CHAPTER 3

VERIFICATION OF THE YIELD SIMULATIONS OVER SOUTH AFRICA

3.1 INTRODUCTION

This chapter describes the results of the yield simulations that are performed with the CERES-Maize model for each of the magisterial districts in the main maize producing area of South Africa (see Figure 2.1). The aim of this Chapter is to quantify the skill of the CERES-Maize model, evaluate the accuracy of the simulated maize yields obtained from each of the different simulation systems, assess the ability of each of the different simulation systems in estimating maize yield and determine the operational potential of this maize yield forecast system. Verification is done by comparing the simulated maize yields to actual maize yields. Firstly, the simulated maize yields are verified spatially over the entire study area, secondly, the inter-seasonal variability in the simulated maize yields are verified for each of the three production regions in the study area and thirdly, the simulated maize yields for each of the three production regions are expressed probabilistically and then verified against actual maize yields.

3.2 SPATIAL VERIFICATION RESULTS

In Figures 3.1 to 3.9 the actual maize yield index and each of the simulated maize yield indices obtained from the different simulation systems are displayed spatially for each of the 9 scenarios in Table 2.8. These spatial maps represent the maize yield index values obtained from averaging over the 19 seasons from 1980/81 to 1998/99. In each of these figures the actual maize yield index is displayed as map (a). The actual maize yield index map provides a view of the distribution of maize yield across the study area and gives an indication of which magisterial districts normally produce higher and which districts normally produce lower maize yields with respect to the entire study area. From the actual maize yield index map a decrease in maize yield can be observed from east to west across the study area. Thus, the study area is characterised by high maize yields in the eastern parts and lower maize yields in the western parts. This gradient in maize yield can most likely be attributed to the fact that the average annual rainfall of the eastern parts of South Africa is higher than that of the western parts of the country (Schulze and Lynch, 2007). Apart from this gradient, a small region with higher maize yields than its surroundings is evident in the Free State, directly next to the border separating the Free State and North West Province from each other (magisterial districts Wesselsbron (19), Bothaville (20) and Viljoenskroon (21)). Furthermore it can be seen that magisterial districts Wesselsbron (19), Viljoenskroon (21), Harrismith (40) and Bethlehem (42) normally produce the highest maize yields and magisterial districts Vryburg (1) and Brandfort (28) the lowest maize yields.

In Figures 3.1 to 3.9 map (b) represents the CERES-Observed weather yield index for each of the 9 scenarios. By comparing the CERES-Observed weather yield index to the actual maize yield index, the ability of the CERES-Maize model can be quantified, as this gives an indication of how realistically the model can simulate maize yield when the weather conditions are perfectly known. In operational maize yield forecasting, the weather conditions will be forecast. Thus, if the CERES-Maize model is unable to produce realistic maize yields under known weather conditions, it will certainly not be able to produce skilful maize yield forecasts under predicted weather conditions. Therefore, the quantification of the CERES-Maize model's ability in simulating South African maize yields is of great importance. The CERES-Observed weather yield index maps of all 9 scenarios show that the CERES-Maize model successfully simulates the east-west decrease in maize yield across the study area. Although, for the long season maize scenarios (Figures 3.7 to 3.9) the CERES-Maize model extends the high maize yields in the east to a much larger and more prominent area than that observed in the actual maize yield index map and for the short season maize scenarios (Figures 3.1 to 3.3) the CERES-Maize model simulates the maize yield of magisterial district 37 (Heilbron) to be unusually low. Furthermore, the CERES-Maize model is unable to capture the high yields of the small region in the Free State described above. The many uncertainties in the soil, cultivar and management input data may have contributed to these misrepresentations. The CERES-Observed weather yield index maps of the medium season maize scenarios (Figures 3.4 to 3.6) seem to show the best agreement with the actual maize yield index map, both in terms of the spatial distribution of the yields as well as the relative magnitude of the yields. Very small differences are distinguishable in the CERES-Observed weather yield index maps for each of the three cultivars (short, medium and long season maize) from the one plant date to the next.

The CERES-CCAM ensemble mean yield index for each of the 9 scenarios is displayed as map (c) in Figures 3.1 to 3.9. All 9 scenarios show that the characteristic pattern of high maize yields in the eastern parts and lower maize yields in the western parts of the study area is captured when the CERES-Maize model is forced with CCAM-simulated fields. The short season maize scenarios (Figures 3.1 to 3.3) show an increase in maize yield in the western parts of the Free State, from plant date 1 to plant date 3, the medium season maize scenarios (Figures 3.4 to 3.6) show higher yields in the Free State than in the North-West Province and the long season maize scenarios (Figures 3.7 to 3.9) show a similar pattern to that evident in the CERES-Observed weather yield index maps, a much larger and more prominent high maize yield area in the east than that observed from the actual maize yield index map.

Map (d) in Figures 3.1 to 3.9 shows the CERES-ECHAM4.5 ensemble mean yield index for each of the 9 scenarios. Once again all 9 scenarios show higher maize yields in the east and lower maize yields in the west. Thus, the CERES-Maize model forced with ECHAM4.5-simulated fields is able to capture the gradient in maize yield across the study area. Although, for the short and medium season maize scenarios (Figures 3.1 to 3.6) the CERES-Maize model simulates the maize yield of the western parts of the North-West province to be slightly higher in comparison to the actual maize yield index map. However, this simulation system performs exceptionally well in capturing the distribution in maize yield in the eastern part of the Free State (except for magisterial district 39 (Vrede)) in two of the short season maize scenarios (plant dates 2 and 3). The CERES-ECHAM4.5 ensemble mean yield index maps of the long season maize scenarios (Figures 3.6 to 3.9) appear almost identical to the CERES-CCAM ensemble mean yield index maps and the CERES-Observed weather yield index maps.

The Multi-Model ensemble mean yield index for each of the 9 scenarios is shown in Figures 3.1 to 3.9 as map (e). From these figures it can be seen that the Multi-Model system also succeeds in capturing the maize yield gradient from east to west across the study area. Once again, two of the short season maize scenarios (Figures 3.2 and 3.3) represent the distribution of maize yield in the eastern parts of the Free State exceptionally well. As this Multi-Model system is a combination between the CERES-CCAM integrations and the CERES-ECHAM4.5 integrations, the slightly higher maize yields evident in the western parts of the North-West Province in the CERES-ECHAM4.5 ensemble mean yield index maps for the short and medium season scenarios are somewhat balanced out by the CERES-CCAM integrations. The long season maize scenarios (Figures 3.7 to 3.8) of the Multi-Model ensemble mean yield index maps are very similar to that of the CERES-CCAM ensemble mean yield index maps and the CERES-ECHAM4.5 ensemble mean yield index maps. Thus, in terms of the spatial distribution of the simulated maize yields, the four different maize yield simulation systems successfully simulate the east-west gradient in maize yield across the study area.

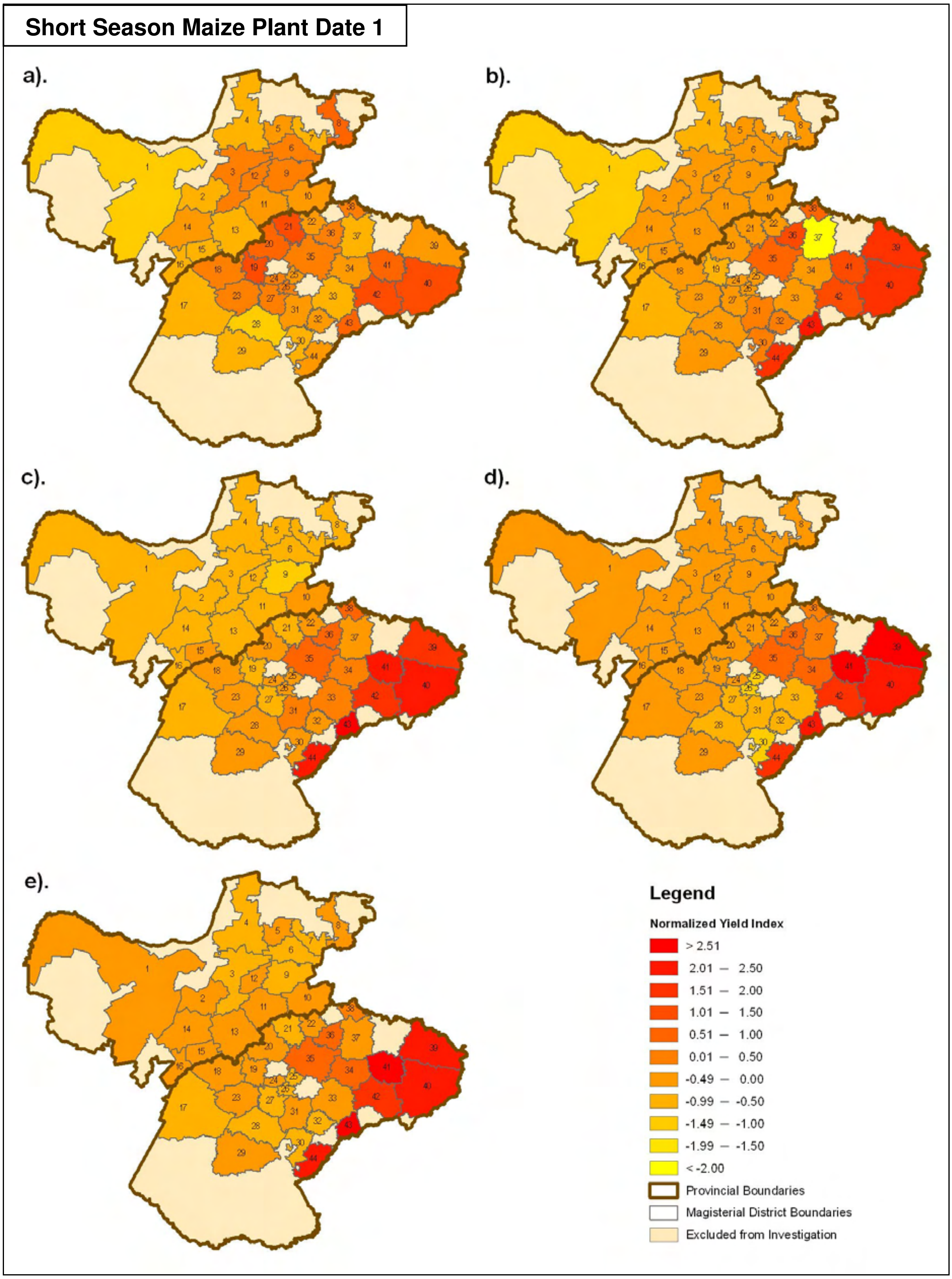


Figure 3.1: Actual maize yield index and simulated maize yield indices for scenario 1 (short season maize planted on plant date 1) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

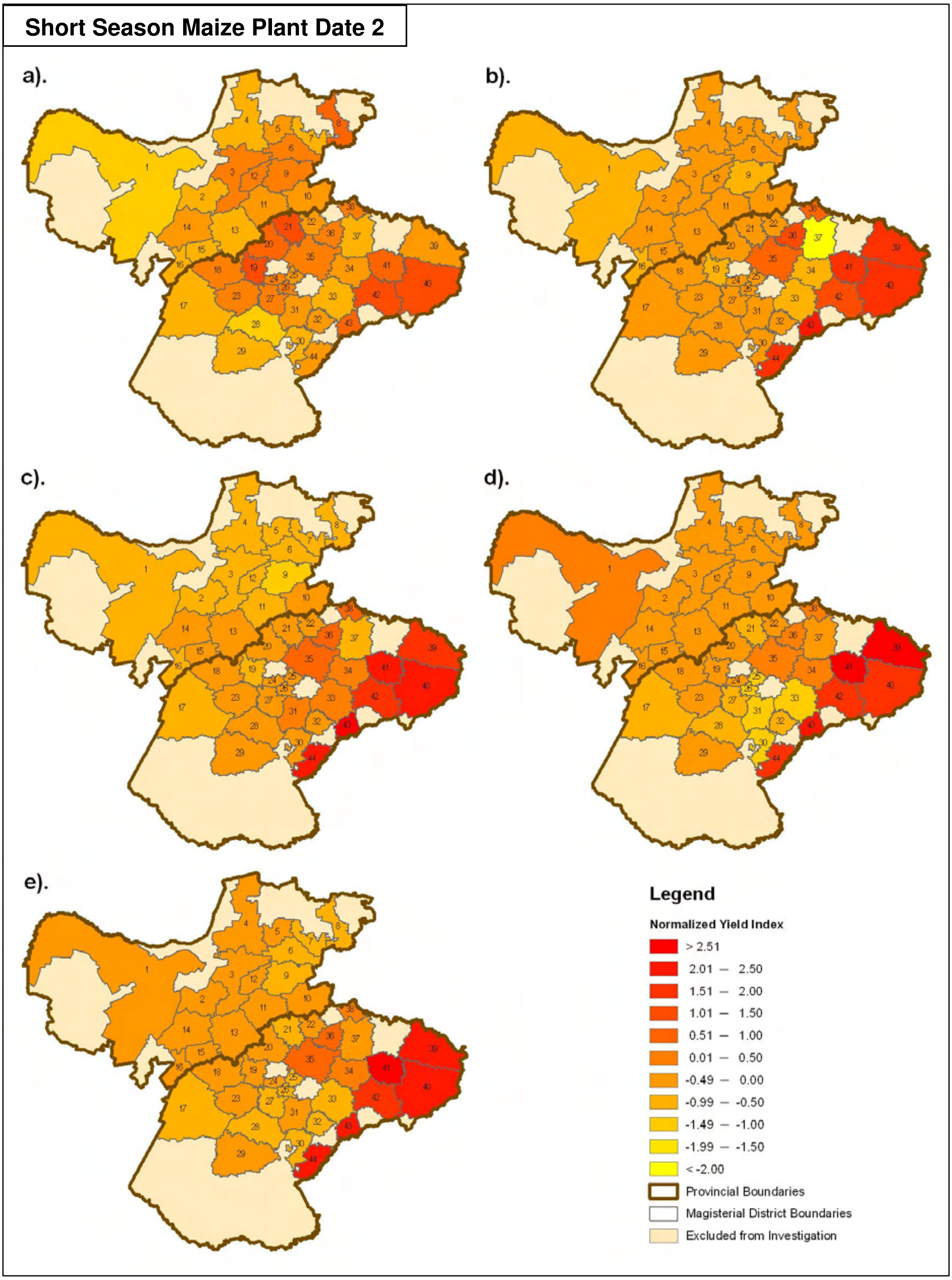


Figure 3.2: Actual maize yield index and simulated maize yield indices for scenario 2 (short season maize planted on plant date 2) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

Short Season Maize Plant Date 3

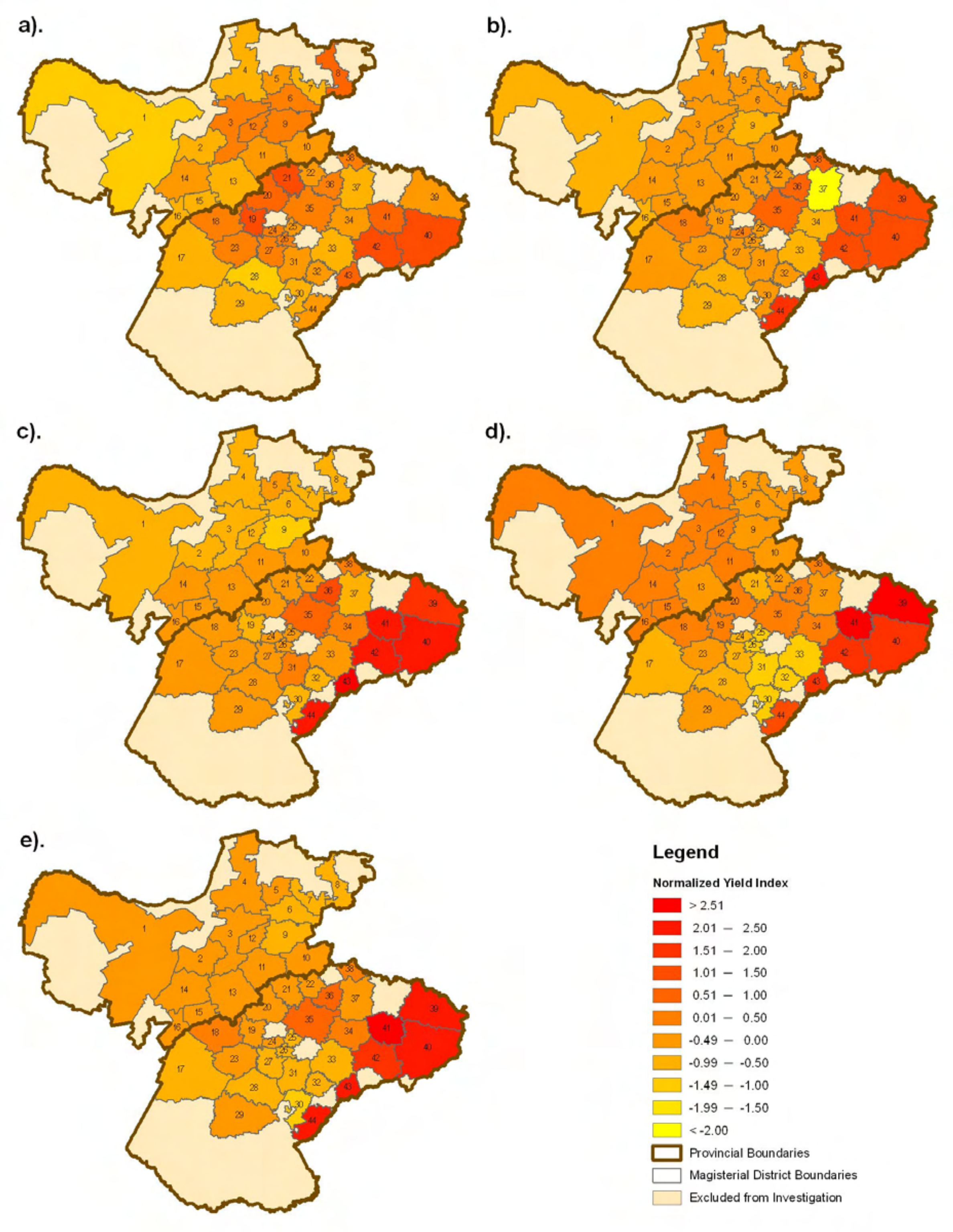


Figure 3.3: Actual maize yield index and simulated maize yield indices for scenario 3 (short season maize planted on plant date 3) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

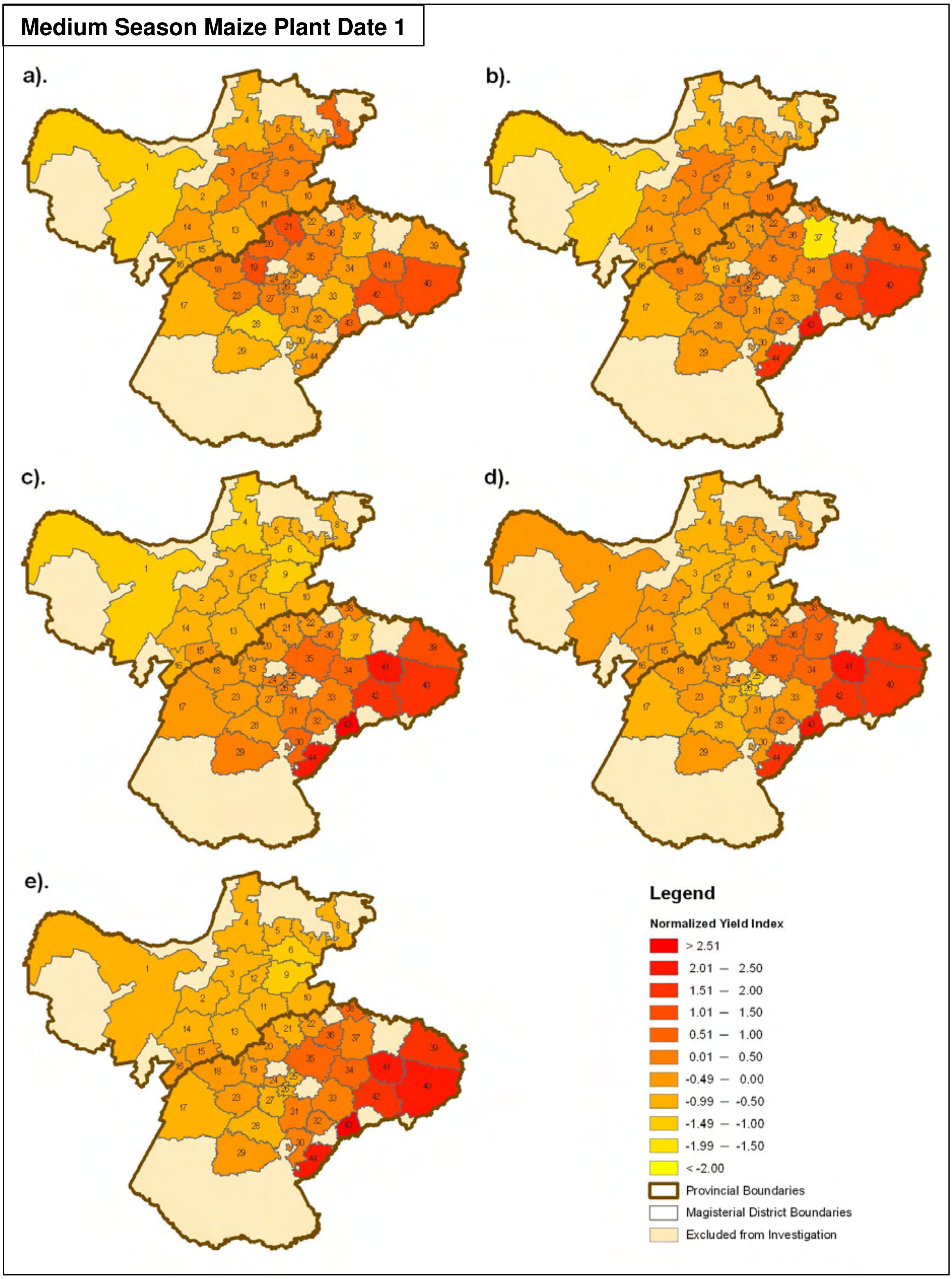


Figure 3.4: Actual maize yield index and simulated maize yield indices for scenario 4 (medium season maize planted on plant date 1) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

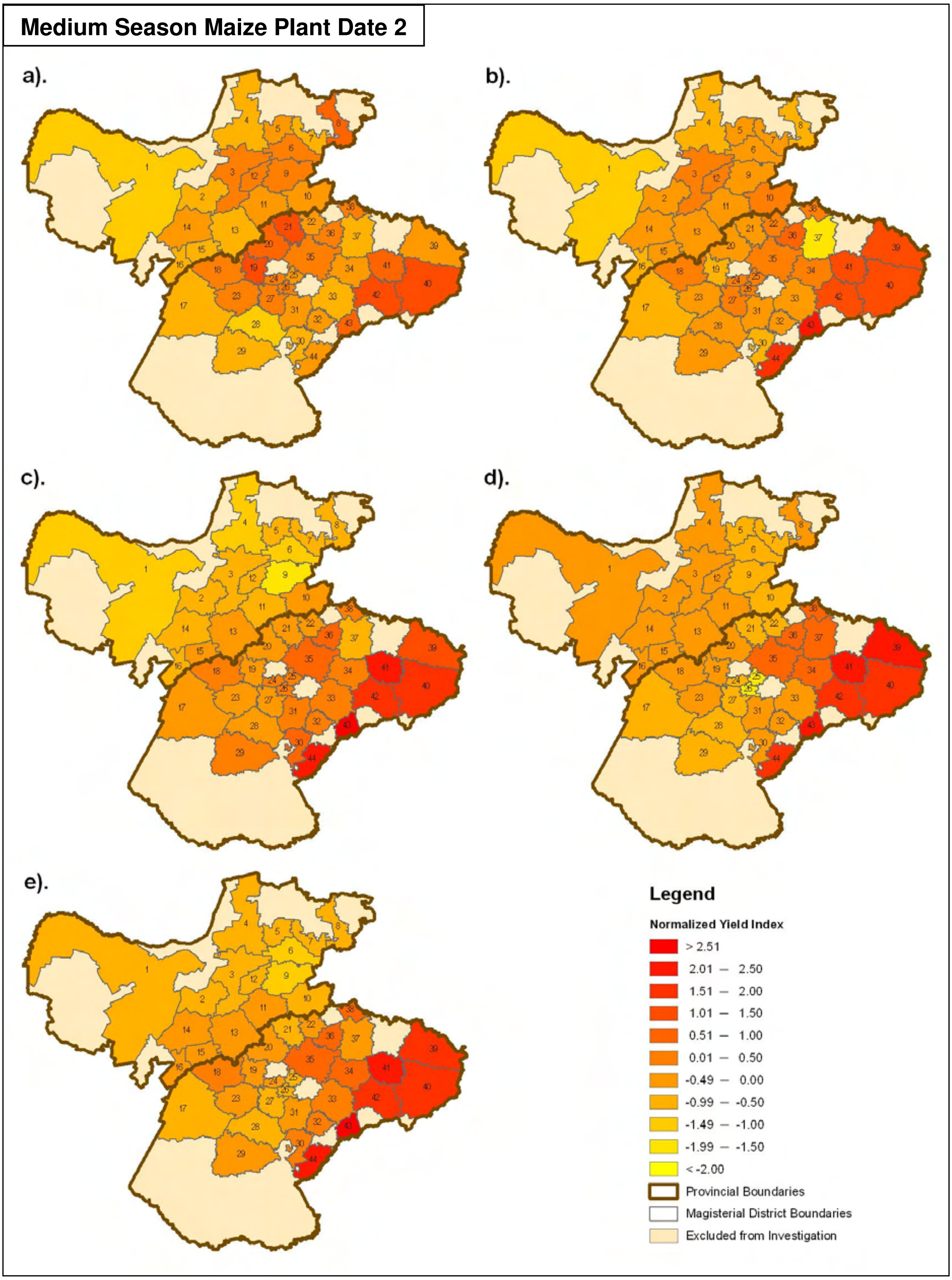


Figure 3.5: Actual maize yield index and simulated maize yield indices for scenario 5 (medium season maize planted on plant date 2) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

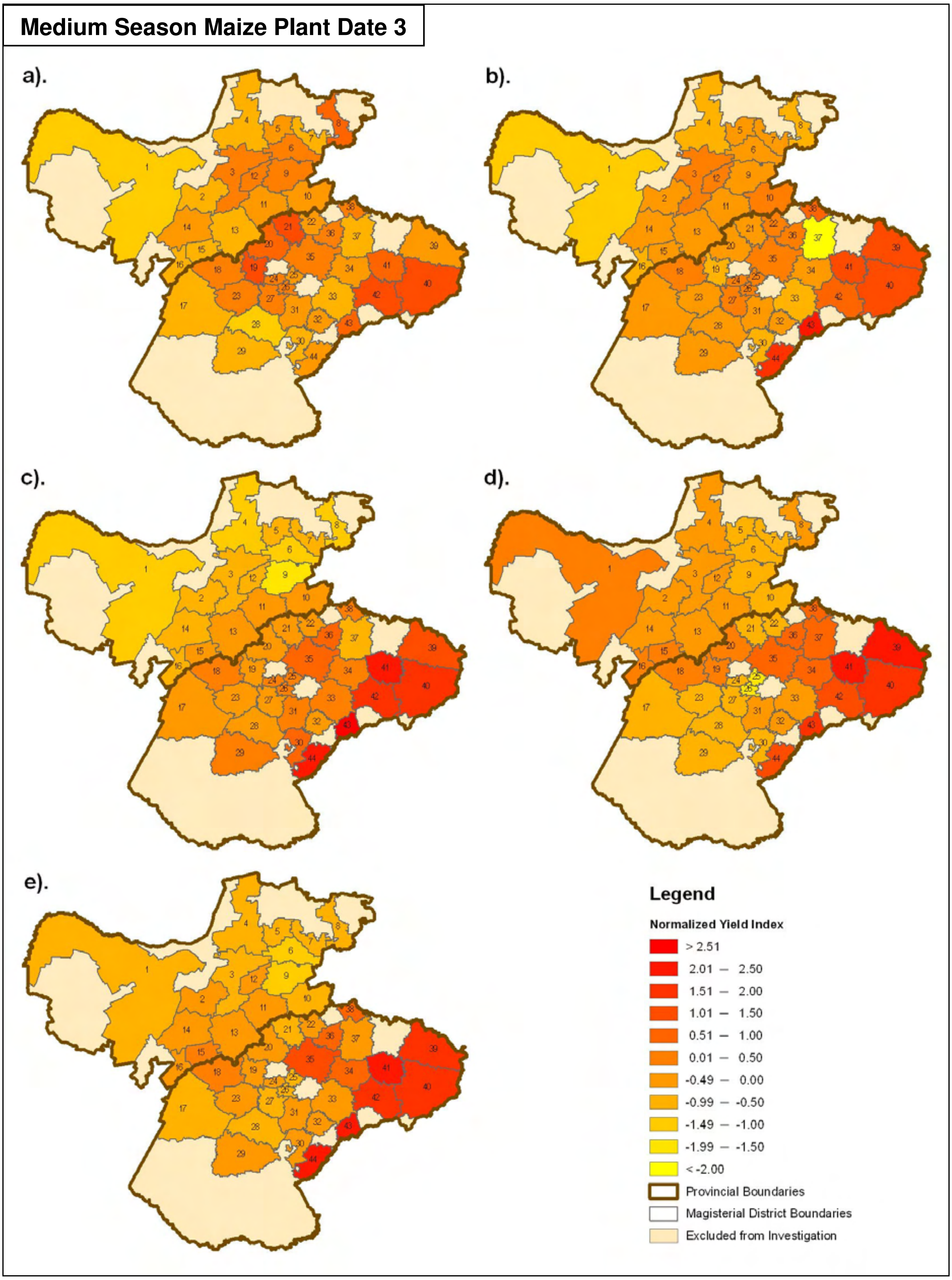


Figure 3.6: Actual maize yield index and simulated maize yield indices for scenario 6 (medium season maize planted on plant date 3) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

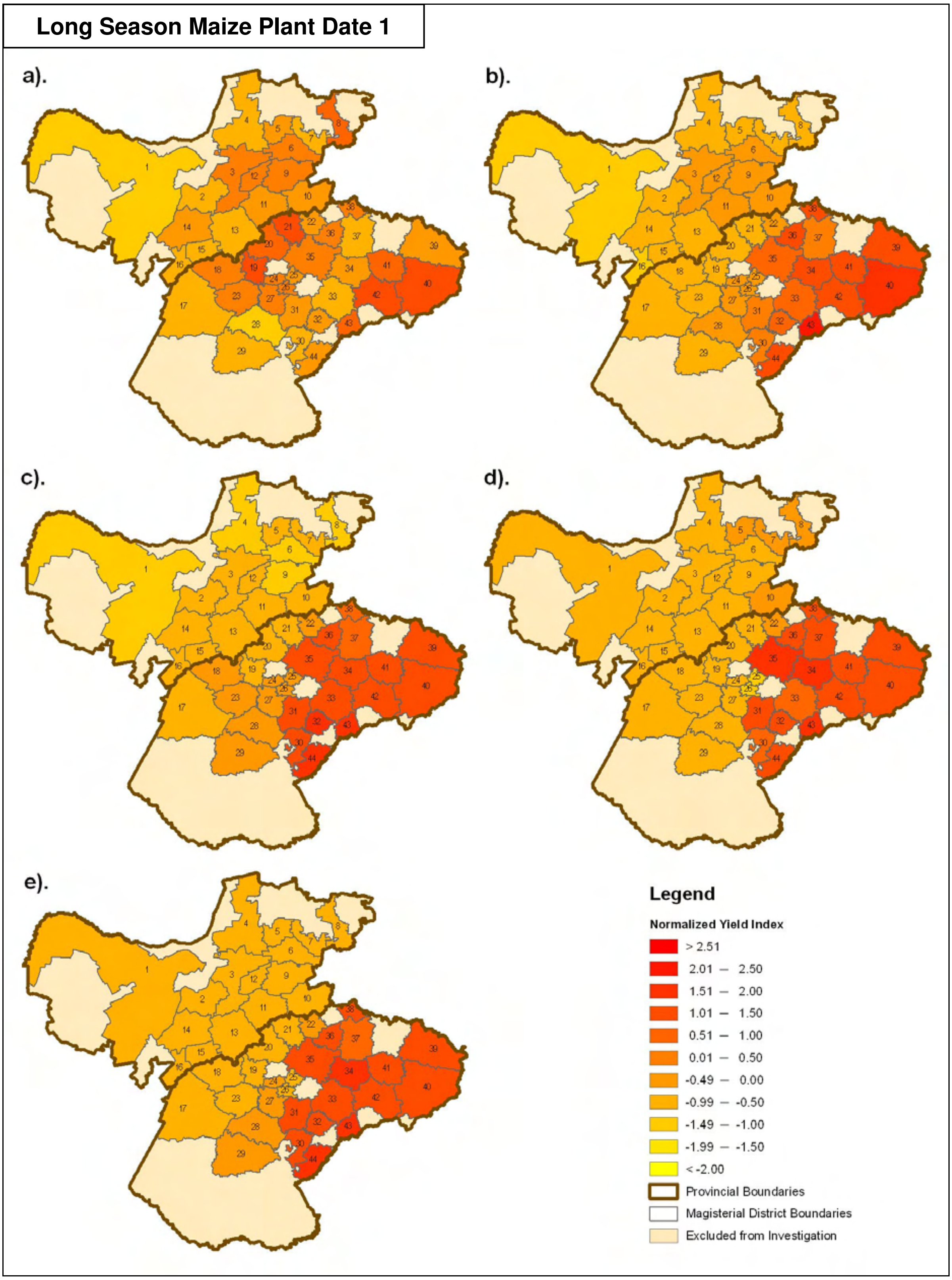


Figure 3.7: Actual maize yield index and simulated maize yield indices for scenario 7 (long season maize planted on plant date 1) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

