmer than preceding ones whilst other years can have more or less precipitation than others as well (Allan et al. 1996). This climatic variation is a result of three large scale features of the Pacific region namely; West Pacific Monsoon, South Pacific Convergence Zone (SPCZ), and Inter-Tropical Convergence Zone (ITCZ). The SPCZ is a wave of heavy rainfall spreading from around the Solomon Islands to just east of the Cook Islands (Power 2011). This phenomenon is most pronounced during the southern hemisphere wet season. The ITCZ extends across the Pacific, north of the equator and unlike the SPCZ, it is strongest during the northern hemisphere wet season (Žagar et al. 2011). The West Pacific Monsoon is influenced by the great differences in land and ocean temperatures and it moves north to mainland Asia during the summer in the northern hemisphere and moves south to Australia in the southern hemisphere summer (Ropelewski and Halpert 1987). The seasonal arrival of the Monsoon every season normally brings with it changes from extreme dry to extreme wet conditions.

The aforementioned phenomena are influenced by the ENSO which is the main cause of the year-to-year climatic variability of the Pacific. ENSO affects the position and strength of the main climate features which ultimately causes variability in cyclone activity, temperature, rainfall ocean currents, winds, and sea level (Thomson et al 2008). However there are other drivers of climate variability which include the occurrence of sunspots and volcanic eruptions though also at times seasonal or year-to-year variation of climate occurs randomly or is not wholly explainable (Allan et al. 1996).

The agriculture industry greatly depends on climate, mostly temperature, radiation and precipitation, as well as local conditions like soil properties and natural communities, in order to thrive (Crane et al. 2009). This means that agriculture is very sensitive to variabilities in local climatic conditions at any particular time or season (Sivakumar 2006; Crane et al. 2009). Through the occurrence of extreme weather events such as droughts, windstorms, floods or hurricanes, climate variability can have massive negative effects for crop production and yield leading to situations like food shortages in some parts of the world (Cantelaube and Terres 2005). Farmers in every season are vulnerable to the risk of losing their crops, and losing their income. In order to reduce the impact of climate variability on crop production and subsequent loss of earnings, the use of available climate information to anticipate, plan for and cope with the related seasonal climate risks is essential (Tarhule 2005; Washington et al. 2006).

Climate information can be acquired from seasonal climate forecasts, providing details that can help farmers manage their crops and livestock to make the most of opportunities during favourable seasons and lessen risks during unfavourable conditions (Ziervogel and Opere 2010). An example of some of the effects of climate variability is the 1997-98 El Nino event which is considered the most powerful ENSO in history with widespread devastating and dramatic effects (Ross et al. 1998). The phenomena led to a rush to research by the scientific community in order to understand the relationship between ENSO and climate variability worldwide. Since then, a lot of researchers have looked to work out the relation between ENSO-based climate variability and crop yields in order to aid farmers to manage similar scenarios in the future (Crane et al. 2010).

2.4 Seasonal climate forecasts

As climate is variable and the variability brings with it some vulnerability for farmers who depend on climate for their yields, there has been a need for quality and timely seasonal climate forecast data that can aid agriculture and minimize production risk. Seasonal forecasts are an approximation of possibilities of the state key climatic variables in upcoming seasons and whether they are dynamical or statistical predictions, they must be able to quantify the probability of each possible outcome all through the full range of possibilities, from extremely wet to extremely dry seasons (Klopper et al. 2006).

Statistical models were the initial models used for climate forecasting since the late 1800s when prediction of the climate one season ahead was first tried. These methods were incited by the famines experienced in India during the late nineteenth century caused by drought as a result of the Indian monsoon failure of the years 1877-78. Subsequent research carried out especially, by Sir Gilbert Walker, led to the identification of the Southern Oscillation (SO) (Troccoli 2010). This was termed the great 'see-saw' because of the differences in atmospheric pressure between the South Pacific and the Indonesian region after a pattern of unusually high pressures were seen extended into western Siberia, southern Australia and northern China during 1877 (Walker 1924; Allan et al. 1996). This is known today as the 1876-77 El Niño.

Since the statistical forecast models initiated in the 1800s, more process-based forecast models have been developed. These models are founded on improvements in the understanding of the interactions of the atmosphere with the sea and land surfaces, which has led to meteorologists developing state-of-the-art forecast systems that allow for more defined seasonal climate predictions (Hansen and Indeje 2004). Meteorologists have since been able to recognize the sensitivity of the atmosphere to changes in sea surface temperatures especially in locations with high sea temperatures like the tropics rather than areas in high latitudes. This is why seasonal climate predictions of the tropics are far more skilful (Thomson et al 2008). This knowledge together with the increased efficiency and capacity of computers today has paved way for more robust methods of climate forecasting, particularly the dynamic models. These are more sophisticated models which usually take into account the atmospheric, land surface, oceanic, and sea ice modules at a high levels of detail. The atmospheric component of dynamic forecasting models is similar to what is used in weather forecasting. The atmospheric initial state for a seasonal forecasts is usually provided from the atmospheric state created to initialize a weather forecast (Troccoli 2010).

2.5 Use of seasonal forecast data and crop simulation models

Seasonal climate variability and climate extremes can have significant impacts on crops, and so the ability to transform seasonal forecasts of climatic variables such as temperature and rainfall into crop yield forecasts on a seasonal timescale has significant economic and humanitarian benefits. Integrating seasonal climate forecast data in crop models has been used in previous studies where crop yield for the upcoming season is predicted (Guillermo A. Baigorria , James W. Jones, 2002, Peiris, Hansen, & Zubair, 2007 & Mishra et al., 2008).

Crop models simulate crop development, growth, and yield given the influence of the crop variety, environmental factors as well as crop management. There are two main types of crop simulation models; empirical models and mechanistic ones, although most crop models contain a mixture of both (Jame and Cutforth 1996). Mechanistic crop models attempt to reproduce the development of the crop in terms of the fundamental biological, chemical, and physical processes from seed initiation to senescence with the use of mathematical formulations (Prusinkiewicz 2004). Empirical crop models express the relationship between crop yield and climatic parameters through the use of statistical techniques like regression or correlation, without considering the physiological processes involved in plant growth (Murthy 2003). Both ways of modelling are effective and the selection of which model to use can only be determined by the purpose for which the model is meant to serve.

Crop modelling can be done either in generic or in crop-specific models, depending on the needs of the user and type of data available. There are a number of operational generic crop simulation models in existence currently. These crop models are set up at various levels of intricacy and model typology is determined by the purpose of the model. Generic crop models work to elucidate the processes of assimilation, respiration, development and growth irrespective of crop species. The model is later adjusted to simulate the physiological and phenological traits of specific crops such as maize, wheat or rice (Yang et al. 2004). Some of the most common generic crop models include AquaCrop (Hsiao et al. 2009)), WOFOST (Diepen et al. 1989), SUCROS (Guérif and Duke 1998), INTERCOM (Jones et al. 2001) and STICS (Brisson et al. 2003). Crop specific models are those models that are developed and fine-tuned to a specific crop's growth and developmental patterns. The CERES models which are included the Decision Support System for Agro-technology Transfer (DSSAT) are one of the most used models in the world particularly CERES-Wheat and CERES-Maize (Mearns et al. 1999; Greenwald et al. 2006; Dente et al. 2008). DSSAT is a collection of independent computer programs working together to simulate crop growth under different conditions, given the data on environmental variables such as climate conditions, soil properties, sensitivity to photoperiod, duration of growth stages, as well as management and crop genotype information (Jones et al. 2003).

Maize has been the focus of many simulation models for decades mostly because of it wide distribution and vulnerability to climate variations. Simulation models specific to maize differ considerably from generic models in both theoretical framework and handling of crucial processes that drive growth and development (Yang et al. 2004). Some of the more common maize models include CERES-Maize (Gungula et al. 2003) and APSIM-Maize (Yang et al. 2004). Maize models take into account that development from emergence to maturity is predominantly driven by temperature and as such, models can be grouped into two categories with respect to how temperature affects development; linear models that assume a linear relationship between temperature and development by making use of the common notion of growing degree days (GDD) or thermal time and nonlinear models that do not consider the linear relation assumption (Streck et al. 2008).

Various studies have looked at modelling maize phenology based on the idea of GDD. The Splinter model and SIMAIZ model both attempt to predict different growth stages but they do not quantify photoperiod sensitivity (Hodges 1990). The INTERCOM model (Jones et al. 2001) works to identify two growth phases in maize; the vegetative phase from emergence to silking and the reproductive phase from silking to maturity (Yang et al. 2004). The CERES-Maize model differentiates among emergence, end of juvenile stage, tassel initiation, tassel, silking, grain-filling and physiological maturity when modelling stages of growth (Yang et al. 2004). In this study, we made use of current seasonal forecast climate data from the ECMWF System 4 coupled ocean-atmosphere general circulation model together with a linear GDD crop model to try and predict two stages of growth; day of silking and day of maturity.

3.0 Materials and Methods

3.1 Site selection

The study focused on three countries; Zimbabwe, Spain and Sweden (south), and from each country four sites were selected using purposive random selection. The three countries represent different spectrums in terms of climatic conditions and agricultural activities - particularly maize production. This selection was done in order to see how the difference in conditions would affect the efficacy of the modelling.

3.1.1 Zimbabwe

Zimbabwe is situated in southern Africa covering with a total area of 390,757km^2, where 42.5% of this is agricultural land (Central Intelligence Agency (CIA) 2015). The climate in Zimbabwe is generally tropical with the wet season being from November to March. However, there are local climate variations, for example the Eastern Highlands have highest rainfall and coolest temperatures whilst southern Zimbabwe is arid and hot. Once known as the “bread basket of Africa”, Zimbabwe produced 1.456 million tons of maize in 2014 (FAO/GIEWS 2016).

