Seasonal forecasts for the Limpopo Province in estimating deviations from grazing capacity

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Abstract

Application of seasonal forecasts in agriculture has significant potential and realized utility. Other sectors that may also benefit from using seasonal forecasts include (but are not limited to) health, hydrology, water and energy. This paper shows that seasonal forecast model data, satellite Pour l'Observation de la Terre (SPOT) dry matter productivity (DMP) data (proxy of grass biomass) along with other sets of data are effectively used to estimate Grazing capacity (GC) over a 12-year test period (1998/99-2009/10) in Limpopo Province. GC comprises a vital consideration in agricultural activities, particularly for a province in South Africa like

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Limpopo, due to its varying climate. The Limpopo Province capitalizes on subsistence farming, including livestock and crop production. Grazing should thus be regulated in order to conserve grass, shrubs and trees thereby ensuring sustainability of rangelands. In a statistical downscaling model, the predictor is the 850 geopotential height fields of a coupled ocean-atmosphere general circulation (CGCM) over Southern Africa to predict seasonal DMP values. This model shows that the mid-summer rainfall totals are important predictors for the November through April (NDJFMA) DMP (as well as grazing capacity) growing season. Forecast verification is conducted using the relative operating characteristics (ROC) and reliability diagrams. The CGCM model shows skill in discriminating high and low DMP (GC) seasons in the Limpopo Province, as well as reliability in the probabilistic forecasts. This paper demonstrates the development of a tailored forecast, an avenue that should be explored in enhancing relevance of forecasts in agricultural production.

Keywords: Grazing capacity; Limpopo Province; Remote sensing; Seasonal forecasts

1 Introduction

Rangelands are essential for livestock grazing purposes in South Africa. It is thus important to estimate or forecast veld conditions in order to regulate grazing patterns in preparation for an approaching season. Grazing should thus be regulated in order to conserve grass, shrubs and trees, thereby ensuring sustainability of rangelands. In South Africa, the existing national grazing capacity (GC) potential map estimate was developed in 1993, and updated in 2005 using National Oceanic and Atmospheric Administration Advanced Very High Resolution Radiometer (NOAA-AVHRR) MODIS satellite data (Department of Agriculture, Forestry and Fisheries, 1993). It is important to note that grazing capacity is sometimes referred to as carrying capacity. Largely due to changing land use practices (as well as changing data availability), there exists a clear need to create a new capacity estimate through the use of current available data including climate and forecast data, remote sensing, etc.

For Limpopo, a province shown to be prone to recent degradation, developing such an updated GC product (adjusted monthly according to seasonal forecasts and monitoring data) may help support more sustainable agricultural practices (De Leeuw and Tothill, 1990; Stroebel *et al*., 2008; Palmer and Bennet, 2013). Mid-summer climatic characteristics, including predicted characteristics, provide a good estimate of how the entire rainfall season may behave for Limpopo Province (Landman *et al*., 2012). Decision making in the agriculture, hydrology, health, water and energy sectors is largely influenced by climatic conditions therefore seasonal forecasts should be incorporated into planning and management strategies. GC over the Limpopo Province is strongly linked to seasonal rainfall totals, and, since seasonal forecast skill over the area is relatively high compared to other areas over South Africa, employing seasonal forecasts over the region should lead to positive and useful results to improve agricultural management and operations (Malherbe *et al*., 2014). It should be noted, however, that climate models have caveats which may affect results negatively (Sivakumar, 2006; Landman & Beraki, 2012).

This paper focuses on estimating GC in the Limpopo Province where convective systems are responsible for rainfall received mainly in the summer season from October to April. Unsustainable grazing may lead to severe impacts on the environment, such as land degradation, erosion and depletion of non-renewable natural resources (De Leeuw and Tothill, 1990; Pickup *et al*., 1994; Calvao and Palmeirim, 2004; Kurtz *et al*., 2010). Several factors contribute to land degradation; including erosion, soil compaction, salinization, as well as, and linked to human activities – dating back to land policies – leading to overgrazing (Archer, 2004;

Vanderpost *et al*., 2011). Current and former communal grazing areas in the provinces of KwaZulu-Natal, Eastern Cape and Limpopo have suffered effects of sharing land for settlement, farming and grazing – later often resulting in inappropriate land use practices. The latter effects have contributed to the intensity of land use exceeding the productive potential. While it is sometimes difficult to indicate the key causes of land degradation, it remains increasingly problematic and a threat to food and livelihood security, hence optimal utilization, aided by estimates of grazing capacity, of rangelands is vital (Pickup *et al*., 1998; Kurtz *et al*., 2010).

GC is defined as the number of herbivores/livestock that the natural rangeland can support without the addition of external feeding sources. Such sources can potentially result in degrading the environment (De Leeuw and Tothill, 1990; Hayward *et al*., 2007). It is clear that the GC of a rangeland should be estimated – ideally before any livestock is introduced therein – in order to be able to manage and monitor its sustainability, acknowledging limitations on such measurement (Roe, 1997; Archer, 2004). The latter has, however, not always been the case in South Africa as farmers and pastoralists in certain areas used to overstock rangelands (Wessels *et al*., 2007a). The assumptions behind this notion generally considered climate vagaries to be solely responsible for land degradation, hence overlooking the contribution made by humans and animal activities (De Leeuw and Tothill, 1990; Wessels *et al*., 2007b).

2 Study area

Limpopo Province is located in the most northern parts of South Africa, north of 22-25°S and west of 26-32°E (Fig. 1). The region is semi-arid, covers approximately 129 910 km^2 of land and topography ranges from mountainous to flat land and the climate is hot and dry. In summer, the days and nights can be extremely hot with average maximum temperatures of 27˚C, but

