AJLP & GS
African Journal on Land Policy and Geospatial Sciences

e-ISSN : 2657-2664, Vol. 5 Issue 4 September 2022

https://revues.imist.ma/index.php/AJLP-GS/index

https://doi.org/10.48346/IMIST.PRSM/ajlp-gs.v5i4.33050 Category of the manuscript: Review paper

Received in: June 16th, 2022 | **Revised in:** August 18th, 2022 | **Accepted in**: September 4th, 2022

REVIEW OF WHEAT YIELD ESTIMATING METHODS IN MOROCCO

[1]Adra Idrissi, [2]Samir Nadem, [3]Abdelghani Boudhar, [4]Tarik Benabdelouahab

[1] Georesources and Environment Laboratory and Remote Sensing team, i_adra2000@yahoo.fr
Faculty of Sciences and Technology, Sultan Moulay Slimane, University Beni Mellal. Morocco

2 Georesources and Environment Laboratory, Faculty of Sciences and Technology, Sultan Moulay Slimane, University Beni Mellal. Morocco
samirmellal@hotmail.com

3 Center for Remote Sensing Applications (CRSA) , Mohammed VI , Polytechnic University , Ben Guerir, Morocco
ab.boudhar@usms.ma

4 Natural Resources and Environment Department, National Institute of Agronomic Research, Rabat, Morocco
tarik.benabdelouahab@gmail.com

ABSTRACT

Context and background:

Wheat is one of the oldest crops in the world and has always been one of the most important staple foods for millions of people around the world, especially in North Africa, where wheat is the most dominant crop. The importance of wheat yield estimation is well known in agricultural management and policy making at regional and national levels.

In semi-arid areas such as the case of Morocco, an operational cereal yield estimating system that could assist decision makers in planning annual imports is needed.

In some developed countries, several effective tools are now available to monitor crops and optimize farm-level decisions by combining crop simulation models with seasonal forecasts. However, few tools are used to effectively manage crops at the farm level to cope with climate variability and risk.

Goal and objectives:

The following article presents an overview of current methods used for wheat yield estimation in the world and in Morocco

Methodology:

Various sections describing traditional methods, simulation models, and remote sensing. Then a section is devoted to the estimation methods used in Morocco and their efficiencies.

Results:

This article is very useful for researchers working on this subject because it brings together all the methods of estimating wheat yields worldwide and classifies them into categories and then situates Morocco, which is a relevant example of a North African country that is a leader in the use of spatial techniques and in the monitoring of crops, and wheat in particular

Keywords

Wheat yield, review, estimating wheat, remote sensing, crop modelling

1. INTRODUCTION

Wheat has been the staple food of the major civilizations of Europe, Western Asia and North Africa for over 8,000 years (FAO, 2022) and continues to be the most important source of food grain for humans. It is the dominant staple food in North Africa and West and Central Asia, providing up to half of all calories consumed in the region. It's consumed by 2.5 billion people in 89 countries (CIMMYT, 2018).

Today, wheat is grown annually on 215 million hectares spread from Scandinavia to South America and across Asia, making it the most widely grown crop. In addition, nearly 50 billion US dollars' worth of wheat are traded each year in the world (FAO, 2002)

According to the FAO; In 2050, the world's population will reach 9.1 billion people, 34% more than today, and almost all of this population increase will occur in developing countries (Le Mouël & Forslund, 2017) ; The world would then need about 840 million tons of wheat, compared to its current production level which is 642 million tons, of course without taking into account the needs of animal feed and taking into account the negative effects of climate change on wheat production.

Thus, it is becoming increasingly important for scientists and policy makers to be able to estimate cereal yields at the regional and national levels in order to plan their annual imports and improve their sector development strategy (Basso et al., 2013).

There are a multitude of techniques for predicting crop yields, both in the scientific literature and in practical applications.

Bruno Basso et al in 2013 prepared a review paper on Review of Crop Yield Forecasting Methods and Early Warning Systems" in which he inventoried all the existing methods of crop yield forecasting and early warning systems as part of the overall strategy to improve agricultural and rural statistics worldwide (Basso et a, 2013). Next, Bernhard Schauberger et al in 2020 presented in his review on local to regional yield forecasting approach a panoptic of existing and mostly successful approaches to forecasting yields weeks or months before harvest, covering almost the entire globe and a wide range of crops, methods and scales. He also described available weather data, satellite products, and crop masks that facilitate yield forecasting. He chose to include a compilation of weather and remote sensing data because of their importance in forecasting. He also included a compilation of crop masks because they are important for scaling up locally effective forecasting techniques to larger areas. where the potential for confusion due to other crops is significant (Schauberger et al., 2020)

In this study, we certainly draw on these two important studies but we will focus on wheat cultivation and not on all crops as it is the case in other reviews.

In addition, in this paper, we will summarize all the wheat yield estimation methods internationally and try to categorize them and study their performance and highlight the operational systems for wheat yield estimation.

Then, we will reserve a session to the methods of wheat yield estimation at the level of Morocco which is a country in the north of Africa characterized by its arid to semi-arid climate especially at the level of the central zone of the country, and which is of cereal vocation.