Zimbabwe is divided into five agro-ecological regions, also known as natural regions based on mean annual rainfall, soil quality and vegetation among other factors (FAO 2006). The quality of the land declines from region I with mean annual rainfall of over 1000mm, good soils and lots of agricultural activities to region V with mean annual rainfall less than 450mm and poor soils unsuitable for crop production (Mugandani et al. 2012). The provinces of Mashonaland West, Midlands, Mashonaland Central and Manicaland were the four highest maize producers in the 2009-10 season (FAO/WFP 2010). The four sites selected based on production and the agro-ecological zones were Zvimba (Mashonaland West) in region II, Mvuma (Midlands) in region III, Mt Darwin (Mashonaland Central) in region II and Nyanga (Manicaland) in region I.

3.1.2 Spain

Spain is a located in the south west of Europe and covers an area of 505,370km^2, where 54.1% of this is agricultural land (Central Intelligence Agency (CIA) 2015). The country is in three climatic zones because of its size, that is, Mediterranean, Maritime and Continental climates (Kottek et al. 2006). Spain is the sixteenth largest producer of maize in the world (FAOSTAT 2013) and the maize is grown from March until August. Maize is grown basically everywhere in Spain and so regions of most productivity were used in the site selection. The first site selected is Castilla y León which accounts for 20 percent of the Spain's total corn production, then second site is Aragon which accounts for 19 percent of total corn production (Solsten and Meditz 1988). The third and fourth sites are Estremadura and Albacete, both in the southern regions and with fertile soils and good temperatures for maze production.

3.1.3 Sweden

Sweden is a located in northern Europe and covers an area of 450,295km^2, where 7.5% of this is agricultural land (Central Intelligence Agency (CIA) 2015). There are three different climate zones in Sweden, that is, the southern parts with warm temperate humid climate, northern regions have sub-arctic climate and the central part has a humid continental climate (Kottek et al. 2006). Agriculture in Sweden faces very different circumstances in the north if compared to the south. The southern province of Skåne has a growing season that is almost 100 days longer compared to Norrland in the north (Jordbrukstverket 2009). This was the basis for site selection in the south of Sweden. The sites selected were Hässleholm, Sjöbo, Olofström, Åstorp.

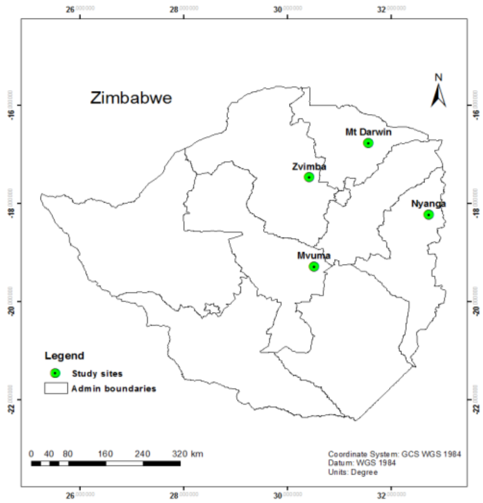
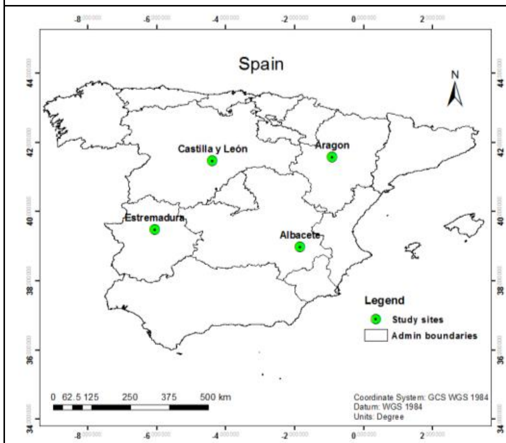
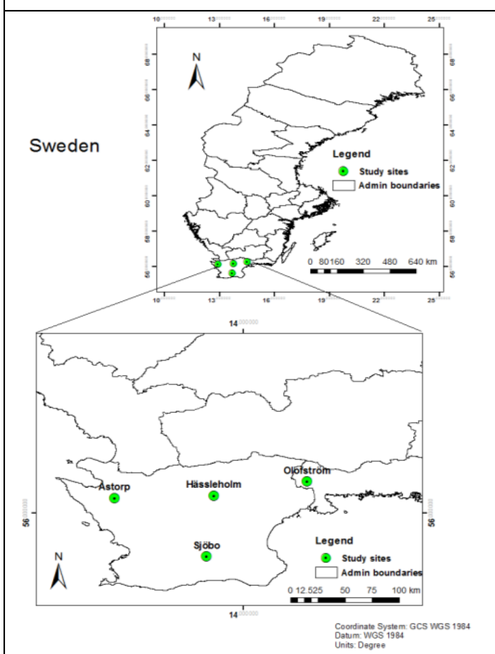
3.2 Data

Maize development and physiology or process functioning is affected by a combination of factors but one of the major factors is ambient temperature (Pastenes and Horton 1996; Harrison et al. 2011). For this study, near surface (2 meter) air temperature observed and forecast data was acquired from the European Climate Observations Modelling and Services Initiative User Data Gateway (ECOMS-UDG) through the interface ecomsUDG. Raccess R package. ECOMS-UDG, developed by the Santander MetGroup is a climate data repository designed to facilitate ease of access to seasonal forecasts and other climate data to end users (Bedia and Magari 2014).

The forecast temperature data acquired was from the ECMWF System 4 coupled general circulation model (GCM). ECMWF has been operating a seasonal forecast system since 1997, with a number of operational systems in place over the years. The latest version of the ECMWF operational seasonal forecasts is the System 4 which has been operational since late 2011 and it has higher resolution forecasts, more ensemble members and a larger hindcast dataset. Hindcasts are retrospective or historical forecasts that are essential for model evaluation as well as for comparison with observation data. The ECMWF System 4 seasonal hindcast data starts from 1981 up to 2010 at 0.75^o x 0.75^o spatial resolution and it includes 15 ensemble members consisting of 7 month simulations released on the 8th of each month (ECMWF 2015). In the system upgrade, it makes use of the most recent atmospheric model version Nucleus for European Modelling of the Ocean (NEMO) as well as a new variational ocean data assimilation system, NEMOVAR, which together improve the mean state and sea surface temperature (SST) forecast skill in the Tropical Atlantic and East Pacific oceans (Molteni et al. 2011). The observation climatology temperature data used in this study was the gridded WATCH-Forcing-Data-ERA-Interim (WFDEI) which runs from 1979 to 2012 with a 0.5^o x 0.5^o spatial resolution, from the European Union funded Water and Global Change (WATCH) project (EU WATCH 2011).

Temperature data was acquired for each of the three countries and four sites (four grid cells) through single point scale selection of the central geographical coordinates for each site (Table 1). Maize productive seasons for each country and site were identified as; for Zimbabwe –November to April (FAO/GIEWS 2016), Spain – March to August (Souza 1994) and Sweden –April to September (Jordbrukstverket 2009). The first day of these seasons were used to initialise the crop model growing period. System 4 data was downloaded for all 15 ensembles at one-month lead time from year 1982 to 2010. Lead time is the time between the issuing time and the beginning of the forecast period and in this case it was one-month lead for the whole season, per year for 28 years. However, because the Zimbabwean crop productive season lies in two years, the data for the four sites in this country was acquired from 1981 to 2009.

Table 1: Summary of the study sites and maize productive seasons for each site

<table>
<tr><th>Country</th><th>Site</th><th>Latitude</th><th>Longitude</th><th>Season</th></tr>
<tr><td rowspan="4">
</td><td>Zvimba</td><td>-17.46</td><td>30.43</td><td rowspan="4">November - April</td></tr>
<tr><td>Mvuma</td><td>-19.28</td><td>30.52</td></tr>
<tr><td>Mt Darwin</td><td>-16.76</td><td>31.57</td></tr>
<tr><td>Nyanga</td><td>-18.22</td><td>32.74</td></tr>
<tr><td rowspan="4">
</td><td>Castilla y León</td><td>41.48</td><td>-4.39</td><td rowspan="4">March - August</td></tr>
<tr><td>Aragon</td><td>41.59</td><td>-0.91</td></tr>
<tr><td>Estremadura</td><td>39.49</td><td>-6.06</td></tr>
<tr><td>Albacete</td><td>38.99</td><td>-1.85</td></tr>
<tr><td rowspan="4">
</td><td>Hässleholm</td><td>56.15</td><td>13.76</td><td rowspan="4">April - September</td></tr>
<tr><td>Sjöbo</td><td>55.63</td><td>13.70</td></tr>
<tr><td>Olofström</td><td>56.27</td><td>14.53</td></tr>
<tr><td>Åstorp</td><td>56.13</td><td>12.94</td></tr>
</table>

3.2.1 Bias Correction

Climate model forecasts are not without fault and at most times will display significant discrepancies from observed data. These differences can be exhibited through the over or underestimation of climatic conditions as a result of systematic and random errors (Teutschbein and Seibert 2013). Bias correction is employed to improve the prediction skill of forecasts by ensuring that model data has similar statistical properties as observed data before being used in impact studies, in this case the crop phenology model. Several methods exist to correct biases in climate forecast data ranging from delta change approach to quantile mapping but for this study the linear-scaling approach (Equation 1) was used (Teutschbein and Seibert 2012). It works with long term monthly mean bias correction factors derived from the difference between observed and forecast ensemble values. These factors are then added to the daily forecast temperature value for each ensemble member.

Equation 1 $$T_{contr\_corrected}(d) = T_{contr}(d) + \mu_m(T_{obs}(d)) - \mu_m(T_{contr}(d))$$

- T_{contr} (d) is the daily temperature of the bias corrected System 4 ensemble data.
- μ_m (T_{obs} (d)) is the long term monthly mean temperature WFDEI data
- μ_m (T_{contr} (d)) is the long term monthly mean, ensemble mean temperature System 4 ensemble data

3.3 Maize phenology modelling

The study focused on modelling two stages of maize development, that is, day of silking and day of maturity. To model these stages of development a temperature driven growing degree days (GDD) model developed in Matlab R2015b was adapted from Yang et al. 2004 and Hou et al. 2014 (Equation 2). GDD is basically the accumulation of heat units above a defined base temperature.