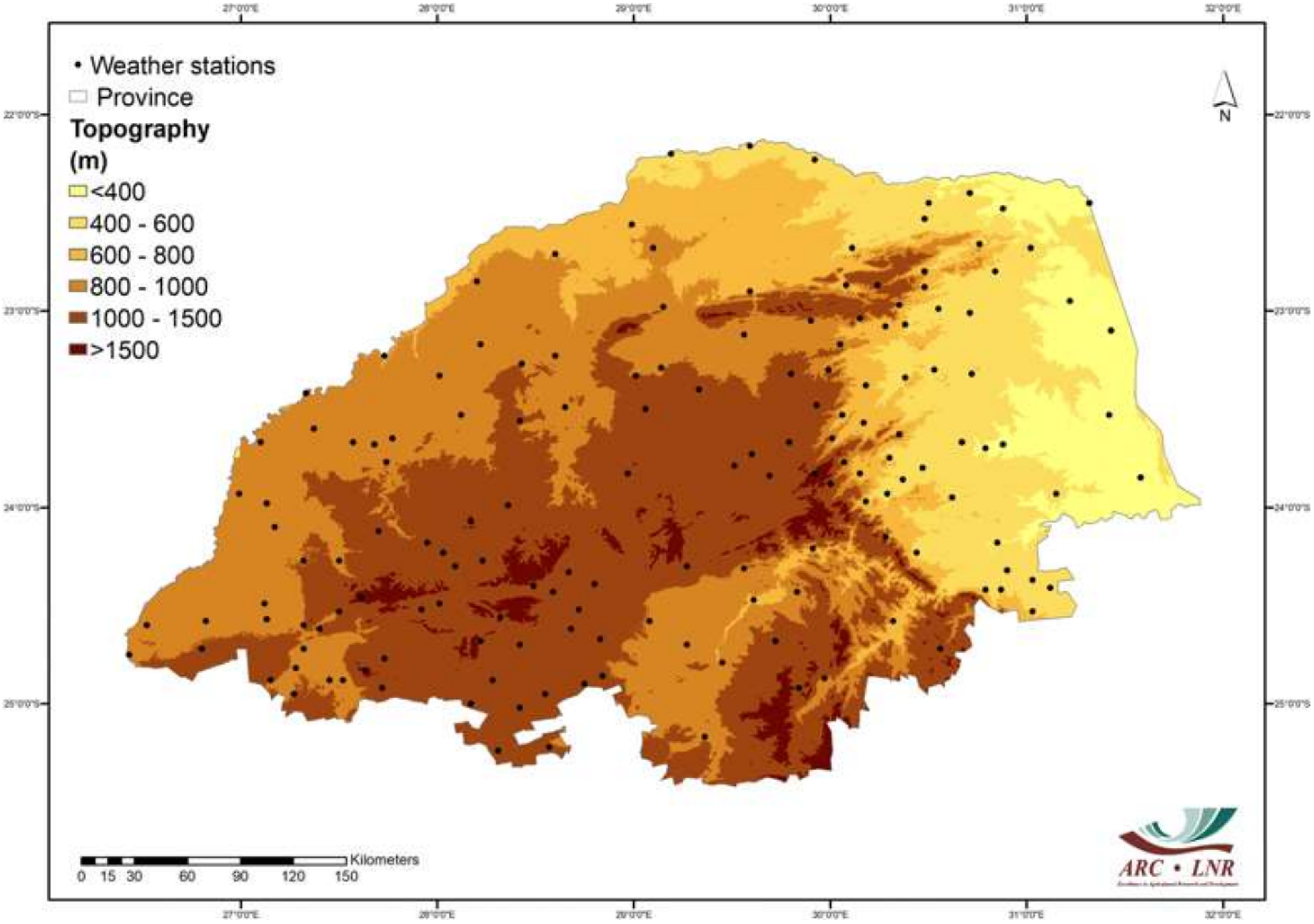

Fig. 1. Map of the Limpopo Province showing the topography of the Province and the location of weather stations used in the study

winter is mild with average minimum temperatures of 18˚C (Schulze, 1965). Limpopo is a summer rainfall region, with an annual rainfall of less than 350 mm in the lower lying areas, while the higher lying Drakensberg escarpment sees more than 1000 mm in certain places. Most parts of Limpopo are rural, supporting extensive livestock farming and ranching operations with irrigated crops (Vogel *et al*., 2010). These areas are in turn vulnerable to climate variability and extreme events (Moeletsi and Walker, 2012). The latter increases rangelands' vulnerability to overgrazing, causing land degradation to worsen in many parts of the province.

Grazing routines in the Limpopo Province, in certain areas, may not be in place or monitored – compounding problems of degradation. It is thus important that GC and deviations thereof for the province be estimated in order to assist in scheduling grazing patterns for farmers, planning for future seasons – based on forecast model outputs and looking into options of land restoration programmes. How the latter is implemented requires a tactful and participatory approach to farmers and local municipalities, including capacity building.

3 Methods

In the past, estimation of GC used to be time consuming and costly. Nowadays, however, various techniques of estimating GC exist, depending on the specific biome, climatic variability and soil texture (Pickup *et al*., 1998; Xia and Shao, 2008). It is important to note that the use of technology has not, however, rendered null the need for fieldwork in order to collect data. It is true that grazing capacities may be estimated without making use of biomass data, but it is advisable to use concrete biomass data as an indicator of production (Morgenthal *et al*., 2004).