2. WHEAT YIELD ESTIMATING METHODS IN THE WORLD

First of all, it is necessary to differentiate between estimation and forecasting of the crop. According to Bruno Basso et al in 2013, the estimation is done after the harvest while the forecast is done before the whole crop is harvested(Basso et al., 2013).

Referring to the literature, It can be said that there is a wide range of techniques for estimating and forecasting crop yields with different degrees of accuracy (Basso et al., 2013; Basso & Liu, 2019; Schauberger et al., 2020). Thus, they can be grouped into three broad categories according to the methods used and the data sources:

1. Traditional methods based on field surveys known as "**Crop cutting experiments** “
2. Methods based on simulation models of the crop from previous data and especially climatologically data (**CSM**);
3. Methods based on remote sensing (**RS)** either directly from indices or in combination with crop simulation models.

2.1. methods based on "crop cutting experiment" surveys

In many countries, crop yield estimation still relies on the technique known as "crop cutting experiments" which are based on traditional approaches of field data collection and reporting. These data are often time-consuming to obtain, costly as they require many surveyors and equipment, and subject to significant errors due to incomplete data. Generally, field observations are incomplete, leading to uncertain estimation of crop area and yield assessment **(**Qader et al., 2018**).**

2.2 crop simulation models (CSM)

Crop simulation models (CSMs) are computerized mathematical simulations of crop growth, development, and yield as a function of soil conditions, weather, and management practices.

Simulation models can be classified into two general groups: deterministic and stochastic. Deterministic models are characterized by a specific outcome while assuming that all plants and soils in the simulation space are uniform.

Stochastic models take into account the uncertainty associated with the simulations. This uncertainty can arise from spatial variability in soil properties, weather conditions, and other abiotic and biotic factors that are not accounted for a deterministic model. These models are needed when the inaccuracy of the input data is certain. This type of model is closer to the reality of the field, but has not been developed to a level of usefulness for decision making.

Deterministic models are still the most frequently used. These models can be classified into three basic types: statistical, mechanistic, and functional (Basso et al., 2013; Basso & Liu, 2019).

- **Statistical models** have historically been used to estimate crop yields and specifically wheat; average yields for large areas and over many years have been regressed over time to reveal a general trend in crop yields. However, the results of these types of models cannot be extrapolated over time and space due to the variation in soil and climatic conditions not considered by these types of models; Statistical models on the other hand can provide a lot of information about previous yields and historical influences and can be used to inform other types of models (Safir et al., 2008)

- **Mechanistic models** have been developed to simulate photosynthetic processes in plants and soil to simulate specific outcomes such as light interception, CO2 uptake, respiration and biomass production; biomass distribution in different plant organs, and CO2 loss during respiration. Mechanistic models are rarely used to solve problems. Rather, they are used for academic purposes to better understand specific processes and interactions(Basso et al., 2013)
- **Functional models**: These models use less input data than mechanistic models, making them simple and more useful Functional models use daily inputs of precipitation, temperature, radiation, and irrigation, and when properly tested, can provide an appropriate level of detail to assess many problems affecting agricultural production. Functional type models are now commonly used in decision support systems. CSMs are not only used to predict yield but more importantly to assess the agronomic consequences of climate variability (Shin et al., 2009).

CSMs can range from simple to complex depending on the number of parameters used. Thus, successful applications of a CSM for yield prediction depend on many factors, but the most important is the amount of parameters needed to describe the relationship between the crop, soil, and atmosphere (Basso et al., 2013).

An example of a successful application of CSM is:

- APSIM (The Agricultural Production Systems Simulator) which accurately predicts crop production based on climate, genotype, soil, and management factors, while considering long-term resource management issues. Since its inception twenty years ago, APSIM has evolved into a framework containing many key models needed to explore changes in agricultural landscapes (Berghuijs et al., 2021)
- The SALUS model, described by Basso et al. (2012, 2010) (www.salusmodel.net), is another successful application of a crop simulation model based on a simple web interface.

However, these models, despite their effectiveness, require a lot of data for their parameterization and calibration. The need for calibration can be very large in terms of data which is not applicable to some developing countries (Gommes, R, 1998).

2.3. Remote sensing and wheat yield estimating

With the development of satellite sensors, and the emergence of space-based remote sensing; the need for crop monitoring and surveillance has increased. Indeed, among the applications of Remote sensing comes crop monitoring and forecasting of agricultural production because it can provide data in a synoptic manner, with greater spatial coverage, potentially on a global scale.

In addition, remote sensing can provide objective and timely (and potentially real-time) crop growth data at relatively low and objective frequencies and at relatively low cost (Qader et al., 2018).

Remote sensing data can be used either directly (Vegetation indices), or indirectly (Via combination with general agrometeorological models) or as surrogates for plant measurements (for further processing in models) (Basso & Liu, 2019).

A- Vegetation indices:

Multiple different vegetation indices can be derived from satellite measurement (Wiegand et al., 1991)(Satir & Berberoglu, 2016) summery in table 1;which NDVI represent the most responsive (Shanmugapriya et al., 2019);

The strength of NDVI is that it not only reflects canopy growth but responds sensitively to vegetation dynamics. It also eliminates some of the negative effects caused by changes in irradiance due to changes in solar angles, surface topography and atmospheric conditions (Ren et al., 2008). Although NDVI is the most widely used, it has a number of limitations: First, the value of NDVI is influenced by the luminance of the soil background and may be different even for vegetation with similar biophysical properties (Huete et al., 1985). Second, NDVI is sensitive to atmospheric effects especially in the red band, which is more sensitive to aerosols (Kaufman & Tanre, 1992). Finally, NDVI becomes saturated with high Leaf area index (LAI) values and the quasi-linear relationship between NDVI and LAI no longer holds (Gitelson, 2004).