Equation 2 $$\text{daily GDD} = \left[\frac{(T_{max} + T_{min})}{2}\right] - T_{base}$$

- T_{max} is the daily maximum air temperature
- T_{min} is the daily minimum air temperature

- T_{base} is the temperature below which the maize development does not occur

The maximum threshold temperature also needs to be defined as it is assumed maize development beyond that threshold does not contribute to development. For this study, 10°C base temperature and 30°C as the maximum temperature threshold were adapted from Hou et al. 2014.

Two types of maize varieties were modelled in this study, each with a different total GDD from emergence to maturity. The early variety had a total GDD of 1100 whilst the late variety had a total GDD of 1500. The choice to look at both varieties of maize was made in order to take into account both extremes of maize seed productivity as well as the difference in the climate of the study countries. The total GDD values were then used to determine the GDD values for silking, and subsequently the day of silking, through Equation 3 below adapted from Yang et al. 2004 based on a regression analysis of temperature and 107 commercial Pioneer hybrids where 100 is the slope and 0.445 is the intercept. GDD value for maturity (Equation 4) was the same as the total GDD.

Equation 3 $$GDD_{silking} = 100+0.445*GDD_{total}$$

Equation 4 $$GDD_{maturity} = GDD \geq GDD_{total}$$

3.4 Skill Score Calculation

Climate forecast data from ensemble prediction systems like System 4 provide a way of creating probabilistic future climate forecasts. The forecast probability where there are ensembles is assessed as the proportion of ensemble members which rightly predict an event occurring. However, because the number of ensembles used in climate forecast models is always limited, this introduces an foreseeable level of sampling error such that the predicted probability will not always be representative of the underlying probability of an event occurring (Richardson 2001).

A measure of the performance of a probability forecasting system in predicting an event occurring set against the observed climate is what is termed forecast skill (Gandin and

Murphy 1992). The skill score or weight is the relative measure of the success of the forecast and some of the more common skill score measures include the Brier Score (BS), the relative operating characteristic (ROC) and the (ETS) equitable threat score (Hamill and Juras 2006). For this study, the universally used Brier Score was used, which is a measure of the mean squared error of probability forecasts for dichotomous events as shown in Equation 5 below (Brier 1950).

Equation 5 $$BS = \frac{1}{N}\sum_{t=1}^{N}(f_t - O_t)^2$$

- f_t is the probability forecast on occasion
- O_t is a binary variable indicating whether the event occurred
- N is the number of forecasts being evaluated

The Brier score is often converted to a skill score when its value is normalized by the Brier Score of a reference climatology, WFDEI observation data in this case (Hamill and Juras 2006). Equation 6 adapted from Wilks 2001 illustrates how the Brier Scores are converted to skill scores (SS) for this study.

Equation 6 $$SS = \frac{BS - BS_{clim}}{BS_{perf} - BS_{clim}} = \frac{BS_{clim} - BS}{BS_{clim}}$$

- BS is the Brier Score, output from Equation 5
- BS_{clim} is the Brier Score from the average monthly temperature of the reference climatology over 28 years
- BS_{perf} is the Brier Score for perfect forecasts
- SS is the skill score from the Brier Score

Brier skill scores range between -∞ and 1 and an ideal Brier skill score would be 0.5 or higher. A skill score of 1.0 indicates a perfect probability forecast whilst a Brier skill score of 0.0 or lower should indicate no skill.

2.5 Data Analysis Flowchart

The data anlysis steps and methods used in this study are shown below (Fig 1).

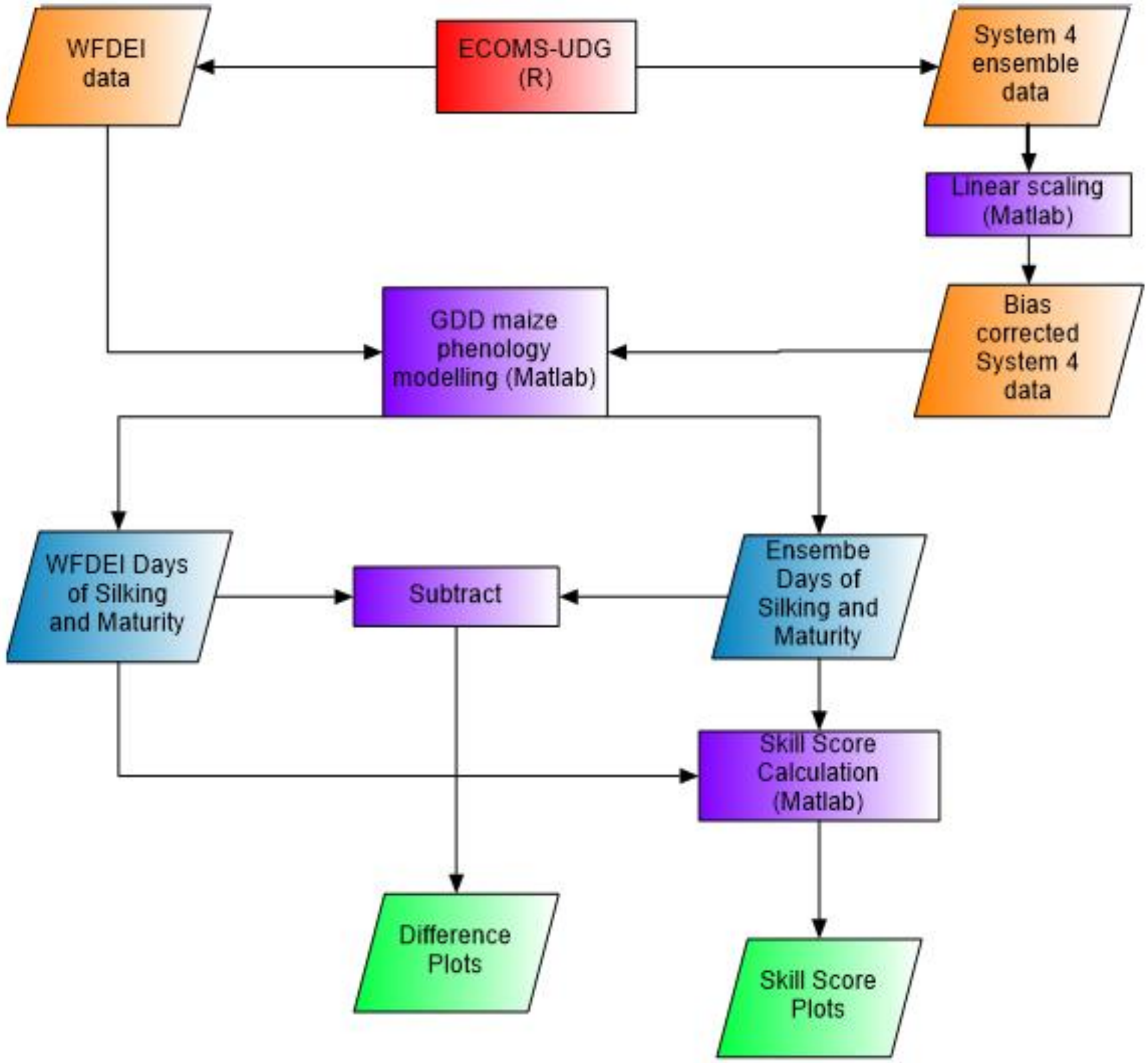


Fig 1: Flowchart illustrating the methodology used in this study

4.0 Results

4.1 Bias-correction

The near surface (2m) air temperature ensemble mean and observed data for all countries and all sites can be observed from the graphs illustrated below (Fig 2) where a visual comparison highlights some differences between the datasets. Some discrepancies are seen where the WFDEI data is lower and the System 4 data is higher over the 28 years as is the case in Zvimba, Zimbabwe or Aragon, Spain. In some cases, like in Nyanga, Zimbabwe there is a distinct underestimation in the forecast data. To quantify the magnitude of the systematic errors, the difference between the observed WFDEI data and the forecast System 4 ensemble mean was calculated, with results shown in graphs below (Fig 3).

The calculations show that there are significant consistent differences between the forecast temperature data and the observed data. These differences are markedly bigger in Spain and Sweden where there is bias towards overestimation of temperature in certain years by the System 4 model in most of the sites by values that are as high or over 10^{o}C. The differences in the temperature data from the System 4 model and WFDEI climatology over the 28 years are also significant in all countries, with biases as high as 5^{o}C. These results then instigated the need to correct the data for biases using the linear scaling bias correction method described in the previous chapter.