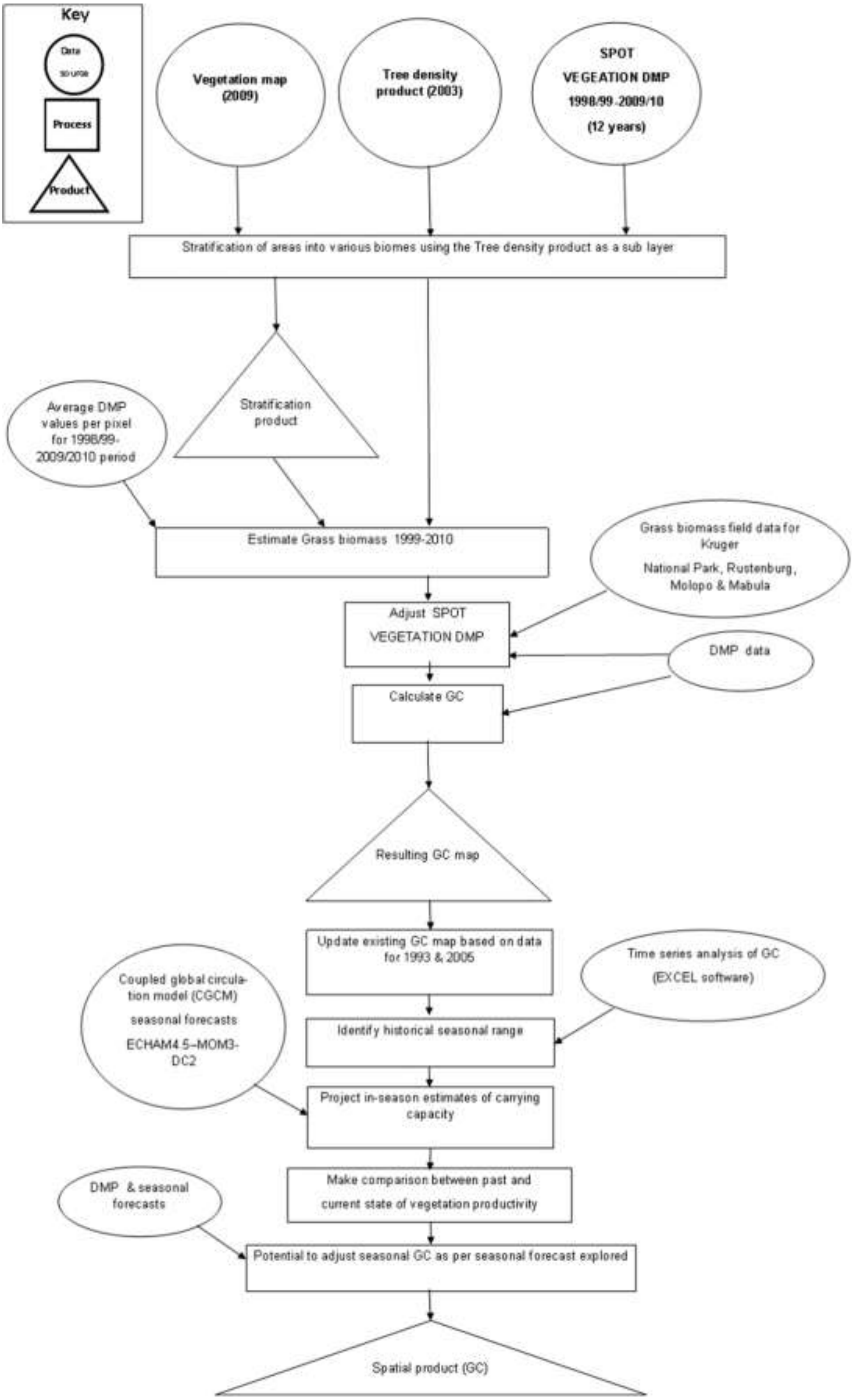

Fig. 2. Flow diagram showing the processes and products involved in estimating GC

Climate data, Remote Sensing (RS) and Geographic Information Systems (GIS) have already been employed for estimating GC, predicting crop yields, climate impact assessment, managing and monitoring of rangelands (Goodchild, 1994; Unganai and Kogan, 1998; Hunt *et al.*, 2003; Prasad *et al.*, 2006; Beye *et al.*, 2007). These techniques have proved successful, time efficient and cost effective (Calvão and Palmeirim, 2004; Joshi *et al.*, 2004; Xie *et al.*, 2008; Becker-Reshef *et al.*, 2010). A range of products, data, and tools are used to estimate GC, but in this study, the application of seasonal forecasts in agriculture is emphasized. We have used a set of methods including seasonal climate forecasts, GIS, Earth Observation System data (EOS) and secondary ground truth data as shown on Fig. 2.

3.1 Tailored forecasts

The Climate predictability tool (CPT) software (Mason and Tippet, 2016) is obtained from the International Research Institute for Climate and Society (IRI) website (http://iri.columbia.edu/). CPT is a statistical prediction and downscaling software that offers the following options: Principal Components Regression (PCR), Canonical Correlation Analysis (CCA), Multiple Linear Regression (MLR) and General Circulation Model (GCM) verification. The CCA option is used in this study since it analyzes linear relationship between two variables – in this case SPOT VEGETATION dry matter productivity (DMP), the representative of GC in this paper, and low-level circulation (850 hPa) of the coupled model. CCA further measures linear combinations of the two variables with maximum correlation, which meets the objective required from CPT.

CPT requires input data in the form of a predictor (typically an output from a climate model) and a predictand (in this case DMP). The domains of interest are selected next in order to represent the predictor domain which covers an area between the equator and 45°S, and 15°W to 60°E and the predictand domain, which covers an area between -22°S and -26°S, and 26°E to 32°E. Statistical downscaling from the climate models to observed data is performed with the CPT in order to represent verification statistics and to identify modes of seasonal-to-interannual co-variability between the predictor and predictand fields during the 12-year period.

3.2 Forecast verification

Verification tests for the forecasts are carried out using relative operating characteristics (ROC) (Mason and Graham, 2002) and reliability (Hamill, 1997, Wilks, 2006) diagrams in order to test the discrimination and reliability attributes of the forecasts. ROC and reliability diagrams are defined and interpreted in more detail in Troccoli *et al*. (2008), Barnston *et al*. (2010) and Wilks (2011), amongst others with an application for South Africa found in Landman *et al*. (2014). Further, hindcasts (re-forecasts) of DMP are generated as probability forecasts using error variances, which are then verified (Troccoli *et al*., 2008). If the ROC score is 1.0 (we want low false alarm rates and high hit rates), then perfect discrimination is achieved, however if the ROC scores are ≤ 0.5, the forecasts show no skill. Reliability diagrams show to what extent forecast probabilities match observed frequencies and show whether or not a forecast system is well calibrated and the level of confidence in the forecasts. When the slope of a weighted reliability regression line lies above (below) the diagonal line of perfect reliability, the forecasts are said to be under-confident (over-confident) − however, if the regression line lies perfectly on the diagonal line then perfect reliability of the forecasts is achieved.

3.3 SPOT VEGETATION DMP data

DMP data are used as a representative of GC in this paper. SPOT VEGETATION DMP for 12 years (1998/99-2009/10) are obtained from the PROBA-V website (http://proba-v.vgt.vito.be/). DMP satellite imagery are produced from a combination of RS and meteorological data from the European Centre for Medium-Range Weather Forecasts (ECMWF). The meteorological data considered in the estimations are solar shortwave radiation and temperature based on the eminent Monteith (1972) model (Nutini *et al*., 2011). Each satellite image represents the maximum value of DMP per month. The SPOT satellite captures high quality global images using the VEGETATION sensor which was launched in 1998, developed by a collaboration between France, European Commission, Belgium, Italy and Sweden (Fraser *et al*., 2000). Although the resolution of SPOT VEGETATION is 1 km, the sensor has numerous advantages such as high temporal resolution and multi spectral bands (Fraser *et al*., 2000; Xiao *et al*., 2002; Bartalev *et al*., 2003). The obtained data consist of DMP dekads (10 day composites) for each month, i.e. 1-10 days; 11-20 and 21 to the last day of the month.