Table 1:The main vegetation indices used to predict crop yields.

Index	Definition	Calculation	power of the index	Reference
NDVI	Normalized Difference Vegetation Index	NDVI= NIR-RED/NIR+RED	used to quantify vegetation greenness	Rouse Jr, Haas et al. 1974
NDWI	Normalized Difference Water Index	*NDWI*= NIR –SWIR/ NIR + SWIR	less sensitive then NDVI to atmospheric scattering and does not saturate as quickly in high LAI ecosystems	Gao,1996
EVI	Enhanced Vegetation Index	**EVI = 2.5*(NIR - Red) / (NIR + 6*Red - 7.5*Blue + 1)**	Used while reducing the background noise, atmospheric noise, and saturation in most cases.	Huete et al, 1999
SAVI	Soil Adjusted Vegetation Index	SAVI = (B4 − B3/B4 + B3 + L) * (1 − L)	Plant green cover and chlorophyll content	content Huete (1988
GVI	Green Vegetation Index	GVI= (b1*−0.2848) + (b2*−0.2435) + (b3* 0.5436) + (b4*0.7243) + (b5*0.0840) + (b7*−0.1800)	Plant green structure	Mather (1999)
WDVI	Weighted Difference Vegetation Index	WDVI= B4 − Soil line slope * B3	Absolute green cover	Richardson and Wiegand (1977)
PVI	Perpendicular Vegetation Index	PVI NIR,RED= [a 1 (N I R) - R E D + ao] / [l + (a1)^2]$^{1/2}$	Plant chlorophyll content	Thiam and Eastman (2012)
WETNESS	Surface wetness	WETNESS= b1*0.2626) + (b2*0.2141) + (b3*0.0926) + (b4*0656) − (b5*0.7629) − (b7*0.5388)	Surface wetness	Wiegand et al., 1991; Huang et al. (2002) Sawasawa, 2003; Panda et al., 2010).

B: Landsat wavebands, “L” value used as 0.5 in SAVI and soil line and slope defined based on soil reflectance relationship between B3 and B4

B- Agrometeorological models:

Values of biophysical variables derived from remote sensing data obtained during the growing season can be used to improve regional crop yield estimation models(Huang et al., 2015).In fact, the meteorological models used for yield forecasting are mainly based on two variables, temperature and precipitation, which are related to crop yield. These parameters can be easily obtained from satellite measurements and these models are usually a simple regression. One of the earliest examples in which production is predicted using satellite remote sensing and ground-based meteorological observations is the Large Area Crop Inventory Experiment (LACIE) project, initiated in 1974, which used remote sensing to predict wheat production in the major wheat-producing countries (Basso et al., 2013).

Doraiswamy et al (2003) used AVHRR NDVI data as a surrogate input to an agro-meteorological model for wheat yield estimation at two different spatial resolutions in northern Dakota (Paul c. Doraiswamy, 2003) of the same, Kogan et al. (2012) estimated winter wheat yields using AVHRR data.

Another commonly used platform is the Moderate Resolution Imaging Spectroradiometer (MODIS) which offered better spectral and spatial resolution than AVHRR. Both have high frequency observations, but both spatial resolutions are rather coarse (250M to 500 for MODIS and 1km to 4km for AVHRR). Kogan et al. (2013) used MODIS(250m) NDVI values to predict wheat yield in Ukraine (Basso et al., 2013).

Another platform with better spatial resolution (30 m) has also been used for yield prediction purposes is the Landsat Thematic Mapper (Rudorff & Batista, 1990)

Despite the fact that the temporal resolution of Landsat is higher than that of the other two, which may be a problem if frequent observations are required at sensitive stages of crop growth. Nevertheless, Idso et al. (1980) used the concept of crop albedo variations throughout the growing season and, using LANDSAT reflectance data and crop senescence, were able to predict grain yield (Idso et al. (1980).

In summary, remote sensing techniques have been widely used in research for yield prediction but have a limited role in understanding the causes of spatial variability of yields, which makes it unsuitable for developing countries due to their stratified agricultural systems and very small farm sizes (Basso et al., 2013); However, the increased availability of high spatial resolution images such as SENTINEL 2 images makes this technique an interesting alternative for yield forecasting.

3. WHEAT YIELD ESTIMATING METHODS IN MOROCCO

3.1 Importance of agriculture in Morocco

Morocco, is the Northwestern most country in the Maghreb region of North Africa. It has a coastline bordered by the Atlantic Ocean that extends beyond the Strait of Gibraltar to the Mediterranean Sea. It is bordered by Spain to the north, Algeria to the east and Mauritania to the south; Morocco extends mainly between 21° and 36°N, and 1° and 17°W. Morocco covers an area of 710,850 km2 with a population of approximately 37 million in 2020 (according to the latest United Nations projections).