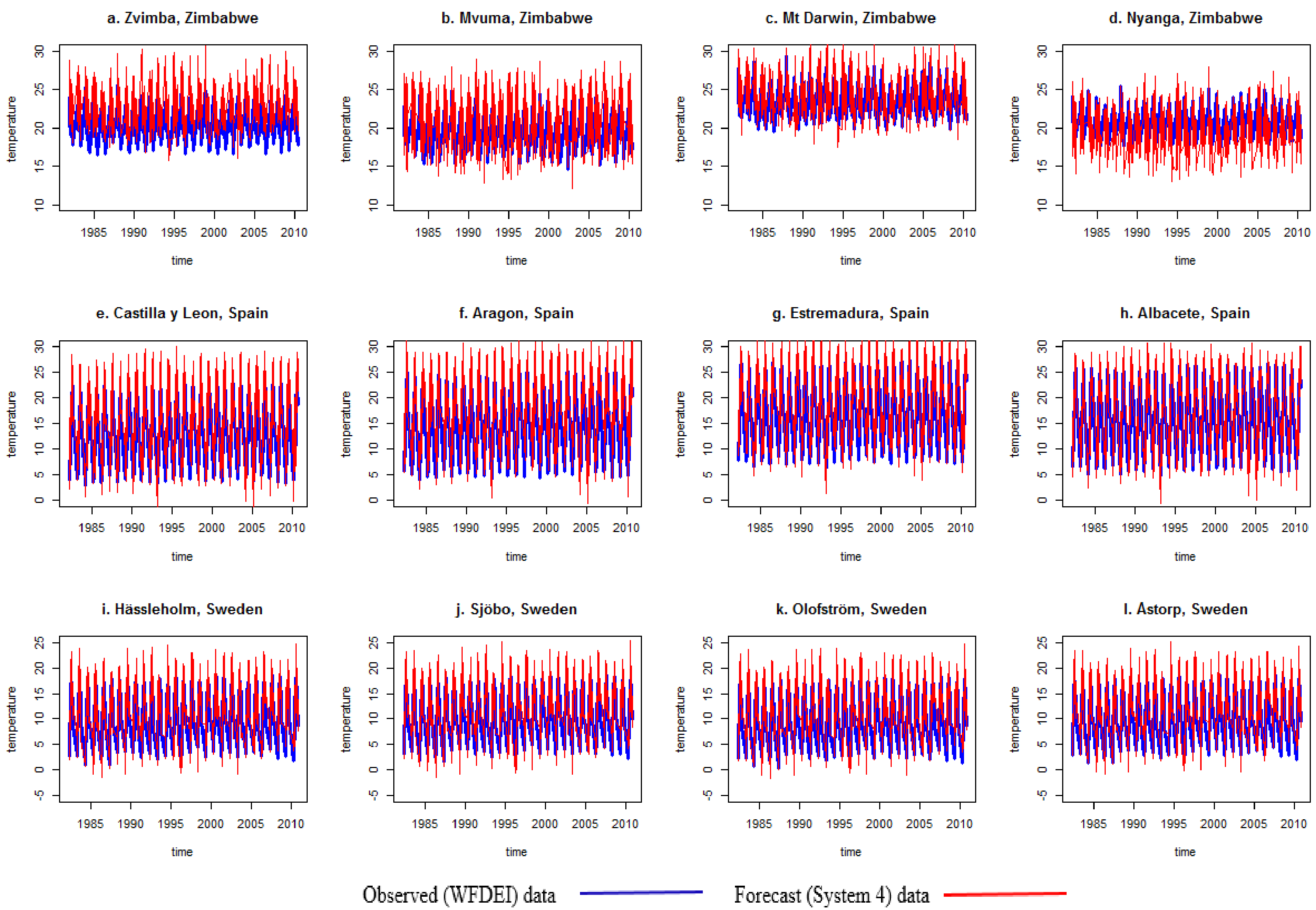


Fig 2: Graphs showing the near surface (2m) air temperature forecast (System 4) ensemble average and observed (WFDEI) data for years 1982 – 2010.

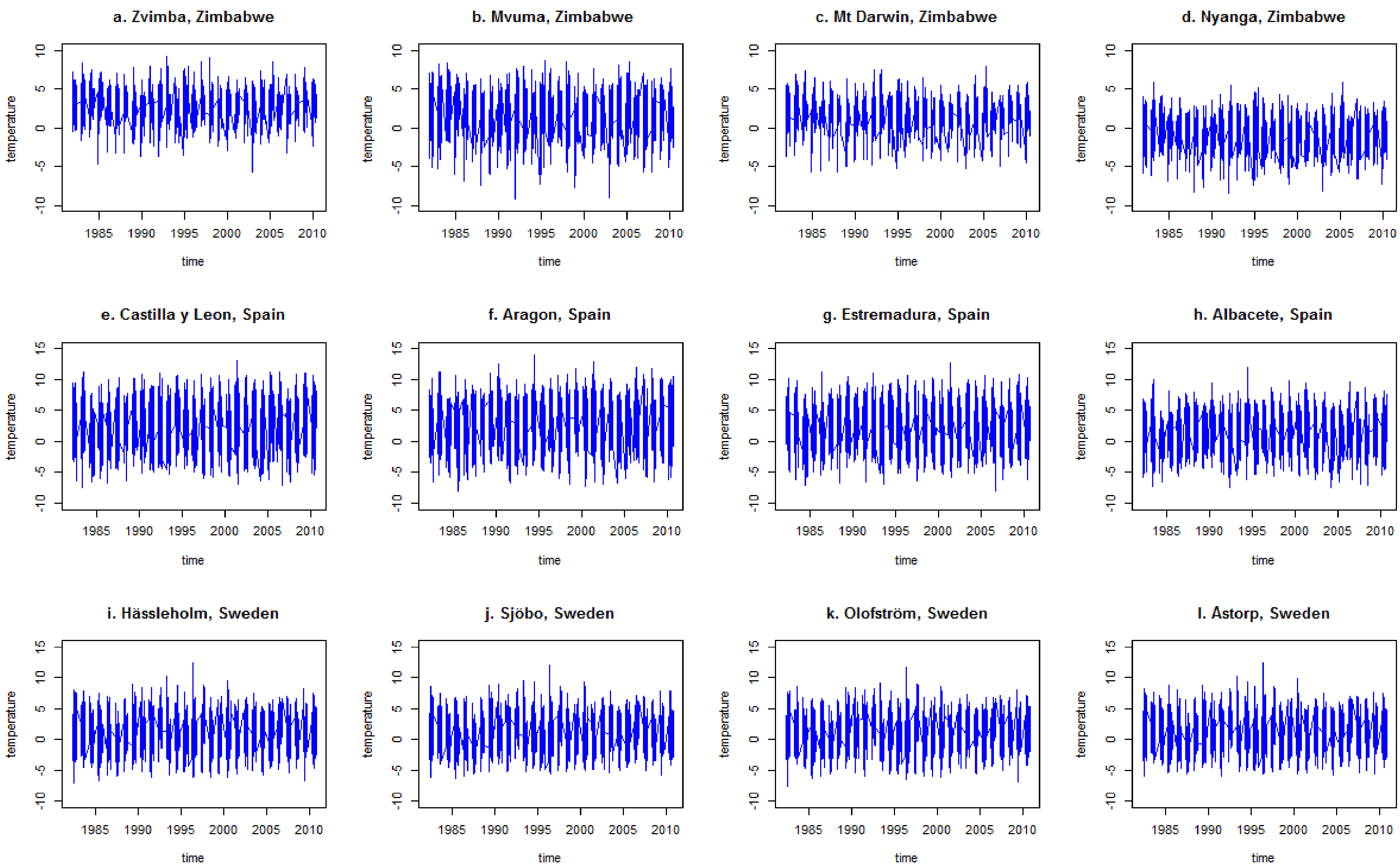


Fig 3: Graphs illustrating the difference between the observed WFDEI data and the forecast System 4 ensemble average data

4.2 Maize phenology modelling

4.2.1 Forecast (System 4) data

The seasonal development of maize was modelled in this case using bias corrected System 4 data and the results for each country and site are illustrated in the graphs below (Fig 4).

Zimbabwe

For the early maize variety, all sites in Zimbabwe except Nyanga exhibit silking mostly around 40 days after the start of the growing season. This is in early December, illustrated by the negative day of year values in the graphs because the growing season in Zimbabwe falls within two years. In Nyanga silking for the early variety of maize is projected to occur in first week of January of the harvesting year, which is about 20 days later than the other sites. The late variety of maize, according to the model, is projected to silk around day 1 of the year (day 60 of the season) for all sites, over the 28 years with the exception of Nyanga. Day of maturity for the Zimbabwe sites shows a bit more variation among the sites. For Zvimba and Mt Darwin, day of maturity for the early variety is around 20 January for the 28 years whilst for Nyanga and Mvuma it is around day 40 and day 50 of the year respectively. Day of maturity over the 28 years for the late variety is varied for all the sites, with maize grown in Mt Darwin expected to have matured earliest around day 50 then Zvimba at around day 60, Mvuma fluctuating from day 60 to around day 80 and Nyanga fluctuating from around day 80 to day 100 of the year.

Spain

For the early variety of maize, the day of silking is projected to happen initially in Estremadura from around day 150 to day 160, with the earliest maturity days being experienced in the year 2005. Aragon and Albacete have similar days of silking of early variety maize around day 160 to 170 of the year. Castilla y León is late in terms of day of silking of the early variety with days fluctuating from day 180 to 190 of the year. It is also predicted to be the most delayed site for silking for the late variety with days fluctuating around day 200 of the year. Aragon and Albacete have similar days for silking for the late variety around day 180 to 190 of the year whilst for Estremadura is fluctuates around day 170 to day 180 of the year. Day of maturity for the early variety is around day 200 to 210 for all sites except Castilla y León which is predicted to experience this development around day 230 of the year. In Castilla y León there is no projected day of maturity for the late variety, whilst for the other three sites the day of maturity is projected to be around day 235 to day 240.

Sweden

Sweden predictions only show the day of silking for the early and late varieties, which both occur late into the season and fluctuate markedly over the 28 years. Day of silking for the early variety is projected to have similar patterns for all four sites with late days of silking around day 245 of the year from 1982 to around 1987, to a fluctuation of an earlier day of silking around day 235 of the year. There is a noticeable dip in the graph showing a year where silking was even earlier, projected at around day 225 in 1997, and another dip in 2002 where the projected day was around day 222 of the year. Fluctuations are also pronounced for all sites for the day of silking for the late variety. For all sites the day of silking for the late variety is projected at around day 235 to 255 of the year, with the exception of the dip around 1998 where the day of silking occurred earlier around day 225 to 230 of the year for all sites. For some years like year 5 and around year 11, there is no predicted day of silking for the late variety and in overall there is no predicted day of maturity for any of the varieties.