Long Season Maize Plant Date 2

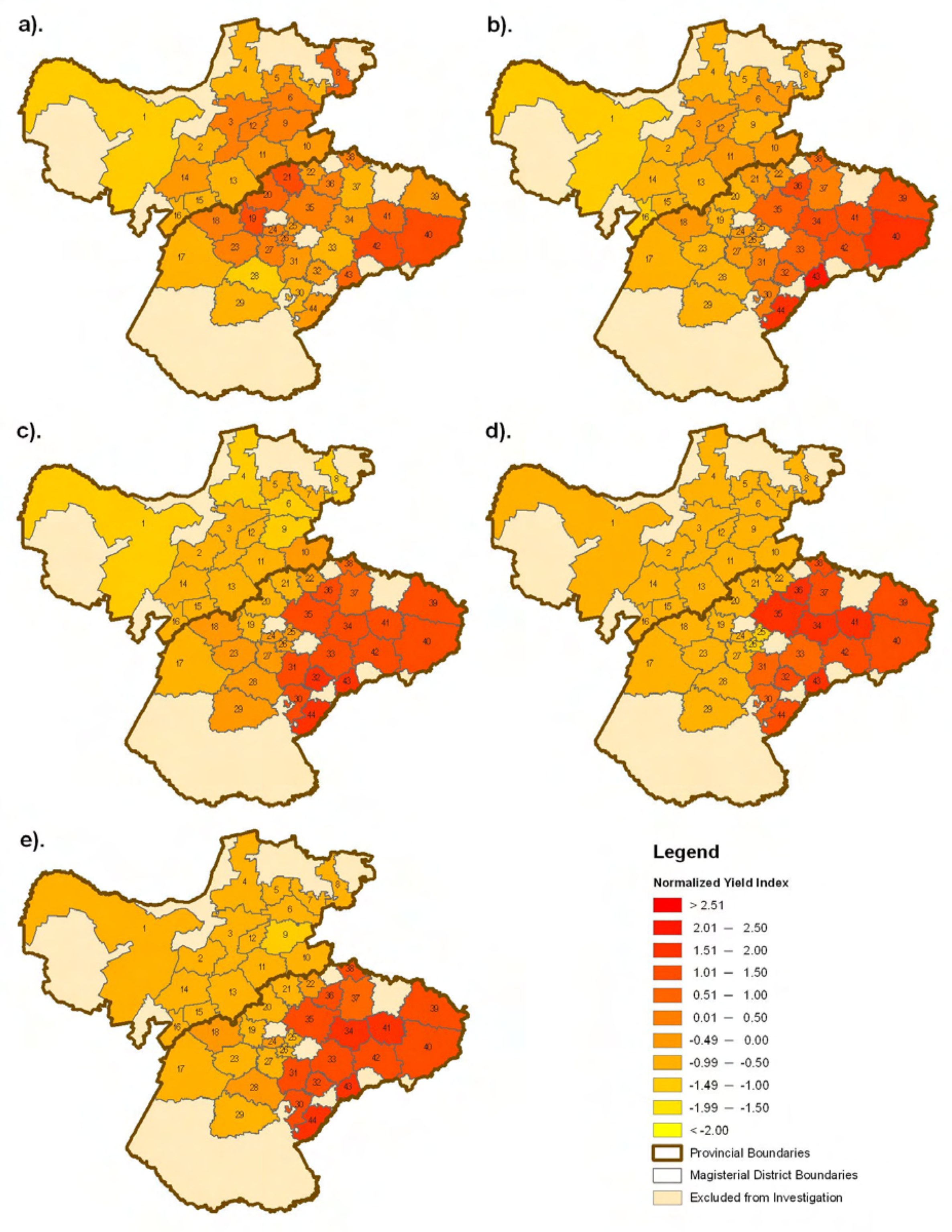


Figure 3.8: Actual maize yield index and simulated maize yield indices for scenario 8 (long season maize planted on plant date 2) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

Long Season Maize Plant Date 3

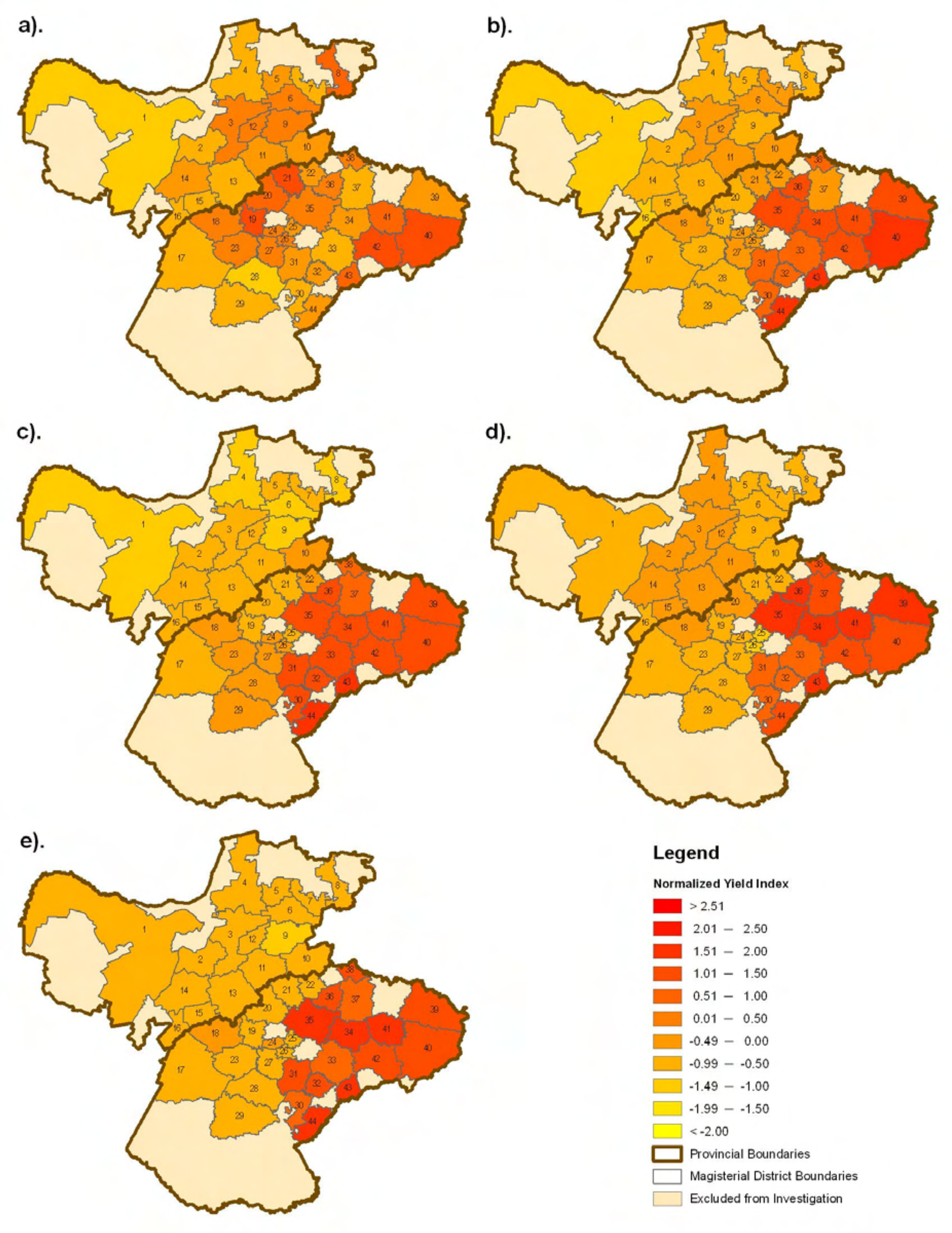


Figure 3.9: Actual maize yield index and simulated maize yield indices for scenario 9 (long season maize planted on plant date 3) averaged over the 19 seasons from 1980/81 to 1998/99. (a) Actual maize yield index, (b) CERES-Observed weather yield index, (c) CERES-CCAM ensemble mean yield index, (d) CERES-ECHAM4.5 ensemble mean yield index and (e) Multi-Model ensemble mean yield index.

3.3 INTER-SEASONAL VARIABILITY VERIFICATION RESULTS

3.3.1 Subjective Validation

3.3.1.1 Dry/Warm Western Region

The time series of the actual maize yield index and simulated maize yield indices, obtained from each of the different simulation systems, are shown for the dry/warm western production region in Figures 3.10 (scenario 1 to 4), 3.11 (scenario 5 to 8) and 3.12 (scenario 9). From the actual yield index time series (AYI - red) it can be observed that over the 20 year period investigated in this study the 1980's (1981/82 – 1987/88) was characterised by much lower maize yields than the late 1990's (1995/96 – 1998/99). This phenomenon can possibly be explained by the advances that took place in technology over this 20 years with respect to improvements in the climatic tolerance of cultivars and improved crop management strategies (Du Toit *et al.*, 2001). Furthermore, it can also be seen that over this 20 year period, the 1995/96 season rendered the highest maize yield and the 1991/92 season the lowest maize yield. A La Niña event (cold ENSO phase) was present during the 1995/96 season and an El Niño event (warm ENSO phase) during the 1991/92 season. La Niña events often coincide with below-normal and El Niño events with above-normal summer rainfall totals over the central and western parts of South Africa (Ropelewski and Halpert, 1987, Rautenbach and Smith, 2001). Even though the 1995/96 La Niña event was relatively weak, this event was associated with significantly wet anomalies over the south-eastern parts of southern Africa (Reason and Jagadheesa, 2005). This could possibly explain the high maize yield obtained for that season. In comparison to the very strong El Niño that occurred during the 1997/98 season, the 1991/92 El Niño event was fairly weak but led to much more severe summer drought conditions over large parts of southern Africa (Reason and Jagadheesa, 2005). These severe summer drought conditions likely led to the low maize yield obtained for the 1995/96 season.

3.3.1.1.1 Short Season Maize

In Figure 3.10, (a), (b) and (c) represent short season maize planted on plant date 1, 2 and 3 respectively. Table 2.4 shows the exact month and day plant date 1, 2 and 3 refers to. By examining the CERES-Observed weather yield index time series (COYI – green) and comparing it to the actual maize yield index time series (AYI – red), it is possible to get an idea of the ability of the CERES-Maize model in simulating the inter-seasonal variability in maize yield in the dry/warm western production region. For all three short season maize scenarios the CERES-Maize model is able to successfully simulate the low maize yield of the 1991/92 season, the season with the lowest maize yield out of the 19 seasons under investigation. It can also be observed that the CERES-Maize model correctly indicates the sign of the anomaly of the yield (above or below normal) of many seasons, especially those seasons with an actual maize yield index value (AYI – red) less than -1 and more than 1. Another prominent feature in all three short season maize scenarios is that the CERES-Maize model struggles to simulate the maize yield of the three seasons from 1984/85 to 1986/87, a La Niña season followed by an ENSO-neutral season followed by an El Niño season. The ability of the CERES-Maize model seems to decrease from plant date 1 to plant date 3, as the number of seasons for which the model successfully simulates the sign of the anomaly of the yield decreases from 15 to 11.

The CERES-CCAM ensemble mean yield index time series (CCYI – blue) for the three short season maize scenarios show that when forced with CCAM-simulated fields the CERES-Maize model is unable to capture the low maize yield of the 1991/92 El Niño season, but instead makes the maize yields of the 1987/88 and 1994/95 El Niño seasons much lower. This also appears for the 1994/95 La Niña season, the CERES-CCAM ensemble mean yield index shows much higher maize yields for the 1988/89 and 1998/99 La Niña seasons than for the 1994/95 season which in reality produced the highest maize yield out of the 19 seasons considered in this study. Furthermore, it also appear as if the CERES-CCAM ensemble mean yield index shows greater variability between seasons than that observed from the actual yield index.

From the CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three short season maize scenarios it can be seen that the CERES-Maize model fails to capture the sign of the anomaly of the yield of almost three quarters of the seasons when it is forced with ECHAM4.5-simulated fields. Another interesting observation that can be made is the fact that the seasons for which the CERES-Maize model forced with ECHAM4.5-simulated fields actually succeeds in capturing the sign of the anomaly of the yield, are primarily ENSO-neutral seasons (1980/81, 1981/82, 1990/91 and 1992/93). The Multi-model system (MMYI – purple) on the other hand performs better in simulating the change in the sign of the anomaly of the yield from one season to another than that of the CERES-ECHAM4.5 maize yield simulation system, but does not perform better than the CERES-CCAM maize yield simulation system.

3.3.1.1.2 Medium Season Maize

The time series of the maize yield indices (actual and simulated) for medium season maize planted on plant date 1, 2 and 3 are shown in Figure 3.10 (d) and Figure 3.11 (e) and (f) respectively. From the CERES-Observed weather yield index time series (COYI – green) it can be seen that the CERES-Maize model successfully simulates the low maize yield of the 1991/92 El Niño season. In all three scenarios the CERES-Maize model performs very well in simulating the relative magnitude of the yields of the 1980/81 and 1983/84 ENSO-neutral seasons. Furthermore, the ability of the CERES-Maize model in simulating the yield appears to improve from plant date 1 to plant date 3, as the number of seasons for which the model correctly indicates the sign of the anomaly of the yield increases from 10 to 15. Similar to the short season maize scenarios, the CERES-Maize model once again struggles to simulate the maize yield of the 4 seasons from 1984/85 to 1987/88.

From the CERES-CCAM ensemble mean yield index time series (CCYI – blue) for the three medium season maize scenarios it can be observed that the medium season maize planted on plant date 2 scenario (Figure 3.11 (e)) shows the best agreement with the actual yield index time-series, both in terms of the sign of the anomaly of the yield and the relative magnitude of the yield. For this scenario the CERES-Maize model is able to correctly simulate the sign of the anomaly of the yield for 15 out of the 19 seasons. Also evident from these three time series graphs is that when forced with CCAM-simulated fields the CERES-Maize model seems to perform the best for seasons with actual maize yield index values (AYI – red) less than -1 and more than 1. This is particularly true for the seasons in the 1980's. As with the short season maize scenarios, the maize yield results of the medium season maize scenarios also show that the CERES-Maize model forced with CCAM-simulated fields fails to capture the low maize yield of the 1991/92 season and the high maize yield of the 1995/96 season, but instead simulates the impact of other El Niño and La Niña events on the maize yield in the dry/warm western production region to be much more severe.

The CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three medium season maize scenarios show that the CERES-Maize model does not perform well in simulating the maize yield of the dry/warm western production region when it is forced with ECHAM4.5-simulated fields. This simulation system can only indicate the sign of the anomaly of the yield for 5 out of the 19 seasons correctly.

The Multi-Model ensemble mean yield index time series (MMYI – purple) for the medium season maize scenarios show little variation from plant date 1 to plant date 3. As this simulation system is a combination between the CERES-CCAM integrations and the CERES-ECHAM4.5 integrations, it performs better than the CERES-ECHAM4.5 simulation system, but does not perform as good as the CERES-CCAM simulation system. Besides this, the Multi-Model ensemble mean yield index captures the relative magnitude of the 1980/81 and 1982/83 yields exceptionally well.

3.3.1.1.3 Long Season Maize

Figure 3.11 (g) and (h) and Figure 3.12 shows the maize yield indices (actual and simulated) for each of the 19 seasons considered in this study for long season maize planted on plant date 1, 2 and 3 respectively. When the CERES-Observed weather yield index time series (COYI – green) of each of the three long season maize scenarios are examined, it can be seen that the CERES-Maize model performs well in simulating both the sign of the anomaly and relative magnitude of the maize yields. The feature that stands out from the CERES-Observed weather yield index time series is the fact that the CERES-Maize model is able to capture both the high maize yield of the 1995/96 La Niña season as well as the low maize yield of the 1991/92 El Niño season. In addition, the CERES-Maize model also represents the relative magnitude of the maize yields of the 1980/81, 1982/83, 1983/84, 1986/87, 1988/89, 1996/97 and 1997/98 seasons exceptionally well. In terms of getting the sign of the anomaly of the yield correct, the CERES-Maize model performs the best for the first plant date (Figure 3.11 (g)), in which the sign of the anomaly of the yield for 15 out the 19 seasons are simulated successfully.

The CERES-CCAM ensemble mean yield index time series (CCYI – blue) shows that the CERES-Maize model forced with CCAM-simulated fields is once again, as in the short and medium season maize scenarios, unable to simulate the high maize yield of the 1995/96 La Niña season and the low maize yield of the 1991/92 El Niño season. In these long season maize scenarios the CERES-Maize model makes the maize yield of the 1998/99 La Niña season the highest and the maize yield of the 1987/88 El Niño the lowest out of the 19 seasons investigated in this study. Those seasons for which the CERES-Maize model forced with CCAM-simulated fields produce realistic yields in comparison to both the actual yield index (AYI – red) and the CERES-Observed weather yield index (COYI – green) include the 1983/84 (see in particular Figure 3.12), 1986/87 (see in particular Figure 3.11 (g)) and 1988/89 (see in particular Figure 3.11 (h)) seasons. In all three scenarios the sign of the anomaly of the yield for 13 out of the 19 seasons are indicated correctly by the CERES-Maize model.

The CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) and Multi-Model ensemble mean yield index time series (MMYI – purple) for the long season maize scenarios show similar results to that found for the short and medium season maize scenarios. When forced with ECHAM4.5-simulated fields the CERES-Maize model does not perform well in simulating the maize yields. This simulation system fails to capture the sign of the anomaly of the yield for 13 out of the 19 seasons. The Multi-Model simulation system on the other hand shows somewhat better results than the CERES-ECHAM4.5 simulation system, with the best results found for the long season maize planted on plant date 1 scenario (Figure 3.11 (g)).

In general, the ability of the different simulation systems in simulating the season-to-season change in maize yield seems to be the lowest for the short season maize scenarios and the highest for the long season maize scenarios. The CERES-Observed weather yield index performs the best in simulating the maize yields of the long season maize planted on plant date 1 scenario.

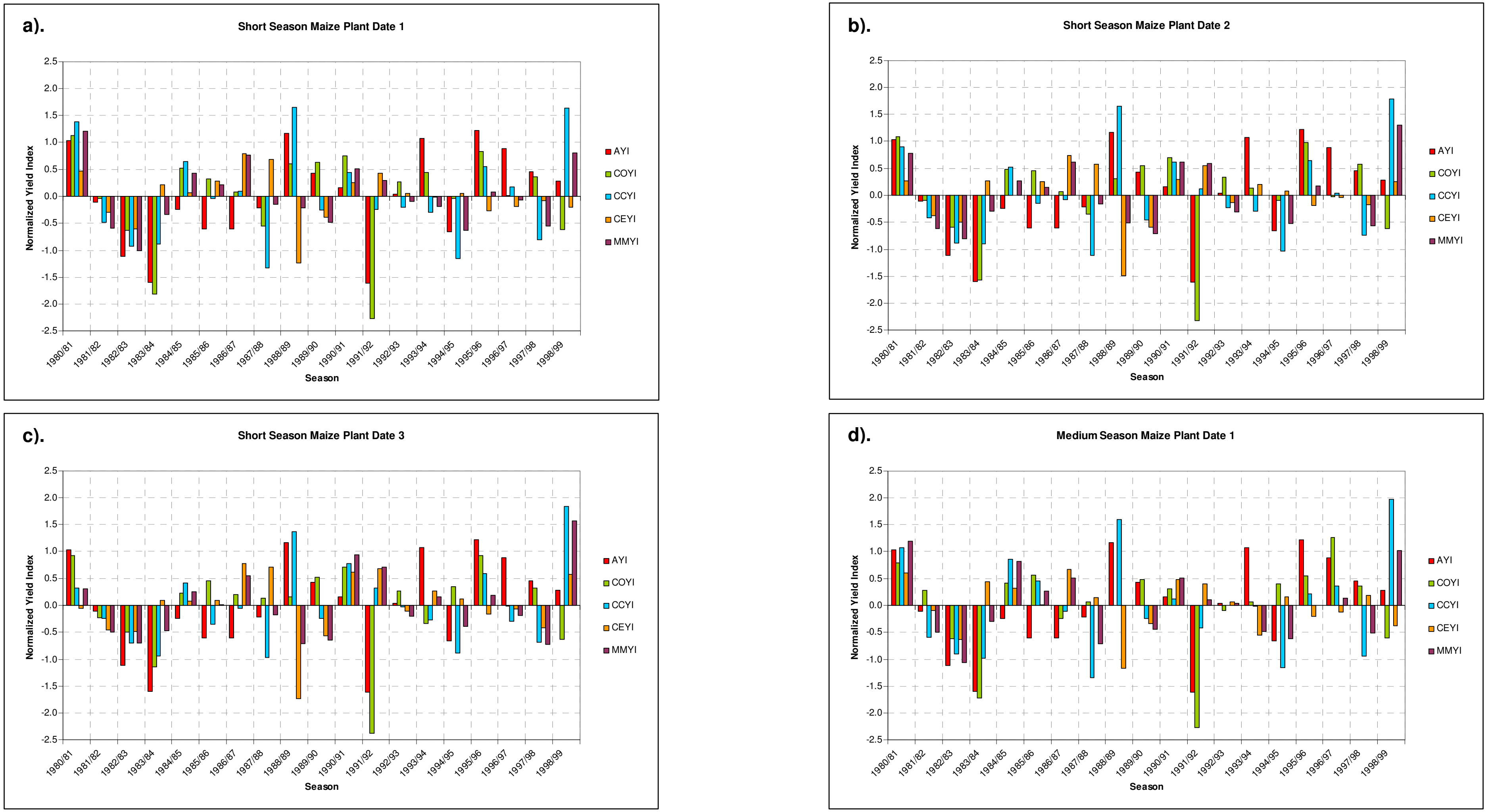


Figure 3.10: Maize yield index time-series (1980/81 – 1998/99) for the Dry/Warm Western Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (a) to (d) represent scenarios 1 to 4, as described in Table 2.8.

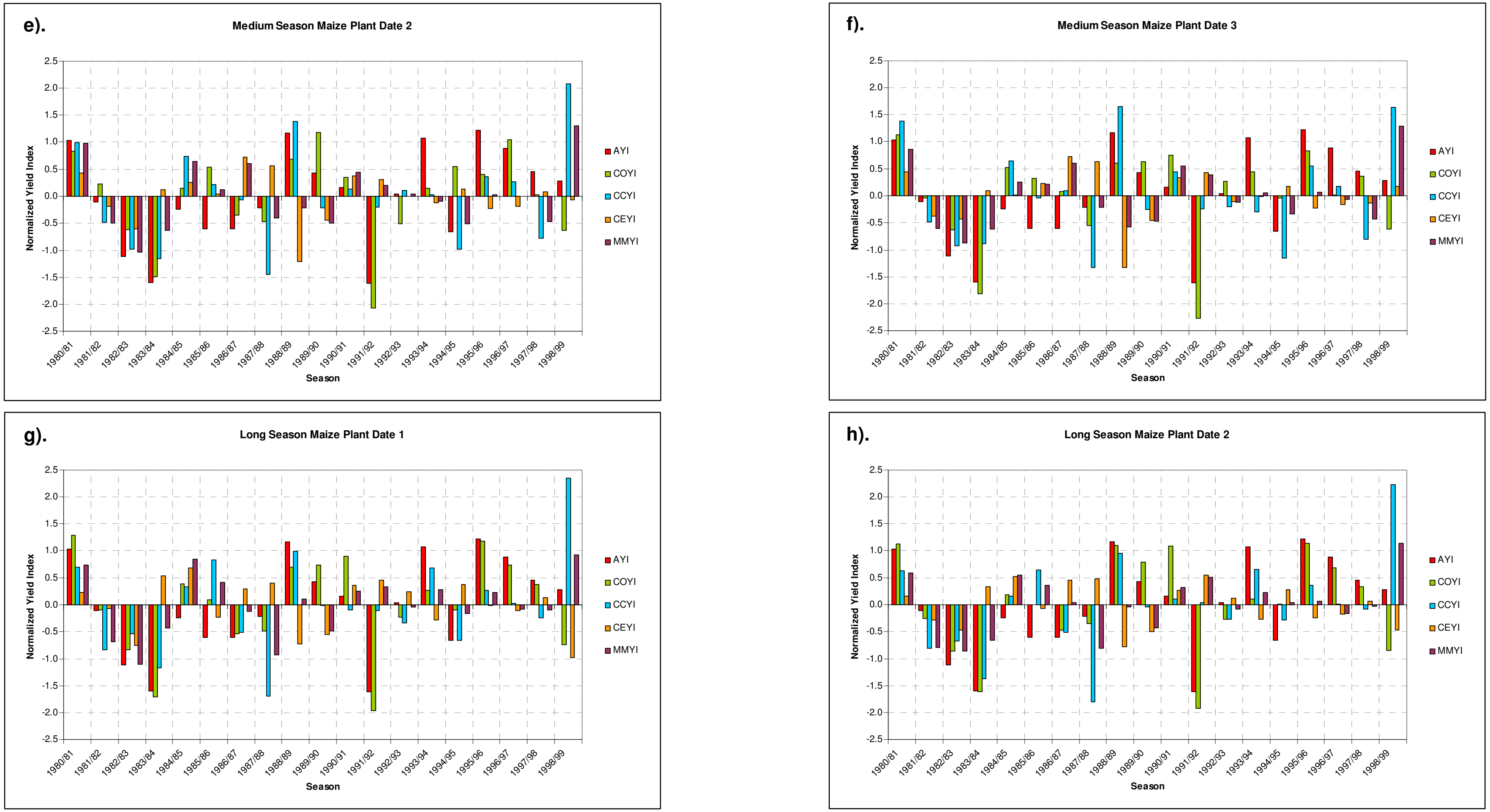


Figure 3.11: Maize yield index time-series (1980/81 – 1998/99) for the Dry/Warm Western Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (e) to (h) represent scenarios 5 to 8, as described in Table 2.8.

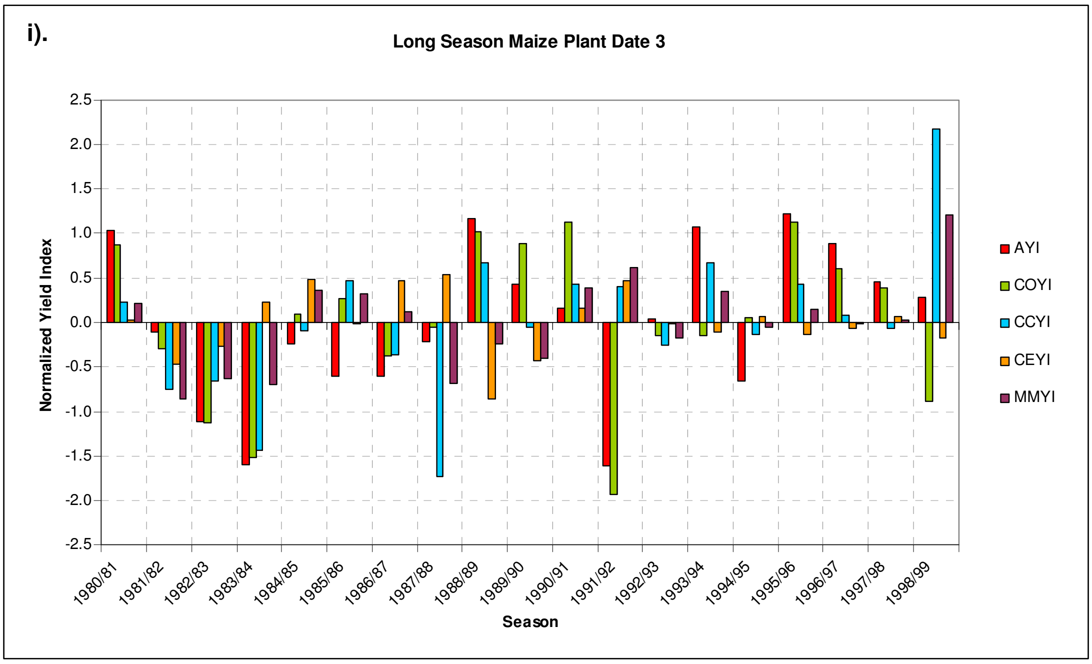


Figure 3.12: Maize yield index time-series (1980/81 – 1998/99) for the Dry/Warm Western Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). This graph represents scenario 9, as described in Table 2.8.

3.3.1.2 Temperate Eastern Region

The time series of the actual maize yield index and simulated maize yield indices, obtained from each of the different simulation systems, are shown for the temperate eastern production region in Figures 3.13 (scenario 1 to 4), 3.14 (scenario 5 to 8) and 3.15 (scenario 9). From the actual yield index time series (AYI - red) it can be observed that the maize yields of the 1980's were generally much lower than the maize yields of the 1990's, except for the 1991/92 and 1994/95 seasons. Two interesting features evident from the actual yield index time series include the increasing trend in the maize yield from the 1982/83 season to the 1988/89 season and the decreasing trend in the maize yield from the 1993/94 season to the 1998/99 season. The decrease in maize yield in the late 1990's could have been due to climatic conditions, rising input costs and the unstable maize price which all added to the fact that maize production with the use of the production systems available at that stage were no longer economically viable (Du Toit *et al.*, 2001). Furthermore, it can also be seen that over this 20 year period, the 1993/94 ENSO-neutral season rendered the highest maize yield and the 1991/92 El Niño season, the same as for the dry/warm western production region, the lowest maize yield. Reasonable variation has been found in the rainfall impacts of ENSO over southern Africa (Reason and Jagadheesa, 2005). Weak El Niño (La Niña) events can lead to more widespread and more severe rainfall impacts over southern Africa than strong El Niño (La Niña) events (Reason and Jagadheesa, 2005). This may explain the fact that in the temperate eastern production region an ENSO-neutral season resulted in the highest maize yield over the 19 seasons, while in the dry/warm western production region a La Niña season produced the highest maize yield.

3.3.1.2.1 Short Season Maize

Figure 3.13, (a), (b) and (c) represent short season maize planted on plant date 1, 2 and 3 respectively. To quantify the ability of the CERES-Maize model in simulating the inter-seasonal variability in maize yield of the temperate eastern production region it is necessary to investigate the CERES-Observed weather yield index time series (COYI – green) and compare it to the actual maize yield index time series (AYI – red). For all three short season maize scenarios the CERES-Maize model is able to successfully simulate the low maize yield of the 1991/92 El Niño season, but unable to simulate the high maize yield of the 1993/94 ENSO-neutral season. The CERES-Maize model performs well in capturing the increase in maize yield from the 1982/83 season to the 1988/89 season, but it is simulated in much more prominent steps than that observed in reality (AYI - red). Furthermore, the CERES-Maize model is able to correctly indicate the sign of the anomaly of the yield for 11 out of the 19 seasons and additionally simulates the relative magnitude of the yield of the 1981/82, 1983/84 and 1992/93 seasons remarkably well.

The CERES-CCAM ensemble mean yield index time series (CCYI – blue) for the three short season maize scenarios show that when forced with CCAM-simulated fields the CERES-Maize model is unable to capture the extremely low maize yield of the 1991/92 season and the high maize yield of the 1993/94 season. It can also be observed that for short season maize this simulation system does not perform well in simulating the relative magnitude of the yields. Furthermore, the ability of the CERES-CCAM simulation system in simulating the maize yield seems to decrease from plant date 1 to plant date 3, as the number of seasons for which the sign of the anomaly of the yield is successfully simulated decreases from 8 to 6.

From the CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three short season maize scenarios it can be seen that for approximately 80% of the seasons the inter-seasonal variability in terms of the sign of the anomaly of the yield follows the same pattern as the CERES-CCAM ensemble mean yield index (CCYI – blue), which results in the Multi-Model ensemble mean yield index (MMYI – purple) also following the same pattern. Similar to the results obtained for the CERES-CCAM simulation system, the CERES-ECHAM4.5 and Multi-Model simulation systems also do not perform well in simulating the relative magnitude of the yields. The 1981/82 season stands out, as for this season the CERES-ECHAM4.5 and Multi-Model simulation systems perform much better in simulating the yield than the CERES-CCAM simulation system.