The calculations are based on satellite data per growing season for the years 1998/99-2009/2010 (12 seasons). Products that are used in this study include gridded observed rainfall from Agricultural Research Council - Institute of Soil, Climate and Water (ARC-ISCW), tree density product_2003 (ARC-ISCW databank), vegetation map of 2009 (http://bgis.sanbi.org/vegmap/map.asp), Moderate Resolution Imaging Spectroradiometer (MODIS) Net Primary Production (NPP) (http://www.nasa.gov/) and grass biomass field data. The data are analyzed using the following tools: Earth Resources Data Analysis System–IMAGINE (ERDAS version 14.00) software (http://www.hexagongeospatial.com/), Excel 2013, and the CPT.

4 Results and Discussions

4.1 SPOT VEGETATION DMP and CPT data analysis

In the CPT software, CCA is used to run tests between the coupled model rainfall data and SPOT VEGETATION DMP. The CCA is used to analyze correlation between these variables. The initial test is run using coupled model rainfall (predictor) and DMP data (predictand) from which a positive correlation is found. Largely positive correlations are seen between model rainfall and DMP (Fig. 3). Other variables than rainfall are explored as predictors namely coupled model regional circulation, e.g. 850 hPa data since models are generally more skilful in simulating circulation than rainfall. Four rainfall seasons are chosen after several tests are run in the CPT, which are November-December-January (NDJ), December-January-February (DJF), January-February-March (JFM) and February-March-April (FMA) respectively. Of these four 3-month seasons, DJF low level circulation season is shown to best predict the four DMP seasons i.e. NDJ, DJF, JFM and FMA. DJF is a proxy for rainfall hence it is chosen to be the only predictor for DMP. A cumulative value for all the four 3-month seasons is also tested as a predictand, ultimately showing DJF low level circulation data to be the best predictor of NDJFMA DMP. In this study, probabilistic forecast verification tests are run retroactively for a 6-year period (2004/05-2009/10) to validate CPT output results. The initial training period for retroactive process is 6 years, extended by 1 year after each integration. The graphs presented in this paper are for the NDJFMA season only.

4.2 Ground truth data and Earth Observation data analysis

The ground truth data are used to analyze the relationship between grass biomass and DMP data – by calculating the coefficient of determination (R^2) using linear regression per veld type.

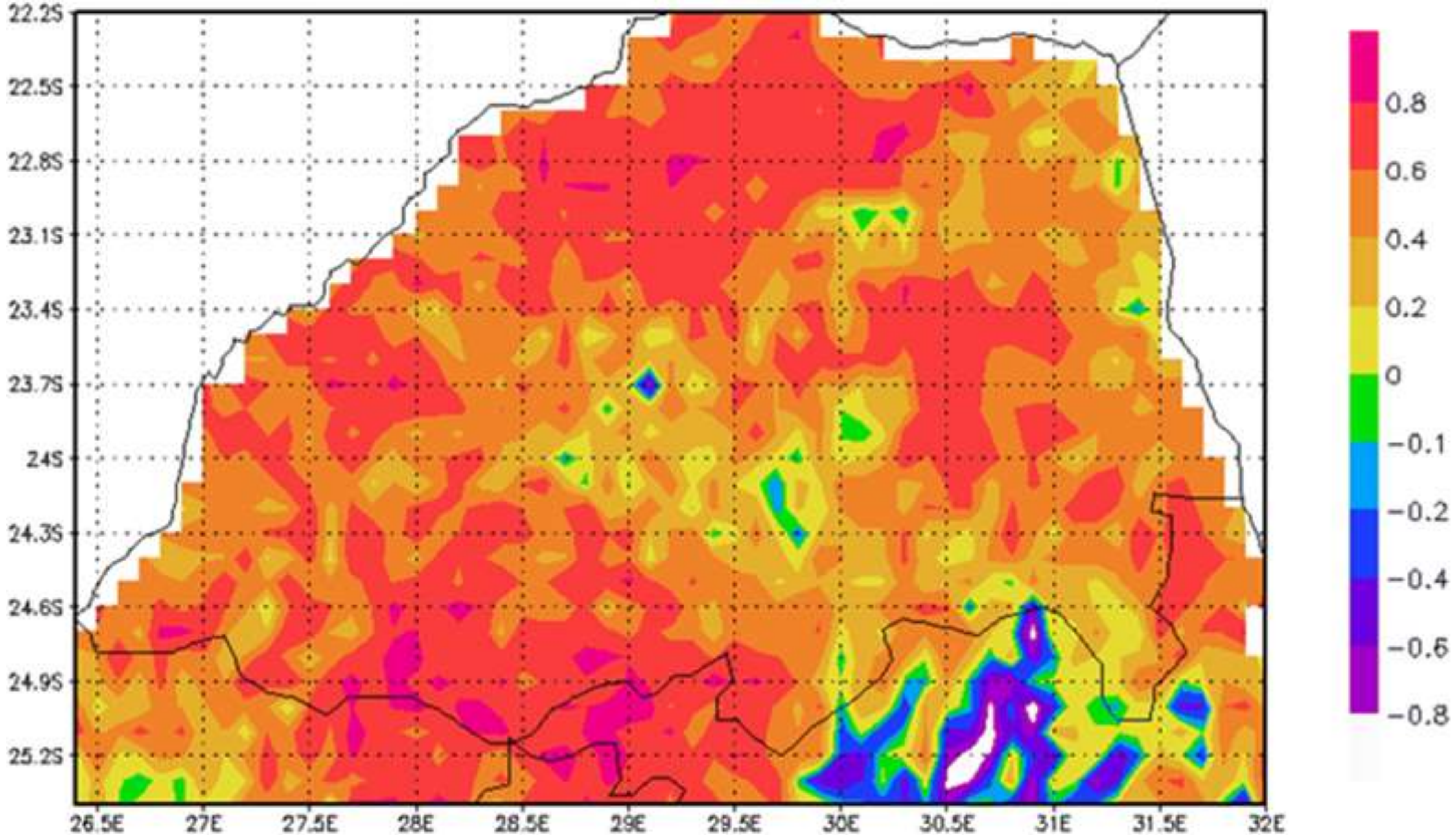

Fig. 3. Spearman's rank correlations for the coupled model DJF rainfall data used as predictor downscaled to NDJFMA DMP values over the Limpopo Province spanning the 12-year period

The veld types that show high R^2 values signify a positive relationship between DMP and ground truth data. Fig. 4 shows that what we observe on the ground is actually what can be seen in RS, therefore in this study RS is effectively used in estimating DMP. The vegetation map is used to delineate the various vegetation types into 6 veld types in the Limpopo Province as follows: Mopane, Lowveld, Azonal, Alluvial, Zonal and Intrazonal and Central bushveld type. Subsequently, the tree density product is used to categorize the data into low (0-10%), medium (10-20%), high tree density (20-30%) and extremely high (30% and above) in order to obtain equations per respective veld type. These equations are later used when estimating GC in GIS models.