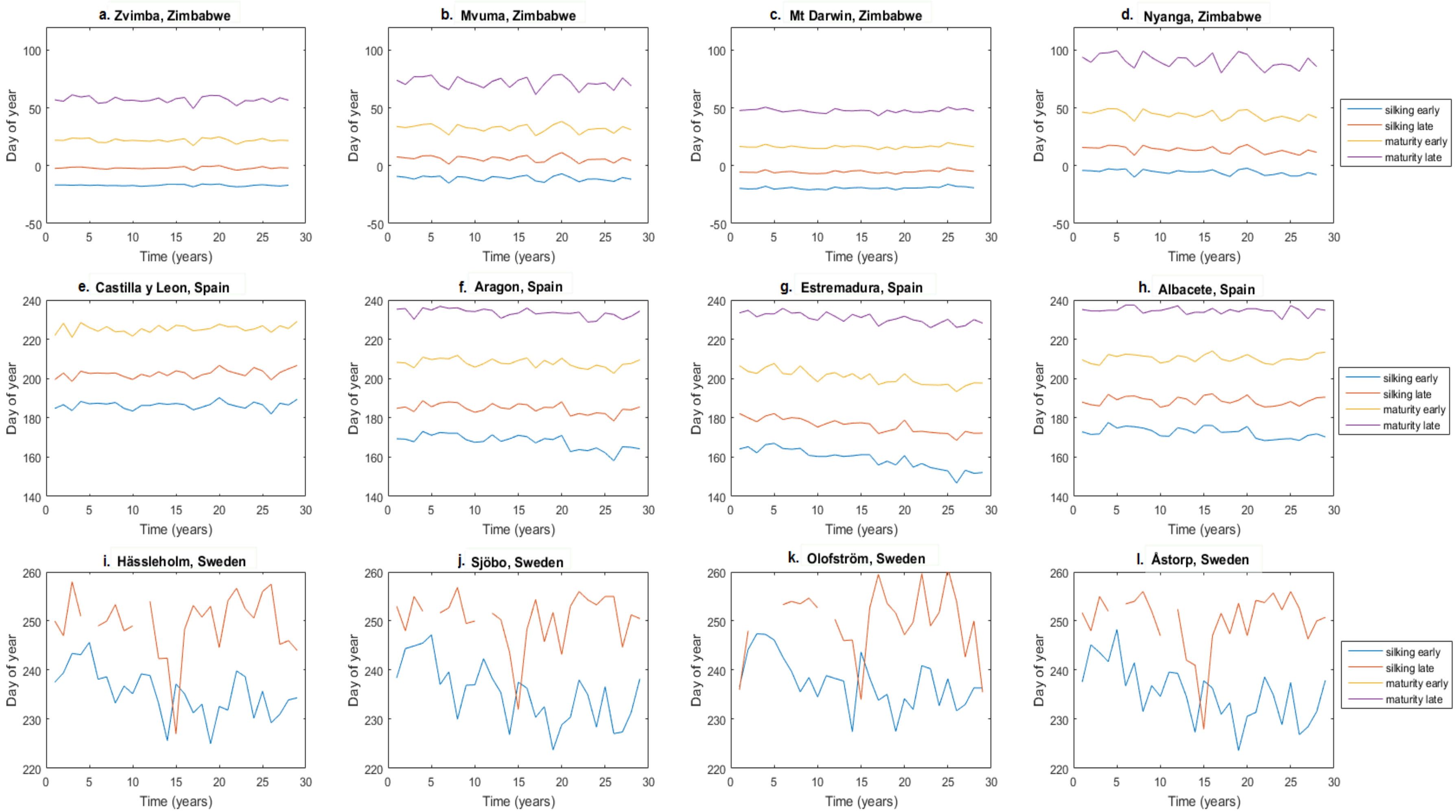


Fig 4: Graphs showing seasonal development of early and late varieties of maize in Zimbabwe, Spain and Sweden, per site from 1982-2010 modelled using System 4 ensemble average forecast data.

4.2.2 Observed (WFDEI) data

The seasonal development of maize was modelled in this case using observed WFDEI data and the results for each country and site are illustrated in the graphs below (Fig 5).

Zimbabwe

The early maize variety, for all sites in Zimbabwe particularly in Zvimba and Mt Darwin, exhibit silking earlier than the other sites around 40 to 45 days after the start of the season. This is also illustrated by the negative day of year values in the graphs. In Nyanga silking for the early variety is about 10 to 15 days later than the other sites. The late variety of maize is projected to silk around day 1 of the year in Zvimba and in some years for Mvuma site however it is projected to occur earlier in Mt Darwin, around day 50 of the season and later in Nyanga around day 70 of the season. For Zvimba and Mvuma, day of maturity for the early variety is around 30 January, varying a bit over the 28 years whilst for Mt Darwin it is projected for the 10th day of the year whilst in Nyanga it is around day 50 of the year, later than the other sites. Over the 28 years, day of maturity for the late variety is varied for all the sites with maize grown in Mt Darwin expected to have matured earliest around day 40 to 50 then Zvimba at around day 60, Mvuma fluctuating around day 70 to 80 and Nyanga fluctuating from around day 80 to day 100 of the year.

Spain

For the early variety of maize, day of silking for the early variety is projected to occur earlier than the other sites in Estremadura just as System 4 predictions, though in this case it is predicted from around day 180 to day 200 of the year. Aragon and Albacete have similar days of silking of early variety around day 185 to day 220 of the year. However, Castilla y León, as in System 4 predictions, has delayed days of silking of the early variety compared to the other sites, with days fluctuating from around day 210 to day 240 of the year. This is also the case for the predicted days for silking for the late variety with days fluctuating from day 220 to day 250 of the year. Aragon Estremadura and Albacete have similar days for silking for the late variety around day 220 to day 230 of the year. Day of maturity for the early variety is around day 240 to 250 for all sites except Castilla y León which is predicted around day 260 of the year. In this same site there is also no projected day of maturity for the late variety, whilst the rest of the sites are projected to reach maturity in some of the years, and not all 28 years completely unlike the System 4 predictions.

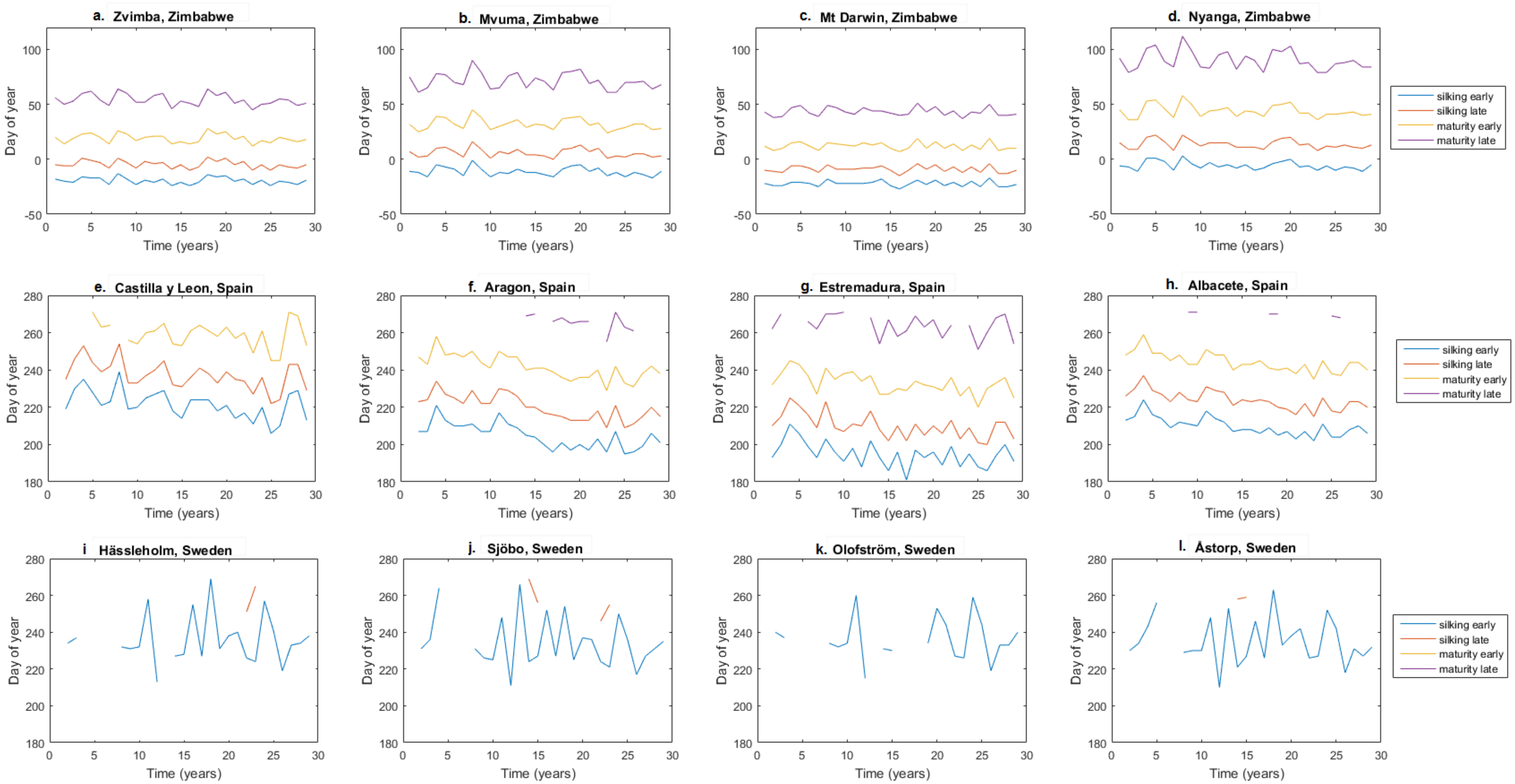


Fig 5: Graphs illustrating the development of early and late varieties of maize in Zimbabwe, Spain and Sweden, per site from 1982 - 2010 modelled using observational WFDEI data.

Sweden

Sweden predictions only show mostly the day of silking for the early maize variety which happens pretty late into the season and fluctuate a lot over the 28 years just like System 4 predictions. Day of silking for the early variety is projected to have similar patterns for all four sites fluctuating from day 220 to day 260 of the year. There are years when early varieties are not predicted to silk in all sites like 1985 to 1987. Olofström is predicted not to have any silking of late varieties whilst the other three sites only have a couple of years where silking of late varieties is projected at around day 260 of the year.

4.3 Model validity

4.3.1 Difference plots

The difference between the days of the year predicted for silking and maturity for the late and early varieties for System 4 data and WFDEI was calculated with the results illustrated below, both as 28-year average (Fig 6) and as differences in each year Fig (7).