It is characterized by a very different climate depending on the region: Mediterranean in the North, oceanic in the West, continental inland and Saharan in the South. Rainfall generally extends from October to May and decreases from North to South. The average annual rainfall is 318 mm. The average annual temperature is 17.5°C, with average monthly temperatures ranging from 9.4°C (December, January) to 26°C (July, August) (climateknowledgeportal.worldbank.org/).

Otherwise, Agriculture has a considerable impact on the country's economy, contributing nearly 15% of Morocco's GDP **(Gross Domestic Product)** and, combined with the fishing and forestry sectors, employing about 45% of the Moroccan workforce.

Following the example of traditional Mediterranean agricultural systems, the result of the combination of diets and agro-ecological possibilities, the dominant Moroccan agricultural system is characterized by the dominance of cereals, livestock and olive trees, with a dominance of cereals in useful agricultural area UAA (5 Million ha ~55%) (Figure1)

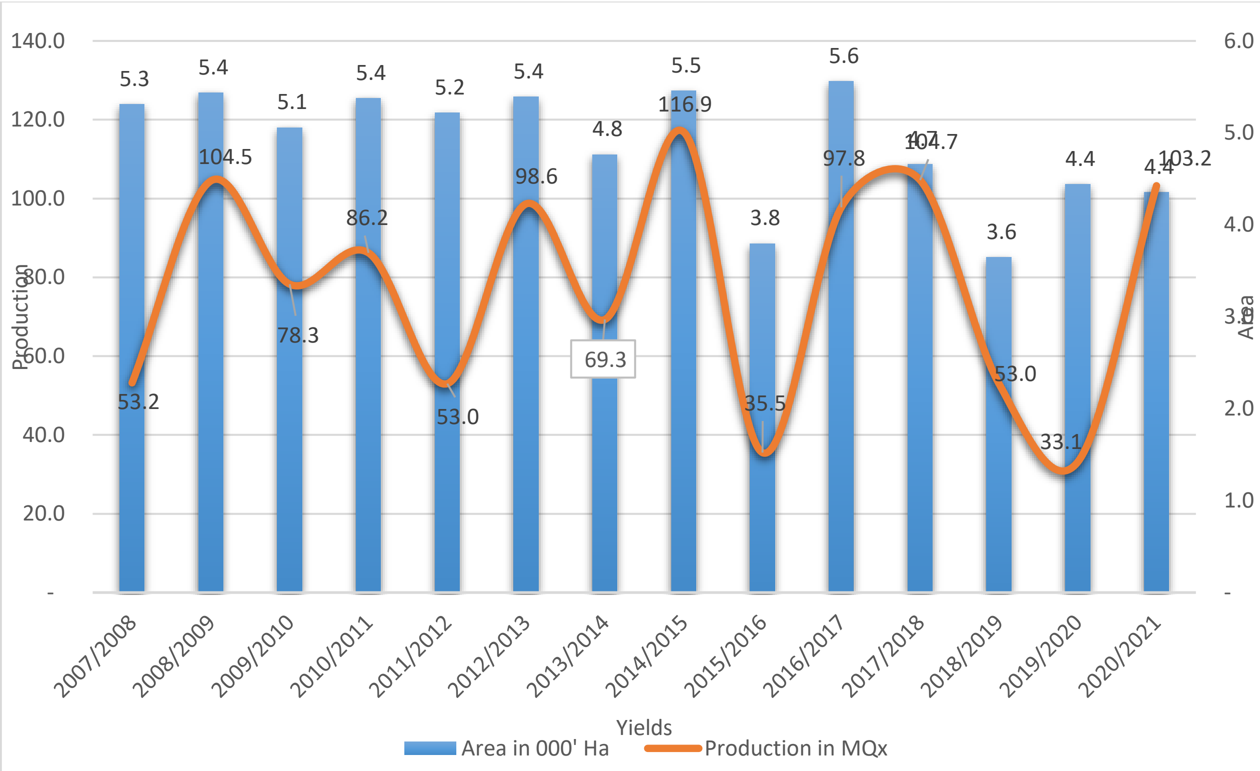

Figure 1:Evolution of the area and production of the three cereal

Source: Ministry of agriculture/Department of statistic

The spatial distribution of cereal production between 2008-2017 shows that the share of provinces with a cereal vocation has been strengthened or stabilized thanks to the "Green Morocco Plan" agricultural strategy (Figure2)