4.3 Estimation of GC

Finally, GC is estimated for the 12-year period per season (1998/99-2009/10) using ERDAS software where GIS models are built to estimate grass biomass. GC is estimated using an equation and expressed in hectares per large stock unit (ha/LSU). GC maps are drawn showing vegetation in different rainfall seasons spanning the 12-year test period (Fig. 5). The results show positively biased values for the 12-year period. The positive bias in the GC estimate may be related to the collection of Disc Pasture Meter data – as the grass may include remnants of the previous growing season (Morgenthal, 2015: Personal communication). Furthermore, the period during which the GC estimate is made for the current study is characterized by higher rainfall than the period during which the earlier estimates (reference to the 2005/1993) are made. Moreover, the current study is more focused on identifying potential deviations before summer than calculating the actual long-term average. It is crucial to have an estimate of GC

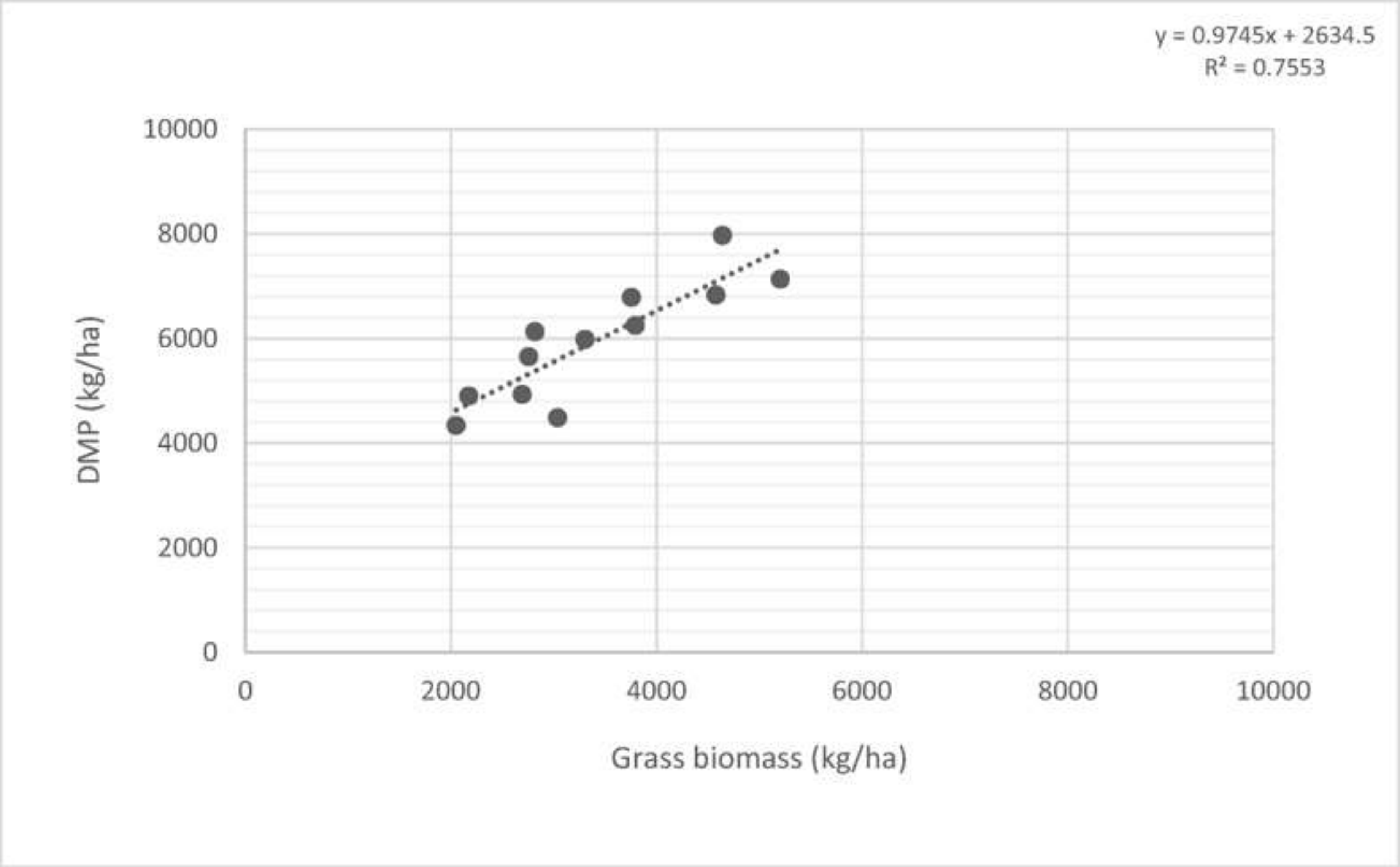

Fig. 4. Relationship between average NDJFMA DMP and grass biomass for all veld types (*n* = 12). The *x*-axis shows grass biomass whilst the *y*-axis shows DMP