3.3.1.2.2 Medium Season Maize

The time series of the maize yield indices (actual and simulated) for medium season maize planted on plant date 1, 2 and 3 are shown in Figure 3.13 (d) and Figure 3.14 (e) and (f) respectively. The first observation that can be made from the CERES-Observed weather yield index time series (COYI – green) for the three medium season maize scenarios, is that both the sign of the anomaly and relative magnitude of the yields are best represented by the CERES-Maize model in the medium season maize planted on plant date 1 and 2 scenarios. The sign of the anomaly of the yield for 16 out of the 19 seasons are simulated successfully by the CERES-Maize model in the medium season maize planted on plant date 1 and 2 scenarios. For the medium season maize planted on plant date 3 scenario, the CERES-Maize model struggles to simulate the relative magnitude of the maize yields of the 1995/1996, 1996/97 and 1997/98 seasons, while the CERES-Maize performs well in capturing the relative magnitude of the yields of these seasons in the other two medium season maize scenarios. In all three scenarios the CERES-Maize model produces the most realistic maize yields for the 1980/81, 1982/83, 1983/84, 1991/92 and 1992/93 seasons.

When the CERES-CCAM ensemble mean yield index time series (CCYI – blue) for each of the three medium season maize scenarios are examined, it can be seen that the CERES-Maize model forced with CCAM-simulated fields fails to simulate the high maize yield of the 1993/94 ENSO-neutral season and the low maize yield of the 1991/92 El Niño season. A prominent feature that can be observed from the CERES-CCAM ensemble mean yield index time series is the extremely high maize yield of the 1998/99 La Niña season. The CERES-CCAM ensemble mean yield index appears to show greater variability between seasons than that observed from the actual yield index. Similar to the CERES-Observed weather yield index, the CERES-CCAM simulation system also performs better in simulating the sign of the anomaly of the yields of the medium season maize planted on plant date 1 and 2 scenarios than the medium season maize planted on plant date 3 scenario.

The CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three medium season maize scenarios show a decrease in performance from plant date 1 to plant date 3. When forced with ECHAM4.5-simulated fields the CERES-Maize model does not capture the low maize yield of the 1991/92 season, but instead simulates the maize yield of the 1988/89 La Niña season to be unusually low. From the Multi-Model ensemble mean yield index time series (MMYI – purple) for the three medium season maize scenarios it can be seen that for several seasons the Multi-Model simulation system provides better yield estimates than the CERES-CCAM or CERES-ECHAM4.5 simulation systems on their own. These seasons include 1981/82 (see Figure 3.13 (d)), 1983/84 (see Figure 3.14 (f)), 1984/85 (see Figure 3.13 (d)) and 1996/97 (see Figure 3.13 (d)).

3.3.1.2.3 Long Season Maize

Figure 3.14 (g) and (h) and Figure 3.15 shows the maize yield indices (actual and simulated) for the 19 seasons considered in this study for long season maize planted on plant date 1, 2 and 3 respectively. By examining the CERES-Observed weather yield index time series (COYI – green) it can be seen that the CERES-Maize model correctly indicates the sign of the anomaly of the yield of almost all the seasons. The CERES-Observed weather yield index shows little variation between the three scenarios. In all three scenarios the CERES-Maize model performs very well in simulating the relative magnitude of the yields of those seasons with actual yield index values less that -1, as can be seen for the 1982/83, 1983/84 and 1991/92 seasons.

The CERES-CCAM ensemble mean yield index time series (CCYI – blue) for the three long season maize scenarios show that for 12 out of the 19 seasons considered here the CERES-CCAM simulation system is able to correctly indicate the sign of the anomaly of the yield. It can also be noted that the CERES-Maize model largely overestimates the maize yields of the 1988/89 and 1998/99 La Niña seasons. In all three scenarios the CERES-Maize model forced with CCAM-simulated fields performs exceptionally well in capturing the relative magnitude of the yield of the 1994/95 El Niño season.

The time series of the CERES-ECHAM4.5 ensemble mean yield index (CEYI – orange) for long season maize planted on plant date 1, 2 and 3 show that even though the CERES-Maize model forced with ECHAM4.5-simulated fields is unable to capture the sign of the anomaly of the yield of almost half of the seasons considered in this study, for several seasons the relative magnitude of the yield is estimated extremely well. In all three scenarios this simulation system captures the relative magnitude of the yield of the 1985/86, 1990/91 and 1997/98 seasons better than any of the other simulation systems.

The combination between the CERES-CCAM and CERES-ECHAM4.5 integrations for the long season maize scenarios is expressed as the Multi-Model ensemble mean yield index (MMYI – purple) in Figure 3.14 (g) and (h) and Figure 3.15. In all three scenarios the Multi-Model simulation system succeeds in simulating the sign of the anomaly of the yield of 10 seasons. This system also performs relatively well in estimating the relative magnitude of the yields of the 1980/81, 1982/83 and 1996/97 seasons. Even though the yield estimates for these seasons are not necessarily an improvement from the CERES-CCAM ensemble mean yield index (CCYI – blue) or CERES-ECHAM4.5 ensemble mean yield index (CEYI – orange), these estimates are still fairly good.

In general, all four simulation systems show a decrease in performance from plant date 1 to plant date 3 in the short season maize scenarios, better performance for plant dates 1 and 2 in the medium season maize scenarios than for plant date 3 and the best performance for the long season maize scenarios. The best results are once again found for the long season maize planted on plant date 1 scenario. For this scenario the CERES-Observed weather simulation system correctly indicates the sign of the anomaly of the yield of almost all 19 seasons.

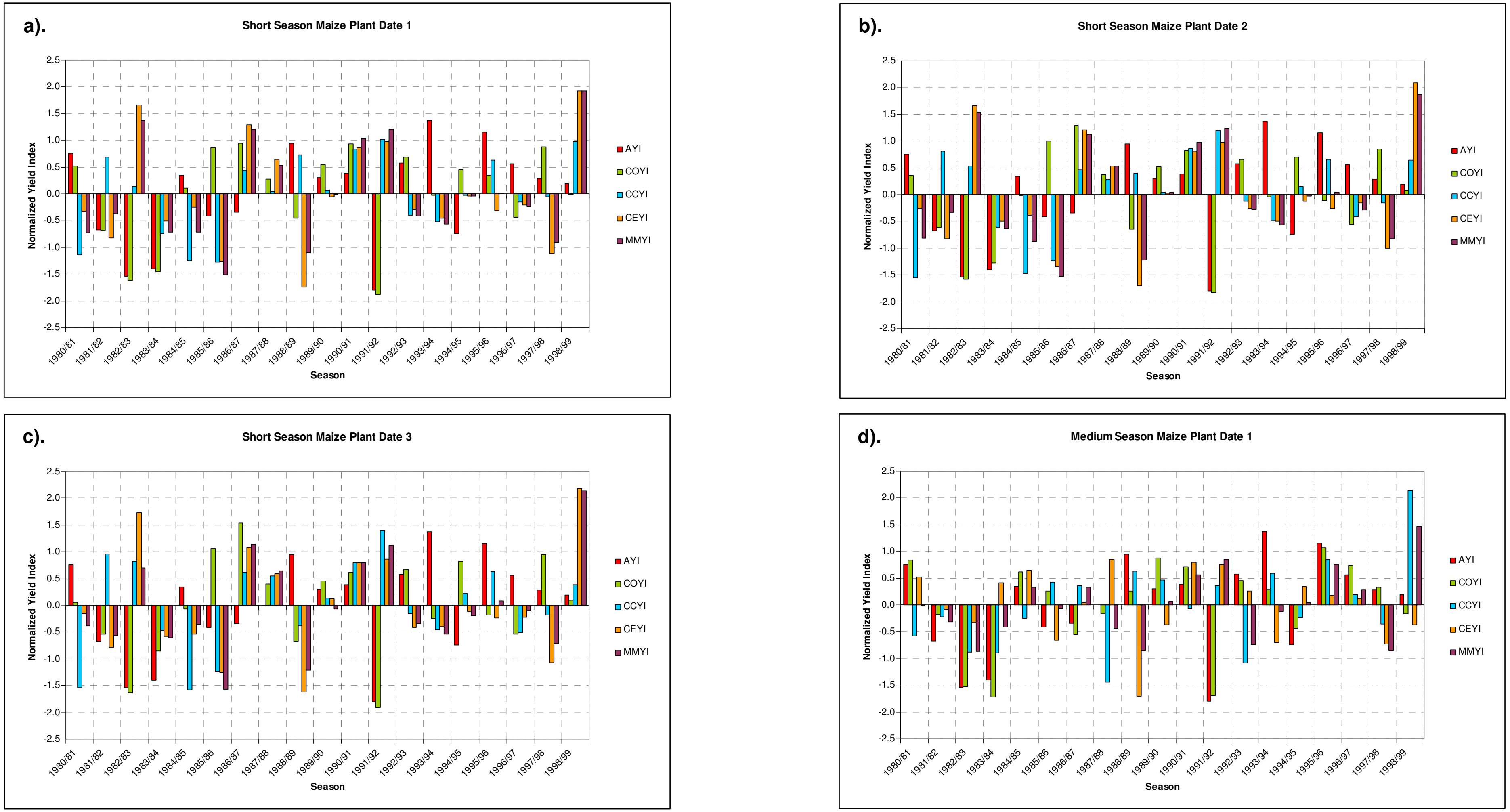


Figure 3.13: Maize yield index time-series (1980/81 – 1998/99) for the Temperate Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (a) to (d) represent scenarios 1 to 4, as described in Table 2.8.

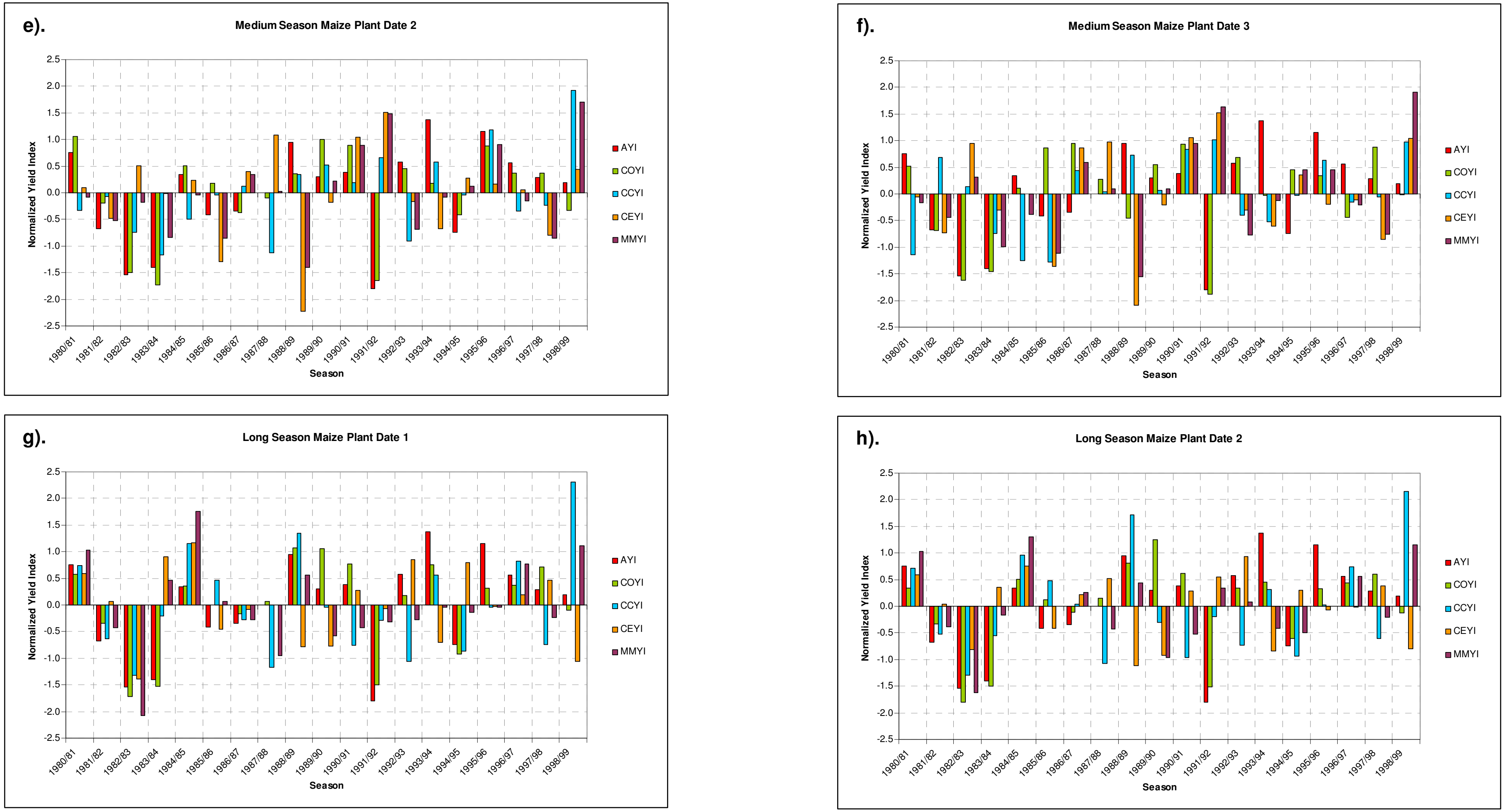


Figure 3.14: Maize yield index time-series (1980/81 – 1998/99) for the Temperate Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (e) to (h) represent scenarios 5 to 8, as described in Table 2.8.

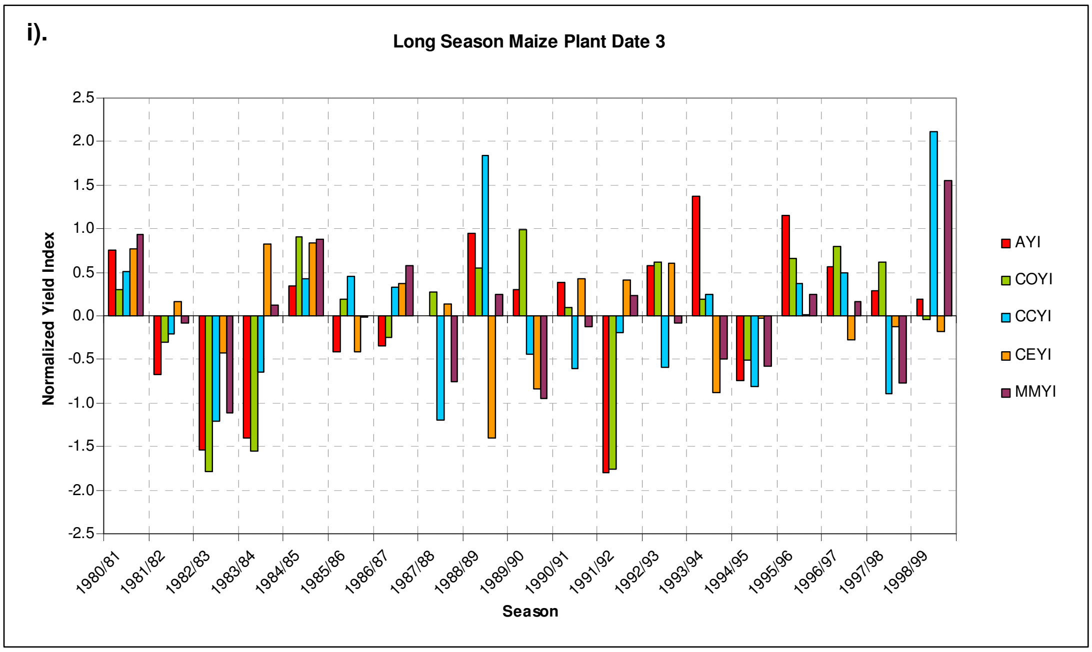


Figure 3.15: Maize yield index time-series (1980/81 – 1998/99) for the Temperate Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). This graph represents scenario 9, as described in Table 2.8.

3.3.1.3 Wet/Cool Eastern Region

The time series of the actual maize yield index and simulated maize yield indices, obtained from each of the different simulation systems, are shown for the wet/cool eastern production region in Figures 3.16 (scenario 1 to 4), 3.17 (scenario 5 to 8) and 3.18 (scenario 9). From the actual yield index time series (AYI - red) it can be observed that maize production in the 1980's in the wet/cool eastern production region was characterised by relatively low maize yields from the 1981/82 season to the 1983/84 season, followed by a period of slightly higher (at least above normal) yields from the 1984/85 season to the 1990/91 season, with the exception of the 1986/87 season. The 1990's on the other hand commenced with the lowest maize yield of the entire 20 year period (1991/92), followed shortly by the highest maize yield of the entire 20 year period (1993/94) where after a decrease in maize yield took place from the 1995/96 season to the 1997/98 season. As mentioned for the dry/warm western and temperate eastern production regions, an El Niño event occurred during the 1991/92 season, while 1993/94 was an ENSO-neutral season.

3.3.1.3.1 Short Season Maize

Figure 3.16 (a), (b) and (c) shows the yield indices (actual and simulated) for short season maize planted on plant date 1, 2 and 3 respectively. It is essential to quantify the ability of the CERES-Maize model in simulating the yield of the wet/cool eastern production region. This is done by examining the CERES-Observed weather yield index time series (COYI – green). From the three graphs it can be seen that the ability of the CERES-Maize model in simulating the sign of the anomaly of the yield decreases from plant date 1 to plant date 3. Even though the relative magnitude of the yields are not simulated that well, in the short season maize planted on plant date 1 scenario (Figure 3.16 (a)) the CERES-Maize model is able to capture the increase in maize yield from 1982/83 to 1985/86. Furthermore it is also evident that when forced with observed weather data the CERES-Maize model fails to simulate the anomalously low maize yield of the 1991/92 El Niño season and the anomalously high maize yield of the 1993/94 ENSO-neutral season. In all three short season maize scenarios the relative magnitude of the yields of the 1980/81, 1983/84 and 1984/85 seasons are simulated very well.

The time series of the CERES-CCAM ensemble mean yield index (CCYI – blue) for short season maize shows that this simulation system struggles to simulate the maize yields of the late 1980's to early 1990's (1985/86 – 1990/91), except for the 1988/89 season. Thus, the CERES-Maize model forced with CCAM-simulated fields performs a great deal better in simulating the maize yields of the early 1980's and late 1990's than it performs for the period in between. In all three short season maize scenarios this simulation system simulates the relative magnitude of the yields of the 1982/83, 1988/89, 1994/95 and 1996/97 seasons extremely well. Another interesting feature is the fact that the CERES-CCAM ensemble mean yield index shows a large overestimation of the yield of the 1998/99 La Niña season

When the CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) of each of the three short season maize scenarios are examined, it can be seen that this simulation system largely underestimates the yield of the 1988/89 La Niña season, but performs better than the CERES-CCAM simulation system in estimating the yield of the 1987/88 El Niño season. Furthermore, the CERES-ECHAM4.5 ensemble mean yield index reveals a realistic maize yield for the 1998/99 season (see in particular Figure 3.16 (b) and (c)).

From the Multi-Model ensemble mean yield index time series (MMYI – purple) it can be seen that this simulation system also severely overestimates the maize yield of the 1998/99 La Niña season, as is the case with the CERES-CCAM simulation system. Another observation that can be made is the fact that the Multi-Model simulation system does not perform well in capturing the sign of the anomaly of the yield of the five seasons from 1989/90 to 1993/94. Furthermore, over the three short season maize scenarios this simulation system is able to correctly indicate the sign of the anomaly of the yield of an average for 9 seasons out of the 19 under investigation.

3.3.1.3.2 Medium Season Maize

Time series of the maize yield indices (actual and simulated) for medium season maize planted on plant date 1, 2 and 3 are shown in Figure 3.16 (d) and Figure 3.17 (e) and (f) respectively. From the CERES-Observed weather yield index times series (COYI – green) for these three scenarios it can be seen that the CERES-Maize model performs well in capturing the sign of the anomaly of the yield, but fails to simulate the relative magnitude of the yields. Furthermore, it also appears as if the relative magnitude of the simulated yields vary considerably between the three scenarios, which makes it difficult to determine for which medium season maize scenario the CERES-Maize model performs the best.

When the CERES-CCAM ensemble mean yield index time series (CCYI – blue) for each of the three medium season maize scenarios are examined, the first observation that can be made is the large overestimation of the yield of the 1998/99 La Niña season. This simulation system performs relatively well in capturing the relative magnitude of the maize yields.

The CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three medium season maize scenarios show that this simulation system succeeds in simulating the sign of the anomaly of the yield for 9 out of the 19 seasons considered in this study. It can also be seen that the CERES-Maize model forced with ECHAM4.5-simulated fields performs the best in simulating the relative magnitude of the maize yields of the medium season maize planted on plant date 2 scenario, as can be seen, for example, for the 1980/81, 1982,83, 1996/97 and 1997/98 seasons.

From the Multi-Model ensemble mean yield index time series (MMYI – purple) for the three medium season maize scenarios it can be seen that even though this simulation system captures the sign of the anomaly of the yield of several seasons, it often fails to simulate the relative magnitude of the maize yields. Although, it can be seen that the relative magnitude of the yields of a number of seasons (1980/81, 1983/84 and 1996/97) are captured the best for the medium season maize planted on plant date 3 scenario.

3.3.1.3.3 Long Season Maize

In Figure 3.17 (g) and (h) and Figure 3.18 the maize yield indices (actual and simulated) for long season maize planted on plant date 1, 2 and 3 can be seen. The CERES-Observed weather yield index time series (COYI – green) for these three long season maize scenarios show that the CERES-Maize model performs well in simulating the sign of the anomaly of the maize yields of the wet/cool eastern production region. In the long season maize planted on plant date 1 scenario (Figure 3.17 (g)) the CERES-Maize model is able to correctly indicate the sign of the anomaly of the yield for 17 out of the 19 season. The high maize yield of the 1993/94 ENSO-neutral season is underestimated by the model and the low maize yield of the 1991/92 El Niño season is overestimated.

The CERES-CCAM ensemble mean yield index time series (CCYI – blue) for the long season maize scenarios show that when forced with CCAM-simulated fields the CERES-Maize model performs well in simulating the relative magnitude of the yields of many seasons. This can primarily be seen for the seasons in the 80's and include 1980/81, 1982/83, 1985/86, 1986/87 and 1988/89. An overestimation of the yield of the 1998/99 La Niña season can once again be seen. This simulation system is able to capture the sign of the anomaly of the yield for 14 out of the 19 seasons under investigation in this study.

From the CERES-ECHAM4.5 ensemble mean yield index time series (CEYI – orange) for the three long season maize scenarios it can be seen that when the CERES-Maize model is forced with ECHAM4.5-simulated fields, the ability to simulate the sign of the anomaly of the yield decreases from plant date 1 to plant date 3, as the number of season for which the model correctly indicates the sign of the anomaly of the yield decreases from 11 to 8. In general, this simulation system struggles to simulate the maize yields of the four seasons from 1986/87 to 1989/90. Furthermore it is also evident that for a number of seasons this simulation system produces more realistic maize yields than the CERES-CCAM simulation system, as can be seen for the 1991/92, 1996/97, and 1997/98 seasons.

From the Multi-Model ensemble mean yield index time series (MMYI – purple) for the long season maize scenarios it can be seen that the Multi-model simulation system performs better in simulating the sign of the anomaly of the yield than the CERES-ECHAM4.5 maize yield simulation system, but does not perform as good as the CERES-CCAM maize yield simulation system. For some seasons the Multi-Model ensemble mean yield index time series show better results in terms of the relative magnitude of the yield than both the CERES-CCAM and CERES-ECHAM4.5 simulation systems, as can be seen, for example, for the 1998/99 season.

In general, all four simulation systems show a decrease in performance from plant date 1 to plant date 3 in the short season maize scenarios, similar results for all three plant dates in the medium season maize scenarios and a decrease in performance from plant date 1 to plant date 3 in the long season maize scenarios. Thus, out of the 9 scenarios investigated, the simulation systems show the best results for the long season maize planted on plant date 1 scenario.

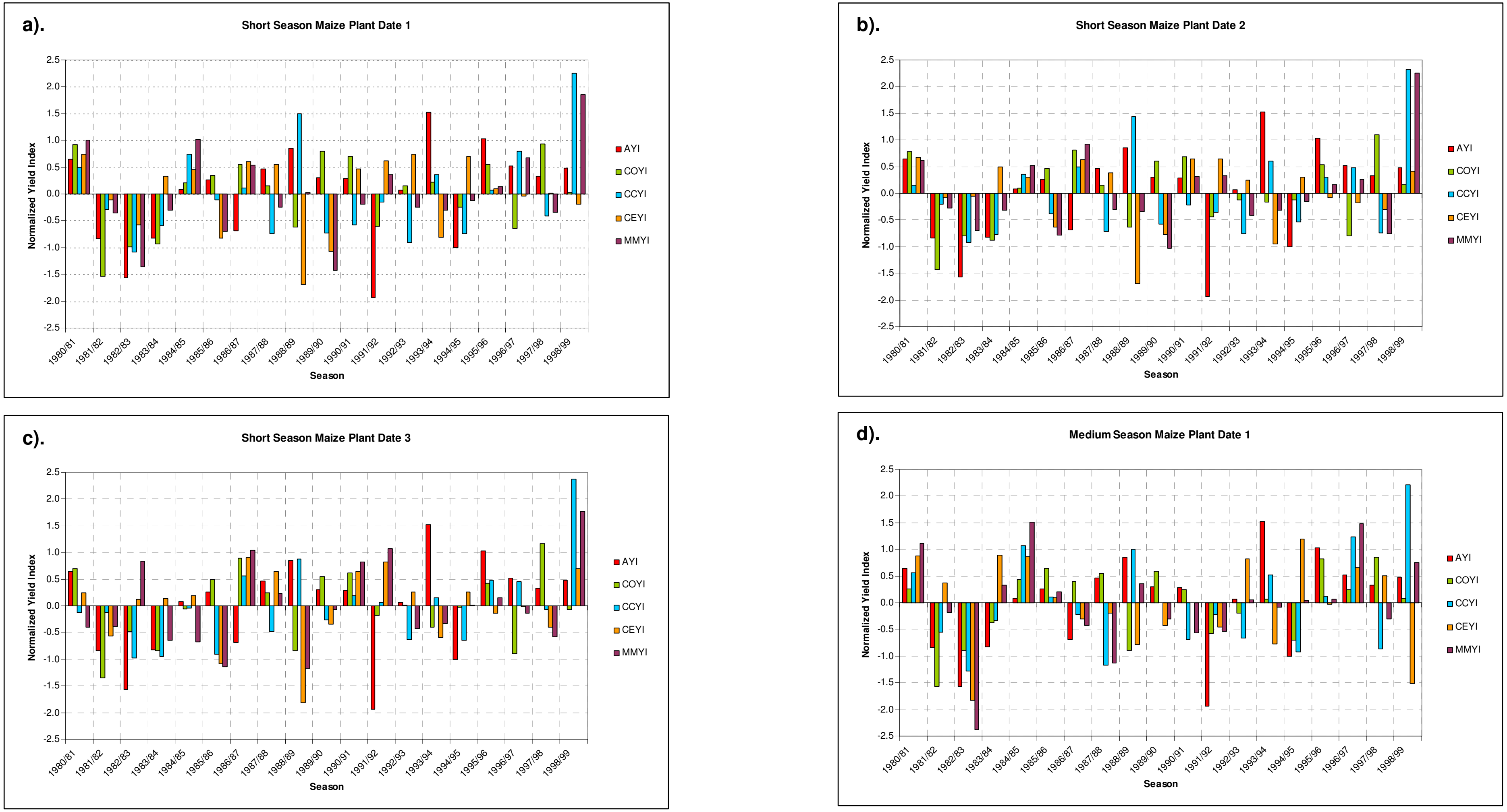


Figure 3.16: Maize yield index time-series (1980/81 – 1998/99) for the Wet/Cool Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (a) to (d) represent scenarios 1 to 4, as described in Table 2.8.

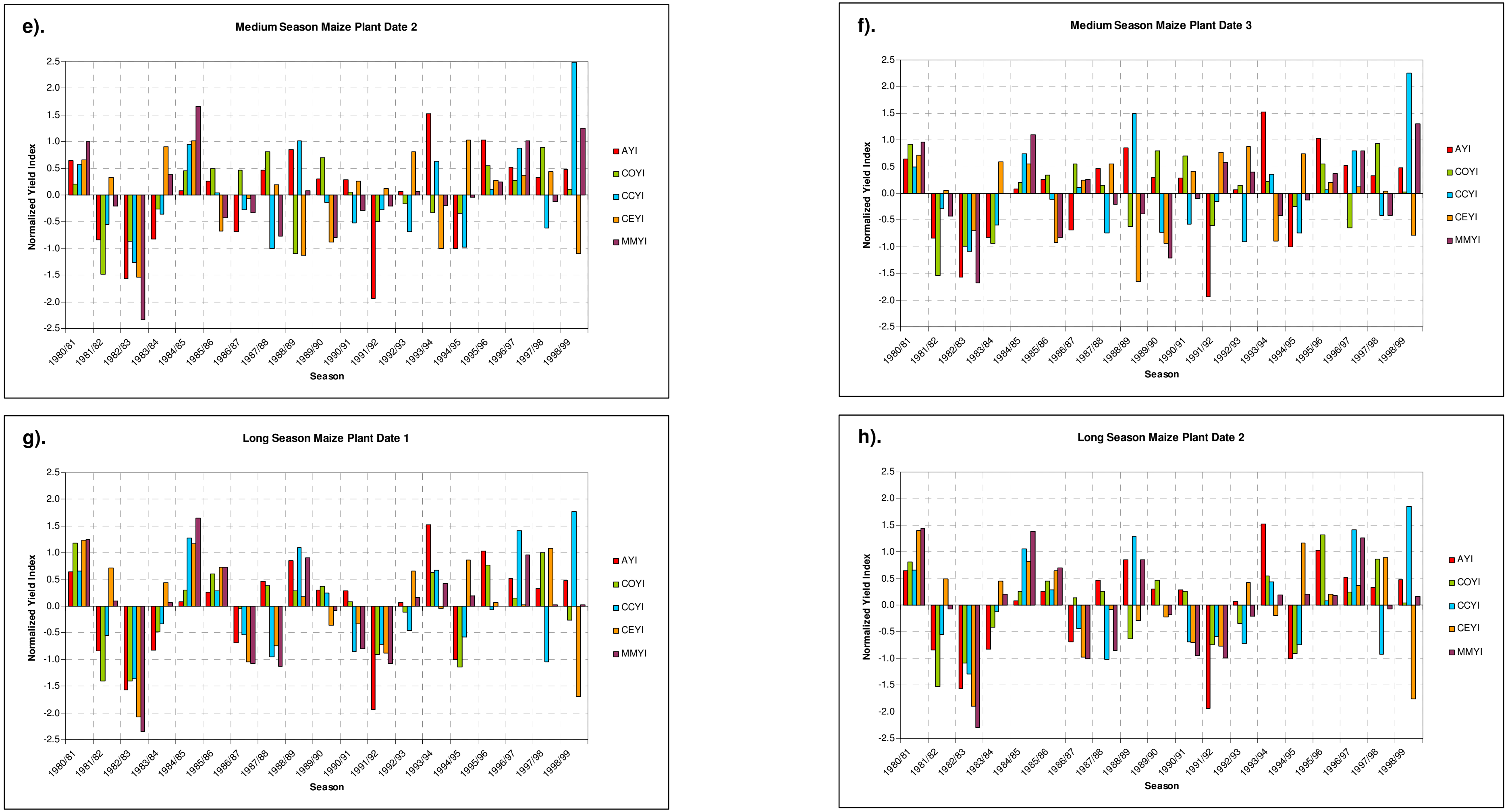


Figure 3.17: Maize yield index time-series (1980/81 – 1998/99) for the Wet/Cool Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). Graphs (e) to (h) represent scenarios 5 to 8, as described in Table 2.8.