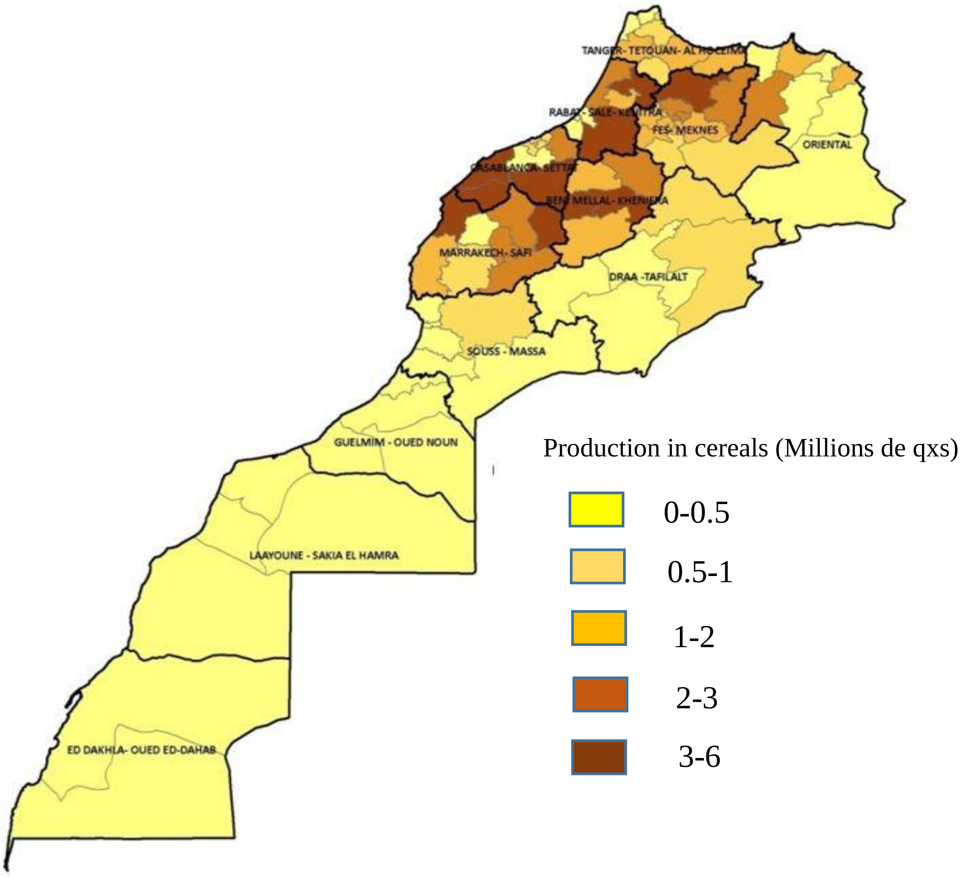

Figure 2: Spatial distribution of production of the three main cereals(2008-2017)

However, national cereal production is strongly influenced by climate change, especially in arid and semi-arid areas, where agricultural production is highly dependent on the amount and spatial-temporal distribution of rainfall (Lionboui et al., 2020).

Thus, spatio-temporal crop yield monitoring systems are widely considered necessary to support agricultural policies, and yield estimating represents an important tool for optimizing crop yield and evaluating crop-area insurance contracts

3.2 Methods to estimate wheat yield in Morocco

Since 1980 and until today, the estimation of the yields of the three cereals is carried out from a field sampling called "areolar", on 3.000 Secondary Survey Units called "segments" carried out during the land use survey. The survey is carried out just before the harvest in a normal year, from June to September depending on the region.

The operation will consist of the identification, recognition and collection of data relating to the observation units called "Segment-points" and which are used as a basis for the measurement of the real yield of cereals, via the sampling and measuring square of 1m^2 placed in these points (Figure 3).

This method named “crop cutting experiment “is operational and allows to estimate the yield of the three cereals in a scientific way from the geostatistical modeling of the segments yields. But, its often time-consuming to obtain, costly as they require many surveyors and equipment (BalaghiI Riad, jleben Mohammed, Tychon Bernard, 2012).

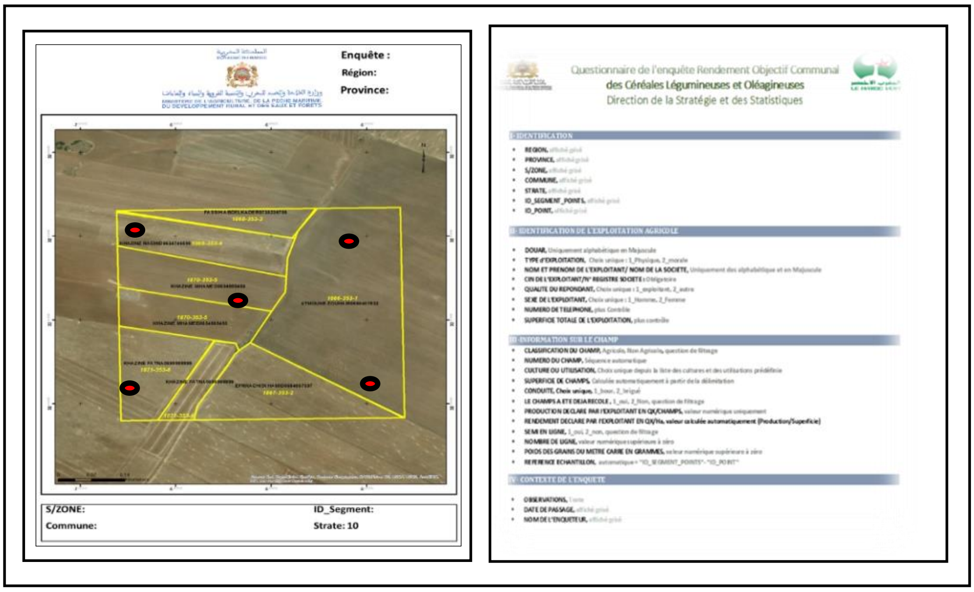

Figure 3: Example of a segment point and its questionnaire

According to Balaghi et al., 2007, there are no operational system for early prediction wheat yield, so he proposed an empirical regression to forecast wheat yield at provincial and National level; this study used NDVI/AVHRR , rainfall and temperature as a predictors (Balaghi et al., 2008)

This proposed model provides early wheat yield forecasts in a rapid and inexpensive manner, it could be considered a promising complement to the survey-based yield assessments applied by the Ministry of Agriculture in Morocco.