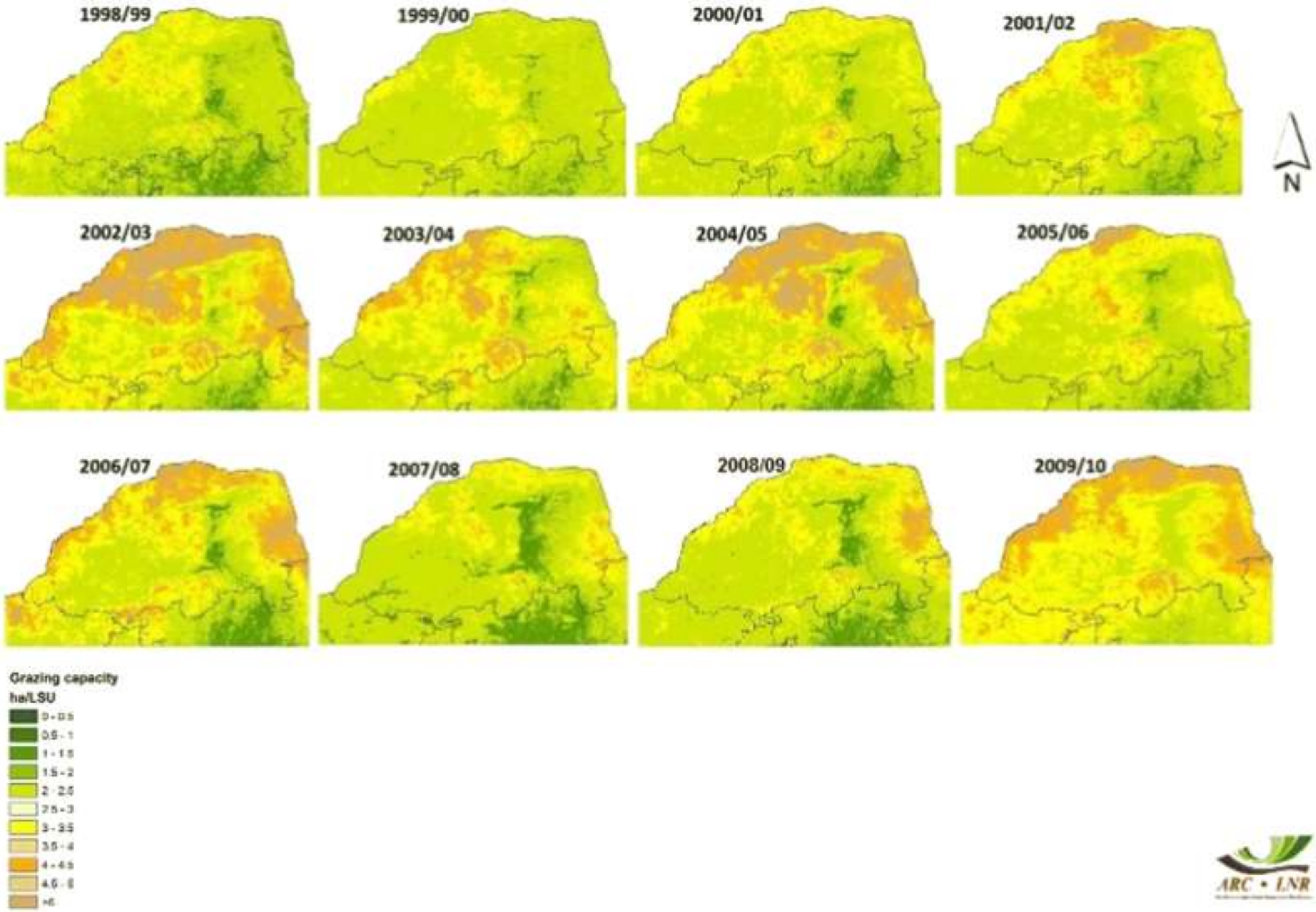

Fig. 5. GC maps per season for the 12-year period, 1998/1999–2009/2010 in the Limpopo Province

and to know the deviation from the capacity prior to and during a growing season due to climate variability.

Fig. 6 shows that the coupled model regional circulation (850 hPa) can predict GC over the Limpopo Province. These positive results therefore prove the prospect of updating the GC product monthly during the growing season in Limpopo Province.

Fig. 7 shows all three ROC curves (above-, below- and near-normal) lying on the left of the diagonal line. The below-normal curve lies to the left of the diagonal, whilst the near-normal lies closely to the diagonal line. The coupled DJF model thus shows good discrimination of the above- and below-normal GC seasons from other seasons, but its discrimination of the near-normal GC seasons is poor. The reliability diagram (Fig. 8) shows higher GC probabilities for both high and low GC seasons, therefore the forecasts are under-confident. The forecast probabilities for high and low GC seasons show high reliability in the forecasts during NDJFMA.

5 Conclusions

This paper shows that seasonal forecasts may successfully be used in agriculture to estimate GC and can thus be explored for more varied uses in different sectors. The ARC-ISCW is represented in the quarterly meeting of the National Agrometeorological Committee. Here,

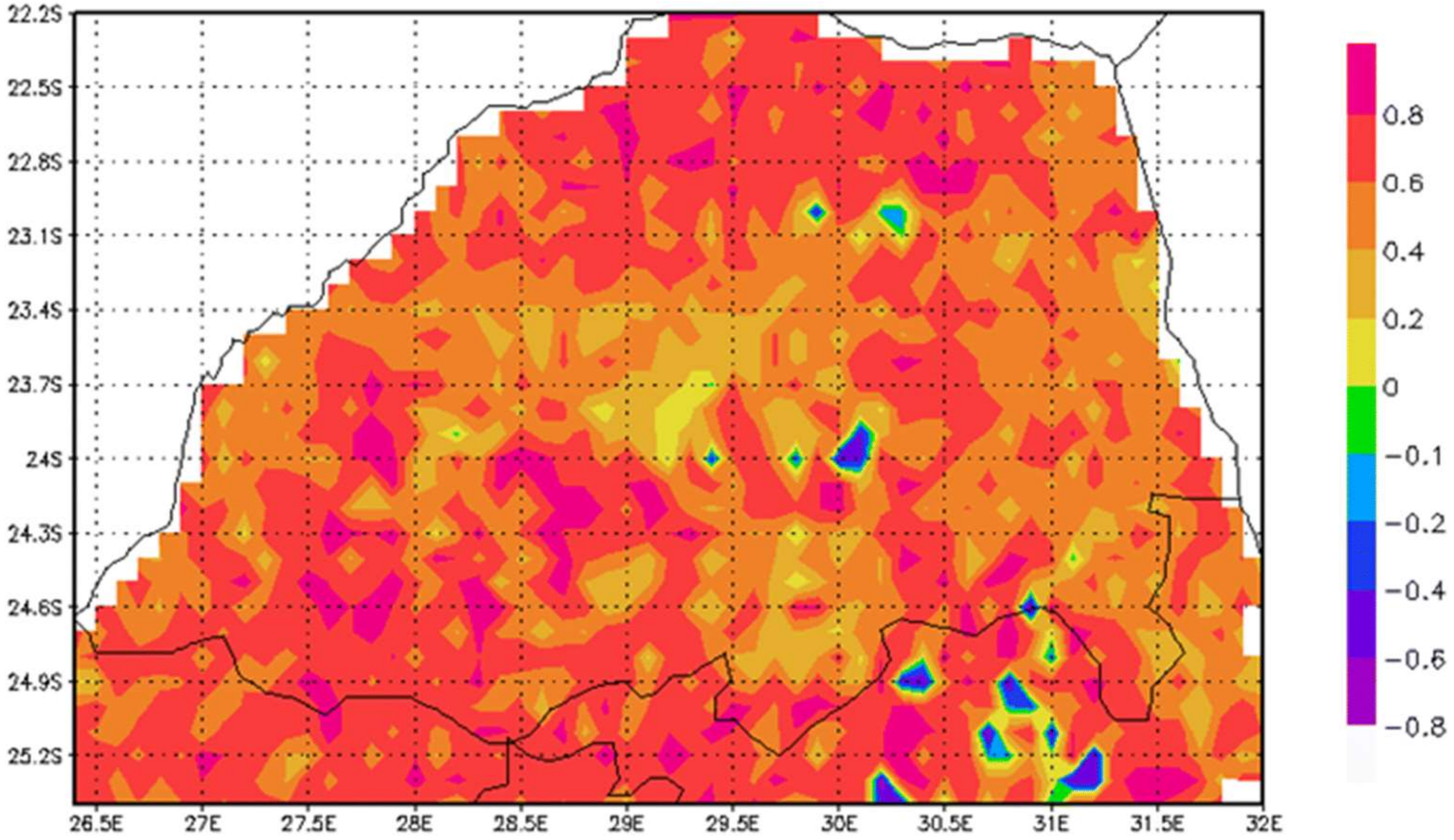

Fig. 6 Spearman's rank correlations for the coupled model DJF 850 hPa geopotential heights downscaled to NDJFMA GC values over the Limpopo Province spanning the 12-year period

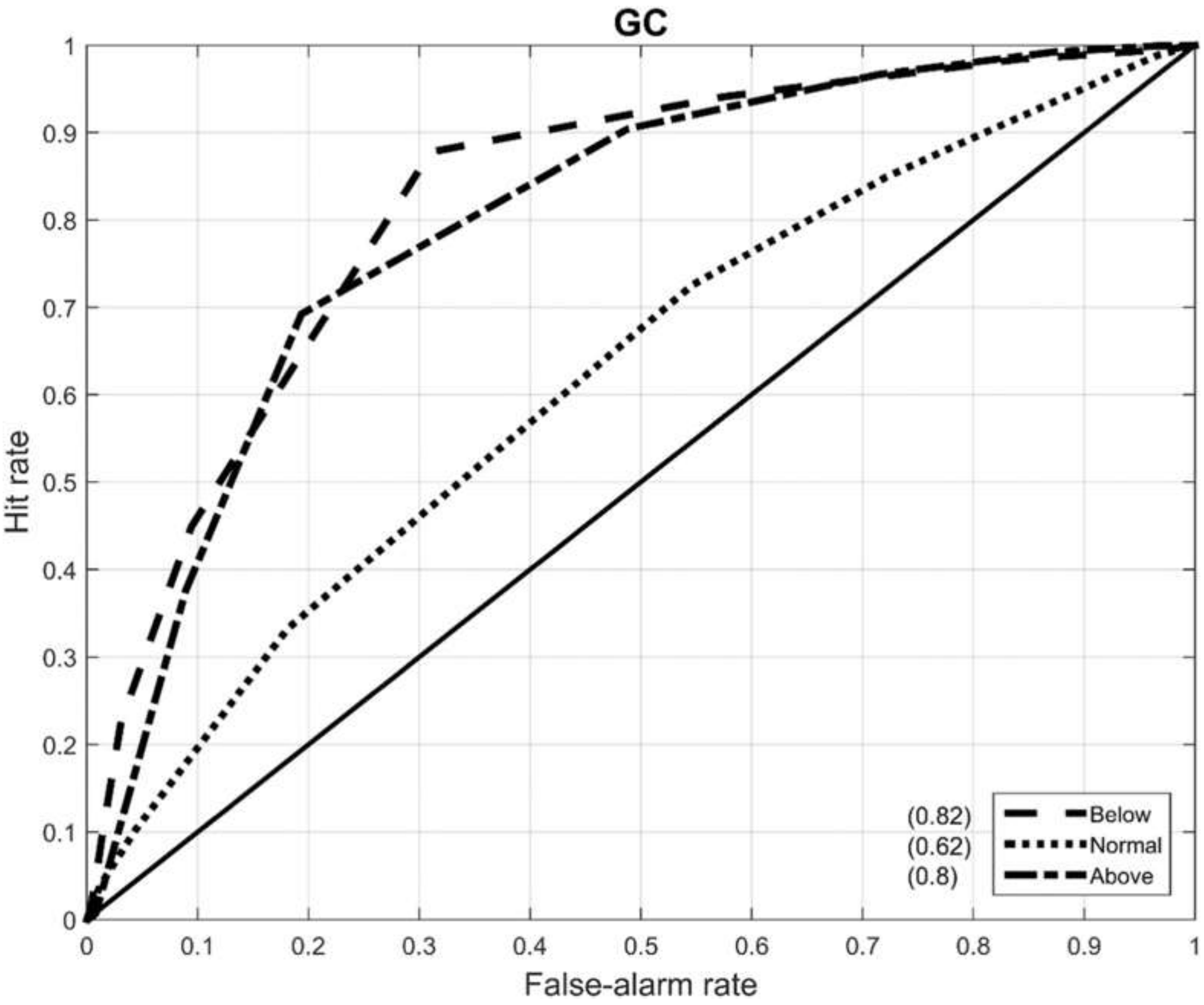

Fig. 7 ROC curves obtained by retroactively predicting GC probabilistically over 6 years (2004/2005–2009/2010) for the NDJFMA season for above-, below- and near-normal tercile values of the climatological record. The areas underneath the respective curves are shown in parenthesis on the figure. The *x*-axis shows false alarm rate, whilst the *y*-axis shows hit rate