On average, there are a few days' difference between the days modelled by System 4 data and those resulting from WFDEI data, as differences go as far as 6 days in both the day of silking and day of maturity. However, the year by year differences show differences as high as 30 days as seen in Sweden. The 28-year average difference for day of silking early variety shows less difference for the sites in Sweden with around 2 days' anomaly, whilst Spain has the highest anomaly of forecast data delay of up 5 to 6 days for all sites. Zimbabwe has forecast data delay average of 2 days in site 1 (Zvimba) and site 3 (Mt Darwin) whilst the rest of the sites are similar to the Swedish sites with a 2-day anomaly. The year by year variation of differences for day of silking for early variety are more pronounced in Sweden, with day of silking occurring 30 days early in 1994 and 30 days later in 1999. The fluctuation is greatest for Sweden than for Spain whose highest difference is 20 days or Zimbabwe whose highest difference is 15 days.

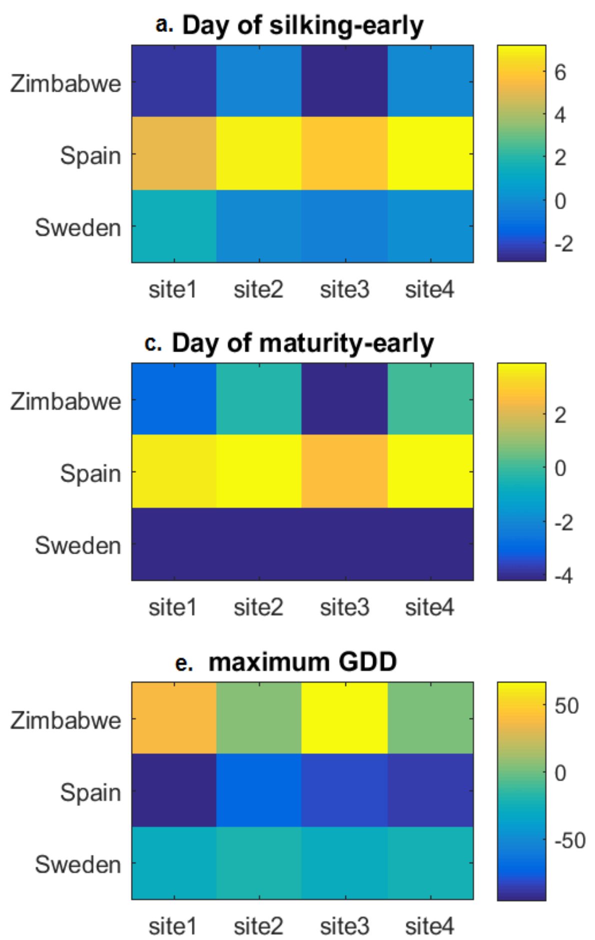


Fig 6: Colorbar illustrations of the 28-year average difference plots between WFDEI and System 4 predicted days of seasonal development in maize grown in Zimbabwe, Spain and Sweden, per site.

The 28-year average difference for day of silking for the late variety shows similar high 5 to 6 day anomalies for all the sites in Spain, as well as site 2 (Sjöbo) and site 4 (Åstorp) in Sweden. Mt Darwin (site 3) in Zimbabwe shows forecast data overestimation with an anomaly of close to 4 days and the rest of the sites show a difference of up to 2 days. The year by year variation of differences for day of silking for late variety are similar to those of the early variety for sites in Spain and Sweden whilst for the sites in Sweden where results of differences are only shown for Hässleholm and Sjöbo in 2005-06 and 1995-96 for Åstorp and Sjöbo.

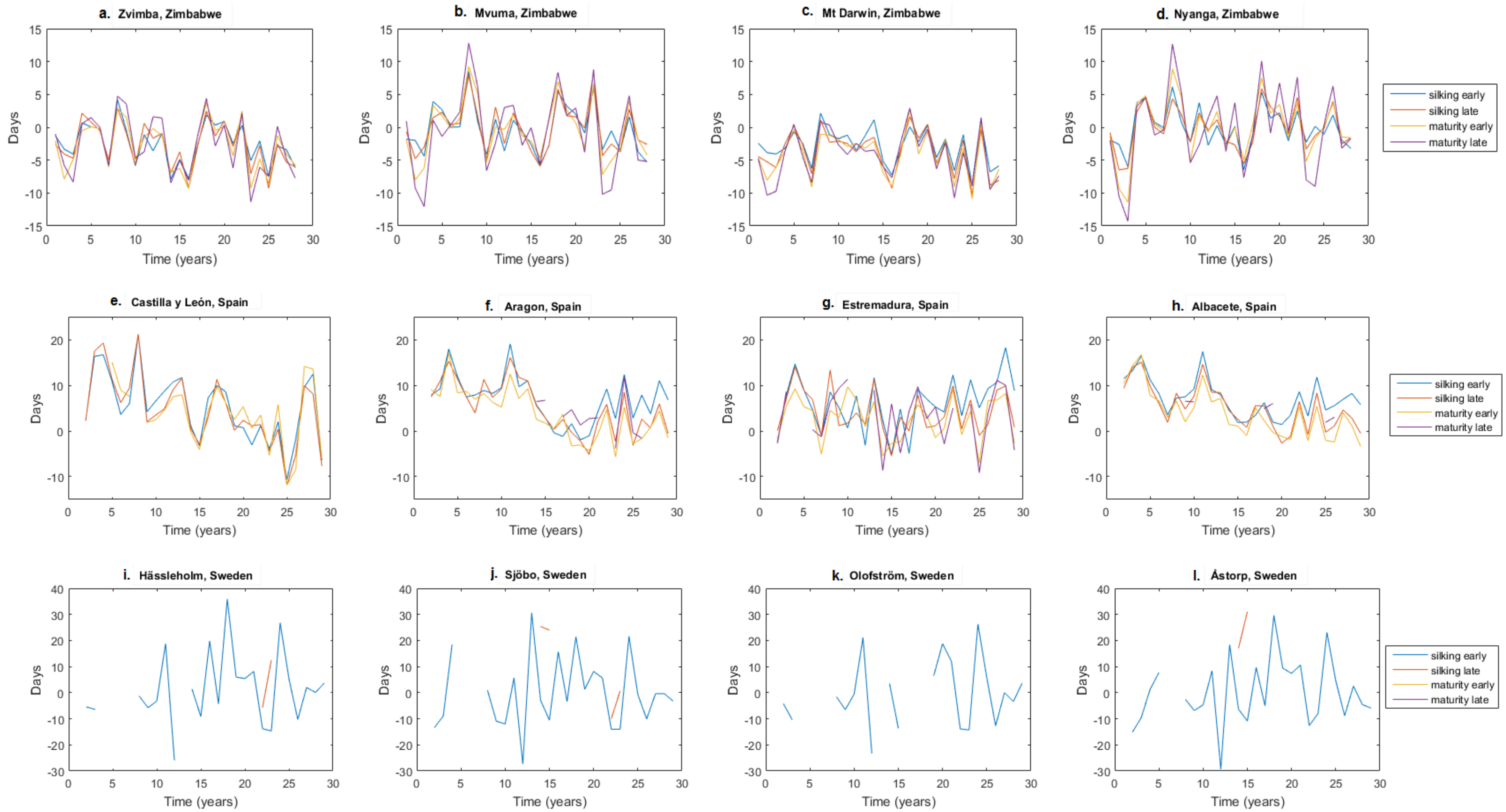


Fig 7: Graphs showing the difference plots between WFDEI and System 4 predicted days of seasonal development in maize grown in Zimbabwe, Spain and Sweden, per site from 1982 to 2010

The 28-year average difference for day of maturity for both varieties of maize show less positive values, showing that there in this case there more of underestimation by the System 4 data than overestimation of the day of maturity. Spain in all sites exhibits the highest difference in days showing forecast data overestimation with difference in days ranging from 2 to 4 days except for site 1 (Castilla y León), for maturity of late variety which has no data. Sweden for all its sites and both varieties also has no data for maturity of maize. Zimbabwe has its highest anomaly in Nyanga (site 4), a difference of up to 4 days whilst the rest of the sites show a forecast data overestimation of 1 to 2 days.

The difference in the maximum GDD reached by System 4 and WFDEI data ranges around an over prediction of 25GDD in all sites for Sweden, and an over prediction of close to 100 GDD in Spain for all sites. Values for Mt Darwin and Nyanga in Zimbabwe show little differences in maximum GDD in the two datasets ranging around 10 GDD difference. Whilst Zvimba and Mvuma show an under prediction ranging from 40 to 55 GDD.

4.3.2 Skill Scores

The measure of the success of the predictions using the Brier skill score method shows that in none of the cases was skill above a score of zero (Fig 8). The skill score for day of silking early variety is between -1.5 and -1 for all sites in Sweden with Sjöbo (site 2) having the highest skill around -0.5. The skill score is lowest in Albacete, Spain with -4, whilst the other three sites in the country have scores between -1.8 to -2. Mt Darwin (site 3), Zimbabwe has the lowest skill score in the country at -3.5, whilst Mvuma (site 2) is highest at around -1. Site 1 (Zvimba) and site 4 (Nyanga) are just below a skill score of -1.

Mt Darwin (site 3), Zimbabwe again has the lowest skill score in the country at -3.5 for day of silking late variety, whilst the other sites range in skill score of -1.3 to -1.6. The skill score is lowest in Albacete (site 4), Spain with -3.2, whilst the other three sites in the country have scores between -1.3 to -1.6 like those in Zimbabwe. In Sweden the skill score is between -1.5 and -2 for all sites in Sweden with Åstorp (site 1) having the highest skill around -1.3.

The skill score for the day of maturity for early variety is highest for Nyanga (site 4) Zimbabwe at -0.6, and Mvuma (site 2) is also close high at around -1.1. Site 3 (Mt Darwin) in Zimbabwe as well as all the sites in Sweden have very low skill scores of less than -3. Site 1 (Castilla y Leon) and site 2 (Aragon) in Spain have skill scores of around -1.5 whilst site 3 (Estremadura) is has a score of -2 and site 4 (Albacete) has lowest score of all the sites in Spain at -2.3.