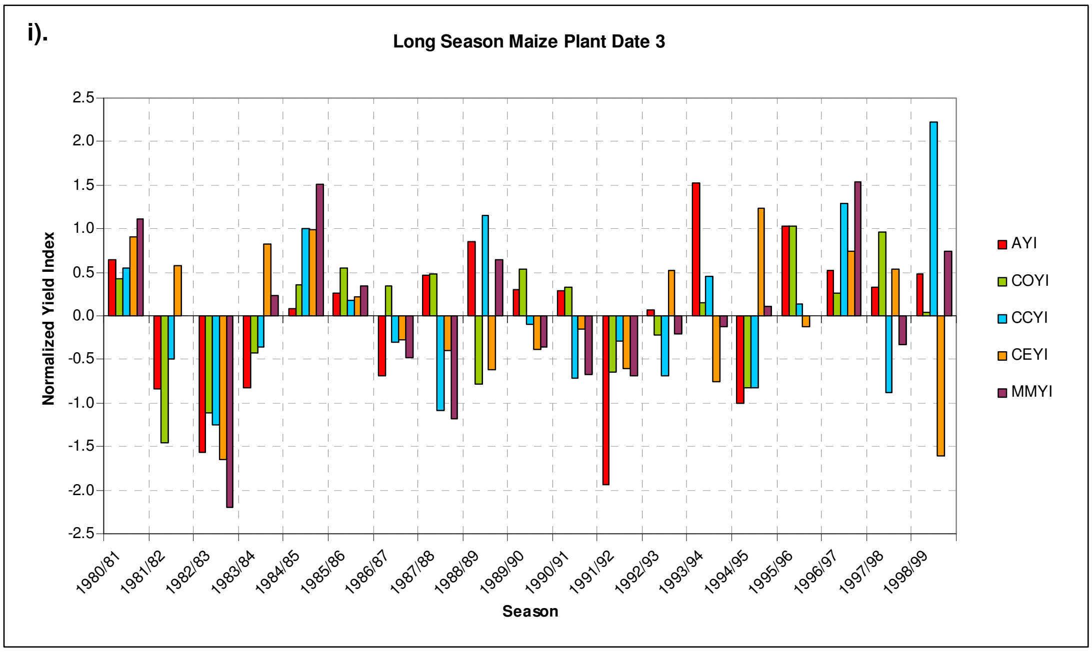


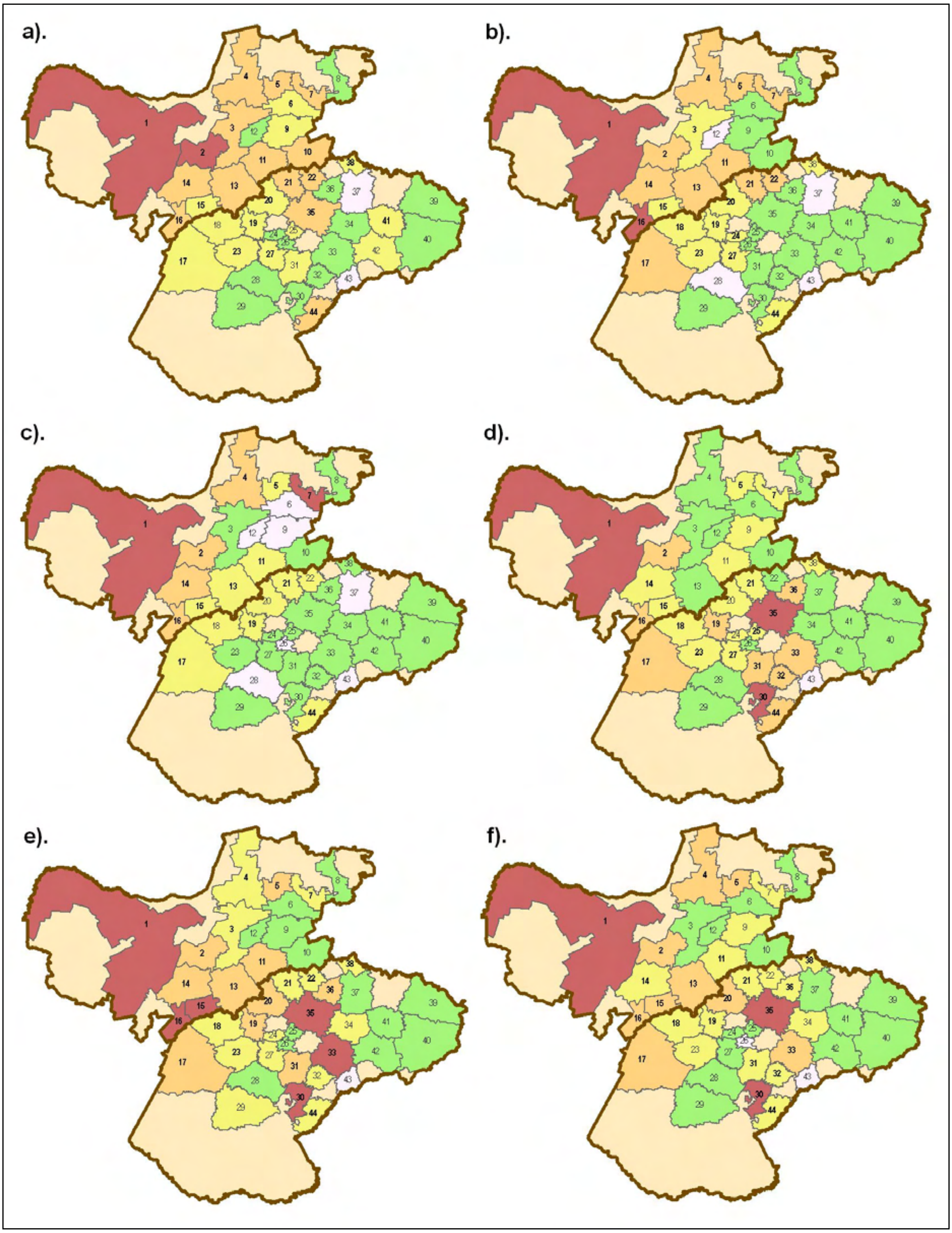
Figure 3.18: Maize yield index time-series (1980/81 – 1998/99) for the Wet/Cool Eastern Region. Actual maize yield index (AYI), CERES-Observed weather yield index (COYI), CERES-CCAM ensemble mean yield index (CCYI), CERES-ECHAM4.5 ensemble mean yield index (CEYI) and Multi-Model ensemble mean yield index (MMYI). This graph represents scenario 9, as described in Table 2.8.

3.3.2 Objective Validation

3.3.2.1 Actual Maize Yield vs. CERES-Observed Weather Maize Yield

Figure 3.19 (a) to (i) shows the Spearman rank correlations between the actual maize yields and CERES-Observed weather maize yields for each of the 9 scenarios in Table 2.8. The magisterial districts with statistically significant correlations are indicated in bold. Strong correlations indicate areas where the association between the actual maize yield and CERES-Observed weather maize yield is greatest, and weak correlations indicate the areas where the association is poor. The threshold correlation for local significance at the 95% level of confidence is approximately 0.46.

The three short season maize scenarios (Figure 3.19 (a), (b) and (c)) show higher correlations for the North-West Province than for the Free State, and also reveal an increase in the correlations from east to west across the study area, with much lower correlations in the east than in the west. In all three short season maize scenarios, the western part of the North-West Province shows the highest correlations. It can also be seen that the skill of the CERES-Maize model decreases from plant date 1 to plant date 3, as 25 magisterial districts (significant at the 95% level, see section 2.5.2.2.2) have statistically significant correlations for plant date 1 (Figure 3.19 (a)), but only 21 (significant at 95% level) for plant date 2 (Figure 3.19 (b)) and 14 (significant at 95% level) for plant date 3 (Figure 3.19 (c)). The short season maize planted on plant date 3 scenario shows that most of the magisterial districts in the Free State do not have statistically significant correlations.



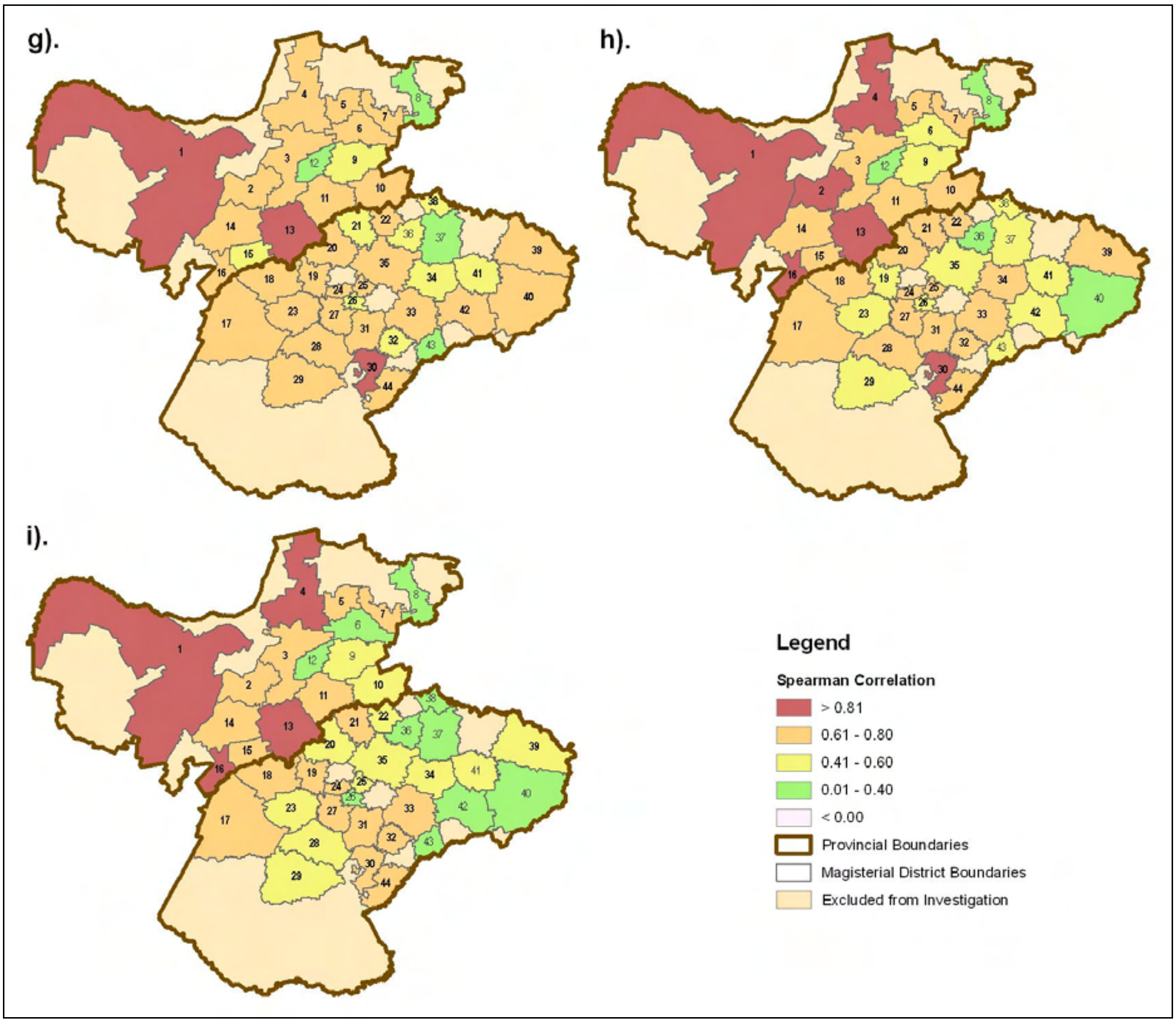


Figure 3.19: Spearman rank correlations calculated between the actual maize yields and CERES-Observed weather maize yields over the 20 year period from 1980 to 1999. (a) Short season maize plant date 1, (b) Short season maize plant date 2, (c) Short season maize plant date 3, (d) Medium season maize plant date 1, (e) Medium season maize plant date 2, (f) Medium season maize plant date 3, (g) Long season maize plant date 1, (h) Long season maize plant date 2 and (i) Long season maize plant date 3. Magisterial districts with statistically significant correlations at the 95% confidence level are indicated in bold.

The three medium season maize scenarios (Figure 3.19 (d), (e) and (f)) also show higher correlations in the western parts of the study area than in the eastern parts of the study area, with the highest correlations (> 0.81) found for the western part of the North-West Province and central part of the Free State. The medium season maize planted on plant date 2 scenario (Figure 3.19 (e)) shows 25 magisterial districts (significant at 95% level) with statistically significant correlations, with only 21 (significant at 95% level) for the medium season maize planted on plant date 1 scenario (Figure 3.19 (d)) and 22 (significant at 95% level) for the medium season maize planted on plant date 3 scenario (Figure 3.19 (f)). All three scenarios reveal that the CERES-Maize model has poor skill in simulating the maize yield of magisterial district Ficksburg (43).

In the three long season maize scenarios (Figure 3.19 (g), (h) and (i)) the highest correlations, greater than 0.81, are evident for the western and central parts of the North-West Province. Once again, as with the short season maize scenarios, the skill of the CERES-Maize model appears to decrease from plant date 1 to plant date 3. Statistically significant correlations can be seen for 39 (significant at 95% level) out of the 44 magisterial districts in the long season maize planted on plant date 1 scenario (Figure 3.19 (g)). The other two scenarios show slightly lower correlations in the east than in the west, with 37 magisterial districts (significant at 95% level) with statistically significant correlations in the long season maize planted on plant date 2 scenario (Figure 3.19 (h)) and 32 (significant at 95% level) in the long season maize planted on plant date 3 scenario (Figure 3.19 (i)).

Thus, in all 9 scenarios the strongest correlations are typically found for the western part of the North-West Province, with correlations frequently exceeding 0.81. Furthermore, all 9 scenarios reveal a stronger association between the CERES-Observed weather maize yields and actual maize yields in the western parts of the study area than in the eastern parts. In general, the skill of the CERES-Maize model increases from the short season maize scenarios to the long season maize scenarios, with the overall highest correlations found for long season maize planted on plant date 1 (Figure 3.19 (g)). This is in agreement with the results found in the subjective validation.

3.3.2.2 Actual Maize Yield vs. CERES-CCAM Ensemble Mean Maize Yield

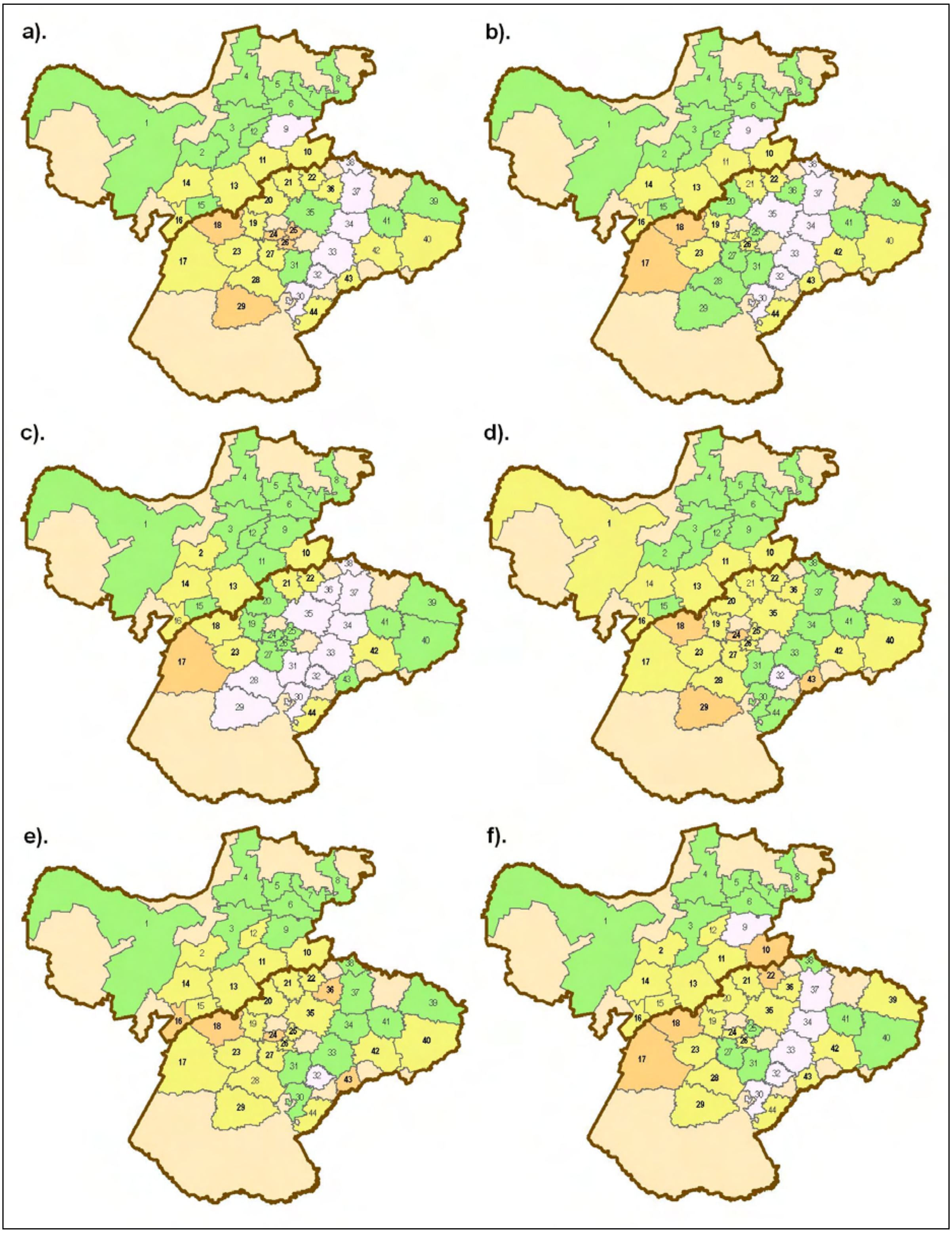
Figure 3.20 (a) to (i) shows the Spearman rank correlations between the actual maize yields and CERES-CCAM ensemble mean maize yields for each of the 9 scenarios in Table 2.8. The skill of the CERES-CCAM simulation system is evaluated in terms of the association between the simulated and actual maize yields. The magisterial districts with statistically significant correlations are indicated in bold. The threshold correlation for local significance at the 95% level of confidence is approximately 0.46.

The first feature that can be observed from the three short season maize scenarios (Figure 3.20 (a), (b) and (c)) is that the highest correlations occur in the western part of the Free State. The correlations of the magisterial districts in the North-West Province are primarily not statistically significant and negative correlations are found for the temperate eastern production region. Thus, the CERES-CCAM simulation system shows poor skill in simulating the maize yields of this production region. It can also be seen that when forced with CCAM-simulated fields the skill of the CERES-Maize model decreases rather drastically from plant date 1 to plant date 3, as 21 magisterial districts (significant at 95% level) have statistically significant correlations for plant date 1 (Figure 3.20 (a)), but only 13 (significant at 95% level) for plant date 2 (Figure 3.20 (b)) and 11 (significant at 95% level) for plant date 3 (Figure 3.20 (c)).

In general, the three medium season maize scenarios (Figure 3.20 (d), (e) and (f)) show more magisterial districts with statistically significant correlations than the short season maize scenarios (Figure 3.20 (a), (b) and (c)). The medium season maize planted on plant date 1 scenario (Figure 4.23 (d)) shows 22 magisterial districts (significant at 95% level) with statistically significant correlations, with 21 (significant at 95% level) for the medium season maize planted on plant date 2 scenario (Figure 3.20 (e)) and 20 (significant at 95% level) for the medium season maize planted on plant date 3 scenario (Figure 3.20 (f)). Thus, the skill of the CERES-CCAM simulation system decreases slightly from plant date 1 to plant date 3. The medium season maize planted on plant date 3 scenario also shows negative correlations for the temperate eastern production region as can be seen in the three short season maize scenarios. The highest correlations occur adjacent to the border separating the Free State from the North-West Province, and in the western part of the Free State.

In the three long season maize scenarios (Figure 3.20 (g), (h) and (i)) the highest correlations (0.61 – 0.8) occur once again in the western part of the Free State and to some extent also in the western part of the North-West Province (see Figure 3.20 (g) and (h)). Similar to the short and medium season maize scenarios, for the long season maize scenarios the skill of the CERES-CCAM simulation system also decreases from plant date 1 to plant date 3. Statistically significant correlations can be seen for 21 (significant at 95% level) out of the 44 magisterial districts in the long season maize planted on plant date 1 scenario (Figure 3.20 (g)), 17 (significant at 95% level) out of the 44 magisterial districts in the long season maize planted on plant date 2 scenario (Figure 3.20 (h)) and 10 (significant at 95% level) out of the 44 magisterial districts for the long season maize planted on plant date 3 scenario (Figure 3.20 (i)). It can also be seen that this simulation system does not perform well in simulating the maize yields of the magisterial districts in the eastern parts of both the Free State and North-West Province.

Thus, in all 9 scenarios the strongest correlations are typically found for the western part of the Free State, with correlations ranging between 0.61 and 0.8. Furthermore, it is evident in all 9 scenarios that the CERES-CCAM simulation system does not perform well in simulating the maize yields of a large part of the temperate eastern production region, with



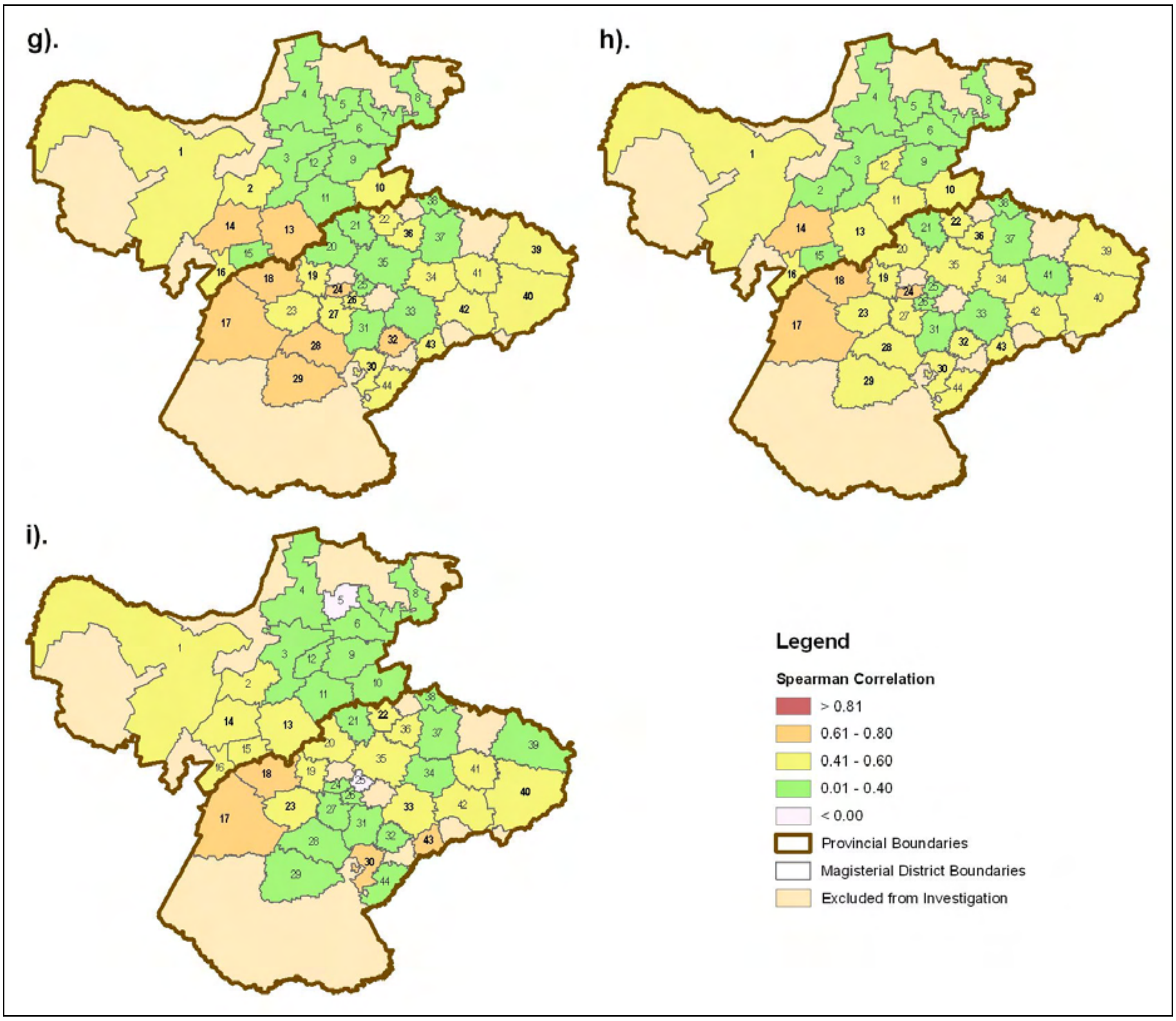


Figure 3.20: Spearman rank correlations calculated between the actual maize yields and CERES-CCAM ensemble mean maize yields over the 20 year period from 1980 to 1999. (a) Short season maize plant date 1, (b) Short season maize plant date 2, (c) Short season maize plant date 3, (d) Medium season maize plant date 1, (e) Medium season maize plant date 2, (f) Medium season maize plant date 3, (g) Long season maize plant date 1, (h) Long season maize plant date 2 and (i) Long season maize plant date 3. Magisterial districts with statistically significant correlations at the 95% confidence level are indicated in bold.

correlations either being negative or not significant. In general, the CERES-Maize model forced with CCAM-simulated fields reveals the highest skill in simulating the maize yields of the first plant dates, thus short season maize planted on plant date 1, medium season maize planted on plant date 1 and long season maize planted on plant date 1 (Figure 3.20 (a), (d) and (g). An increase in skill from the short season maize scenarios to the long season maize scenarios are also revealed, with the highest correlations found for long season maize planted on plant date 1 (figure 3.20 (g)). This phenomenon can also be seen in the CERES-CCAM simulated maize yields discussed in the subjective validation section (3.3.1).

3.3.2.3 Actual Maize Yield vs. CERES-ECHAM4.5 Ensemble Mean Maize Yield

The Spearman rank correlations between the actual maize yields and CERES-ECHAM4.5 ensemble mean maize yields are not shown, since the skill of this simulation system is poor. A number of factors could have contributed to this result. The ECHAM4.5-simulated fields are on a course grid of approximately 2.8° x 2.8°. Raw output from ECHAM4.5 is used as input into the CERES-Maize model. The same is done for the CERES-CCAM simulation system. Raw output from CCAM is used as input into the CERES-Maize model, but the simulated fields produced by CCAM are written out on a 1° x 1° grid. Due to the higher spatial resolution of the CCAM-simulated fields, the CERES-CCAM simulation system has an advantage over the CERES-ECHAM4.5 simulation system. As a result of the low spatial resolution of the ECHAM4.5-simualted fields it is possible that the ECHAM4.5 GCM is not skilful in providing a good representation of sub-grid scale features like precipitation. GCMs tend to overestimate rainfall over southern Africa, and often also distort the spatial pattern of the rainfall (Joubert and Hewitson, 1997). It may be possible to improve on the spatial resolution of the ECHAM4.5-simulated fields by nesting a Regional Climate Model (RCM) within the ECHAM4.5 GCM. In this study from the gridded GCM output a nearest neighbour approach is used to obtain representative GCM-simulated weather-type data for each magisterial district (see section 2.4.3.2). Thus, the use of a different interpolation routine may also improve the reliability of the GCM-simulated fields.

By investigating the seasonal long-term mean simulated fields of both ECHAM4.5 and CCAM, it is found that ECHAM4.5 has lower skill than CCAM in simulating mid-summer rainfall over the study area. So, it is not too surprising that CCAM produced more reliable weather-type data than ECHAM4.5. Mid-summer is a critical period in the development of the maize plant and therefore any misrepresentations in the rainfall in this season could have led to discrepancies in the maize yields simulated by the CERES-ECHAM4.5 simulation system.

3.3.2.4 Actual Maize Yield vs. Multi-Model Ensemble Mean Maize Yield

Figure 3.21 (a) to (i) shows the Spearman rank correlations between the actual maize yields and Multi-Model ensemble mean maize yields for each of the 9 scenarios in Table 2.8. The magisterial districts with statistically significant correlations are indicated in bold. Strong correlations indicate high skill and weak correlations indicate poor skill. The threshold correlation for local significance at the 95% level of confidence is approximately 0.46.

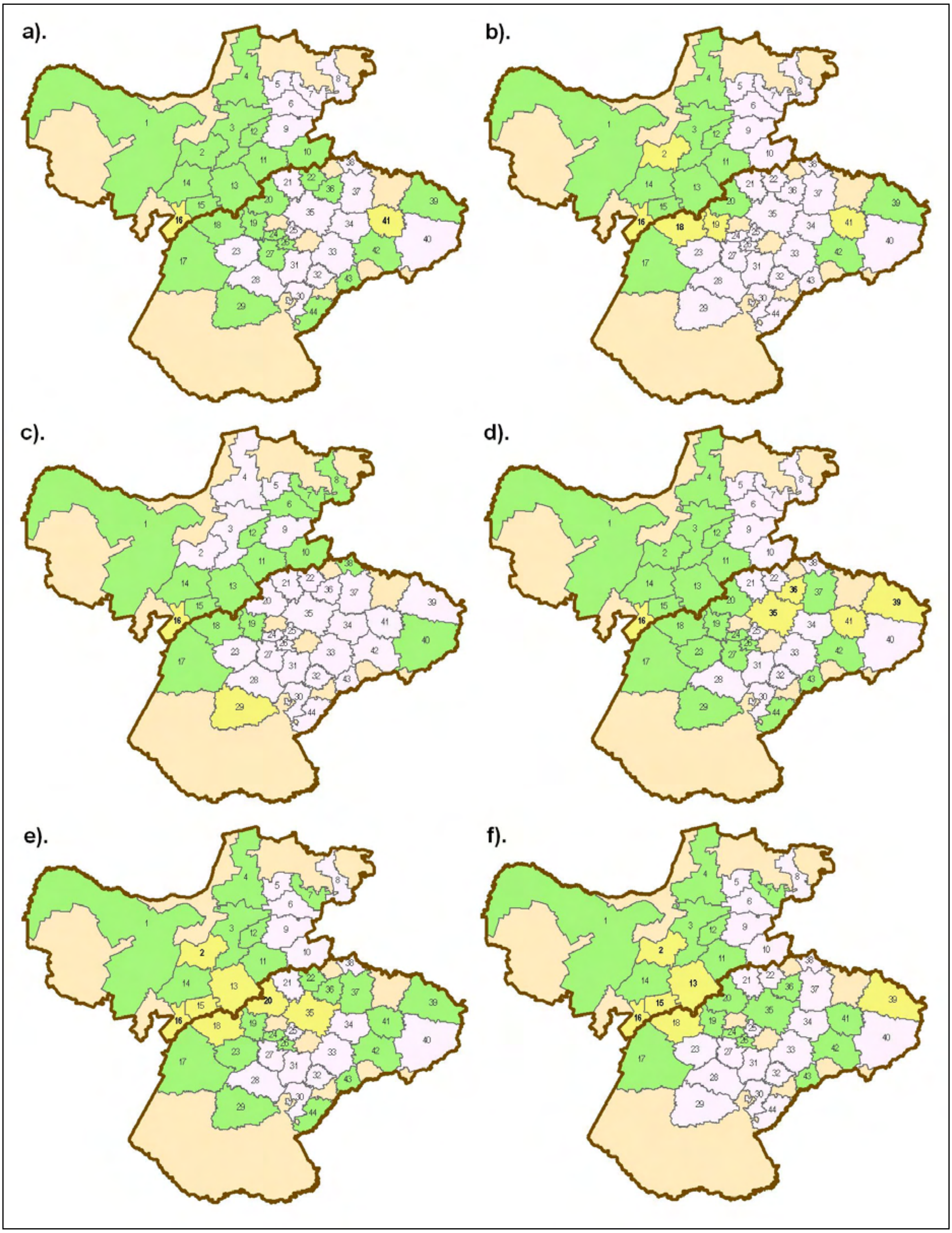
The three short season maize scenarios (Figure 3.21 (a), (b) and (c)) show higher correlations for the North-West Province than for the Free State. It can also be seen that in all three scenarios only a few magisterial districts have statistically significant correlations. The highest correlations primarily occur in the western parts of the study area.

From the three medium season maize scenarios (Figure 3.21 (d), (e) and (f)) it can be seen that the highest correlations are either found in the eastern part of the Free State or in the western part of the North-West Province or adjacent to the border separating the Free State from the North-West Province. It also appears as if the Multi-Model simulation system performs better in simulating the maize yields of the western parts of the study area than the eastern parts of the study area. The medium season maize planted on plant date 1 and plant date 3 scenarios (Figure 3.21 (d) and (f)) both show 4 magisterial districts (not significant at 95% level) with statistically significant correlations, while only 3 (not significant at 95% level) is evident for the medium season maize planted on plant date 2 scenario (Figure 3.21 (d)).

Similar to the medium season maize scenarios the long season maize scenarios (Figure 3.21 (g), (h) and (i)) also show the highest correlations either in the eastern part of the Free State or adjacent to the border separating the Free State from the North-West Province. In all three scenarios negative correlations are found for the eastern part of the North-West Province. Statistically significant correlations can be seen for 6 (not significant at 95% level) out of the 44 magisterial districts in the long season maize planted on plant date 1 scenario (Figure 3.21 (g)), 4 (not significant at 95% level) out of the 44 magisterial districts in the long season maize planted on plant date 2 scenario (Figure 3.21 (h)) and 3 (not significant at 95% level) out of the 44 magisterial districts for the long season maize planted in plant date 3 scenario (Figure 3.21 (i)). Thus, the skill of the Multi-Model simulation system in simulating the maize yields decreases from plant date 1 to plant date 3.

Thus, all 9 scenarios illustrate relatively poor skill. This can be explained by the fact that the Multi-Model simulation system is a combination between the CERES-CCAM simulation system and the CERES-ECHAM4.5 simulation system. Therefore, even though good skill is obtained for the maize yields produced by the CERES-CCAM simulation system, the low skill of the CERES-ECHAM4.5 simulation system negatively affects the skill of the Multi-

Model simulation system. In the construction of the Multi-Model simulation system used in this study, equal weights are given to both the CERES-GCM based simulation systems regardless of the skill of each individual simulation system. By giving the simulation systems weights proportional to their skill may perhaps improve the skill of the multi-model simulation system, but this should be investigated.



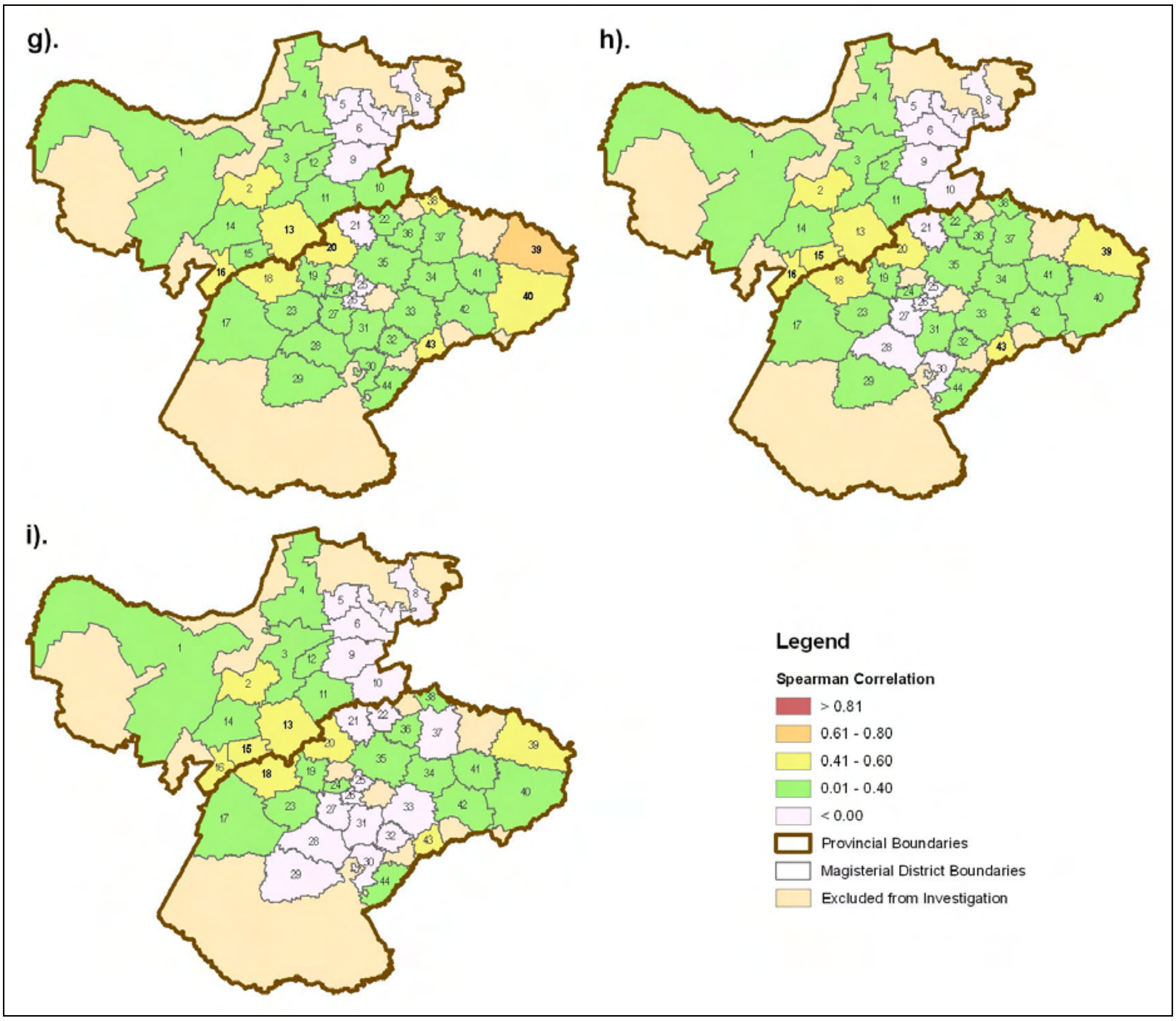


Figure 3.21: Spearman rank correlations calculated between the actual maize yields and Multi-Model ensemble mean maize yields over the 20 year period from 1980 to 1999. (a) Short season maize plant date 1, (b) Short season maize plant date 2, (c) Short season maize plant date 3, (d) Medium season maize plant date 1, (e) Medium season maize plant date 2, (f) Medium season maize plant date 3, (g) Long season maize plant date 1, (h) Long season maize plant date 2 and (i) Long season maize plant date 3. Magisterial districts with statistically significant correlations at the 95% confidence level are indicated in bold.

Once again the skill of the Multi-Model simulation system increases from the short season maize scenarios to the long season maize scenarios, with the highest correlations found for the long season maize planted on plant date 1 scenario. This result can be confirmed by the results found in the subjective validation.

3.4 PROBABILITY DISTRIBUTION RESULTS

3.4.1 Subjective Validation

3.4.1.1 Dry/Warm Western Region

3.4.1.1.1 Short Season Maize

In Figure 3.22 the simulated short season maize yields are expressed probabilistically. The actual maize yields and CERES-Observed weather maize yields are displayed deterministically at the top op the graph. When the CERES-Observed weather maize yields are compared to the actual maize yields it can be seen that the CERES-Maize model is able to correctly indicate the category of the yield (above-normal, near-normal or below-normal) for 8 out of the 19 seasons considered in this study, of which 4 seasons are ENSO-neutral seasons, 3 are El Niño seasons and 1 is a La Niña season. Another interesting feature that can be observed for the other 11 seasons is the fact that the CERES-Observed weather maize yields are always within one category of the actual maize yields and never two categories away from the actual maize yields, as can be seen, for example, for the 1981/82 season in which the actual maize yield is near-normal and the CERES-Observed weather maize yield is below-normal.

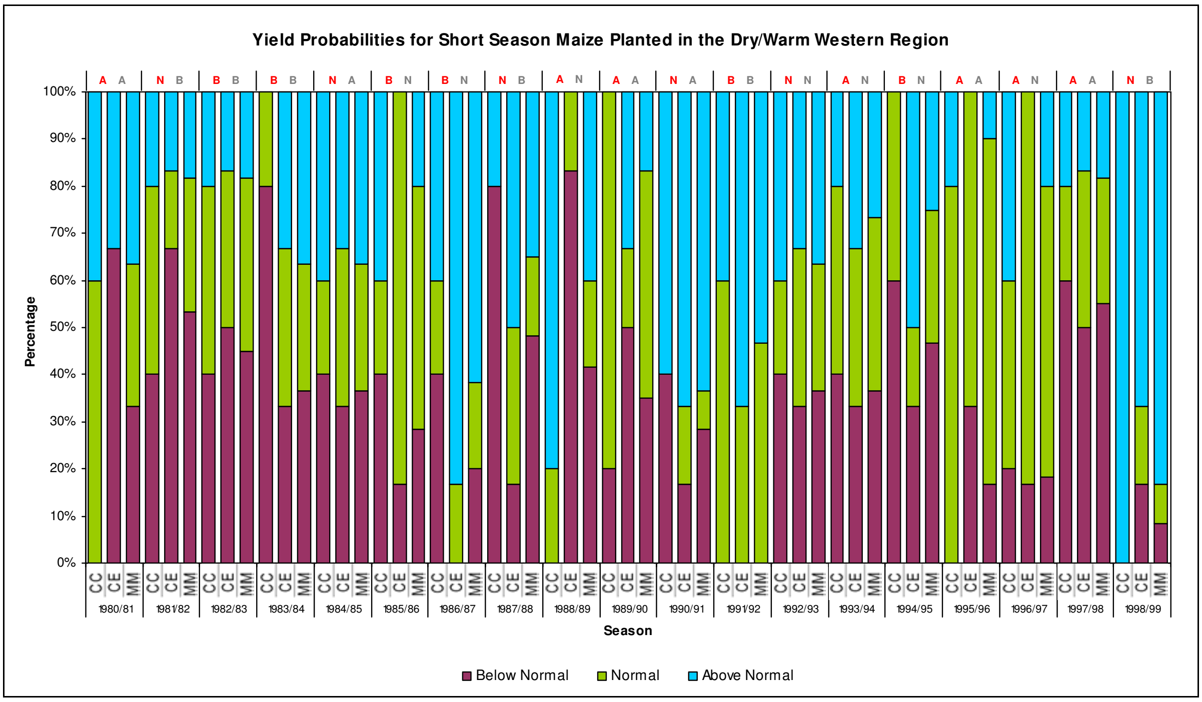


Figure 3.22: Simulated short season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

When the probabilistic short season maize yields, obtained from the different simulation systems, are compared to the actual maize yields, the 1980/81 ENSO-neutral season stands out, as for this season the Multi-Model simulation system performs better than the single model simulation systems (CERES-CCAM and CERES-ECHAM4.5), although the level of confidence in the probability for above-normal maize yields is not very high (37%). The probability distributions for the 1982/83, 1983/84 and 1994/95 seasons show that one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) and the Multi-Model simulation system correctly indicates the category of the yield (above-normal, near-normal or below-normal), while the probabilities of the other single model system are less reliable. Another interesting season is the 1988/89 season for which the CERES-CCAM simulation system correctly simulates the maize yield to be above-normal with a high level of confidence (80%).

3.4.1.1.2 Medium Season Maize

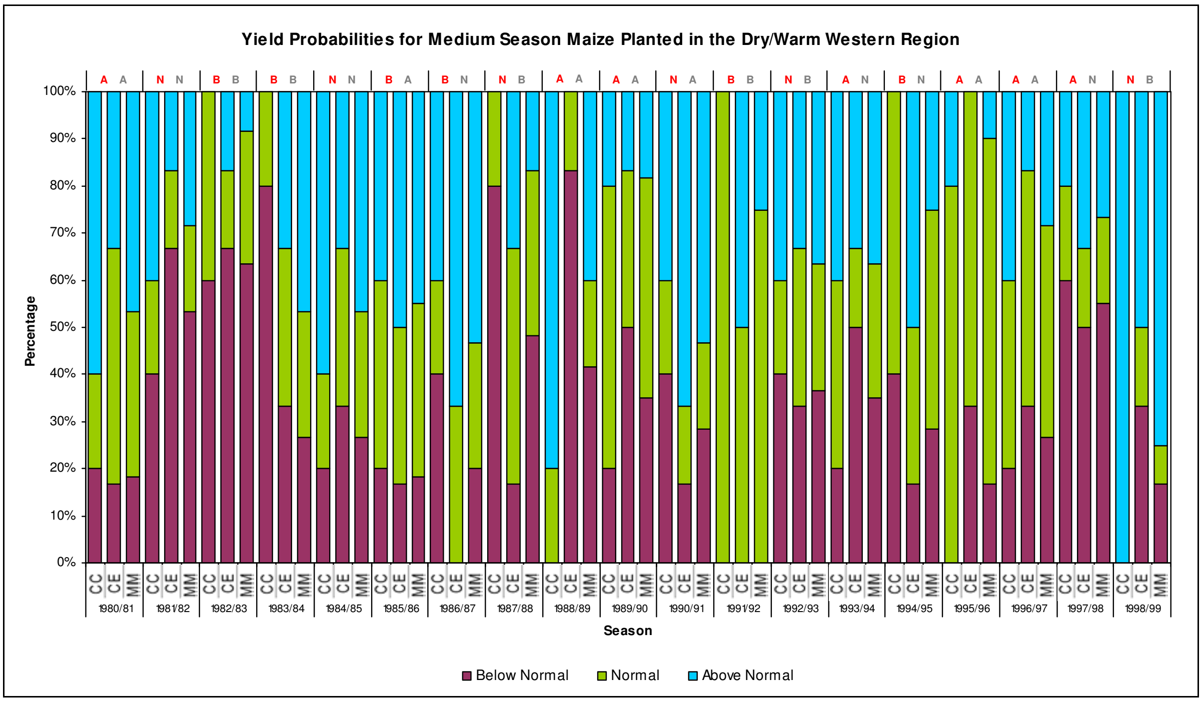


Figure 3.23: Simulated medium season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

The probability distributions for medium season maize, as simulated by each of the different simulation systems, are shown in Figure 3.23. In comparison to the actual maize yields the

CERES-Observed weather maize yields reveal that the CERES-Maize model is able to correctly simulate the category of the yield (above-normal, near-normal or below-normal) for 10 out of the 19 seasons considered in this study. From the actual maize yields it can be seen than 7 out of the 19 seasons are above-normal maize yield seasons. The CERES-Maize model correctly indicates the category for 5 out of the 7 above-normal maize yield seasons. Thus, the CERES-Maize model appears to perform the best in simulating the maize yields of the above-normal maize yield seasons. Furthermore, the CERES-Maize model performs exceptionally well in capturing the category of the maize yields of the early 1980's (1980/81 – 1984/85). For one season, 1985/86, the CERES-Observed weather maize yield is two categories away from the category of the actual maize yield, which shows that the CERES-Maize model failed in this season.

When the probabilities of the simulated medium season maize yields are assessed, the 1982/83 El Niño season stands out, as for this season all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) successfully simulates the category of the maize yield with relatively high probabilities of 60% and higher. For the 1993/94 season, the Multi-Model simulation system performs better than the single model simulation systems (CERES-CCAM and CERES-ECHAM4.5), but once again the level of confidence in the above-normal category is relatively low (37%). The probability distributions for the 1980/81 and 1983/84 seasons show that both the CERES-CCAM and Multi-Model simulation systems are reliable, while the CERES-ECHAM4.5 simulation system is unable to represent the correct outcome (above-normal, near-normal or below-normal maize yields). The CERES-CCAM simulation system once again simulates the category of the maize yield of the 1988/89 season correctly, with a high probability of 80%. The 1991/92 season was one of the driest seasons on record. The CERES-CCAM, CERES-ECHAM4.5 and Multi-Model simulation systems simulates a 0% probability for below-normal maize yield for this season, while the CERES-Observed weather simulation system correctly indicated the below-normal category. This is a result of the fact that GCMs did not anticipate the excessively dry conditions of the 1991/92 season. From this it can be seen that the CERES-Maize model is highly dependant on the weather input data with which it is forced.

3.4.1.1.3 Long Season Maize

Figure 3.24 shows the simulated long season maize probabilities. From the actual maize yields and CERES-Observed weather maize yields displayed deterministically at the top op the graph, it can be seen that the CERES-Maize model is able to correctly indicate the category of the yield (above-normal, near-normal or below-normal) for 13 out of the 19 seasons investigated in this study. Here, the category of 6 out of the 7 above-normal maize yield season are simulated correctly by the CERES-Maize model which once again points to the fact that the CERES-Maize performs better in capturing above-normal maize yield seasons than near-normal and below-normal maize yields seasons. Moreover, for the other seasons the CERES-Observed weather maize yields are always within one category of the actual maize yields and never two categories away from the actual maize yields.

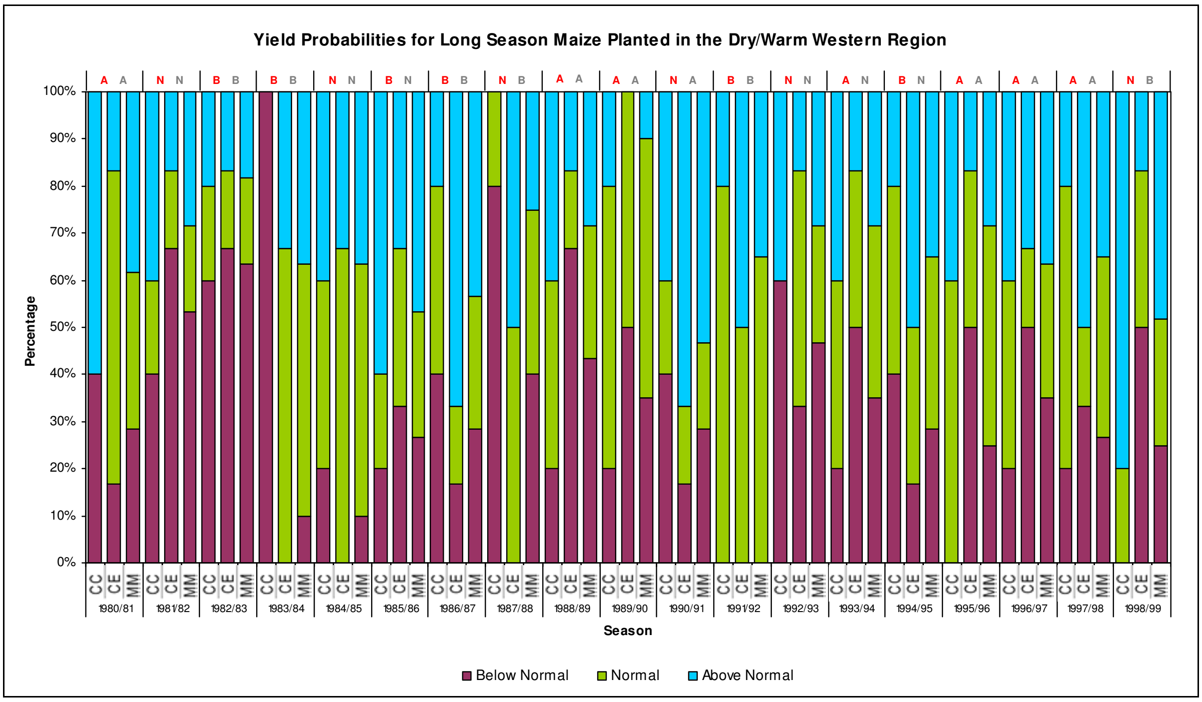


Figure 3.24: Simulated long season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

When the long season maize yield probabilities, obtained from the different simulation systems, are examined, it can be seen that the maize yield of the 1982/83 El Niño season is once again successfully simulated by all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) with relatively high probabilities of 60% and higher. For the 1996/97 season, the Multi-Model simulation system performs better than the single model simulation systems (CERES-CCAM and CERES-ECHAM4.5), but the level of confidence in the above-normal category is relatively low (37%). The probability distributions for the 1980/81, 1983/84 and 1984/85 seasons show that one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) and the Multi-Model simulation system correctly indicates the category of the yield (above-normal, near-normal or below-normal), while the probabilities of the other single model system is less reliable. The 1992/93 and 1996/97 seasons are very interesting as for these two seasons the CERES-ECHAM4.5 simulation system is the only system able to correctly simulate the category of the maize yields.

In general, it can be seen that the ability of the CERES-Observed weather simulation system in simulating the category of the maize yield increases from the short season maize scenario to the long season maize scenario, with the best performance in capturing above-normal maize yield seasons. The CERES-CCAM simulation system performs relatively well in all three scenarios, while the CERES-ECHAM4.5 simulation system does not perform well. The Multi-Model simulation system performs the best in simulating below-normal maize yields.

3.4.1.2 Temperate Eastern Region

3.4.1.2.1 Short Season Maize

The probability distributions of the simulated short season maize yields are shown in Figure 3.25. The actual maize yields and CERES-Observed weather maize yields are displayed deterministically at the top op the graph. When the CERES-Observed weather maize yields are compared to the actual maize yields it can be seen that the CERES-Maize model is able to correctly indicate the category of the yield (above-normal, near-normal or below-normal) for 9 out of the 19 seasons investigated in this study, of which 4 seasons are ENSO-neutral seasons, 3 are El Niño seasons and 2 are La Niña seasons. From the actual maize yields it can be seen that 6 out of the 19 seasons are below-normal maize yield seasons, and the CERES-Maize model is able to correctly simulate the category for 4 out of the 6 below-normal seasons. Thus, the CERES-Maize model performs better in simulating the maize yields of below-normal maize yield seasons than above-normal and near-normal maize yield seasons. Another notable feature is the fact that for four seasons the CERES-Observed weather maize yields are two categories away from the actual maize yields, as seen for example for the 1985/86 (1988/89) season in which the actual maize yield is below-normal (above-normal) and the CERES-Observed weather maize yield is above-normal (below-normal).

In comparison to the actual maize yields, the simulated short season maize yield probabilities show that for the 1985/86, 1987/88 and 1989/90 seasons all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) successfully simulate the maize yields with reasonably high probabilities ranging between 50% and 83%. The probability distributions for the 1983/84 and 1991/92 seasons show that one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) and the Multi-Model simulation system correctly indicates the category of the yield (above-normal, near-normal or below-normal), while the probabilities of the other single model system is either over or under confident and consequently gives a different category the highest probability. Other interesting seasons include the 1986/87, 1995/96 and 1998/99 seasons for which the CERES-CCAM simulation system correctly simulates the category of the maize yields with probabilities of 60% and higher, and the 1981/82 season for which the CERES-ECHAM4.5 simulation system correctly indicates the category of the maize yield with a probability of 67%.

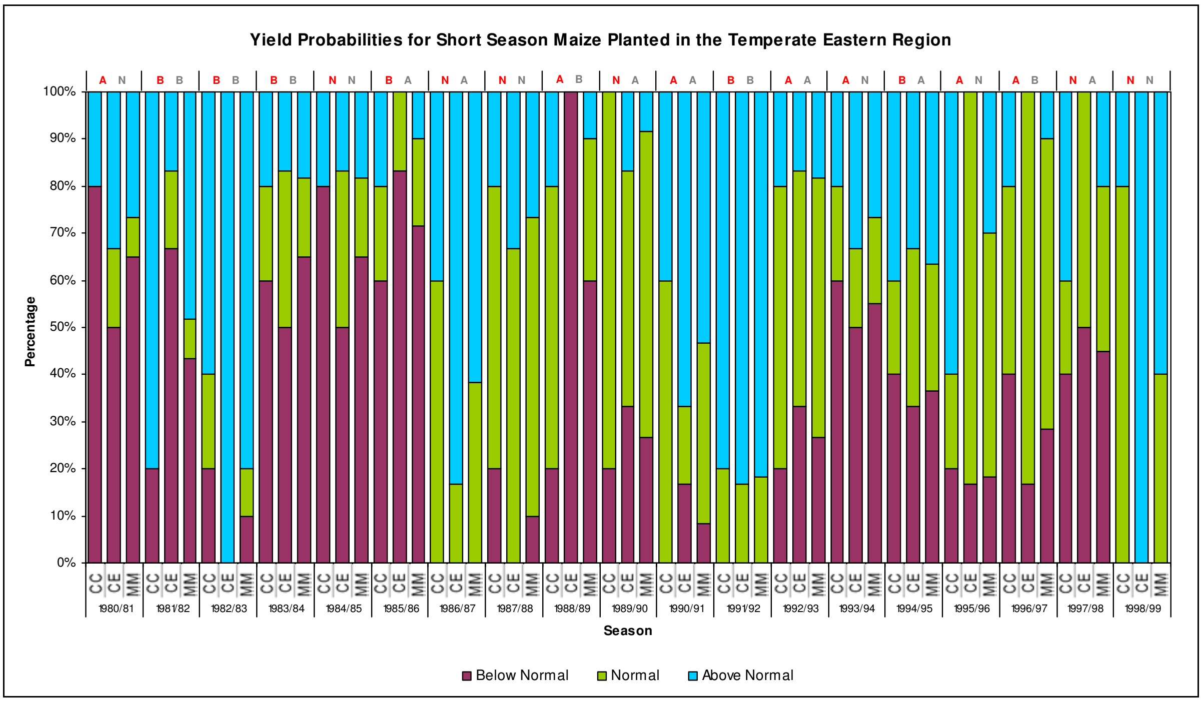


Figure 3.25: Simulated short season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

3.4.1.2.2 Medium Season Maize

The simulated medium season maize yield probabilities are shown in Figure 3.26. In comparison to the actual maize yields the CERES-Observed weather maize yields reveal that the CERES-Maize model is able to correctly simulate the category of the yield (above-normal, near-normal or below-normal) for 13 out of the 19 seasons considered in this study.

The CERES-Maize model once again appears to perform the best in capturing the maize yields of the below-normal maize yield seasons, with the category for 5 out of the 6 seasons indicated correctly. Furthermore, it can also be seen that the maize yields of the 1980's (1980/81 – 1983/84) and late 1990's (1994/95 – 1998/99) are simulated exceptionally well by the CERES-Maize model.

From the probability distributions of the simulated medium season maize yields it can be seen that for the 1981/82, 1985/86, 1989/90, 1990/91 and 1993/94 seasons one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) and the Multi-Model simulation system correctly indicates the category of the yield (above-normal, near-normal or below-normal), while the other single model simulation system is unable to represent the correct category. For the 1983/84 and 1995/96 seasons the CERES-CCAM simulation system successfully simulates the maize yields with probabilities of 60% and for the 1980/81 season the CERES-ECHAM4.5 simulation system correctly indicates the maize yield with a somewhat lower probability of 50%.

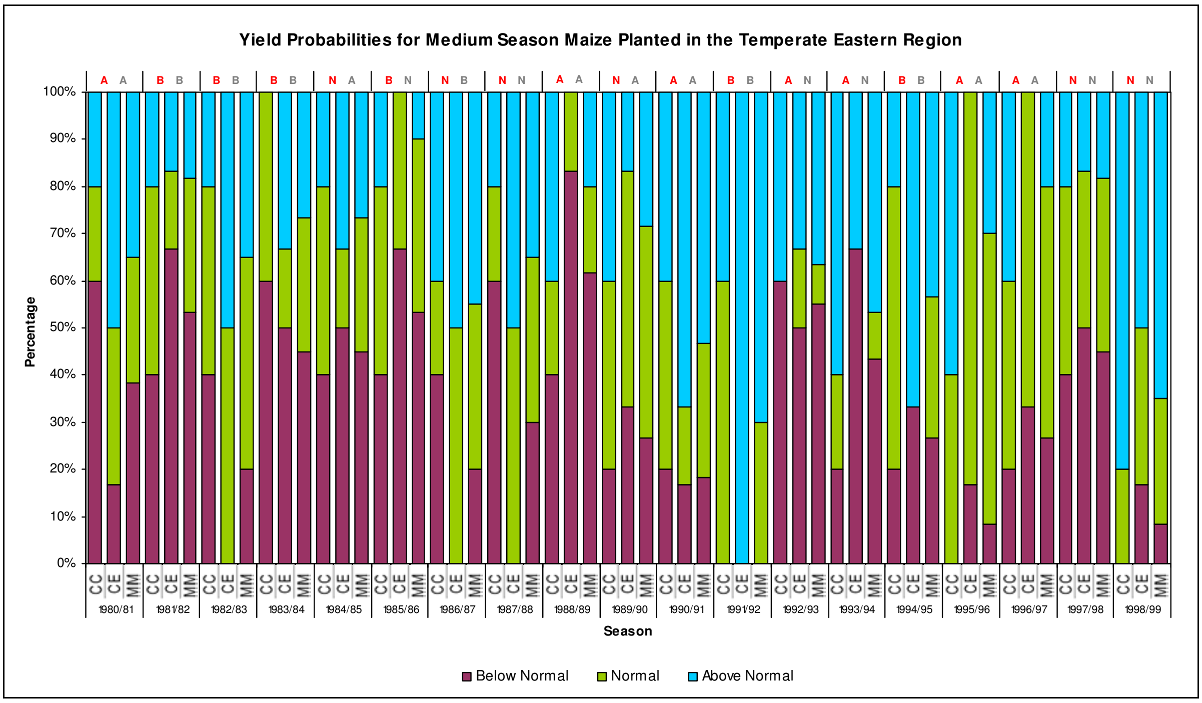


Figure 3.26: Simulated medium season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

3.4.1.2.3 Long Season Maize

In Figure 3.27 the simulated long season maize yields are expressed probabilistically. The actual maize yields and CERES-Observed weather maize yields are displayed deterministically at the top op the graph and shows that the CERES-Maize model is able to correctly indicate the category of the yield (above-normal, near-normal or below-normal) for 11 out of the 19 seasons considered in this study. Here the CERES-Maize model also appears to perform the best in simulating the maize yields of below-normal maize yield seasons, with the category of 5 out of the 6 below-normal seasons indicated correctly. For the remainder of the seasons, it can be seen that the CERES-Observed weather maize yields are always within one category of the actual maize yields, as seen for the 1984/85 season in which the actual maize yield is near-normal and the CERES-Observed weather maize yield is above-normal.

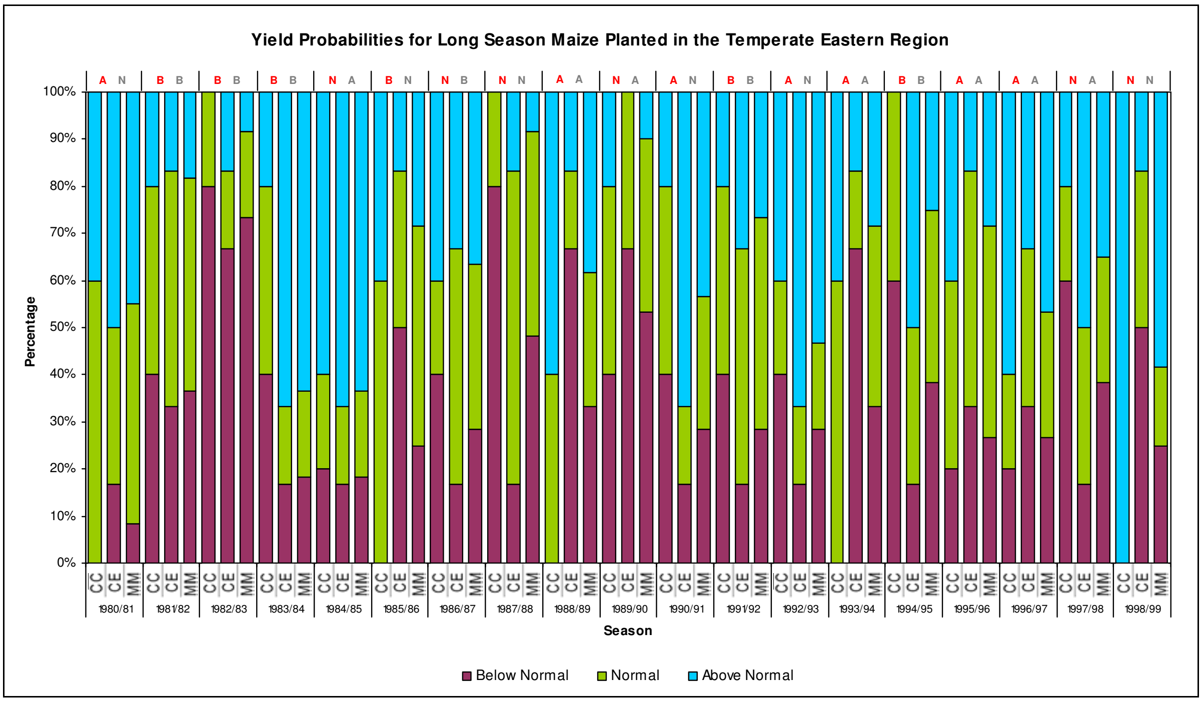


Figure 3.27: Simulated long season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

When the probabilities of the simulated long season maize yields are compared to the actual maize yields, the 1982/83 El Niño season stands out, as for this season all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) successfully simulate the maize yield to be below-normal with reasonably high probabilities ranging between 67% and 80%. The probability distributions of the 1988/89, 1990/91, 1992/93, 1994/95 and 1996/97 seasons show that one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) and the Multi-Model simulation system are able to correctly indicate the category of the yield (above-normal, near-normal or below-normal). Furthermore, the 1980/81, 1985/86, 1986/87 and 1987/88 seasons are also interesting as for these seasons the CERES-ECHAM4.5 simulation system is the only system that successfully simulates the outcome of the maize yields.

In general, it can be seen that the performance of the CERES-Observed weather simulation system in simulating the category of the maize yield is the best for the medium season maize scenario. This simulation system performs very well in simulating below-normal maize yields. The CERES-CCAM simulation system performs better in simulating above-normal maize yields that below-normal and near-normal maize yields, while the CERES-ECHAM4.5 simulation system shows the best performance for near-normal maize yield seasons.

3.4.1.3 Wet/Cool Eastern Region

3.4.1.3.1 Short Season Maize

The probability distributions of the simulated short season maize yields are shown in Figure 3.28. The actual maize yields and CERES-Observed weather maize yields displayed at the top of the graph show that the CERES-Maize model correctly indicates the category of the yield (above-normal, near-normal or below-normal) for 8 out of the 19 seasons, of which 4 seasons are ENSO-neutral seasons, 2 are El Niño seasons and 2 are La Niña seasons. As for the remainder of the seasons, the CERES-Observed weather maize yields are mostly within one category of the actual maize yields, although for three seasons (1986/87, 1988/89 and 1996/97) the CERES-Observed weather maize yields are two categories away from the actual maize yields, but this is in the minority of cases.

When the probabilistic short season maize yields, obtained from the different simulation systems, are compared to the actual maize yields, it can be seen that all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) are able to successfully simulate the above-normal maize yield of the 1998/99 La Niña season, with probabilities ranging between 50% and 100%. The 1993/94 season is also a prominent season, since the Multi-Model simulation system correctly indicates the above-normal maize yield of this season, while the single model systems (CERES-CCAM and CERES-ECHAM4.5) do not.

The probabilities of the CERES-CCAM and Multi-Model simulation systems both correctly indicates the category of the maize yields (above-normal, near-normal or below-normal) of the 1982/83, 1983/84, 1989/90, 1992/93, 1996/97 and 1997/98 seasons, while the probabilities of the CERES-ECHAM4.5 simulation system is less reliable. Four of these seasons are ENSO-neutral seasons and the other two are El Niño seasons. Moreover, the CERES-CCAM simulation system is the only system able to correctly simulate the below-normal maize yield of 1981/82 season and the above-normal maize yield of the 1988/89 season with probabilities of 50% and higher.

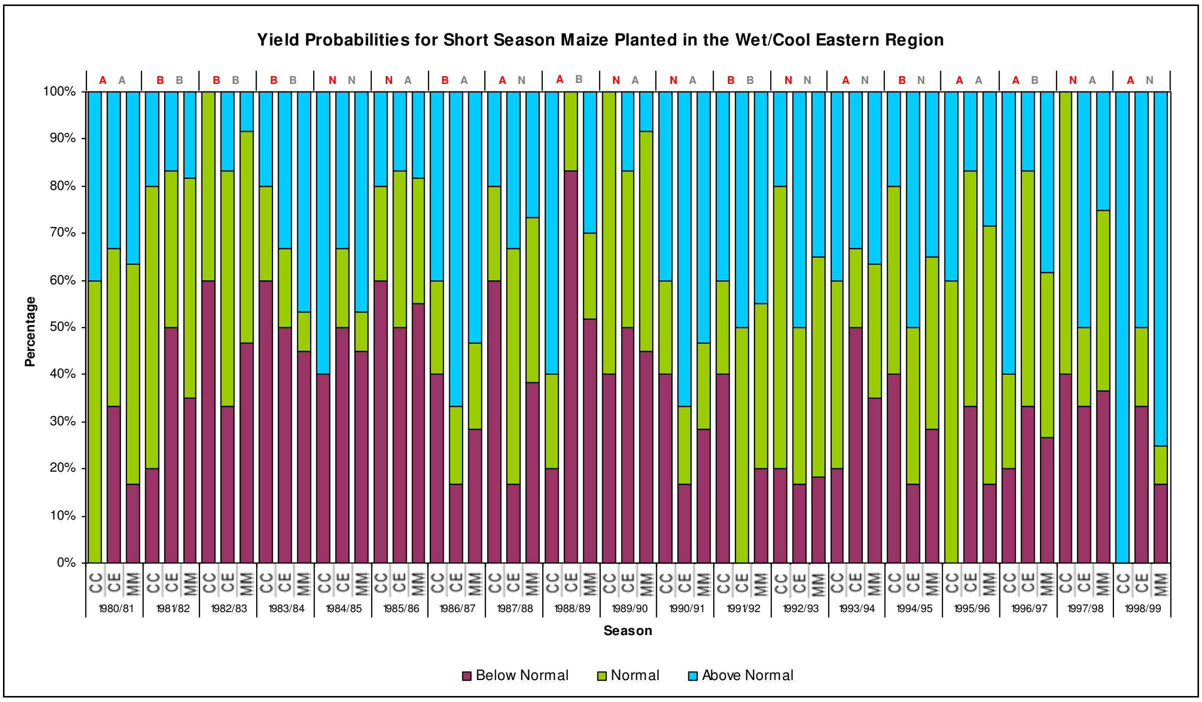


Figure 3.28: Simulated short season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM45 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

3.4.1.3.2 Medium Season Maize

The simulated medium season maize yield probabilities are shown in Figure 3.29. In comparison to the actual maize yields the CERES-Observed weather maize yields reveal that the CERES-Maize model is able to correctly simulate the category of the yield (above-normal, near-normal or below-normal) for 9 out of the 19 seasons considered in this study. Furthermore it appears as if the CERES-Maize model performs the best in capturing the maize yields of the below-normal maize yield seasons, with the category of 5 out of the 6 seasons indicated correctly. The 1986/87 and 1988/89 seasons are the only two seasons in which the CERES-Observed weather maize yields are two categories away from that of the actual maize yields.

In comparison to the actual maize yields, the simulated medium season maize yield probabilities show that for the 1982/83 and 1996/97 seasons all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) successfully simulates the maize yields with relatively high probabilities ranging between 50% and 80%. The probability distributions of the 1986/87, 1988/89, 1990/91 and 1998/99 seasons show that one of the single model simulation systems (CERES-CCAM or CERES-ECHAM4.5) as well as the Multi-Model simulation system correctly indicates the category of the maize yields (above-normal, near-normal or below-normal), while the other single model system is either over or under confident and therefore simulates a different category to have the highest probability. For the 1991/92 season the Multi-Model simulation system shows an improvement from the two single model systems (CERES-CCAM and CERES-ECHAM4.5), while for the 1994/95 season the CERES-CCAM simulation system is the only system able to correctly indicate the below-normal maize yield.

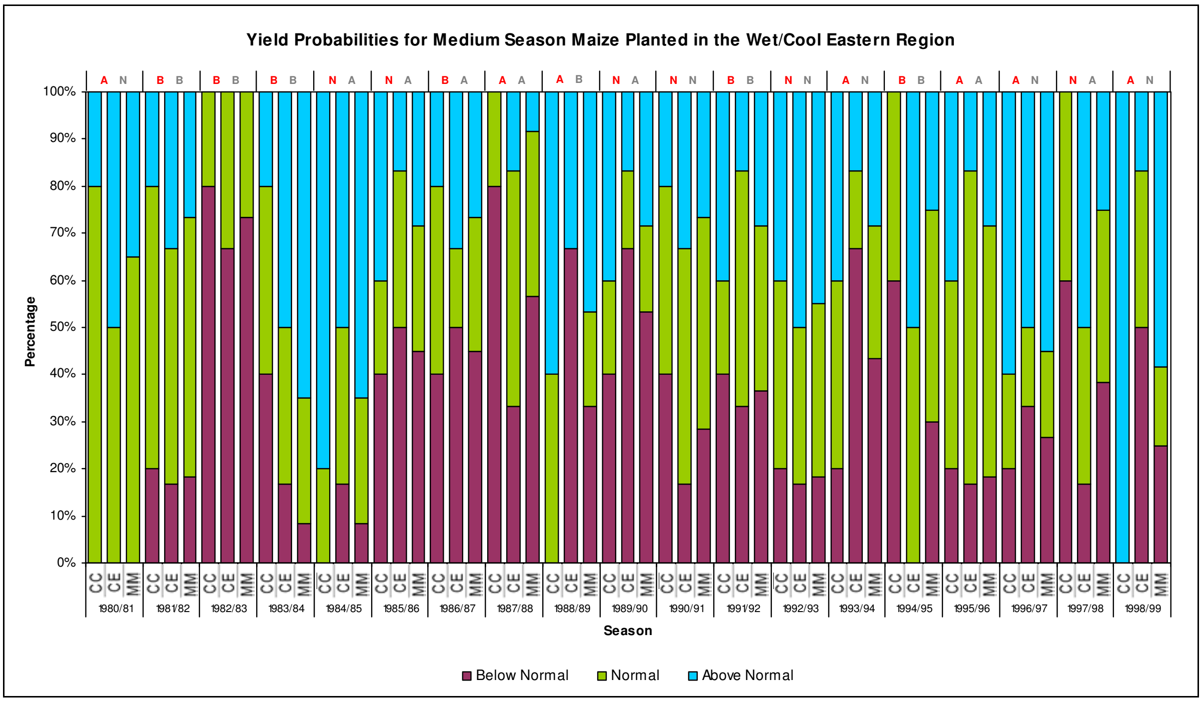


Figure 3.29: Simulated medium season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

3.4.1.3.3 Long Season Maize

Figure 3.30 shows the simulated long season maize probabilities. The actual maize yields and CERES-Observed weather maize yields are displayed deterministically at the top op the graph. When the CERES-Observed weather maize yields are compared to the actual maize yields it can be seen that the CERES-Maize model is able to correctly indicate the category of the yield (above-normal, near-normal or below-normal) for 11 out of the 19 seasons investigated in this study. From the actual maize yields it can be seen that 6 out of the 19 seasons are below-normal maize yield seasons, and the CERES-Maize model is able to correctly indicate the category of 5 out of the 6 below-normal seasons. Thus, the CERES-Maize model performs better in simulating the maize yields of below-normal maize yield seasons than above-normal and near-normal maize yield seasons. Furthermore, the CERES-Maize model performs well in capturing the category of the maize yields of the early 1980's (1980/81 – 1984/85).

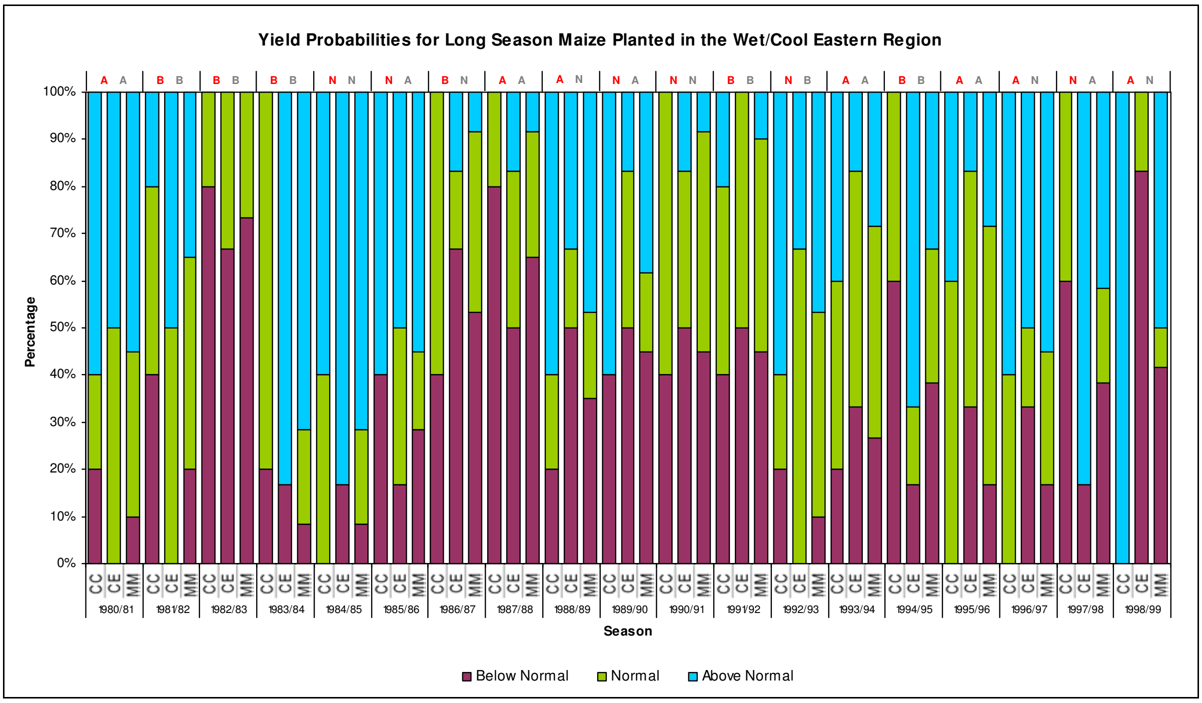


Figure 3.30: Simulated long season maize yield probabilities. CERES-CCAM yield (CC), CERES-ECHAM4.5 yield (CE) and Multi-Model yield (MM). The actual maize yield (red) and CERES-Observed weather yield (grey) are denoted as A (above-normal), N (near-normal) or B (below-normal) at the top of the graph.

From the probability distributions of the simulated long season maize yields it can be seen that for the 1982/83 El Niño season and 1996/97 ENSO-neutral season all three simulation systems (CERES-CCAM, CERES-ECHAM4.5 and Multi-Model) successfully simulate the below-normal (1982/83) and above-normal (1996/97) maize yields for these two seasons. The probability distributions for the 1980/81, 1988/89, 1990/91, 1994/95 and 1998/99 seasons show that the CERES-CCAM simulation system and Multi-Model simulation system correctly indicates the category of the maize yields (above-normal, near-normal or below-normal), while the CERES-ECHAM4.5 simulation system fails to get the category correct. The 1992/93 season is also interesting as for this season the CERES-CCAM simulation system is the only system able to correctly simulate the category of the maize yield with a high probability of 67%. Furthermore, for many season all three simulation systems simulates the same incorrect category to have the highest probability, as can be seen, for example, for the 1984/85 season in which all three simulation systems gives the highest probability to the near-normal category.

In general, it can be seen that the performance of the CERES-Observed weather simulation system in simulating the category of the maize yield increases from the short season maize scenario to the long season maize scenario, with the best performance evident for below-normal maize yields. The CERES-CCAM and Multi-Model simulation systems seem to perform the best for above-normal maize yield seasons, while the CERES-ECHAM4.5 simulation system does not perform well.

3.4.2 Objective Validation

3.4.2.1 Dry/Warm Western Region

3.4.2.1.1 Short Season Maize

Figure 3.31 shows the short season maize ROC curves for each of the maize yield simulation systems. The CERES-CCAM simulation system (a) shows the best skill in simulating below-normal maize yields for the dry/warm western production region. The ROC curves of the CERES-ECHAM4.5 simulation system (b) falls beneath the no-skill diagonal, which indicates that this simulation system does not have skill in simulating any of the probability categories. Similar to the CERES-CCAM simulation system the Multi-Model simulation system (c) also reveals the highest skill in simulating below-normal maize yields with considerably less skill for the other two categories (near-normal and above-normal). Table 3.1, which shows the ROC scores, confirms these results. All the ROC scores are either equal to or less that 0.5 except for the below-normal category of the CERES-CCAM and Multi-Model simulation systems which are 0.65 and 0.62 respectively.

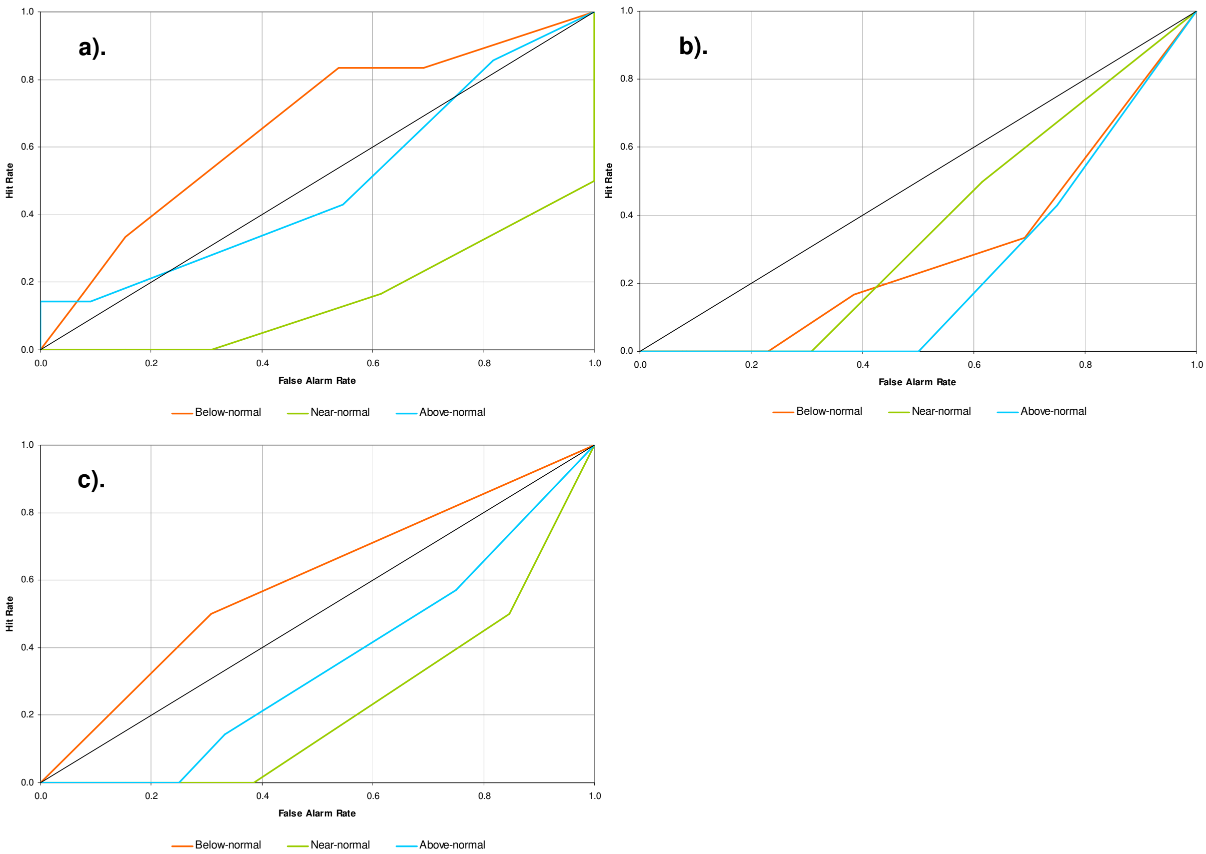


Figure 3.31: ROC curves for above-normal, near-normal and below-normal simulated short season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.65	0.08	0.51
CERES-ECHAM4.5	0.31	0.41	0.26
Multi-Model	0.62	0.20	0.35

Table 3.1: ROC scores for the simulated short season maize yield probabilities.

3.4.2.1.2 Medium Season Maize

The ROC curves for medium season maize can be seen in Figure 3.32. The maize yield simulations performed by the CERES-CCAM simulation system (a) show somewhat higher skill for the above-normal category than for the below-normal category and substantially less skill for the near-normal category. This is not a surprising result, as the skill of GCMs in capturing the main summer seasonal rainfall variability over southern Africa tends to be higher in ENSO years (Landman and Mason, 1999b). Thus, GCMs are more skilful in El Niño and La Niña years than in ENSO-neutral years. El Niño years greatly enhances the probabilities for below-normal maize yields and La Niña years greatly enhances the probabilities for above-normal maize yields. The ROC curves of the CERES-ECHAM4.5 simulation system (b) are once again beneath the no-skill diagonal with ROC scores ranging between 0.17 and 0.43 (see Table 3.2). The Multi-Model simulation system shows poor skill in simulating any of the probability categories.

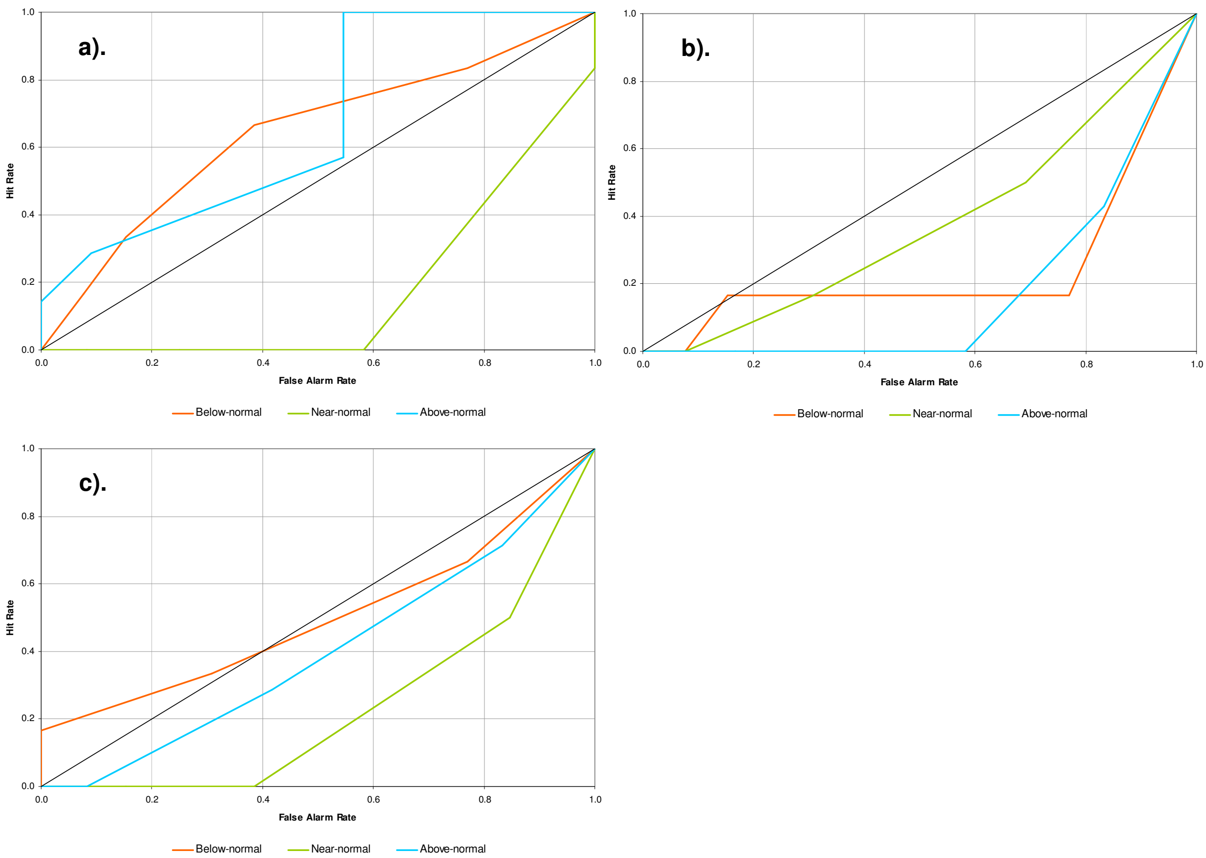


Figure 3.32: ROC curves for above-normal, near-normal and below-normal simulated medium season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.63	0.18	0.74
CERES-ECHAM4.5	0.33	0.38	0.18
Multi-Model	0.47	0.20	0.39

Table 3.2: ROC scores for the simulated medium season maize yield probabilities.

4.6.2.1.3 Long Season Maize

In Figure 3.33 the long season maize ROC curves are shown for each of the maize yield simulation systems. From the ROC curves for the CERES-CCAM simulation system (a) it can be observed that the highest skill occurs for above-normal maize yields, with slightly lower skill for below-normal maize yields and much reduced skill for near-normal maize yields. The CERES-ECHAM4.5 simulation system (b) shows relatively high skill for the near-normal category, but with the curves of the below-normal and above-normal categories falling beneath the no-skill diagonal. The Multi-Model simulation system (c) on the other hand shows low skill for all three probability categories. Table 3.3 shows the ROC scores for each of the simulation systems and for each of the equiprobable categories. The highest ROC scores are evident for the above-normal category of the CERES-CCAM simulation system (0.62) and the near-normal category of the CERES-ECHAM4.5 simulation system (0.62).

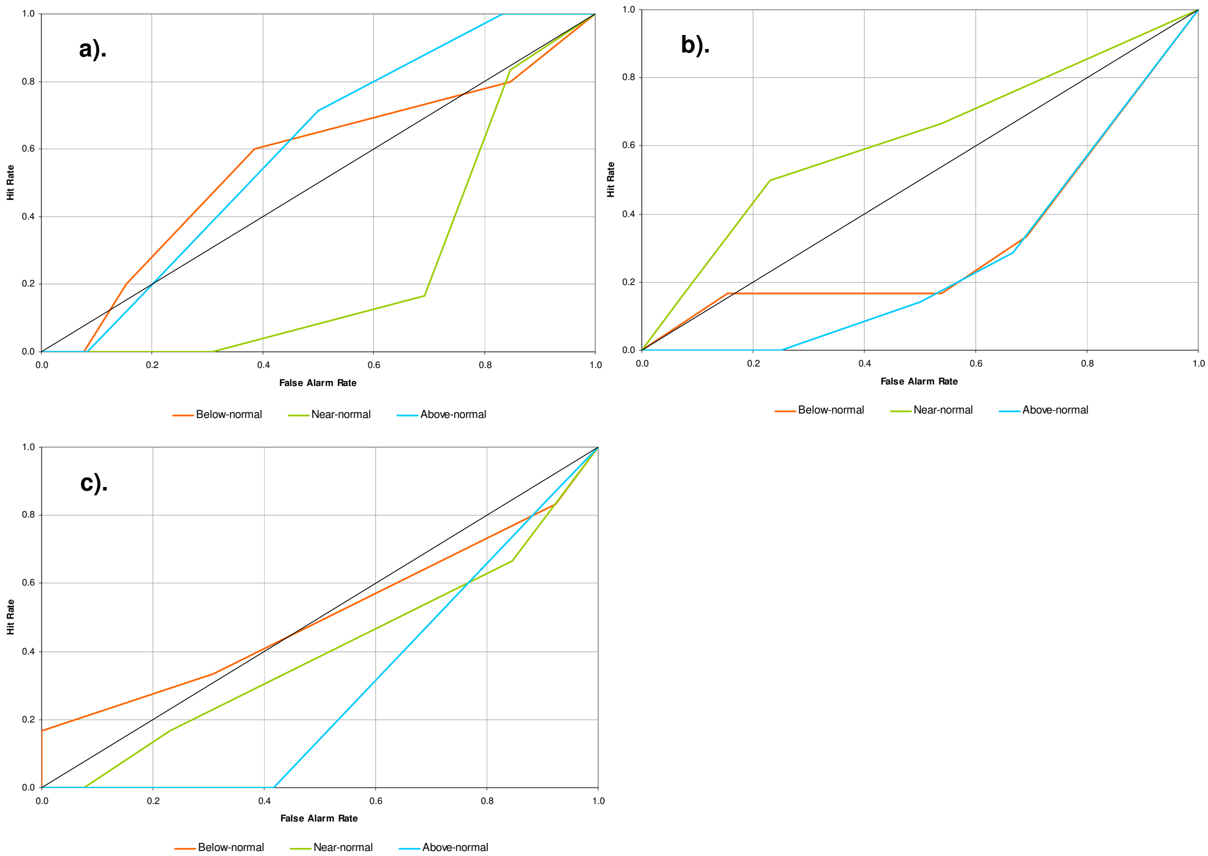


Figure 3.33: ROC curves for above-normal, near-normal and below-normal simulated long season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.56	0.24	0.62
CERES-ECHAM4.5	0.35	0.62	0.26
Multi-Model	0.47	0.40	0.36

Table 3.3: ROC scores for the simulated long season maize yield probabilities.

In general, the ROC scores seem to increase from the short season maize scenario to the long season maize scenario. Although, the highest ROC score (0.74) is evident for the medium season maize scenario (Table 3.2).

3.4.2.2 Temperate Eastern Region

3.4.2.2.1 Short Season Maize

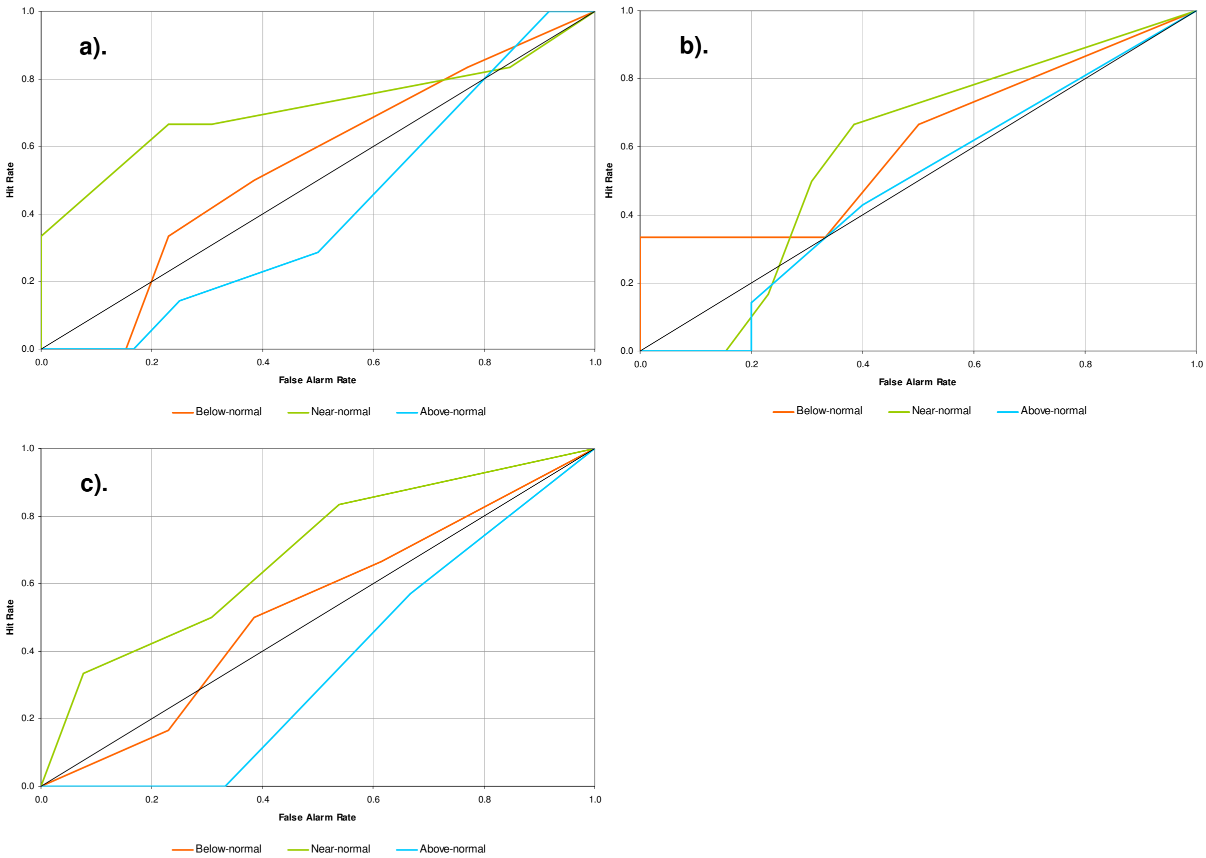


Figure 3.34: ROC curves for above-normal, near-normal and below-normal simulated short season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.58	0.72	0.45
CERES-ECHAM4.5	0.55	0.58	0.47
Multi-Model	0.51	0.70	0.35

Table 3.4: ROC scores for the simulated short season maize yield probabilities.

The ROC curves for short season maize can be seen in Figure 3.34. The CERES-CCAM simulation system (a) shows that for the near-normal category the hit rate largely outscores the false alarm rate. Thus, the below-normal and above-normal categories are somewhat less skilful than the near-normal category. The ROC curves of the CERES-ECHAM4.5 simulation system (b) shows that the near-normal curve deviates furthest away from the no-skill diagonal, which implies that this simulation approach has highest skill in simulating near-normal maize yield seasons. The Multi-Model simulation system (c) also indicates highest skill for the near-normal category; with a ROC score of 0.70 (see Table 3.4).

3.4.2.2.2 Medium Season Maize

Figure 3.35 shows the medium season maize ROC curves for each of the maize yield simulation systems. The CERES-CCAM simulation system (a) shows the best skill in simulating above-normal maize yields for the temperate eastern production region. The ROC curves of the CERES-ECHAM4.5 simulation system (b) shows best skill for the near-normal category, with much lower skill for the above-normal and below-normal categories.

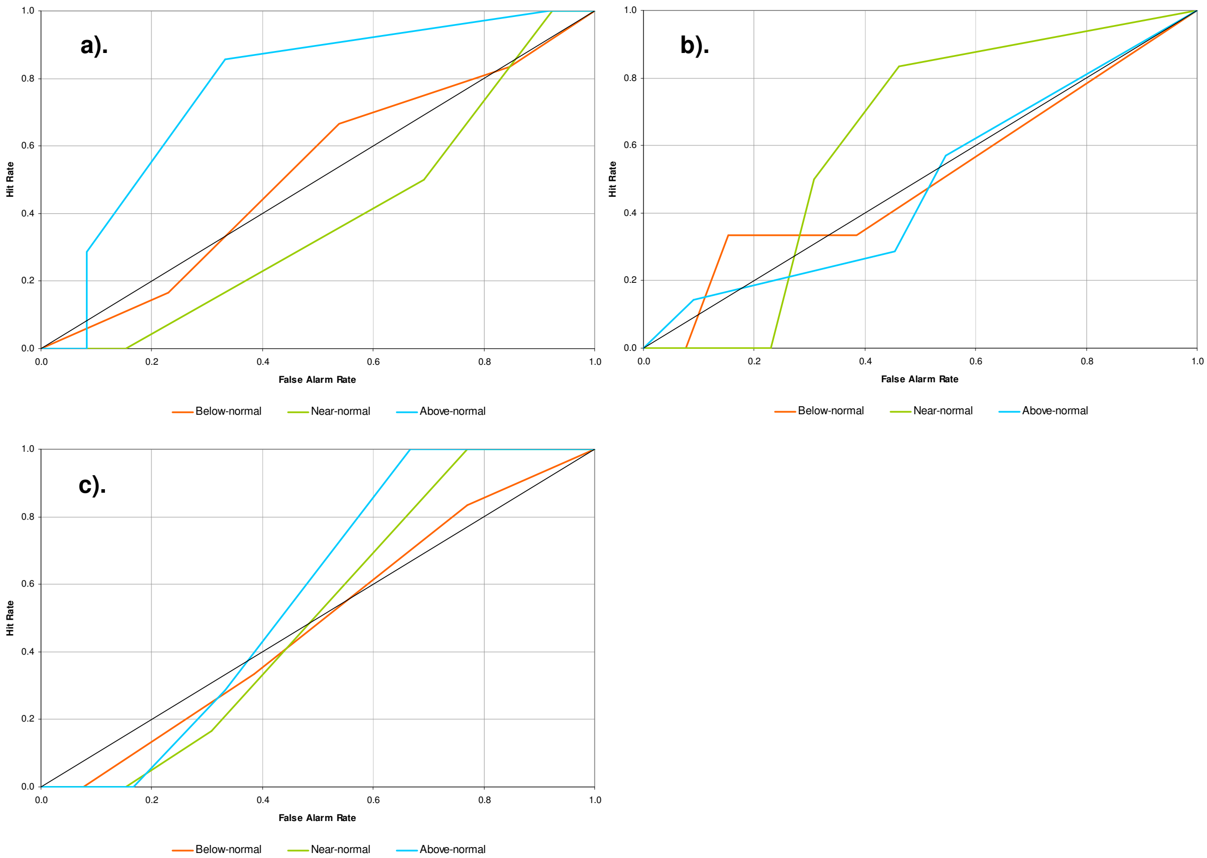


Figure 3.35: ROC curves for above-normal, near-normal and below-normal simulated medium season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

The ROC curves of the Multi-Model simulation system (see Table 3.5) shows that this simulation system performs the best in simulating above-normal maize yields, with ROC scores of 0.65 for above-normal, 0.55 for near-normal and 0.5 for below-normal.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.50	0.41	0.79
CERES-ECHAM4.5	0.53	0.70	0.49
Multi-Model	0.50	0.55	0.65

Table 3.5: ROC scores for the simulated medium season maize yield probabilities.

3.4.2.2.3 Long Season Maize

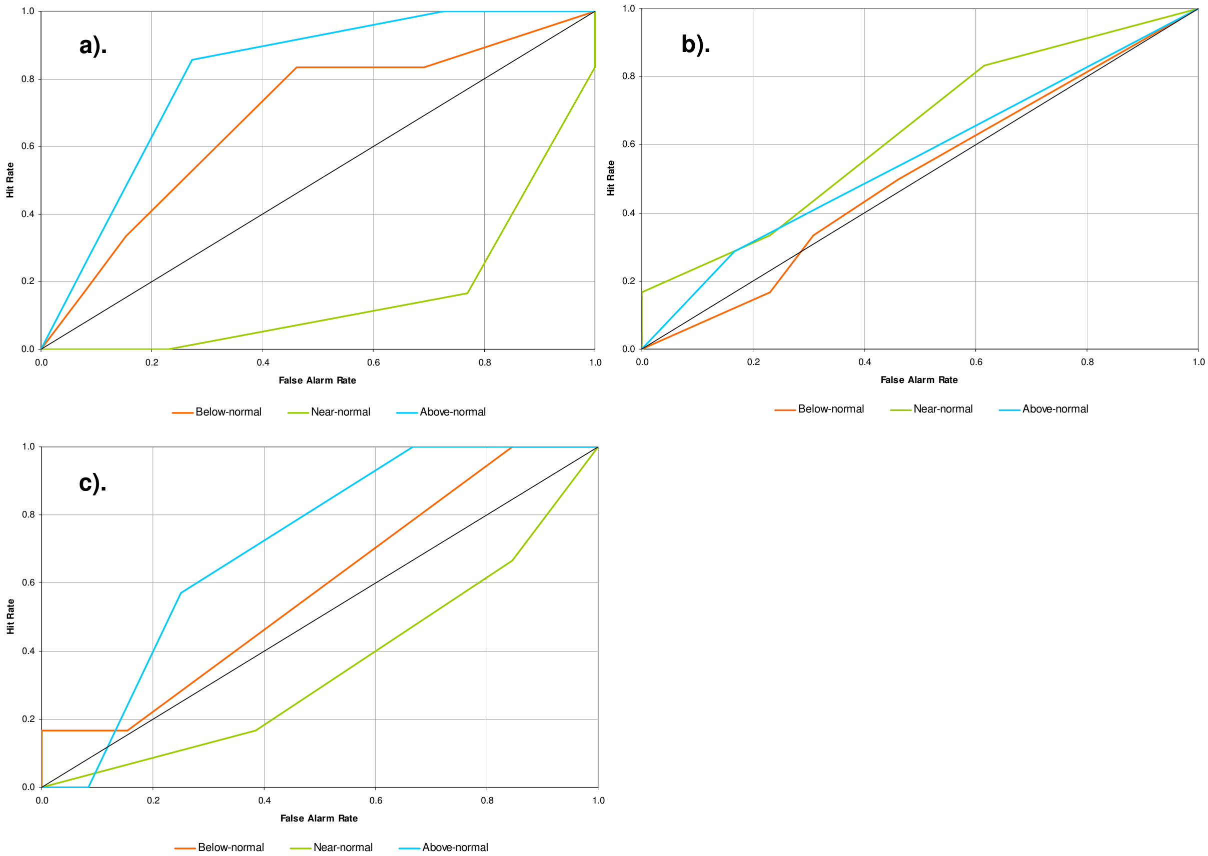


Figure 3.36: ROC curves for above-normal, near-normal and below-normal simulated long season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

In Figure 3.36 the long season maize ROC curves are shown for each of the maize yield simulation systems. From the ROC curves for the CERES-CCAM simulation system (a) it can be observed that both the above-normal and below-normal categories show high skill, with ROC scores of 0.83 and 0.66 respectively (see Table 3.6). The CERES-ECHAM4.5

simulation system (b) reveals once again best skill for the near-normal category. The ROC curves of the Multi-Model simulation system show that the above-normal simulations produced by this simulation system are most reliable.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.66	0.08	0.83
CERES-ECHAM4.5	0.49	0.62	0.57
Multi-Model	0.64	0.33	0.85

Table 3.6: ROC scores for the simulated long season maize yield probabilities.

In general, in the short season maize scenario the highest ROC scores occur for the near-normal category, while in the medium season maize scenario and long season maize scenario the highest ROC scores occur for the above-normal category. The highest ROC score of 0.85 is evident for the long season maize scenario (Table 3.6).

3.4.2.3 Wet/Cool Eastern Region

3.4.2.3.1 Short Season Maize

Figure 3.37 shows the short season maize ROC curves for each of the different simulation systems. From the ROC curves for the CERES-CCAM simulation system (a) it can be observed that all three curves are almost completely above the no-skill diagonal line with ROC scores of 0.83 for above-normal, 0.77 for below-normal and 0.57 for near-normal (see Table 3.7). Thus, this simulation system performs best in simulating above-normal maize yields. The CERES-ECHAM4.5 simulation system (b) shows that all three curves fall beneath the no-skill diagonal line, which means that this simulation system does not have skill in simulating any of the equiprobable categories. The Multi-Model simulation system (c) on the other hand shows some skill for the below-normal and above-normal categories.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.77	0.57	0.83
CERES-ECHAM4.5	0.28	0.35	0.32
Multi-Model	0.57	0.48	0.54

Table 3.7: ROC scores for the simulated short season maize yield probabilities.

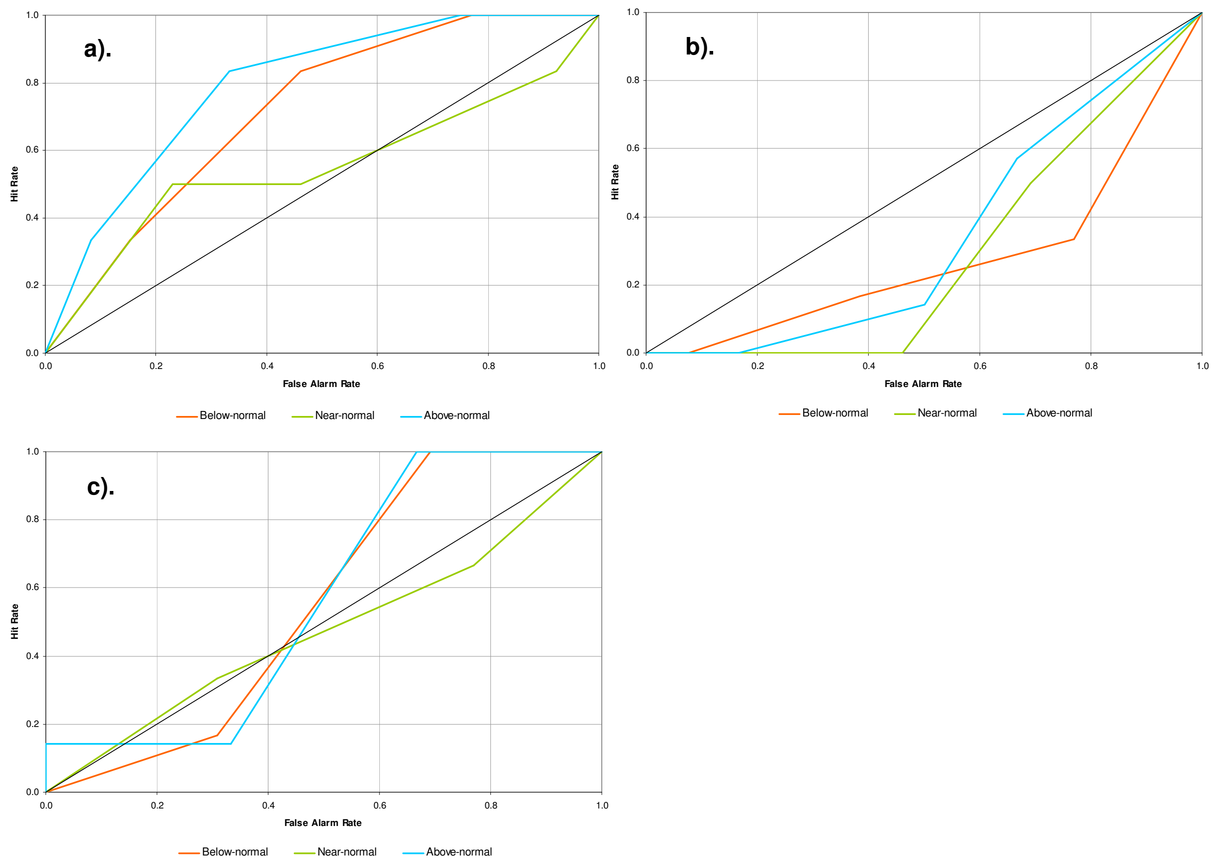


Figure 3.37: ROC curves for above-normal, near-normal and below-normal simulated short season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

3.4.2.3.2 Medium Season Maize

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.74	0.48	0.68
CERES-ECHAM4.5	0.46	0.43	0.37
Multi-Model	0.56	0.41	0.57

Table 3.8: ROC scores for the simulated medium season maize yield probabilities.

The ROC curves for medium season maize can be seen in Figure 3.38. The maize yield simulations performed by the CERES-CCAM simulation system (a) show somewhat higher skill for the below-normal category than for the above-normal category and substantially less skill for the near-normal category. The ROC curves of the CERES-ECHAM4.5 simulation system (b) are mainly beneath the no-skill diagonal with ROC scores ranging between 0.37 and 0.46 (see Table 3.8). The Multi-Model simulation system shows some skill for the below-normal and above-normal categories, but no skill for the near-normal category.

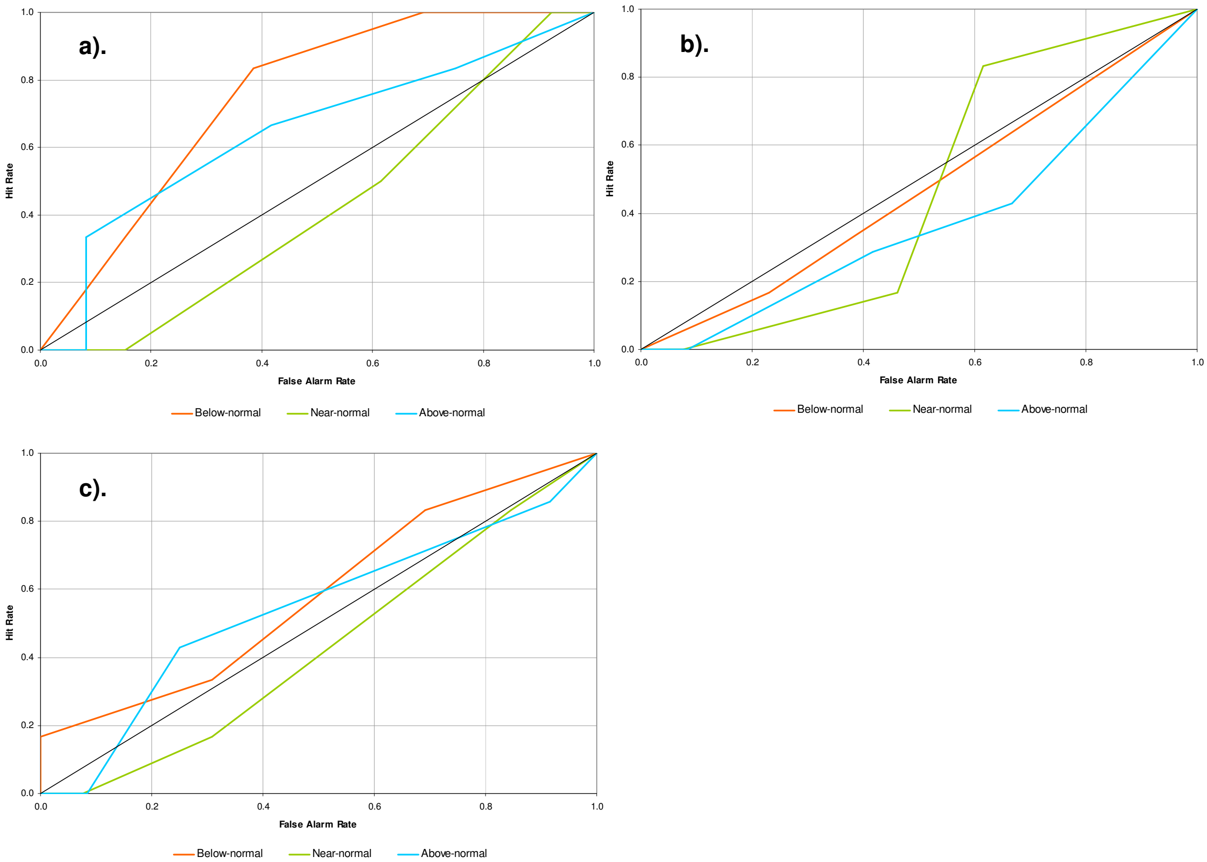


Figure 3.38: ROC curves for above-normal, near-normal and below-normal simulated medium season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

3.4.2.3.3 Long Season Maize

Figure 3.39 shows the long season maize ROC curves for each of the maize yield simulation systems and Table 3.9 shows the ROC scores. The CERES-CCAM simulation system (a) shows highest skill for above-normal maize yields (ROC score = 0.75), slightly lower skill for below-normal maize yields (ROC score = 0.74) and much reduced skill for near-normal maize yields (ROC score = 0.38). The ROC curves of the CERES-ECHAM4.5 simulation system (b) reveals highest skill for the below-normal category, with the above-normal and near-normal curves falling beneath the no-skill diagonal. It can be seen from the ROC curves of the Multi-Model simulation system that this simulation system is a combination between the CERES-CCAM and CERES-ECHAM4.5 simulation systems. The

ROC scores of the Multi-Model simulation system are 0.70 for the above-normal category, 0.63 for the below-normal category and 0.41 for the near-normal category.

Simulation system	Below-normal	Near-normal	Above-normal
CERES-CCAM	0.74	0.38	0.75
CERES-ECHAM4.5	0.59	0.48	0.40
Multi-Model	0.63	0.41	0.70

Table 3.9: ROC scores for the simulated long season maize yield probabilities.

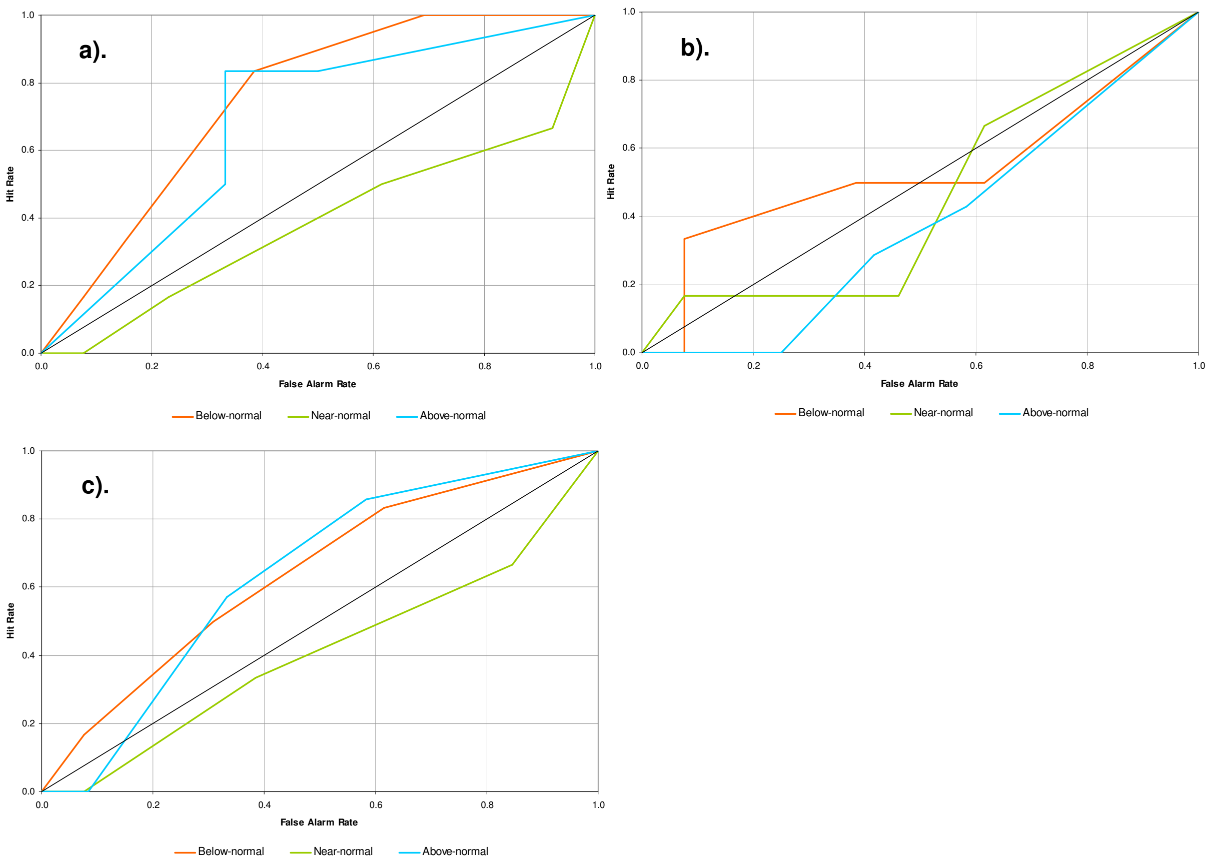


Figure 3.39: ROC curves for above-normal, near-normal and below-normal simulated long season maize yields. (a) CERES-CCAM maize yield simulation system, (b) CERES-ECHAM4.5 maize yield simulation system and (c) Multi-Model maize yield simulation system.

In general, the ROC scores of the below-normal category remain similar in all three scenarios. The above and below-normal categories of all three scenarios show relatively high ROC scores with the highest ROC score (0.83) evident for the short season maize scenario (Table 3.7).

3.5 SUMMARY

The simulated maize yields obtained from the different simulation systems for the primary maize producing region of South Africa have been presented. The simulation systems are tested over 19 seasons from 1980/81 to 1998/99. The simulation systems are constructed by forcing the CERES-Maize model with observed weather data, CCAM-simulated fields and ECHAM4.5 simulated fields. The combination between the CERES-CCAM simulated maize yields and CERES-ECHAM4.5 simulated maize yields forms the Multi-Model system.

In terms of the spatial distribution of the simulated maize yields, the four different maize yield simulation systems capture the east-west gradient in maize yield across the study area. The ability of the different simulation systems in simulating the season-to-season change in maize yield seems to be the lowest for the short season maize scenarios and the highest for the long season maize scenarios. The long season maize planted on plant date 1 scenario stands out as the scenario for which most of the simulation systems show the best results.

The CERES-Maize model shows high skill in simulating South African maize yields, with statistically significant correlations found for several magisterial districts across the study area. The CERES-CCAM simulation system produces skill levels comparable to that of the CERES-Observed weather simulation system. The CERES-ECHAM4.5 simulation system reveals overall poor skill. Since the CERES-Maize model is highly dependant on the weather input data, improved ECHAM4.5-simulated fields will most probably improve the maize yield simulations from the CERES-ECHAM4.5 simulation system. The CERES-ECHAM4.5 simulated maize yields negatively affect the Multi-Model system, as a simple un-weighted averaging approach is used as the combination method to construct the Multi-Model system. The ECHAM4.5-simulated fields can possibly be improved through downscaling and the use of a different combination method which can lead to improved Multi-Model simulations.

CHAPTER 4

SUMMARY AND CONCLUSIONS

South Africa's climate is highly variable and crop production in the country is predominantly rain-fed. Since weather is the primary source of uncertainty in crop management, unexpected climatic extremes can have detrimental effects on South African crop yields. Therefore, weather and climate variations can be seen as the main factors responsible for year-to-year variations in the crop yields. An investigation on ways to reduce the uncertainty in expected weather regime changes of a forthcoming season has therefore become essential. However, farmers can benefit more from information when it is presented in terms of production outcomes rather than from a weather or seasonal forecast that only gives an indication of variations in rainfall and temperature.

Since maize is the primary crop grown in South Africa, this dissertation has investigated the use of seasonal climate forecasts in the prediction of South African maize yields. To do this, a crop model has been run with both observed weather data and GCM-simulated fields. The ability of the crop model to simulate South African maize yields has been established by comparing the maize yield output obtained from forcing the crop model with observed weather data to actual maize yields. The maize yields produced by the crop model-GCM based maize yield simulation systems have been investigated to establish whether these simulation systems can produce skill levels similar to the target skill level set by the crop model forced with observed weather data. Finally, the two crop model-GCM based maize yield simulation systems have been combined through simple un-weighted averaging of the simulated maize yields to form a multi-model maize yield simulation system to establish whether the skill of this multi-model system outscores the skill of the best crop model-GCM based simulation system. The simulation systems have been tested over 19 seasons from 1980/81 to 1998/99.

The findings of the research are summarised as follows:

A. Quantifying the skill of the CERES-Maize model

1. The east to west decrease in maize yield across the study area has been successfully simulated by the CERES-Maize model. The spatial distribution of the

medium season maize (65 – 70 days to flowering) yields seem to show the best agreement with the spatial distribution of the actual maize yields.

2. For all three of the production regions, the CERES-Maize model has performed the best in simulating the inter-seasonal variability of the long season maize (70 – 75 days to flowering) yield scenarios (especially for the first plant date). The CERES-Maize model has performed well in simulating both the relative magnitude and the sign of the anomaly of the maize yields.

3. All 9 scenarios have shown high skill for the western part of the North-West Province (correlations > 0.81). The association between the CERES-Observed weather maize yields and actual maize yields has been found to be stronger for the western parts of the study area than for the eastern parts of the study area. The highest correlations are evident for the long season maize planted on plant date 1 scenario, with the correlations of 39 out of the 44 magisterial districts being statistically significant at the 95% level of confidence and a high level of field significance.

4. In simulating the category of the maize yields (above-normal, near-normal or below-normal) of the dry/warm western production region, the skill of the CERES-Maize model seems to increase from the short season maize (60 – 65 days to flowering) scenario to the long season maize scenario. Highest skill levels have been found for above-normal maize yields. The categorical simulations for the temperate eastern production region have shown high skill levels for the medium season maize scenario and for simulating below-normal maize yields. For the wet/cool eastern production region skill has decreased from the long season maize scenario to the short season maize scenario, and the CERES-Maize model has performed the best in simulating below-normal maize yields.

B. Simulating maize yields with the CERES-CCAM simulation system

1. The CERES-CCAM simulation system has captured the characteristic pattern of high maize yields in the eastern parts and lower maize yields in the western parts of the study area.

2. Overall, the CERES-CCAM simulation system has performed better in simulating the sign of the anomaly of the maize yields than the relative magnitude of the maize

yields. However, this simulation system has failed to correctly simulate the season with the lowest maize yield and the season with the highest maize yield.

3. All 9 scenarios have shown high skill for the western part of the Free State (correlations between 0.61 and 0.8). High skill levels have been found in simulating the maize yields of the first plant dates, thus short season maize planted on plant date 1, medium season maize planted on plant date 1 and long season maize planted on plant date 1. The simulated maize yields for the medium season maize scenarios have shown the most magisterial districts with statistically significant correlations (22 out of the 44) and high levels of field significance.

4. The probabilistic simulations have shown that for the dry/warm western production region the CERES-CCAM simulation system has performed better in simulating the above-normal yield category of the medium season maize scenario than simulating near-normal and below-normal maize yields. For the temperate eastern production region highest skill has been found for the above-normal category of the long season maize scenario and for the wet/cool eastern production region highest skill has been found for the above-normal category of the short season maize scenario.

C. *Simulating maize yields with the CERES-ECHAM4.5 simulation system*

1. The CERES-ECHAM4.5 simulation system has also captured the gradient in maize yield across the study area and in the short season maize scenarios this system has performed well in simulating the distribution in maize yield in the eastern part of the Free State.

2. Possibly due to the low spatial resolution of the ECHAM4.5-simulated fields, the CERES-ECHAM4.5 simulation system has struggled to simulate the sign of the anomaly of the yields over the 19 seasons considered in this study. However, in the long season maize scenarios for the temperate eastern production region this simulation system has produced more realistic maize yields (in terms of the relative magnitude of the yield) for the 1985/86, 1990/91 and 1997/98 seasons than that produced by the, CERES-CCAM and Multi-Model simulation systems. In the long season maize scenarios for the wet/cool eastern production region the CERES-ECHAM4.5 simulation system has performed better than the CERES-CCAM simulation system in simulating the relative magnitude of the maize yields of the 1991/92, 1996/97, and 1997/98 seasons.

3. The probabilistic simulations have shown that for the dry/warm western and wet/cool eastern production regions the CERES-ECHAM4.5 simulation system has no skill in simulating any of the categories for the short and medium season maize scenarios, but show at least some skill in simulating near-normal maize yields and below-normal maize yields for the long season maize scenario in the dry/warm western production region and wet/cool eastern production region respectively. For the temperate eastern production region the CERES-ECHAM4.5 simulation system has shown to have some skill in simulating both below-normal and near-normal maize yields for the short season maize scenario, relatively high skill in simulating near-normal maize yields for the medium season maize scenario and some skill in simulating the near-normal and above-normal categories for the long season maize scenario.

4. Improved GCM-simulated fields should result in more skilful maize yield simulations. It may be possible to improve on the spatial resolution of the ECHAM4.5-simulated fields by nesting a Regional Climate Model (RCM) within the ECHAM4.5 GCM. This process of downscaling will provide more detailed simulated fields, which will represents sub-grid scale features, like precipitation, much better.

D. *Simulating maize yields with the Multi-Model simulation system*

1. Similarly to the two single model simulation systems (CERES-CCAM and CERES-ECHAM4.5) the Multi-Model simulation system has also captured the east to west decrease in the spatial distribution of the maize yield across the study area.

2. Even though this Multi-Model simulation system has performed better than both the CERES-CCAM and CERES-ECHAM4.5 simulation systems in simulating the relative magnitude of the maize yields of 1981/82, 1983/84, 1984/85 and 1996/97 seasons in the temperate eastern production region, overall the inter-seasonal variability in maize yields as simulated by the Multi-Model simulation system was only slightly better than that of the CERES-ECHAM4.5 simulation system and did not outscore the CERES-CCAM simulation system.

3. The Multi-Model simulated maize yields expressed probabilistically have shown that for the dry/warm western production region this simulation system has no skill in simulating any of the categories for the medium and long season maize scenarios, but has some skill in simulating below-normal maize yields for the short season

maize scenario. For the temperate eastern production region the Multi-Model simulation system has shown relatively high skill levels in simulating both above-normal and near-normal maize yields, while for the wet/cool eastern region some skill has been seen for the above-normal and below-normal categories.

4. The combination between the CERES-CCAM simulated maize yields and CERES-ECHAM4.5 simulated maize yields did not improve on the CERES-CCAM simulation system's skill in simulating South African maize yields. Due to the fact that the CERES-ECHAM4.5 simulation system has not performed well, the potential advantage to use an equal-weights multi-model system has not been demonstrated in this study.

The CERES-Maize model has been used to simulate maize yields for each of the magisterial districts in the main maize producing area of South Africa. The crop model has been forced with observed weather data, CCAM-simulated fields and ECHAM4.5-simulated fields. The simulated maize yields from the CERES-CCAM simulation system and CERES-ECHAM4.5 simulation system have been combined, using simple un-weighted averaging, to form a multi-model maize yield system. The simulated maize yields from the different simulation systems have been compared to actual maize yields. From the CERES-Observed weather simulated maize yields it has been found that the CERES-Maize model has significant skill in simulating South African maize yields. This crop model can possibly be used in an operational environment, provided that the forcing fields (e.g. CCAM-simulated fields and ECHAM4.5-simulated fields) are adequately skilful. The CERES-CCAM simulation system has shown comparable skill levels to that of the CERES-Observed weather simulation system, but the CERES-ECHAM4.5 simulation system has shown poor skill. Due to this, the Multi-Model simulation system did not outscore the skill of the best single-model simulation system (CERES-CCAM). Provided that the GCM-simulated fields can be improved, the multi-model simulation system has the potential to improve significantly. This can possibly be achieved by downscaling the raw output from the GCMs.

The most important conclusion of this dissertation is that the potential for seasonal maize yield forecasting in South Africa using a multi-model ensemble system is high. However, before this goal can be realized, it will be necessary to improve the GCM fields that will be used to force the CERES-Maize model.

The maize yield forecast system proposed in this study can provide farmers with usable information on the possible successes of short, medium and long season maize. This study has shown that it is possible to simulate maize yield for South Africa with raw output from high resolution GCMs, which are already being used operationally. Thus, maize yield forecasts with a usable level of skill can be made with the use of an objective maize yield forecast system that incorporates GCMs. Such a system does not currently exist in South Africa.

REFERENCES

Allan, R.J., 2000: ENSO and climate variability in the last 150 years. In: Diaz, H.F. and Markgraf, V. (Eds.), *El Niño and the southern oscillation: multi-scale variability, global and regional impacts*, Cambridge University Press, Cambridge, 3 – 56 pp.

Allan, R., Lindesay, J. and Parker, D., 1996: *El Niño Southern Oscillation and climate variability*. CSIRO Publishing, Victoria, Australia, 405 pp.

ARC-GCI (Agricultural Research Council - Grain Crops Institute), 2008: Maize Information Guide 2008, Agricultural Research Council, Pretoria, 11 – 17 pp.

Arndt, C., Hazell, P. and Robinson, S., 2000: Economic value of climate forecasts for agricultural systems in Africa. In: Sivakumar, M.V.K. (ed), *Climate prediction and agriculture,* International START Secretariat, Washington DC, 157 – 180 pp.

Bannayan, M. and Crout, N.M.J., 1999: A stochastic modelling approach for real-time forecasting of winter wheat yield. *Field Crops Res.*, **62**, 85 – 95.

Barnston, A.G., Mason, S.J., Goddard, L., DeWit, D.G. and Zebiak, S.E., 2003: Multimodel ensembling in seasonal climate forecasting at IRI. *Bull. Amer. Meteor. Soc.*, **84**, 1783 – 1796.

Barnston, A.G., Thiao, W. and Kumar, V., 1996: Long-lead forecasts of seasonal precipitation in Africa using CCA. *J. Climate*, **11**, 506 – 520.

Barnston, A.G., van den Dool, H.M., Zibiak, S.E., Barnett, T.P., Ji, M., Rodenhuis, D.R., Cane, M.A., Leetmaa, A., Graham, N.E., Ropelewski, C.R., Kousky, V.E., O'Lenic, E.A. and Livezey, R.E., 1994: Long-lead seasonal forecasts – Where do we stand? *Bull. Amer. Meteor. Soc.*, **75** (11), 2097 – 2114.

BFAP (Bureau for Food and Agricultural Policy), 2008: The South African Agricultural Baseline. Bureau for Food and Agricultural Policy Report, 22 – 28 pp.

Boote, K.J., Jones, J.W. and Pickering, N.B., 1996: Potential uses and limitations of crop models. *J. Agronomy*, **88**, 704 – 716.

Botha, A.D.P. and Eisenberg, B.E., 1992: Estimation of soil water retention from clay content and cation exchange capacity values of soils. *S.Afr.J.Plant Soil,* **10(3)**, 141 – 143.

Cane, M.A., 2004: The evolution of El Niño, past and future. *Earth. Planet. Sci. Lett.*, **164**, 1 – 10.

Cane, M.A., Eshel, G. and Buckland, R.W., 1994: Forecasting Zimbabwean maize yield using eastern equatorial Pacific sea surface temperature. *Nature*, **370**, 204 – 205.

Cantelaube, P. and Terres, J., 2005: Seasonal weather forecasts for crop yield modelling in Europe. *Tellus*, **57A**, 476 – 487.

Carson, D.J., 1998: Seasonal forecasting. *Ouart. J. Roy. Meteor. Soc.*, **124**, 1 – 26.

Challinor, A.J., Slingo, J.M., Wheeler, T.R. and Doblas-Reyes, F.J., 2005: Probabalistic simulations of crop yield over western Indai using the DEMETER seasonal hindcast ensembles. *Tellus*, **57A**, 498 – 512.

Chen, D., Zebiak, S.E., Busalacchi, A.J. and Cane, M.A., 1995: An improved procedure for El Niño forecasting: Implications for predictability. *Science,* **269**, 1699 – 1702.

Chenje, M. and Johnson, P., 1994: *State of the Environment in Southern Africa.* Southern African Research and Documentation Center, 332 pp.

Chimeli, A.B., Mutter, C.Z. and Ropelewski, C., 2002: Climate fluctuations, demography and development: Insights and opportunities for northeast Brazil. *J. Int. Affairs*, **56**, 213 – 234.

Colberg, F., Reason, C.J.C. and Rodgers, K., 2004: South Atlantic response to ENSO induced climate variability in an OGCM. *J. Geophys. Res.*, **109**, 12 – 15.

Cook, C., Reason, C.J.C. and Hewitson, B.C., 2004: Wet and dry spells within particularly wet and dry summers in the South African summer rainfall region. *Clim. Res.*, **26**, 17 – 31.

Cox, H.G., McLean, G. and King, C., 2004: Natioanl Whopper Cropper – risk management support software. In: Fisher, T., Turner, N., Angus, J., McIntyre, L., Robertson, M., Borrell, A. and Lloyd, D. (Eds.), New directions for a diverse planet. Proc 4th Int Crop Sci Congr, 26 Sep – 1 Oct 2004, Brisbane, Australia.

Crimp, S.J., Lutjeharms, J.R.E. and Mason, S.J., 1998: Sensitivity of a tropical-temperate through to sea-surface temperature anomalies in the Agulhas retroflection region. *Water SA.*, **24**, 93 – 100.

CSIRO (Commonwealth Scientific and Industrial Research Organisation), 1998: Ocean and agriculture changing the odds. Newsletter 9, November. CSIRO Marine Research, Hobart.

D'Abreton, P.C. and Tyson, P.D., 1995: Divergent and non-divergent water vapour transport over southern Africa during wet and dry conditions. *Meteorol. Atmos. Phys.*, **55**, 47 – 59.

Devereux, S., 2000: Famine in the twentieth century. Working Paper, Institute of Development Studies, Sussex.

DoA (Department of Agriculture), 2007: *Strategic plan for the Department of Agriculture.* Department of Agriculture, Pretoria, 12 – 17 pp.

Doblas-Reyes, F.J., Hagedorn, R. and Palmer, T.N., 2006: Developments in dynamical seasonal forecasting relevant to agricultural management. *Climate Res.*, **33**, 19 – 26.

Du Pisani, A.L., 1987: The CERES-Maize model as a potential tool for drought assessment in South Africa. *Water SA*, **13** (3), 159 – 164.

Du Plessis, J., 2003: Maize Production, Department of Agriculture.

Du Toit, W., 1997: *Handleiding vir die verbouing van Mielies in die Somerreënvalgebied*. LNR-Instituut vir Graangewasse, Potchefstroom, 2 – 33 pp.

Du Toit, A.S., Booysen, J. and Human, J.J., 1994: Evaluering en kalibrering van CERES-Maize 2, Groeistadia voorspellings. *S. Afr. J. Plant Soil*, **11(3)**, 121 – 125.

Du Toit, A.S., Prinsloo, M.A., Durand, W. and Kiker, G., 2000: Vulnerability of maize production to climate change and adaptation assessment in South Africa. In: Kikier, G., *Climate Change Impacts in Southern Africa.* Report to the National Climate Change Committee, Department of Environmental Affairs and Tourism, Pretoria, South Africa.

Du Toit, A.S., Prinsloo, M.A., Wafula, B.M. and Thornton, P.K., 2002: Incorporating a water-logging routine into CERES-Maize, and some preliminary evaluations. *Water SA*, **28(3)**, 323 - 328.

Du Toit, D.L., Smallberger, S.A. and Du Toit, A.S., 2001: The use of a weather analogue model to manage seasonal variability. Unpublished paper presented at the Integrated Managemnt for Sustainable Agriculture, Forestry and Fishereis workshop, 28 – 31 August, Cali, Columbia.

Egli, D.B. and Bruening, W., 1992: Planting date and soybean yield: evaluation of environmental effect with a crop simulation model: SOYGRO. *Agric. For. Meteorol.*, **62**, 19 – 29.

Engelbrecht, F.A., McGregor, J.L. and Engelbrecht, C.J., 2009: Dynamics of the Conformal-Cubic Atmospheric Model projected climate-change signal over southern Africa. *Int. J. Climatol.,* **29**, 1013 - 1033.

Engelbrecht F.A., Rautenbach, C.J. deW., McGregor, J.L. and Katzfey, J.J., 2002: January and July climate simulations over the SADC region using the limited-area model DARLAM. *Water SA,* **28**, 361-374.

Fageria, N.K., 1992: Maximizing crop yields. Marcel Dekker, New York.

Fodor, N. and Kovacs, G.J., 2003: Sensitivity of 4M maize model to the inaccuracy of weather and soil input data. *Appl. Ecol. Environ. Res.*, **1**, 75 – 85.

Frost, C., 2006: Using spatial rainfall and products from the MODIS sensor to improve an existing maize yield estimation system. Unpublished MSc. Dissertation, University of Witwatersrand, Johannesburg.

Gebregiorgis, M.F. and Savage, M.J., 2006: Field, laboratory and estimated soil-water content limits. *Water SA*, **32(2)**, 155 – 161.

Goddard, L. and Mason, S.J., 2002: Sensitivity of seasonal climate forecasts to persisted SST anomalies. *Climate Dyn.*, **19**, 619 – 631.

Goddard, L., Mason, S.J., Zebiak, S.E., Ropelewski, C.F., Basher, R. and Cane, M.A., 2001: Current approaches to seasonal to interannual climate predictions. *Int. J. Climatol.*, **21**, 1111 – 1152.

Gong, X., Barnston, A.G. and Ward, M.N., 2003: The effect of spatial aggregation on the skill of seasonal precipitation forecasts. *J. Climate*., **16**, 3059 – 3071.

Gordon, H.B., Rotstayn, L.D., McGregor, J.L., Dix, M.R., Kowalczyk, E.A., O'Farrell, S.P., Waterman, L.J., Hirst, A.C., Wilson, S.G., Collier, M.A., Watterson, I.G. and Elliott, T.I., 2002: The CSIRO Mk3 Climate System Model. CSIRO Atmospheric Research, Australia. 130 pp.

Hagedorn, R., Doblas-Reyes, F.J. and Palmer, 2005: The rationale behind the success of multi-model ensembles in seasonal forecasting, I, Basic concept. *Tellus*, **A57**, 219 – 233.

Hammer, G.L., Hasen, J.W., Phillips, J.G., Mjelde, J.W., Hill, H. and co-authors, 2001: Advances in application of climate prediction in agriculture. *Agric. Sys.*, **74**, 515 – 553.

Hammer, G.L., Holzworth, D.P. and Stone, R., 1996: The value of skill in seasonal climate forecasting to wheat crop management in a region with high climatic variability. *Aust. J. Agic. Res.*, **47**, 717 – 737.

Hansen, J.W., Challinor, A., Ines, A., Wheeler, T. and Moron, V., 2006: Translating climate forecasts into agricultural terms: advances and challenges. *Climate Res.*, **33**, 27 – 41.

Hansen, J.W. and Indeje, M., 2004: Linking dynamic seasonal climate forecasts with crop simulation for maize yield prediction in semi-arid Kenya. *Agric. For. Meteor.*, **125**, 143 – 157.

Hanway, J.J., 1966: How a corn plant develops. Special Report, Iowa State University, Unite States of America, 48 pp.

Harrison, M.S.J., 1984: A general classification of South African summer rain-bearing synoptic systems. *J. Climatol.*, **4**, 547 – 560.

Harrison, M., 2003: Report to the Commission for Agricultural Meteorology Working Group on the use of seasonal forecasts and climate prediction in operational agriculture. 13th Sess Comm Agric Meteorol World Meteorol Org, October 2002, Ljubjana, Slovenia.

Hattle, J.B., 1968: Polar fronts of the southern hemisphere. Notos: South African Weather Bureau, **17**, 15 – 22 pp.

Hoerling, M.P. and Kumar, A., 1997: Why do North American climate anomalies differ from one El Niño event to another? *Geophys. Re. Lett.*, **24**, 1059 – 1062.

Hoffman, R.N. and Kalnay, E., 1983: Lagged average forecasting, an alternative to Monte Carlo forecasting. *Tellus*, **35A**, 100 – 118.

Hollinger, S.E., 1988: Modeling the effects of weather and management practices on maize yield. *Agric. For. Meteor.*, **44**, 81 – 97.

Holton, J.R., 1979: *Numerical prediction: An introduction to Dynamic Meteorology.* 2nd edition, Academic Press, San Diego, 173 – 213 pp.

Hoogenboom, G., 2000: Contribution of agrometeorology to the simulation pf crop production and its applications. *Agric. For. Meteorol.*, **103**, 137 – 157.

Hoogenboom, G., Jones, J.W. and Boote, K.T., 1992: Modeling growth, development, and yield of grain legumes using SOYCRO, PNUTGRO, and BEANGRO: a review. *Trans. ASAE*, **35**, 2043 – 2056.

Hunt, B.G., Zebiak, S.E. an Cane, M.E., 1994: Experimental predictions of climate variability for lead times of twelve months. *Int. J. Climatol.*, **14**, 507 – 526.

Isard, S.A., Welford, M.R. and Hollinger, S.E., 1995: A simple soil moisture index to forecast crop yields. *Phys. Geog.*, **16(6)**, 524 – 538.

Jinghua, W. and Erda, L., 1996: The impacts of potential climate change and climate variability on simulated maize production in China. *Water, Air and Soil Pollution*, **92**, 75 – 85.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J. and Ritchie, J.T., 2003: The DSSAT cropping system model. *Europ. J. Agronomy*, **18**, 245 – 265.

Joubert, A.M. and Hewitson, B.C., 1997: Simulating present and future climate of southern Africa using general circulation models. *Prog. Phys. Geog.*, **21**, 51 – 78.

Jury, M.R., 2002: Economic impacts of climate variability in South Africa and development of resource prediction models. *J. Appl. Meteor.*, **41**, 46 – 55.

Jury, M.R. and Pathack, B., 1991: A study of weather and climate variability over the tropical southwest Indian Ocean. *Meteorol. Atmos. Phys.*, **47**, 37 – 48.

Jury, M.R., Valentine, H.R. and Lutjeharms, J.R.E., 1993: Influence of the Agulhas current on summer rainfall on the southeast coast of South Africa, *J. Appl. Meteorol.*, **32**, 1282 – 1287.

Jury, M.R., White, W.B. and Reason, C.J.C., 2004: Modelling the dominant climate signals around southern Africa. *Climate Dyn.*, **23**, 717 – 726.

Kgatuke, M.M., Landman, W.A., Beraki, A. and Mbedzi, M.P., 2008: The internal variability of the RegCM3 over South Africa. *Int. J. Climatol.*, **28**, 505 – 520.

Kharin, V.V. and Zwiers, F.W., 2003: On the ROC scores of probability forecasts. *J. Climate*, **16**, 4145 – 4150.

Klopper, E., 1999: The use of seasonal forecasts in South Africa during the 1997/98 rainfall season. *Water SA*, **25**, 311 – 316.

Klopper, E. and Landman, W.A., 2003: A simple approach for combining seasonal forecasts for southern Africa. *Meteorol. Appl.*, **10**, 319 – 327.

Krishnamurti, T.N., Kishtawal, C.M., LaRow, T.E., Bachiochi, D.R., Zhang, Z., Willford, C.E., Gadgil, S. and Surendran, S., 1999: Climate forecasts from multimodel superensemble. *Science*, **285**, 1548 – 1550.

Landman, W.A., Engelbrecht, F.A., Beraki, A., Engelbrecht, C.J., Mbedzi, M., Gill, T. and Ntsangwane, L., 2008. Model output statistics applied to multi-model ensemble long-range forecasts over South Africa. Water Research Commission Project Report, in press, Pretoria.

Landman, W.A. and Goddard, L., 2002: Statistical recalibration of GCM forecasts over southern Africa using Model Output Statistics. *J. Climate*, **15**, 2038 – 2055.

Landman, W.A. & Goddard, L., 2003: Model output statistics applied to multi-model ensemble forecasts for southern Africa. Proceedings of the Seventh International Conference on Southern Hemisphere Meteorology and Oceanography. Wellington, New Zealand. 24 – 28 March 2003, 249 – 250 pp.

Landman, W.A. and Mason, S.J., 1999a: Change in association between Indian Ocean sea-surface temperatures and summer rainfall over South Africa and Namibia. *Int. J. Climatol.*, **19**, 1477 – 1492.

Landman, W.A. and Mason, S.J., 1999b: Operational long-lead prediction of South African rainfall using canonical correlation analysis. *Int. J. Climatol.*, **19**, 1073 – 1090.

Landman, W.A. and Mason, S.J., 2001: Forecasts of near-global sea surface temperatures using canonical correlation analysis. J. Climate, 14, 3819 – 3833.

Landman, W.A., Mason, S.J., Tyson, P.D. and Tennant, W.J., 2001: Retro-active skill of multi-tiered forecasts of summer rainfall over southern Africa. *Int. J. Climatol.*, **21**, 1 – 19.

Land Type Survey Staff, 1972 – 2008: Land Types of South Africa: Digital map (1:250 000 scale) and soil inventory databases. ARC-Institute for Soil, Climate and Water, Pretoria.

Lawless, C. and Semenov, M.A., 2005: Assessing lead-time for predicting wheat growth using a crop simulation model. *Agric. For. Meteorol.*, **135**, 302 – 313.

Leith, C.E., 1974: Theoretical skill of Monte Carlo forecasts. *Mon. Wea. Rev.*, **6**, 409 – 418.

Lorenz, E.N., 1963: Deterministic nonperiodic flow. *J. Atmos. Sci.*, **20**, 130 – 141.

Macvicar, C.N., De Villiers, J.M., Loxton, R.F., Verster, E., Lambrechts, J.J.N., Merryweather, F.R., Le Roux, J., Van Rooyen, T.H. and Harmse, H.J.Von.M., 1977: *Soil Classification: A Binomial System for South Africa*. The Soil and Irrigation Research Institute, Department of Agriculture Technical Services, Pretoria, 34 – 115 pp.

Mason, I., 1982: A model for assessment of weather forecasts. *Aust. Wea. Forecasting*, **14**, 713 – 725.

Mason, S.J., 1995: Sea-surface temperature – South African rainfall associations, 1910 - 1989. *Int. J. Climatol.*, **15**, 119 – 135.

Mason, S.J., 1998: Seasonal forecasting of South African rainfall using a non-linear discriminant analysis model. *Int. J. Climatol.*, **18**, 147 – 164.

Mason, S.J., 2001: El Niño, climate change, and Southern African climate. *Environmetrics*, **12**, 327 – 345.

Mason, S.J., 2008: From dynamical model predictions to seasonal climate forecasts. In: Troccoli, A., Harrison, M., Anderson, D.L.T. and Mason, S.J., 2008, *Seasonal Climate: Forecasting and Managing Risk*, Springer, The Netherlands, 205 – 234 pp.

Mason, S.J., Goddard, L., Graham, N.E., Yelaeva, E., Sun, L. and Arkin, P.A., 1999: The IRI seasonal climate prediction system and the 1997/98 El Niño event. *Bull. Amer. Meteor. Soc.*, **80**, 1853 – 1873.

Mason, S.J. and Graham, N.E., 1999: Conditional probabilities, relative operating characteristics, and relative operating levels. *Wea. Forecasting*, **14**, 713 – 725.

Mason, S.J., Joubert, A.M., Cosijn, C. and Crimp, S.J., 1996: Review of seasonal forecasting techniques and their applicability to southern Africa. *Water SA*, **22**, 203 – 209.

Mason, S.J. and Jury, M.R., 1997: Climate variability and change over southern Africa: a reflection on underlying processes. *Prog. Phys. Geog.*, **21**, 23 – 50.

Martin, R.V., Washington, R. and Downing, T.E., 2000: Seasonal maize forecasting for South Africa and Zimbabwe derived from an agroclimatological model. *J. Appl. Meteor.*, **39**, 1473 – 1479.

Matthews, R., 2002: Where to now with crop modelling? In: Matthews, R. and Stephens, W. (Eds.), Crop-soil simulation models, applications in developing countries, CABI publishing, Wallingford, New York, 209 – 229 pp.

Mavromatis, T. and Jones, P.D., 1998: Evaluation of HadCM2 and direct use of daily GCM data in impact assessment studies. *Clim. Change*, **41**, 583 – 614.

McFarlane, N.A., 1887: The effect of orographically excited gravity-wave drag on the general circulation of the lower stratosphere and troposphere. *J. Atm. Sci.*, **44**, 1775 – 1800.

McGregor, J.L., 1996: Semi-Lagrangian advection on conformal-cubic grids. *Mon. Wea. Rev.*, **124**, 1311 – 1322.

McGregor, J.L., 2005a: C-CAM: Geometric aspects and dynamical formulation. CSIRO Atmospheric Research Technical Paper, No 70, 41 pp.

McGregor, J.L., 2005b: Geostrophic adjustment for reversibly staggered grids. *Mon. Wea. Rev.*, **133**, 1119-1128.

McGregor, J.L. and Dix, M.R., 2001: The CSIRO conformal-cubic atmospheric GCM. In: Hodnett, P.F. (Ed.), IUTAM Symposium on Advances in Mathematical Modelling of Atmosphere and Ocean Dynamics, Kluwer: Dordrecht, 197 – 202 pp.

McGregor, J.L. & Nguyen, K.C. 1999: Simulations of the East Asian and Australian monsoons and aspects of the diurnal rainfall behaviour. *Atmospheric Research*, **1**, 1-12.

Neelin, J.D., Battisti, D.S., Hirst, A.C., Jin, F., Wakata, Y. and co-authors, 1998: ENSO theory. *J. Geophys. Res.*, **103**, 14261 – 14290.

Nicholls, N., 1985: Impact of the southern oscillation on Australian crops. *J. Climatol.*, **5**, 553 – 560.

Nicholson, S.E. and Entekhabi, D., 1986: The quasi-periodic behaviour of rainfall variability in Africa and its relationship to the Southern Oscillation. *Arch. Met. Geophys. Bioklim. Ser.*, **34**, 311 – 348.

Nonhebel, S., 1994: Inaccuracies in weather data and their effects on crop growth simulation results II, Water-limited production. *Clim. Res.*, **4**, 61 – 74.

Oram, P.A., 1989: Sensitivity of agricultural production to climatic change, an update. In: *Climate and food security*, International Rice Research Institute (IRRI), Manila, 25 – 44 pp.

Palmer, T.N., Alessandri, A., Andersen, U., Cantelaube, P., Davey, M., Delecluse, P., Deque, M., Diez, E., Doblas-Reyes, F.J., Feddersen, H., Graham, R., Gualdi, S., Gueremy, J.F., Hagedorn, R., Hoshen, M., Keenlyside, N., Latif, M., Lazar, A., Maisonnave, E., Marletto, V., Morse, A.P., Orfila, B., Rogel, P., Terres, J.M. and Thomson, M.C., 2004: Development of a European Multi-Model Ensemle System for Seasonal to Inter-Annual Prediction (DEMETER). Unpublished internal report, Technical Memorandum No. 434, European Centre for Medium-Range Weather Forecasts, England.

Palmer, T.N. and Anderson, D.L.T., 1994: The prospects for seasonal forecasting. *Ouart. J. Roy. Meteor. Soc.*, **120**, 755 – 793.

Palmer, T.N., Shutts, G.J., Hagedorn, R, Doblas-Reyes, F.J., Jung, T. and Leutbecher, M., 2005: Representing model uncertainty in weather and climate prediction. *Annu. Rev. Earth Planet Sci.*, **33**, 163 – 193.

Palmer, T.N., Shutts, G.J. and Swinbank, R., 1986: Alleviation of a systematic westerly bias in general circulation and numerical weather prediction models through an orographic gravity wave drag parameterization. *Quart. J. Roy. Meteor. Soc.*, **112**, 1001 – 1031.

Pathack, B.M.R., Jury, M.R., Shillington, F.A. and Courtney, S., 1993: South African rainfall variability and its association with the marine environment. Water Research Commission Report, 278/1/94.

Petr, J., 1991: Weather and Yield. Elsevier, Amsterdam, Netherlands.

Phillips, J.G., Cane, M.A. and Rosenzweig, C., 1998: ENSO, seasonal rainfall patterns and simulated maize yield variability in Zimbabwe. *Agric. For. Meteorol.*, **90**, 39 – 50.

Podesta, G.P., Messina, C.D., Grondona, M.O. and Magrin, G.O., 1999: Associations between grain crop yields in Central-Eastern Argentina and El Nino – Southern Oscillation. *J. Appl. Meteor.*, **38**, 1488 – 1498.

Porter, J.R. and Semenov, M.A., 1999: Climate variability and crop yields in Europe. *Nature*, **400**, 724.

Potgieter, C.J., 2007: Short-range weather forecasting over southern Africa with the conformal-cubic atmospheric model. Unpublished MSc. Dissertation, University of Pretoria, Pretoria.

Preston-Whyte, R.A. and Tyson, P.D., 1993: *The atmosphere and weather of southern Africa*. Oxford University Press, New York, 207 - 249 pp.

Rautenbach, C.J.deW. and Smith, I.N., 2001: Teleconnections between global sea-surface temperatures and the interannual variability of observed and model simulated rainfall over southern Africa. *J. Hydrol.*, 254, 1-15.

Rawls, W.J., Brakensiek, D.L. and Saxton, K.E., 1982: Estimation of Soil Water Properties. *Trans. ASAE*, 1316 – 1320.

Reason, C.J.C., 2002: Sensitivity of the southern African circulation to dipole SST patterns in the South Indian Ocean. *Int. J. Climatol.*, **22**, 377 – 393.

Reason, C.J.C., Allan, R.J., Lindesay, J.A. and Ansell, T.J., 2000: ENSO and climate signals across the Indian Ocean basin in the global context, part 1: Interannual composite patterns. *Int. J. Climatol.*, **20**, 1285 – 1327.

Reason, C.J.C., Engelbrecht, F., Landman, W.A., Lutjeharms, J.R.E., Piketh, S., Rautenbach, C.J.deW. and Hewitson, B.C., 2006b: A review of South African research in atmospheric science and physical oceanography during 2000-2005. *SA J. Sci.*, **102**, 35 – 45.

Reason, C.J.C. and Jagadheesha, D., 2005: A model investigation of recent ENSO impacts over southern Africa. *Meteorol. Atmos. Phys.*, **89**, 181 – 205.

Reason, C.J.C., Landman, W. and Tennant, W., 2006a: Seasonal to decadal prediction of southern African climate and its links with variability of the Atlantic Ocean. *Bull. Amer. Meteor. Soc.*, **87**, 941 – 955.

Reason, C.J.C. and Mulenga, H., 1999: Relationships between South African rainfall and SST anomalies in the South West Indian Ocean. *Int. J. Climatol.*, **19**, 1651 – 1673.

Reason, C.J.C. and Rouault, M., 2002: ENSO-like decadal patterns and South African rainfall. *Geophys. Res. Lett.*, **29**, 1010 – 1029.

Reddy, V.R. and Pachepsky, Y.A., 2000: Predicting crop yields under climate change conditions from monthly GCM weather projections. *Environmental Modelling and Software*, **15**, 79 – 86.

Ritchie, J.T., 1994: Classification of crop models. In: Uhlir, P.F. and Carter, G.C. (Eds.), *Crop modelling and related environmental data*, 3 – 14 pp.

Ritchie, S.W., Hanway, J.J. and Benson, G.O., 1993: How a corn plant develops. Iowa State Univeristy of Science and Technology, Cooperative Extension Service, Ames, Iowa Special Rep. 48, 21 pp.

Roeckner, E., Arpe, K., Bengtsson, L., Christoph, M., Claussen, M., Dumenil, L., Esch, M., Giorgetta, M., Schlese, U. and Schulzweida, U., 1996: The atmospheric general circulation model ECHAM-4: Model description and simulation of present-day climate. Report 218, Max Planck Institute for Meteorology, Hamburg, Germany.

Ropelewski, C.F. and Halpert, M.S., 1987: Global and regional scale precipitation patterns associated with the El Niño/southern oscillation. *Mon. Wea. Rev.*, **115**, 1606 – 1626.

Rosenthal, W.D., Hammer, G.L. and Butler, D., 1998: Predicting regional grain sorghum production in Australia using spatial data and crop simulation modelling. *Agric. For. Meteorol.*, **91**, 263 – 274.

Rosenzweig, R. and Iglesias, A., 1994: Implication of climate change on international agriculture: Crop Modeling Study. U.S. Environmental Protection Agency, Office of Policy, Planning and Evaluation, Climate Change Division, Adaptation Branch, Washington, DC.

Rotstayn, L.D., 1997: A physically based scheme for the treatment of stratiform clouds and precipitation in large-scale models, I: Description and evaluation of the microphysical processes. *Quart. J. Roy. Meteor. Soc.*, **123**, 1227 – 1282.

Schoeman, J.L., Van der Walt, M., Monnik, A.K., Thachrah, A., Malherbe, J. and Le Roux, R.E., 2000: Development and application of a land capability classification system for South Africa. Agricultural Research Council, Institute for Soil, Climate and Water report, GW/A/2000/57, Pretoria.

Schulze, R.E., 1985: Hydrological characteristics and properties of soils in Southern Africa 1: Runoff response. *Water SA.* **11(3)**, 121 – 128.

Schulze, R.E. and Lynch, S.D., 2007: Annual Precipitation. In: Schulze, R.E. (Ed.) 2007, *South African Atlas of Climatology and Agrohydrology*, Water Research Commission, Pretoria, RSA, WRC Report 1489/1/06, Section 6.2.

Schulze, R.E. and Maharaj, M., 2007: Rainfall Seasonality. In: Schulze, R.E. (Ed). 2007, *South African Atlas of Climatology and Agrohydrology,* Water Research Commission, Pretoria, RSA, WRC Report 1489/1/06, Section 6.5.

Schulze, R.E., Warburton, M., Lumsden, T.G. and Horan, M.J.C., 2005: The Southern African Quaternary Catchment Database: Refinements to, and links with, the *ACRU* System as a Framework fro Modelling of Climate Change on Water Resources. In: Schulze, R.E. (Ed) *Climate Change and Water Resources in Southern Africa: Studies on Scenarios, Impacts, Vulnerability and Adaptation.* Water Research Commission, Pretoria, RSA, WRC Report 1430/1/05. Chapter 8, 111 – 139 pp.

Schwarzkopf, M.D and Fels, S.B., 1991: The simplified exchange method revisited: an accurate, rapid method for computation of infrared cooling rates and fluxes. *Journal of Geophysical Research,* **96**, 9075-9096.

Shannon, L..V., Boyd, A.J., Brundrit, G.B. and Taunton-Clark, J., 1986: On the existence of an El Niño-type phenomenon in the Benguela system. *J. Marine. Res.*, **44**, 495 – 520.

Sivakumar, M.V.K., 2006: Climate prediction and agriculture: current status and future challenges. *Climate Res.*, **33**, 3 – 17.

Soil Classification Working Group, 1991: *Soil Classification: A Taxonomic System for South Africa*. The Soil and Irrigation Research Institute, Department of Agriculture Development, Pretoria, 50 – 190 pp.

Soil Survey Staff, 2008: Soil Profile descriptions and soil analyses data. In: ARC-ISCW Soil Profile Information System. ARC-Institute for Soil, Climate and Water, Pretoria.

Stanski, H.R., Wilson, L.J. and Burrows, W.R., 1989: Survey of common verification methods in meteorology. WMO World Weather Watch Tech. Rep. 8 WMO TD 358, 114 pp.

Stefanova, L. and Krishnamurti, T.N., 2002: Interpretation of seasonal climate forecast using brier skill score, The Florida State University Superensemble, and the AMIP-1 dataset. *J. Climate*, **15**, 537 – 544.

Steyn, A.G.W., Smit, C.F., Du Toit, S.H.C. and Stransheim, C., 1998: Moderne statistiek vir die praktyk. 6th Edition, J.L. van Schaik publishers, Pretoria, 130, 615 pp.

Sun, L., Li, H. and Ward, N.M., 2007: Climate variability and corn yields in semiarid Ceara, Brazil. *J. Appl. Meteor.*, **46**, 226 – 240.

Sun, L., Moncunill, D.F., Li, H., Moura, A.D. and Filho, F.D.A.D.S., 2005: Climate downscaling over Nordeste Brazil ysing NCEP RSM97. *J. Climate*, **18**, 551 – 567.

Tadross, M.A., Gutowski, W.J., Hewitson, B.C., Jack, C. and New, M., 2006: MM5 simulations of interannual change and the diurnal cycle of southern African regional climate. *Theor. Appl. Climatol.*, **86**, 63 – 80.

Tadross, M.A., Hewitson, B.C. and Usman, M.T., 2003: The interannual variability of the onset of the maize growing season over South Africa and Zimbabwe. *J. Climate*, **18**, 3356 – 3372.

Taljaard, J.J., 1986: Change of rainfall distribution and circulation patterns over southern Africa in summer. *J. Climatol.*, **6**, 579 – 592.

Tennant, W.J. and Hewitson, B.C., 2002: Intra-seasonal rainfall characteristics and their importance to the seasonal prediction problem. *Int. J. Climatol.*, 22, 1033 – 1048.

Todd, M. and Washington, R., 1998: Extreme daily rainfall in southern African and southwest Indian Ocean tropical-temperate links. *S. Afr. J. Sci.*, **94**, 64 – 70.

Tsuji, G.Y., 1998: Network management and information dissemination for agrotechnology transfer. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), *Understanding Options for Agricultural Production,* Kluwer Academic Publishers, Dordrecht, The Netherlands, 367 – 381 pp.

Tyson, P.D., 1986: *Climatic change and variability over southern Africa*. Oxford University Press, Cape Town, 220 pp.

Uehara, G. and Tsuji, G.Y., 1998: Overview of IBSNAT. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), *Understanding Options for Agricultural Production*, Kluwer Academic Publishers, Dordrecht, The Netherlands, 1 – 7 pp.

Van Heerden, J., Terblanche, D.E. and Schulze, G.C., 1988: The southern oscillation and South Africa summer rainfall. *J. Climatol*., **8**, 577 – 597.

Vogel, C. and O'Brien, K., 2006: Who can eat information? Examining the effectiveness of seasonal climate forecasts and regional climate-risk management strategies. *Climate Res*., **33**, 111 – 122.

Vossen, P., 1995: Early crop production assessment of the European Union, the system implemented by the MARS-STAT Project. Agrometeorological models: theory and application in the MARS project. Publication EUR 16008 EN of the Office for Official Publications of the European Communities, Luxembourge.

Walker, N.D., 1990: Links between South African summer rainfall and temperature variability of the Agulhas and Benguela current systems. *J. Geophys. Res*., **B 95**, 3297 – 3319.

Walker, N.D. and Lindesay, J.A., 1989: Preliminary observations of oceanic influences on the February-March 1988 floods in central South Africa. *S. Afr. J. Sci*., **85**, 164 – 169.

Walter, M.W., 1967: Mis(management) of droughts in South Africa: Past, present, future. *South Afr. J. Sci*., **86**, 382 – 386.

Wang, Y., Leung, L.R., McGregor, J.L., Lee, D.K., Wang, W.C., Ding, Y. and Kimura, F., 2004: Regional climate modeling: Progress, challenges, and prospects. *Journal of the meteorological society of Japan,* **82**, 1599-1628.

Wilks, D., 2006: *Statistical methods in the atmospheric sciences*. 2nd Edition, Elsevier Academic Press, California, Unites States of America.

Williamson, D.L. and Rasch, P.J., 1994: Water vapor transport in the NCAR CCM2. *Tellus*, **46A**, 34 – 51.

Whisler, F.D., Acock, B., Baker, D.N., Fry, R.E., Hodges, H.F., Lamber, J.R., Lemmon, H.E., MacKinnion, J.M. and Reedy, V.R., 1986: Crop simulation models in agronomic systems. *Adv. Agron*., **40**, 141 – 208.

Ziervolgel, G., Bithell, M., Washington, R. and Downing, T., 2005: Agent-based social simulation: a method for assessing the impact of seasonal climate forecasts applications among smallholder farmers. *Agric. Syst*., **83**, 1 – 26.