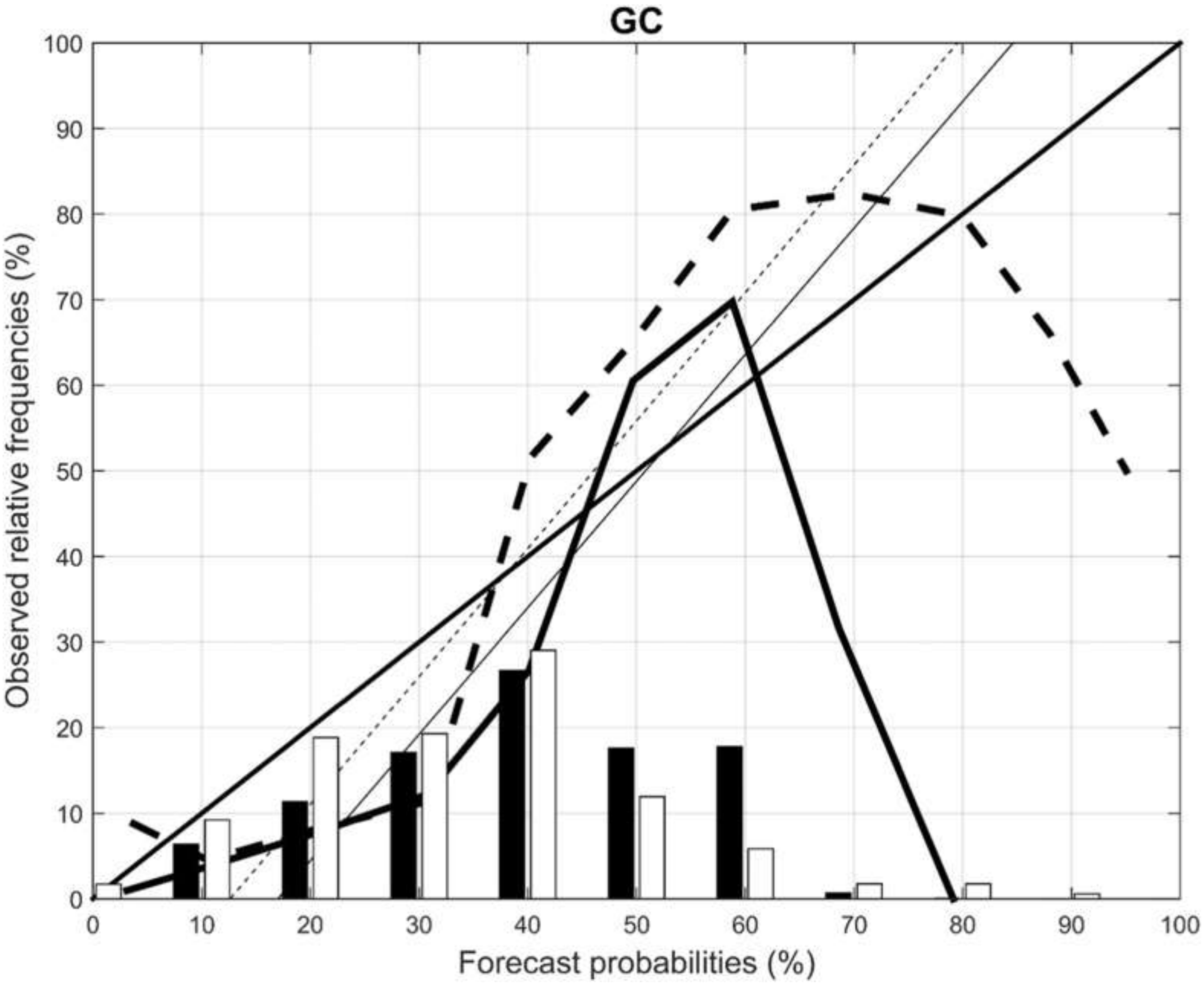

Fig. 8 Reliability diagram and frequency histogram for above- (66th tercile) and below- (33rd tercile) normal GC values obtained by downscaling the coupled model's low-level circulation. The thick black diagonal line represents perfect reliability. The thick (dashed) black curve and the thick (white) bars represent high (low) GC category. The thin solid black (dashed) line is the weighted least squares regression line of the high (low) GC reliability curve

various monitoring and early-warning products and messages are assembled and combined in an advisory that is distributed through the Provincial Department of Agriculture (DOA) to the extension service structure. The deviation from GC, as derived in this study, will play an important role in providing practical advice to livestock farmers in the north-eastern parts of South Africa. The motivation to have undertaken this study in the first place is to assist the Limpopo DOA with managing of rangelands and controlling grazing pastures on a seasonal to inter-annual basis. Seasonal forecasts (compiled from coupled global circulation model output) are employed to analyze predictability of DMP over the Limpopo Province. These models can produce probabilistic forecasts for favourable or unfavourable grazing in order to advise farmers regarding the available pasture in the coming season. As indicated earlier, such information provided to all relevant parties may guide good management practices, supporting proactive adaptive management. Where seasonal forecasts display sufficient skill, an opportunity is presented where monitoring data can be used in conjunction with such forecasts to make assumptions regarding expected deviations from a long-term average recommended GC.

A recent scenario would be the current 2015/16 El Niño, characterized by drought and heat stress conditions, that has negatively impacted the livestock sector across South Africa with the following provinces: KwaZulu-Natal, North West, Free State, Limpopo and the Northern Cape classified as disaster areas. The costs for drought relief are an imminent setback to the country’s finances, especially for the above mentioned provinces. However, if the described GC system had been in place prior to the 2015/16 El Niño drought, agricultural advisory could have guided livestock farmers with precautionary measures to minimize loss and damage, as well as finding cost effective means of obtaining supplementary feed for livestock as well as reducing the size of livestock herds. GC would have been estimated by substituting the relevant inputs to estimate GC. The GC maps can as a result of this research be produced operationally and adjusted during a growing season. ROC and reliability diagrams are used for forecast verification and the results show that CGCM has skill discriminating above- and below-normal GC seasons. Reliability of the probability forecasts is good, showing underconfidence for both high and low GC thus these results can be used to warn farmers of approaching high and low GC conditions.

The need for tailored forecasting in the agricultural sector should not be overlooked. The use of these forecasts for grazing can potentially minimize overgrazing, resulting in sustainable veld maintenance. The uptake of modelling and seasonal forecasts by farmers and decision makers remains, however, challenging. More effort needs to be channelled towards reaching out to farmers and communities by providing interactive training sessions focusing on seasonal forecasts and their use in agricultural production. Indigenous methods of weather forecasting and GC estimations are also potentially valuable topics to investigate. However, unavailability of documentation with regards to empirical methods, their implementation, results and/or verification remains a challenge. Finally, the technique may be improved by working from a more detailed baseline GC product. For future studies, more field data (30 years or more) should be acquired, together with relevant satellite data, to allow for an optimal correlation time period. More field data could potentially yield improved results as there would be more data to be used for verification tests.

Acknowledgements

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