With respect to crop models used to estimate yields in Morocco, a review was recently prepared in 2022 based on a systematic method by the team of Terens Epule et al (Epule et al., 2022) and found the following conclusions :

14 key models are frequently used in Morocco of which the most used is the AQUACROP model (20%); The second is CROPSYST (14%), followed by APSIM (12%) and EPIC (12%).

Indeed, AQUACROP was developed by FAO to assess the response of crops to various environmental conditions. This model is characterized by simplicity, accuracy and robustness. It uses a relatively small number of parameters that are explicit and its objective is to describe plant physiological processes and soil water balance with a largely acceptable accuracy.

AQUACROP has made crop modeling faster because simulations can be performed quickly. In contrast, field experimentation typically takes two to three years to obtain initial results.

As for empirical crop models, 13 models have been identified regression based (21.7%) followed by machine learning models (17.4%). Then comes in third place (8.7%) Pearson correlation, data mining algorithms and the modified Penman model (Epule et al., 2022)

Regression models, on the other hand, focus on valuing the relationship between a dependent variable, which is often yield, and the independent variables which are precipitation, temperature, CO2, soil moisture, water table depth, livestock, fertilization and irrigation, among others.

In addition, for both process-based and empirical regression models of crop production wheat is the most studied crop in Morocco due to its importance in the national economy

In terms of conclusion we can say that Crop production is complex and often influenced by several variables not only climatic. However, most process-based models have focused on climatic and biophysical factors such as weather, soil properties and soil management. Some empirical models go further and currently incorporate non-climatic and non-biophysical factors such as poverty rate, literacy rate, and farm income (Araos et al., 2016).

With respect to the use of satellite data for yield estimation in Morocco, it can be said that remotely sensed data have also been used as input to crop simulation models.

In fact, several studies have shown a strong correlation between the Normalized Difference Vegetation Index (NDVI) and cereal yields in Morocco due to the semi-arid climate. Estimation of cereal production based on this index was found to be more efficient (Balaghi, Tychon et al. 2008).

Thus, the first cereal yield estimation system in Morocco, called (CGMS_MA), was implemented based on a combined approach between satellite and meteorological data. Estimates were based on 10-day NDVI/AVHRR, 10-day rainfall amounts, and monthly mean air temperatures (Balaghi, Tychon et al. 2008). This system allowed for yield estimates at the communal and provincial level but is not suitable for estimating yield at the field level as the image used has a lower resolution of 1.1 kilometers at nadir,

Since the year 2000, MODIS images of high resolution (250M) have become available and their exploitation in crop simulation models offer better results. This product offers an excellent opportunity to estimate wheat yield at the regional level and also allows tracking spatial evolution (Benabdelouahab, 2019).

Since 2015, and with the introduction of new satellite sensors with spatial resolutions of 10 m or more have the possibility to track the fields of small farmers. In addition, the improved temporal resolution of Sentinel-2 images (5 days) since the beginning of 2017 and Planet scope (daily) since the end of 2017, now allows the observation of smallholder fields at a much higher frequency.

4. CONCLUSION

Wheat is a crop of great economic importance at both national and regional levels. Thus, its estimation is essential to allow reliable yield forecasts and consequently improve agronomic management planning and adaptation measures, it will also serve to stabilize farmers' income and thus could become an integral component of early warning systems for food security.

In this review, we have first tried to review the different methods of estimating wheat yields worldwide and classify them into three main categories: Traditional methods, crop simulation models, and methods based on spatial remote sensing either directly through image-derived vegetation indices or indirectly by incorporating these data into crop models; This study represented a contribution to situate the state of wheat yield estimation in Morocco, which is a model of North African countries.

In fact, Morocco is an agricultural country with cereal vocation, they occupy a great importance in its agriculture with a surface of more than 5 million ha and more than 50 million quintals of production, its estimation is essential to be able to plan the agricultural strategy of the country;

The department of agriculture until now still uses the traditional method of estimating the yield called " Crop cutting " which is more or less scientific and based on a sample based on segment but remains too costly and tedious. A recent study entitled "A systematic national inventory of crop models in Morocco" where the authors inventoried all crop models used to estimate wheat yield in Morocco; they concluded that there are two type for crop models used:

- Crop models which the most used is the AQUACROP model followed by CROPSYST.
- Empirical crop models which the most used is regression based followed by machine learning models.

They also concluded that crop production is complex and often influenced by several variables not only climatic. However, most process-based models have focused on climatic and biophysical factors such as weather, soil properties and soil management. Some empirical models go further and currently incorporate non-climatic and non-biophysical factors such as poverty rate, literacy rate, and farm income

These cropping models can use remote sensing data as an input to better estimate wheat yield. Thus, the first cereal yield estimation system in Morocco, called (CGMS_MA), was implemented based on a combined approach between satellite and meteorological data. Other studies have used MODIS images, which are characterized by high spectral and temporal resolution and data availability since 2000. This product offers an excellent opportunity to estimate wheat yield at the regional level and also allows us to follow spatial evolution.

