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# Irrigated winter wheat yield forecast using remotely sensed vegetation indices at field level, in Matobo district of Zimbabwe

Bright Chisadza [a,1], Phibion Chiwara [a], Sethi Sibanda [a], Onalenna Gwate [a], Webster Gumindoga [b]

[a] *Lupane State University, Lupane, Zimbabwe*
[b] *University of Zimbabwe, Harare, Zimbabwe*

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**Abstract**

Crop monitoring and yield forecasting is a crucial step in addressing food security challenges. This is particularly important for cereals such as maize and wheat which are grown at large scale and constitute the main staple diet for many regions. While, consumption of bread and other wheat products has been on the increase, the national wheat production has been on the decline. Therefore, wheat yield forecasting is vital for providing advance planning on imports to meet the production deficit. This study sought to develop a winter wheat yield forecast model. Observed winter wheat yield data was collected from ARDA farm records for 3 years 2016-2018. Sentinel 2 imagery data was used to extract NDVI values coinciding with the centre-pivots where winter wheat was growing. Maximum NDVI data at anthesis growth stage and observed wheat yield data were regressed to develop a predictive equation. The two datasets were correlated ($R2 = 0.8$, $p < 0.001$). The developed algorithm was used to predict yields and validated using observed yield data. The root mean squared error was 0.53 tons $ha^{-1}$ when averaged observed yield was 6.8 tons $ha^{-1}$. Therefore, the algorithm successfully reproduced observed yields indicating that SENTENEL data could be confidently used in winter wheat yield forecasting at field level. Lack of historical observed yield data and satellite imagery from SENTINEL 2 hindered adequate analysis for longer time frames. The model needs to be further tested as more SENTENEL data accumulates.

*Keywords:* NDVI, Remote sensing, SENTINEL 2**,** Wheat yield, forecasting model.

## 1. Introduction

Agriculture plays an important role in the supply of cereals. The potential for expansion of agricultural land, however, is limited. Increased production of biofuels, land degradation, volatile grain markets, limited arable land and water resources, and extreme weather events, such as, severe droughts and floods present global agricultural production challenges (FAO, 2017). Accordingly, increasing agricultural production efficiency is an essential way of satisfying the future food demand. As the human population is projected to reach 9 billion by 2050, cereal demand is expected to rise (Vermeulen *et al.*, 2010). The lack of access to food in the past has resulted in hunger, poverty, and conflict. As such, food security remains at the forefront on the international agenda. Consequently, crop production is increasingly demanding reliable, accurate and comprehensive agricultural intelligence. Reliable crop yield forecasts play a significant role in regulating markets and anticipating market imbalances, developing agricultural policies and mitigating food shortages efficiently.

[1] Corresponding author. *Email addresses*: bchisadza@lsu.ac.zw, brightate@gmail.com (B. Chisadza); pchiwara8@hotmail.com (P. Chiwara); sethilana@gmail.com (S. Sibanda); onalennag37@gmail.com (O. Gwate)

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