The skill score for the day of maturity for late variety is highest for Nyanga (site 4) and Mvuma (site 2) at around -0.5. Site 3 (Mt Darwin) in Zimbabwe is lowest among the sites at clost to -2.8. Site 1 (Castilla y Leon) and site 4 (Albacete) in Spain as well as all the sites in Sweden have very low skill scores of less than -4. Site 2 (Aragon) and site 3 (Estremadura) in Spain have skill scores of around -2.

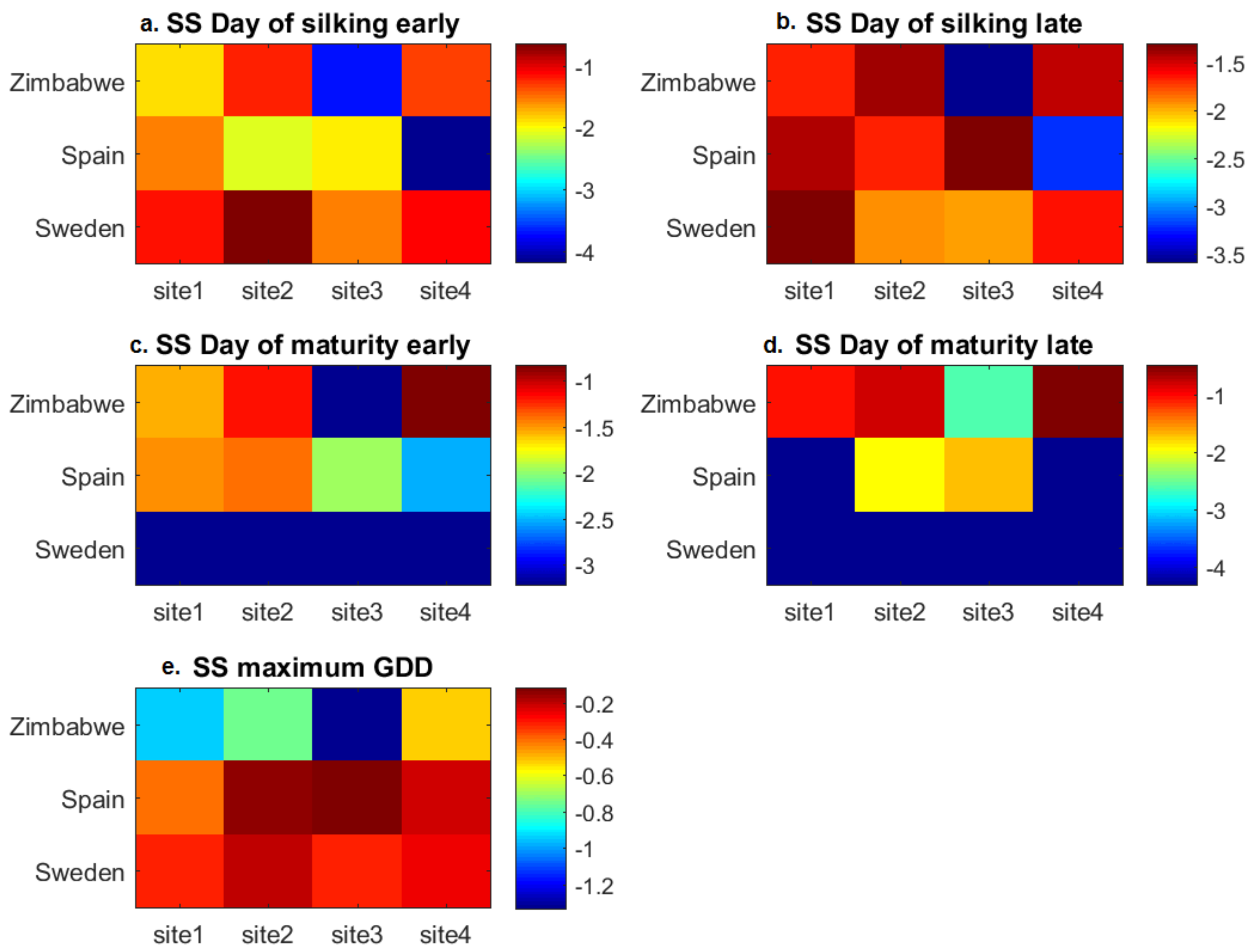


Fig 8: Colorbar illustrations of the Skill Scores (SS) of the predicted days of seasonal development of maize grown in Zimbabwe, Spain and Sweden, per site.

The skill score of the maximum GDD reached by System 4 and WFDEI data is highest in Spain and Sweden. Site 2 (Aragon) and site 3 (Estremadura) in Spain have skill scores of about -0.1, whilst site 4 (Albacete) has a score of -0.2 and site 1 (Castilla y Leon) has -0.4. In Sweden, the skill scores are between -0.3 and -0.2 for all the sites for maximum GDD reached. Zimbabwe sites are more varied, and have lowest skill scores in maximum GDD out of all the countries. Mt Darwin (site 3) has the lowest score in all the sites at -1.4, followed by site 1 (Zvimba) with a score of -0.9 and then site 2 (Mvuma) with -0.7. Site 4 (Nyanga) has the highest skill score for maximum GDD amongst the sites in Zimbabwe with a score of -0.5.

4.4 Effect of bias-correction

Seasonal maize development of maize was also modelled using data that was not bias corrected to see the effect of bias correction on the skill of ensemble forecast data. The difference plots show that when the data is bias corrected before analysis, the difference between the number of days predicted for development ranges around 6 days, whilst for the data not corrected for bias the difference increases up to 40 days as is the case in the day of maturity for the late variety of maize (Fig 9 (i)). The difference in the maximum GDD in System 4 and WFDEI data also increases significantly up to 600 GDD when data that is not bias corrected is used for modelling seasonal development.

The skill scores from the analysis with data that is bias corrected has its lowest value at -4 for the prediction of day of maturity for the late variety of maize. However, for data that is not bias corrected the skills are extremely low, going as low as -60 when used to also predict day of maturity for the late variety (Fig 8 (ii)). The skill of the maximum GDD in System 4 and WFDEI data also increases significantly to -40 when data that is not bias corrected is used for analysis compared to -1.2 skill score from bias corrected data. It is important to note that development up to maturity for maize in Sweden does not occur and so this is reflected by the really low values in Fig 9.

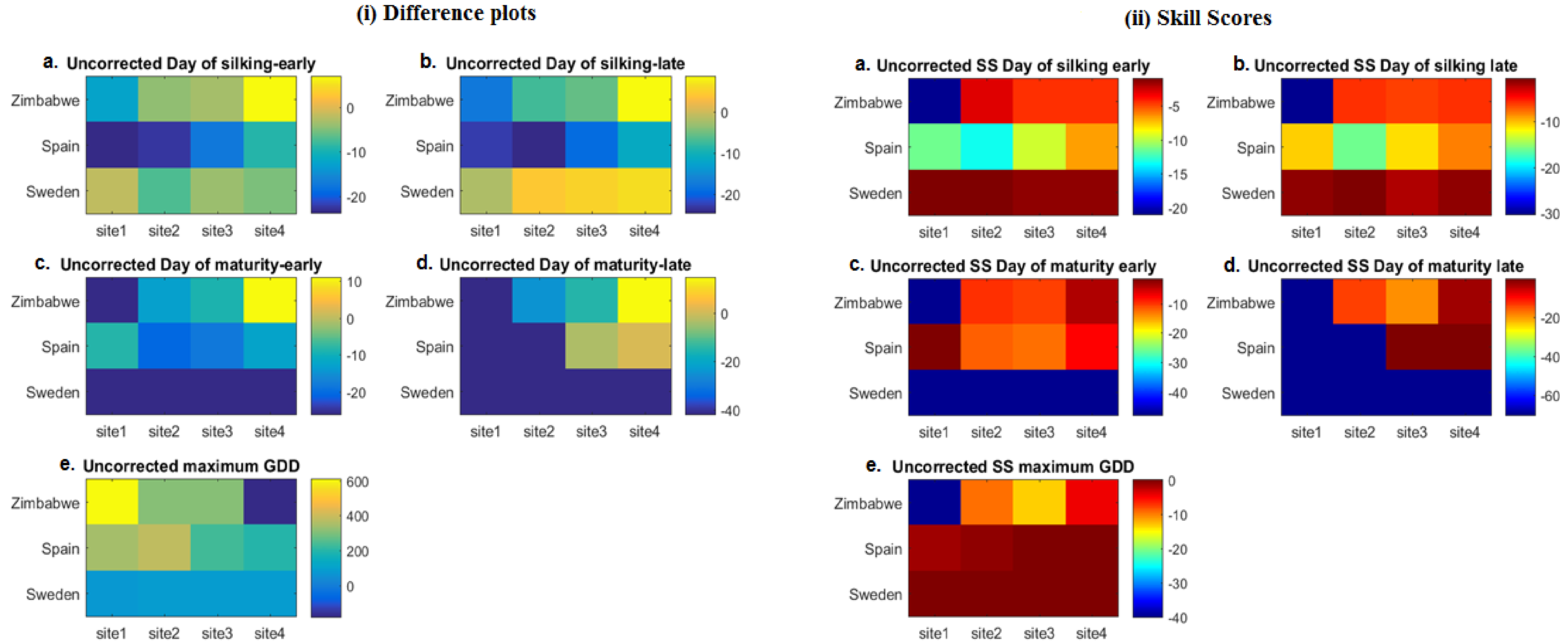


Fig 9: Colorbar illustrations of the difference plots (i) and skill scores (ii) of the predicted days of seasonal development of maize grown in Zimbabwe, Spain and Sweden, per site modelled using data that is not bias corrected.

5.0 Discussion

This study made use of ensemble climate forecast data to investigate, through the GDD model, if maize phenology could be successfully determined for upcoming seasons in Zimbabwe, Spain and Sweden. The skill scores of the model runs show that contrary to our first hypothesis, model prediction of the day of silking and day of maturity for both the early and late varieties of maize from the forecast data was not successful in any of countries or sites and therefore it is not possible to predict maize phenology successfully with this data.

5.1 GDD Maize Model findings

The model results from both forecast and observed data show that seasonal development of maize differs among the three countries, affirming the second hypothesis of the study. Using the forecast data, maize in Zimbabwe is predicted to develop faster compared to Spain or Sweden and the same trend is noticeable using the observed data. Zimbabwe is in the tropics and so the growing season has higher daily temperatures (and more heat units per day) compared to those in Sweden or Spain. Maize grown in Zimbabwe will develop faster than Spain or Sweden by being the first to reach the GDD necessary for silking and maturity for both varieties of maize. We did not have observed maize phenology data and so we compared the results obtained in this study with maize phenology studies done in the past. Previous work on maize phenology in Zimbabwe has placed the day of silking between day 60 and day 75 of the season, depending on the sites physical conditions as well as the varieties used for analysis (Shamudzarira and Robertson 2002; Magorokosho 2007; Mhizha et al. 2014) This aligns with our findings from the observed data for the late variety of maize for Zimbabwe with silking days between day 50 and day 70 of the season, rather than the early variety.

Spain is in the Mediterranean region with higher temperatures than South Sweden's nemo-boreal climate but colder climate than Zimbabwe. Previous studies in Spain and in the Mediterranean bio-climate determined that day of silking is normally between day 190 and day 214, whilst day of maturity is between day 240 and day 270 of the year, also depending on site characteristics and maize variety (Ben Nouna et al. 2000; Oteros et al.

2015). The temperatures in Sweden are too low and though they do allow for maize to silk in July from day 191 to day 203 of the year, the temperatures do not allow for the accumulation of enough heat units to enable maize to reach maturity (Kenny and Harrison 1992). The findings of this study reflect this point as analysis with observed data shows that maize silks late in the season from day 220 to day 260 for the early variety. This, together with the absence of data for days of maturity, corroborates with how maize is grown mostly for fodder in Sweden due to the low temperatures that do not allow for maturity of the grain (Eckersten et al. 2012).

The variation in maize development as assessed from the observed climate data within the countries, among the sites is also notable. Development in Nyanga, Zimbabwe is later for both maize varieties than the other three sites in Zimbabwe. This can be because Nyanga is the north-eastern mountainous part of Zimbabwe, which is reasonably cooler and has lower temperatures than the other three sites. Late development is also noted in Castilla y León where for both forecast and observed data, development is predicted later than the other sites and there are no predicted days of maturity of the late variety of maize which we can attribute this to the lack of the accumulation of enough heat sums for this stage of development. There is little variation in the projected development of maize in Sweden because the sites were purposefully selected in Skåne county and also Olofström in Blekinge County but this is still really close to Skåne.

The results of the seasonal development of maize show low skill scores of the forecast data, alluding that the ensemble data cannot successfully be used to determine the phenology of maize. Jame and Cutforth 1996 note the necessity of empirical models such as the one used in this study, to calibrate the model to the environment against which the model is being run with details of the soil and climate conditions in order to get the best model predictions. As such, most ecosystem models that get high validation scores do take into account the initial conditions of the study area (Gungula et al. 2003; Cantelaube and Terres 2005; Costa, Simone M.S.; Coelho 2007; Mishra et al. 2008; Zinyengere et al. 2011). The low skill scores in this study can be attributed to the fact that the model utilized in this study was not calibrated to pre-existing physical conditions of the different sites used in the study. The model ran the analysis for three countries and four sites each, and they all have different physical conditions such as earlier temperature conditions, soil type and water conditions which are all factors that aid in correctly determining maize development. It is interesting to note that though all the sites had low skill scores, the skill for the prediction of day of silking for both varieties of maize was better than for day of maturity (Fig 6). This can be because the closer to the lead time the forecast is, the more reliable it is. This reliability decreases with time and hence the lower the skills for the prediction of the days of maturity for both varieties.

5.2 Data uncertainties

The difference plots show that there are some distinct differences in the predictions of maize development with observed climate data and those with forecast climate data. The difference in the values for the maximum GDD for the two datasets goes as high as 50 and these differences as well as the low skill scores of the forecast predictions allude to possible discrepancies in the data used.

5.2.1 Forecast (System 4) data

Climate models only show a simplification of the processes that occur in the atmosphere and their accuracy is limited by how the model mirrors the real-life complex atmospheric processes. Some atmospheric processes can be challenging to model with high precision and this leads to errors developing over time. Also mentioned earlier, climate forecasting is only possible within a specific window period, and at specific locations where the strength of the interaction between the land and ocean with the atmosphere is adequate enough to enable climate models to simulate the climate conditions (Thomson et al 2008). These conditions combined can explain the large biases that were observed in the System 4 forecast data.

The evaluation of the System 4 near surface air temperature forecast data set against the WFDEI observed data for the period of 1982-2010 for all three countries in the study shows tendencies of the forecast data greatly underestimating as well as overestimating temperatures by up to 10^{o} C at times, in Spain and Sweden. These biases however seem bigger than those in similar studies, for example, Christensen et al. 2008 analysed the systematic biases in temperature data for an ensemble of thirteen regional climate models (RCMs) over Europe and the biases ranged mostly between 1 to 3^{o}C and also the Terink et al. 2010 study showed temperature biases of forecast data varying from -1.5 to 3.5^{o}C. Kim et al. 2012 attributes some of the large biases seen in forecast data on the uncertainties that exist in the observation datasets used for model evaluation, and this could be the case for the data used in this study. Uncertainties also arise from the fact that the System 4 forecast data has a 0.75^{o} x 0.75^{o} spatial resolution, which are relatively large grid cells and this would particularly be a problem for the sites selected for Sweden because Skåne is relatively close to the water. The forecast given for these sites might be taking in influence from the water and this causes discrepancies in the temperature values given.

The linear scaling method in bias correction was effective by reducing the large differences between WFDEI and System 4 data over 6 fold and increasing the skill from the lowest of -60 to a low of -4. Though the bias correction increased the skill of the prediction, the skill is still too low for a successful prediction. Teutschbein and Seibert 2012 calculated the performance of different bias correction methods and concluded that though linear scaling was able to correct temperature forecast data, it performed the worst among the procedures which improved temperature forecasts with less variability.

Challenges were experienced when trying to use the ECOMS-UDG recommended package for bias correction, the downscaleR in R package. DownscaleR is used for accessing and analysing climate data particularly statistical downscaling and bias correction of daily climate data. For this study, site selection for both observed and forecast data was based on single point selection whilst the bias correction function in the downscaleR package was only adapted to regional selections and not to single point selections. Communication with the developers of ECOMS-UDG revealed that the functionality for single point selections has not yet been developed since most of their work cover regional selections and hence for this study we resorted to linear scaling in Matlab.

It is essential to note that the use of 15 ensemble members and analysis with the ensemble average does remove some uncertainties that come with forecast data. This is because ensembles reduce errors that may exist in any one climate model through the application of multiple initial conditions to give multiple realizations of the climate model. Baigorria and Jones 2002 note that the use of hindcast ensemble mean in crop simulation models gives less variability of forecasts and better skill.

5.2.2 Observed (WFDEI) data

The WFDEI data used in this study comes with some uncertainties as well that can contribute to the lack of skill of the model predictions. WFDEI based on the ECMWF ERA-Interim forecast data reanalysis which are interpolated to 0.5° x 0.5° resolution (Weedon et al. 2014). To maintain consistency after interpolation, successive elevation modification of surface meteorological variables is done together with monthly bias correction using gridded Climate Research Unit (CRU) observations (Weedon et al. 2011). The utilisation of CRU observations for monthly bias correction inevitably incorporates inaccuracies related to creation of the gridded data. Reanalysis is basically an interpolation, where numerical estimates of recent climate variables such as temperature or precipitation are produced for areas without recorded observed data by combining climate model forecast data with observations and this is applicable to all locations on earth, over a long period of time of up to decades (Madsen et al. 2014).The density of weather station networks can also be a contributing factor to how and why the available observed data can have discrepancies. The number of weather stations in a country affects how much actual observed meteorology data is available for the interpolation. For this study this is more so the case in Zimbabwe rather than Spain and Sweden (WMO 2016).

5.3 Further Research

Though the need for bias correction was identified and linear scaling was applied, there are an assortment of bias correction methods available and it can be debatable as to which correction methods are more effective. Further research could attempt bias correction using a different method like quantile mapping method to ascertain if the skill would improve. It would also be interesting to see the results of seasonal forecast modelling using forecast data that are continuously updated throughout the season which would increase the reliability of the forecast data. Supplementary research can also try to work on the modelling of the maize seasonal development by use of a model that calibrates for the different initial physical conditions that each site has. It would also be interesting to incorporate a more comprehensive process based model like LPJ-GUESS that not only takes into account temperature, but other limiting factors for maize growth like precipitation and radiation.

6.0 Conclusion

Seasonal forecast data provides an overall idea of how the season will develop and the use of forecast data in predicting the seasonal development of maize, one of the most grown cereals in the world, is of particular interest to farmers. It provides a means for farmers to know what to expect in terms of the ideal time to sow, harvest as well as potential maize yield for the coming season. This information helps stakeholders to alleviate the risks that come with maize production.

This study focused on running a temperature driven maize phenology model in order to ascertain if the current ECMWF System 4 data could help predict the day of silking and maturity of maize. The results showed that all the sites had low skill scores, however the skill for the prediction of day of silking for both varieties of maize was better for prediction of day of silking than for day maturity. Analysis also showed that though the data had been corrected for biases, there were still some big differences between the forecast data and the observation data. This was evident through the difference in a maximum GDD of up to 50 as was the case in all the sites in Spain as well as Mt Darwin, Zimbabwe, alluding to some uncertainties in both the data used in the study as well as the bias correction method employed. This being said, the findings of the study showed that the System 4 forecast data cannot conclusively be used for the modelling of the maize (*Zea mays* L.) crop phenology, particularly the date of silking and the date of maturity based on the very low skills that were achieved in the analysis.

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