In general, the estimation of wheat yield in Morocco and developing countries in general is still based on traditional methods and other techniques remain purely scientific research that does not evolve to the establishment of an operational system based on satellite data and advanced machine learning techniques for yield estimation.

Thus, we strongly recommend the exploitation of these researches and others in progress for the establishment of an operational platform based on satellite images at very high resolution namely SENTINEL 2 or other and which uses advanced techniques of machine learning for the early estimation of the yield of wheat one to 2 months ahead.

5. ACKNOWLEDGEMENT

I would like to thank all the collaborating professors who guided me in this synthetic study and who, thanks to them, were able to carry out a review of all the methods for estimating the yield of wheat, this fundamental crop in the agricultural of Morocco.

6. FUNDING

NO FUNDING

7. AUTHORS' CONTRIBUTIONS

Only the authors listed on the home page who contributed to this work:

Ms. Adra IDRISSI the main author
Mr. Samir NADEM, Mr. Abdelghani BOUDHAR and Mr. Tarik BENABDELOUAHAB are the supervisors of this work

8. References

Araos, M., Berrang-Ford, L., Ford, J. D., Austin, S. E., Biesbroek, R., & Lesnikowski, A. (2016). Climate change adaptation planning in large cities: A systematic global assessment. *Environmental Science & Policy*, *66*, 375–382. https://doi.org/10.1016/J.ENVSCI.2016.06.009

Balaghi, R., Tychon, B., Eerens, H., & Jlibene, M. (2008). Empirical regression models using NDVI, rainfall and temperature data for the early prediction of wheat grain yields in Morocco. *International Journal of Applied Earth Observation and Geoinformation*, *10*(4), 438–452. https://doi.org/10.1016/j.jag.2006.12.001

Balaghi Riad, JLEBENE Mohammed, TYCHON Bernard, E. H. (2012). La Rediction Agrometerologie Ds Rendements Cereales Au Maroc. *La Priductin Agrometeologique Des Rendements Cereales Au Maroc.*

Basso, B., Cammarano, D., & Carfagna, E. (2013). *Review of Crop Yield Forecasting Methods and Early Warning Systems*.

Basso, B., & Liu, L. (2019). Seasonal crop yield forecast: Methods, applications, and accuracies. *Advances in Agronomy*, *154*, 201–255. https://doi.org/10.1016/BS.AGRON.2018.11.002

Berghuijs, H. N. C., Weih, M., van der Werf, W., Karley, A. J., Adam, E., Villegas-Fernández, Á. M., Kiær, L. P., Newton, A. C., Scherber, C., Tavoletti, S., & Vico, G. (2021). Calibrating and testing APSIM for wheat-faba bean pure cultures and intercrops across Europe. *Field Crops Research*, *264*(January). https://doi.org/10.1016/j.fcr.2021.108088

CIMMYT. (2018). *New publications: The importance of wheat in the global food supply to a growing population – CIMMYT*. Importance of Wheat in the World. https://www.cimmyt.org/publications/new-publications-the-importance-of-wheat-in-the-global-food-supply-to-a-growing-population/

Epule, T., Chehbouni, A., Chfadi, T., Ongoma, V., Martínez-cruz, L., Lytia, E., Er-raki, S., Khabba, S., Etongo, D., Achli, S., Salih, W., Chuwah, C., Jemo, M., & Chairi, I. (2022). *A Systematic National Stocktake of Crop Models in Morocco*. *470*(May). https://doi.org/10.1016/j.ecolmodel.2022.110036

FAO. (2002). *Wheat in the world - B.C. Curtis*. (Wheat in the World.

FAO. (2022). *FAO Cereal Supply and Demand Brief | World Food Situation | Food and Agriculture Organization of the United Nations*.

Huang, J., Tian, L., Liang, S., Ma, H., Becker-Reshef, I., Huang, Y., Su, W., Zhang, X., Zhu, D., & Wu, W. (2015). Improving winter wheat yield estimation by assimilation of the leaf area index from Landsat TM and MODIS data into the WOFOST model. *Agricultural and Forest Meteorology*, *204*, 106–121. https://doi.org/10.1016/j.agrformet.2015.02.001

Le Mouël, C., & Forslund, A. (2017). How can we feed the world in 2050? A review of the responses from global scenario studies. *European Review of Agricultural Economics*, *44*(4), 541–591. https://doi.org/10.1093/erae/jbx006

Lionboui, H., Benabdelouahab, T., Htitiou, A., Lebrini, Y., Boudhar, A., Hadria, R., & Elame, F. (2020). Spatial assessment of losses in wheat production value: A need for an innovative approach to guide risk management policies. *Remote Sensing Applications: Society and Environment*, *18*(February), 100300. https://doi.org/10.1016/j.rsase.2020.100300

Paul c. Doraiswamy, S. M. (2003). *crop yield assesment from Romte sensing.pdf*.

Qader, S. H., Dash, J., & Atkinson, P. M. (2018). Forecasting wheat and barley crop production in arid and semi-arid regions using remotely sensed primary productivity and crop phenology: A case study in Iraq. *Science of the Total Environment*, *613–614*, 250–262. https://doi.org/10.1016/j.scitotenv.2017.09.057

Ren, J., Chen, Z., Zhou, Q., & Tang, H. (2008). Regional yield estimation for winter wheat with MODIS-NDVI data in Shandong, China. *International Journal of Applied Earth Observation and Geoinformation*, *10*(4), 403–413. https://doi.org/10.1016/j.jag.2007.11.003

Rudorff, B. F. T., & Batista, G. T. (1990). Yield estimation of sugarcane based on agrometeorological-spectral models. *Remote Sensing of Environment*, *33*(3), 183–192. https://doi.org/10.1016/0034-4257(90)90029-L

Safir, G. R., Gage, S. H., Colunga-Garcia, M., Grace, P., & Rowshan, S. (2008). Simulation of corn yields in the Upper Great Lakes Region of the US using a modeling framework. *Computers and Electronics in Agriculture*, *60*(2), 301–305. https://doi.org/10.1016/J.COMPAG.2007.09.004

Satir, O., & Berberoglu, S. (2016). Crop yield prediction under soil salinity using satellite derived vegetation indices. *Field Crops Research*, *192*, 134–143. https://doi.org/10.1016/j.fcr.2016.04.028

Schauberger, B., Jägermeyr, J., & Gornott, C. (2020). A systematic review of local to regional yield forecasting approaches and frequently used data resources. In *European Journal of Agronomy* (Vol. 120). Elsevier B.V. https://doi.org/10.1016/j.eja.2020.126153

Shanmugapriya, P., Rathika, S., Ramesh, T., & Janaki, P. (2019). Applications of Remote Sensing in Agriculture - A Review. *International Journal of Current Microbiology and Applied Sciences*, *8*(01), 2270–2283. https://doi.org/10.20546/ijcmas.2019.801.238

Wiegand, C. L., Richardson, A. J., Escobar, D. E., & Gerbermann, A. H. (1991). Vegetation indices in crop assessments. *Remote Sensing of Environment*, *35*(2–3), 105–119. https://doi.org/10.1016/0034-4257(91)90004-P

Wu, S., Yang, P., Ren, J., Chen, Z., & Li, H. (2021). Regional winter wheat yield estimation based on the WOFOST model and a novel VW-4DEnSRF assimilation algorithm. *Remote Sensing of Environment*, *255*(April 2020). https://doi.org/10.1016/j.rse.2020.112276

Zhang, T., Su, J., Liu, C., & Chen, W. H. (2021). State and parameter estimation of the AquaCrop model for winter wheat using sensitivity informed particle filter. *Computers and Electronics in Agriculture*, *180*(June 2020), 105909. https://doi.org/10.1016/j.compag.2020.105909

Zhang, T., Su, J., Liu, C., & Chen, W. H. (2021). State and parameter estimation of the AquaCrop model for winter wheat using sensitivity informed particle filter. *Computers and Electronics in Agriculture*, *180*(June 2020), 105909. https://doi.org/10.1016/j.compag.2020.105909

Zhao, Y., Potgieter, A. B., Zhang, M., Wu, B., & Hammer, G. L. (2020). Predicting wheat yield at the field scale by combining high-resolution Sentinel-2 satellite imagery and crop modelling. *Remote Sensing*, *12*(6). https://doi.org/10.3390/rs12061024

Zhou, X., Wang, P., Tansey, K., Zhang, S., Li, H., & Tian, H. (2020). Reconstruction of time series leaf area index for improving wheat yield estimates at field scales by fusion of Sentinel-2, -3 and MODIS imagery. *Computers and Electronics in Agriculture*, *177*(17), 105692. https://doi.org/10.1016/j.compag.2020.105692

Zhou, X., Wang, P., Tansey, K., Zhang, S., Li, H., & Tian, H. (2020). Reconstruction of time series leaf area index for improving wheat yield estimates at field scales by fusion of Sentinel-2, -3 and MODIS imagery. *Computers and Electronics in Agriculture*, *177*(17), 105692. https://doi.org/10.1016/j.compag.2020.105692

9. ADDITIONAL READING

Seasonal crop yield forecast: Methods, applications, and accuracies. Advances in Agronomy, 154, 201–255. https://doi.org/10.1016/BS.AGRON.2018.11.002

A systematic review of local to regional yield forecasting approaches and frequently used data resources ; Schauberger, B., Jägermeyr, J., &Gornott, C. (2020)

Applications of Remote Sensing in Agriculture - A Review, Shanmugapriya, P., Rathika, S., Ramesh, T., & Janaki, P. (2019)

A Systematic National Stocktake of Crop Models in Morocco. Epule, T., Chehbouni, A., Chfadi, T., Ongoma, V., Martínez-cruz, L., Lytia, E., Er-raki, S., Khabba, S., Etongo, D., Achli, S., Salih, W., Chuwah, C., Jemo, M., &Chairi, I. (2022)

10. KEY TERMS AND DEFINITIONS

Crop simulation models: These are models that predict plant growth and development as a function of environmental conditions and crop management, these data are specified for the model as input data.

Remote sensing: The process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance