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Determining optimal stock of grain for national food security in Malawi: A two objective grain sizing dynamic optimization approach

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ABSTRACT

Food insecurity remains an issue of great concern in Malawi. As such, the Government of Malawi through the National Food Reserve Agency (NFRA) and the Agricultural Development and Marketing Corporation (ADMARC) introduced the Strategic Grain Reserve (SGR) in 1979 to be able to store grain that can be used in responding to vulnerable households, during food shortages amidst climate change concerns. However, past estimations of how much grain the SGR is supposed to hold employed static models that did not consider the dynamic nature of food requirements presented by climate change and volatile food prices, let alone the duo objectives of achieving food security whilst minimizing storage costs. Through understanding the dynamic and evolving goals of the country, the current study employed dynamic optimization algorithms using GEKKO and Numpy libraries in Python. In terms of how much grain the SGR is supposed to hold, the study found that the optimal stocks to be held for 3 months with another 3 months lead time to mobilize grains under public-private-partnership capacity is 316,350 MT to effectively offset any historical shortfalls in supply, 674,178 MT for the emergency reserve and 191,267.9 MT as buffer stocks. Nonetheless, the country's physical storage space is not adequate and too costly to hold such a quantity of grain. The study therefore advises using futures contracts and virtual stock programs, such as grain banks, to ensure a swift and effective response in emergencies.

1. Introduction

Strategic Grain Reserves (SGR) remain crucial in Sub-Saharan Africa (SSA) due to the region's susceptibility to extreme weather events and economic and political instability. Food reserves are an ancient idea, responding to inherent characteristics of agriculture. Primarily, the food security debate often focuses on a trade-off between trade and relying on domestic stocks. Keeping reserve stocks of staple foods is about as old as mankind and food reserves have always been an instrument in 'food security policies' by rulers and governments (Drechsler, 2021).

Food reserves can be a valuable tool for improving access to and distribution of food. They can support farmers by helping them to predict their markets, and by countering concentrated market power downstream from production (Baulch and Botha, 2020). They can contribute to local, national, and regional markets, where resources are lacking. Reserve stocks can compensate for shortfalls in foreign currency (which make imports difficult), offset supply shocks or spikes in demand, stabilize food prices on the market and facilitate humanitarian response to food emergencies. Reserves can also help countries cope with climate change and its impact on food production and supply (IATP, 2010). Although the importance and practice of holding food reserves as a strategic food security policy option is as old a practice as mankind, the global food security crisis of 2007/2008 rekindled the debate around food reserves. Since then, several other events such as the global pandemic of COVID-19 have continued to energize this debate.

Rashid and Lemma (2011) studied several reserve systems in Africa and found that institutional design, suitability of the stock size and the degree of integration with other transfers and social protection programs play a role in the performance of strategic grain reserves. It should be noted that countries with large populations hold stock reserves that serve significant purposes and strengthen domestic as well as worldwide food security (Drechsler, 2021). The decline in rice output in India in 2002/03, could have caused major instabilities in international markets of rice if India had decided to greatly expand its import base, rather the

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country opted to utilize its own domestic reserves. China and India, for example, have domestic rice consumption that outpaces the total amount of rice that is being traded across the international markets. This implies that relying on present rice production and trade alone would be a hazardous strategy (USDA, 2020).

In Malawi, a large proportion of households are caught in a trap where poverty and food insecurity reinforce one another and where periods of food deficits and severe food crises are frequent occurrences (IFPRI, 2018). In the year 2022/2023, the Malawi Vulnerability Assessment Committee (MVAC) estimated that a total of 3,818,554 people were classified as acute food insecure. These statistics are seconded by those recorded in 2018/2019 where 3,306,405 were also classified as acute food insecure. However, 2021/22 also showed a significant number of acute food insecure people at 1,496,394 (MVAC, 2022). The assessment shows that food insecurity was at least lowest in 2017/18 and 2019/20 which recorded 1,042,412 and 1,062,663 people in acute food insecurity category, respectively. This was due to good climate conditions that were recorded in those two seasons (GoM, 2022). Nonetheless, the numbers remain on the higher side as at their minimum they have represented more than 15 percent of the population, thus calling for robust food security interventions and initiatives (MVAC, 2022).

Among the three regions in the country, food insecure households are most accrued to the southern regions of Malawi, with Central and Northern region as the least affected. Again in 2022, all the 13 districts in the Southern regions were categorized in IPC Phase 3 which is a food crisis phase (MVAC, 2022). This is because most districts in the south are rain shadow areas. Fig. 1 further attests to the vulnerability in the southern region.

The food insecurity situation in Malawi, is further affected by frequent occurrence of climate-related shocks, mainly tropical storms which lead to flooding in many parts of the country. These tend to alternate with drought, sometimes during the same rainy season. In January 2015, persistent rainfall resulted in floods, particularly in the southern districts of Malawi (GoM, 2016). The floods affected more than 1.1 million people in 15 districts across the country, displaced more than 336,000 people, leaving about 104 people dead and 172 people reported missing. Again, in 2016, Malawi experienced El Nino which resulted in drought. Since then, there have been several other climate-related disasters, with the most recent, Tropical Cyclone Freddy which, devastated most of the Southern Region of Malawi in 2022/2023 (MVAC, 2022). This has affected the food security status of the country. Relief Web (2022) revealed that the Global Hunger Index of 20.7 ranked Malawi 87th out of 121 countries categorized as seriously food insecure countries. This has mainly been due to the inability of the country to adapt to the effects of climate change in the past decades.

The over-dependency on own production in achieving food security objectives in Malawi emphasizes the need to enhance and maximize its strategic food reserve capacity. The SGR system's last reference stock level is about 217,000 metric tons and was estimated in 2016 (GoM, 2016). However, the population growth and climate change risks which include eight tropical storms, drought, and non-weather factors since the year 2018 necessitates new stock management models, stocking levels, and best practices. Furthermore, the addition of more storage facilities to 547,000 metric tons challenges the previous estimations and can be defined as under-utilization with the current approach (MVAC, 2022). The rapid evolution of technology, globalization, and growing customer demands have made it imperative for SGR to frequently adapt its strategies to remain competitive and ensure an evidence-based approach initiative.

The country's overreliance on maize further brings in more vulnerability to external factors like climate change. Indeed, Malawi's food system is built around a single crop. Maize supplies roughly 60–65 % of national calorie intake, dominates more than 80 % of smallholder plots, and absorbs the bulk of state attention in production subsidies, price stabilization, and strategic-grain-reserve policy. While this focus reflects historical consumption habits and political economy, it also creates a set of inter-locking vulnerabilities that constrain the country's ability to achieve stable, nutritious and climate-resilient food security. Malawi's National Agriculture Policy (GoM, 2016) and the National Resilience Strategy (GoM, 2018) both champion diversification, yet operational linkages with SGR decision-makers remain weak. The SGR still fails to diversify the stocks it can hold as the food security agenda in the country is still centrically maize. This positions the SGR at a tight spot as a narrow staples basket amplifies price spikes. With almost no substitutes perceived as "meal equivalents" in the country, small reductions in supply trigger disproportionate increases in demand for market purchases. For instance, retail maize prices quintupled between January and November 2016 despite only one-third production shortfall (FEWSNET, 2017). In contrast, countries with diversified staple basket like Tanzania and Nigeria experience lower pass-through from drought to staple prices because consumers and traders can switch among commodities. These further calls stock diversification initiatives to ensure the SGR achieves its mandate.

The current study hence employs modern dynamic optimization techniques to guide the stocking quantities for the SGR, a strategic policy framework that complements Malawi's efforts in achieving the United Nations' Sustainable Development Goal number 2 (Zero Hunger).[1] This goal aims at enabling countries to have enough food for their population in two-fold: to minimize the warehouse stocking costs and address issues of social protection by maximizing the food security objectives. This study thus estimates the optimal stocking levels in a dynamic environment that has been affected by climate change overtime and rapid population growth.

2. Methodology

2.1. Analytical approach

Von Braun and Torero (2009) argue that the implementation of a physical food reserve that facilitates smooth response to food emergencies should be complemented with a virtual reserve to keep prices reasonably stable in the long run. This approach and method imply that the estimation of the optimal size of the SGR is not constrained by the physical storage capacity but rather the consumption needs of the population. The innovative method ensures minimum storage costs; further avoiding poor management of stocks.

Considering that the NFRA is expected to release maize to cushion the effect of high prices at different times of the year, such a function might be limited because of the low levels of stocks that the government agency can hold. For instance, with a total storage space of 547 (000 MT) (GoM, 2016) against a total maize supply of 3692 (000 MT) in 2020 (FAOSTAT, 2022; and FEWSNET, 2022), the NFRA plus ADMARC could only hold less than 15 percent of the national grain requirement, leaving over 85 percent in the hands of the private sector whose activities determine the availability and accessibility of grains in the markets. These further shadows the price stabilization function of the SGR.

2.1.1. Computational procedures for determining optimal stocks and capacity

i) Optimal stocks

Optimal stock implies the exact amount of inventory a warehouse/storage needs to hold to satisfy the regular demand without being out of stock. It involves a simultaneous maximization of profits and minimization of cost during storage. According to Kornher (2016), the following formula designates the food market identity:

[1] https://sdgs.un.org/goals/goal2.

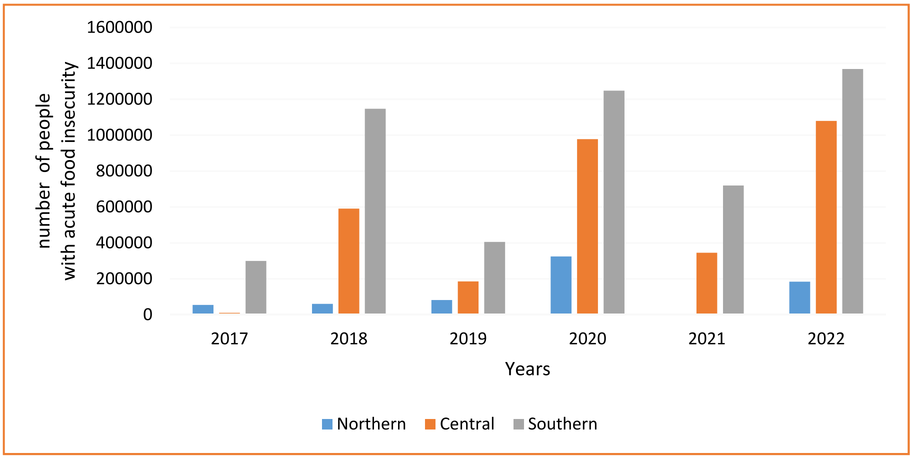

Fig. 1. Regional distribution of acute food insecurity.
Source: MVAC (2022).

$$C_t = Q_t + IM_t - EX_t = X_t \ldots \tag{1}$$

Where (C_t) is Total consumption; (Q_t) is Production; (IM_t) is Imports; (EX_t) represents Exports; and (X_t) is the total national supply. From equation (1), total consumption equals the sum of Production and Imports minus Exports. Therefore, the total national supply (X_t) is made up of imports and production. Where acceptable levels of production are not met in a year; it is assumed that imports should satisfy the country's minimum consumption. However, various shocks such as COVID-19, droughts and floods have made food availability difficult. Due to volatile nature of international markets food prices, the need for emergency stocks in Malawi cannot be overlooked.

Another approach for estimating total consumption or otherwise demand is to utilize the concept of Consumption per Capita (CpC_t) designated as kilograms per person per year (Kg/person/year). Conceptually, the approach is illustrated as follows:

$$X_t = PP_t{*}CpC_t \ldots \tag{2}$$

Where PP_t designates the total country's population in year *t,* while CpC_t is the Consumption per Capita at time *t*. The Total Supply in time t (TS_t) is given by the summation of Domestic Production (DP_t) and Imports (IM_t) as follows:

$$TS_t = DP_t + IM_t \ldots \tag{3}$$

Statistically, it makes sense to compute the allowable lower bound in consumption described by Konandreas et al. (1978) as target consumption level c* which is a certain percentage (i.e., 95 %) of some long-term trends. This is thus the statistical "floor'' for consumption which is tied to the long-run trend (ten years maize consumption data) in demand. Let $c^*E[C_t]$ be the smoothed (trend) estimate of total consumption in year t. The equation fixes a target level typically 95 % of that trend so that consumption never drops more than 5 % below its expected long-term path. The stock required in year t for annual consumption is given by:

$$S_t^* = \max[c^*E[C_t] - (X_t)] \mathit{for}\ t = t_1, \ldots, t_n \ldots \tag{4}$$

Where S_t^* is the optimal stock; X_t is the actual supply at time *t* while $c^*E[C_t]$ is the target consumption based on the anticipated supply which is deduced from previous values. In a situation where $X_t > c^*E[C_t]$, then total supply equals (or greater than) consumption, while in the case of the opposite, necessitates a release of reserve stock to cover up the established gap. Since consumption is always expected to equal or be less than supply, then it means to compensate the shortfalls in supply stock reserve is needed.

Problems of optimization try to either maximize or minimize functions, therefore, the function $\max[c^*E[C_t], (X_t)]$ in equation (4) gives the largest historical supply (production plus net imports) shortfall over the given period ($t_1, \ldots, t_n$) (which in our case is 10 years, 2010–2020) while S_t^* is the optimal value of stocks. In principle, *the optimal stock value* S_t^* is the minimal amount that must be stocked to maintain a safe degree of food security. That is, the worst-case supply deficit is considered in optimal stock estimation. In optimal reserve, this yields the best stocks for the grain under consideration. Thus, following HAPA (2022) computation of optimal stocks, this is the given value of the optimal stock of the SGR.

ii) Emergency Reserve

Fundamentally, food emergency reserves have been part of food security and disaster preparedness narratives (Lassa et al., 2019). Many governments have prescribed this approach as a type of contingency planning and risk management strategy for uncertain periods such as droughts, wars, catastrophes etc. The theory assumes that during the worst-case scenario of catastrophe; all means of food supply get interrupted and the only means to provide food is through reserves. The historical values of consumption for a considerable period should guide the determination of the right quantity for reserve. Most importantly, the highest value, for the food consumption within the period should be desirable to be on the safe side, since history tends to repeat itself (HAPA, 2022). Therefore, the total target minimum consumption of all grains is specified as:

$$SC^* = \sum_{i=1}^{n} SC_i^*\ max_t\left[X_{i|t}^*\right] \ldots \tag{5}$$

The right-hand side of equation (5) provides the optimal capacity (SC^*), by summing all highest target consumption of all grains, $X_{i|t}^*$. *i* indexes all grains under consideration, while *t* indexes the number of periods (i.e., years, months).

iii) Buffer stock

In a contrasting manner to the preceding section, the concept of buffer stocks is taken from the classical storage literature (Gustafson, 1958). This narrative considers stock as being part of national supply and demand whereby from the available Total Supply (TS_t), a constant portion (γ) is stored as stocks in reserve (Kornher and Kalkuhl, 2016). Nonetheless, the estimation follows a two-phase approach with the first focusing on the price stabilization objective only. The second approximation offers a more robust method, incorporating multiple assumptions and acknowledging that using reserve stocks to stabilize prices must also protect domestic consumption.

2.1.1.1. Linear model (stock-to -use ratio). The first approximation follows a linear approach that Gustafson developed. This implies that stock levels will always change with time, for instance, stock levels will be relatively high after the years of experiencing good yield and the opposite will apply after bad harvest. Mathematically, the market relationship given in equation (1.0) can be written as follows:

$$TS_t = S_{t-1} + X_t \ldots \tag{6}$$

Where all parameters are defined the same as the above equations (i.e. TS_t is Total Supply in time period t; X_t is the actual supply from production and net imports at time *t;* and S_{t-1} is carryover stock from last year). S_t is the opening stock available for consumption at time *t.* So, according to (HAPA, 2022), a rule of storage states that S_t is a function of the carryover stock (S_{t-1}) and X_t as below.

$$S_t = \gamma_t(S_{t-1}, X_t) \ldots \tag{7}$$

The relationship can also be written as:

$$S_{t+1} = \gamma(S_t + X_{t+1}) \ldots \tag{8}$$

In this case, S_t are the opening stocks available for consumption in the current year while S_{t+1} are the stocks to be carried over to the next period. γ represents a constant portion of the total supply (TS_t) that is available to be carried over to the next period. Considering that the approach follows a linear approximation, we can substitute equation (1) into (8) and including a disturbance term, we end up having a linear equation;

$$S_{i|t} = \gamma_i\left(S_{i|t-1} + Q_t + IM_{i|t} - EX_{i|t}\right) + \varepsilon_i \ldots \tag{9}$$

The parameters are again defined as above (i.e. $S_{i|t}$ is the actual stock in time t; $S_{i|t-1}$ is the actual carryover stock in time t; Q_t is production; $IM_{i|t}$ are actual imports in time t; and $EX_{i|t}$ are exports at time t). We can therefore estimate the optimal stock under the national stockholding using actual stock data and the stocking parameter can be obtained by estimating equation (9) using an Ordinary Least Square method (HAPA, 2022). Since we have the stock data over ten-year period, time series modeling was employed in this case.

The expected value of S_{t+1} is equal to the expected value of S_t, then $E[S_t] = E[S_{t-1}]$ because the closing stocks in one time period should equal the opening stock in the next period. Therefore, the optimal stock level for stabilization reserve is calculated using the formula below:

$$S_t^* = \frac{\gamma E\left[X_t^*\right]}{1-\gamma} \ldots \tag{10}$$

$$\beta^* = \frac{\gamma}{1-\gamma} \ldots \tag{11}$$

Where X_t^* is the target consumption; $E\left[X_t^*\right]$ is the expected target consumption; β^* is the corresponding stock-to-use ratio; and γ is the constant portion of stocks stored as reserve. However, for robustness check, the study also employed a strategy of identifying, estimating and forecasting a time series data generation process called ARIMA (p, d, q) which was pioneered by Box & Jenkins (1976). A non-patterned ARIMA model is classified as an "ARIMA (p, d, q)" model where "p" is the number of autoregressive terms, "d" is the number of times a series has to be differenced for it to be stationary while "q" represent the number of lagged forecast errors in the prediction equation (Krishna et al., 2022). In the forecasting equation, the lags of a stationary series are called the Autoregressive (AR) terms, and lags of the forecast errors are called Moving Averages (MA) terms, while a time series which requires differencing for it to attain stationarity if referred to as an "Integrated" version of a stationary series (Sharma et al., 2018).

The ARIMA model can be expressed as:

$$S_{i|t} = \varphi_1\left(S_{i|t-1} + Q_t + IM_{i|t} - EX_{i|t}\right) + \mu - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots.\theta_q\varepsilon_{t-q} + \varepsilon_t \ldots. \tag{12}$$

Where $S_{i|t}$ is the optimal stock at time t; $S_{i|t-1}$ is the optimal stock for the previous period; Q_t is the production at time t; $IM_{i|t}$ is the Imports for the country at time t; $EX_{i|t}$ is the Exports for the country at time t; μ is constant, $\theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \ldots.\theta_q\varepsilon_{t-q}$ are the errors in the previous periods; φ_1 are coefficient to be estimated in AR process; θ_q are coefficients to be estimated in MA process; ε_t is the forecast error.

2.1.1.2. The dynamic optimization model. Equation (1) through *12* are synthesized and processed in a dynamic optimization model that is more robust in the sense that the estimates consider different constraints which are ideal in the SGR framework. The dynamic optimization model has two objectives which are to maximize food security and minimize storage costs. The dynamic optimization capitalizes on a cobweb model. In a descriptive cobweb model, equilibrium is achieved through market clearance and not through imposed public objectives, and that is modelled through equation (13) through (*15*). Nonetheless, a grain reserve sizing technique is not intended to be descriptive but prescriptive (Baulch and Botha, 2020). An equilibrium model of grain reserve sizing would relate demand to supplies via price-mediated market activity. Equilibrium is imposed through market allocations that result from prices but involve Government storage or withdrawal behavior which responds to explicit objectives. Price is no longer the residual effect of equilibrating supplies and demands (World Bank, 2021). The resulting equilibrium can be affected by price as a decision variable. that states three elements explicitly as follows;

$$Y_t = P_{t-1} + \varepsilon_t \quad for\ t = 1, 2, \ldots., n \ldots \tag{13}$$

$$C_t = P_t + \mu_t \quad for\ t = 1, 2, \ldots., n \ldots \tag{14}$$

$$Y_t = C_t \quad for\ t = 1, 2, \ldots.n \ldots \tag{15}$$

Where Y_t is production in year t; C_t is consumption in year t; P_t is the average annual price in year t; P_{t-1} is the previous time period price; and ε_t and μ_t are the error terms. To present that, a reserve-oriented optimization version will replace equation (13);

$$Y_t = C_t + S_t - S_{t-1} \quad for\ t = 1, 2, \ldots.., n \quad \ldots \tag{16}$$

Where S_t is the storage level in year t; Y_t is production; C_t is consumption in year t; and S_{t-1} is the storage level in the previous year. To understand the grain supply, then we can model the expected grain supply in any year as follows;

$$E_t = \alpha + \beta_t + Y_t + X_t + P_{t-1} \quad for\ t = 1, 2, \ldots n \quad \ldots \tag{17}$$

Where E_t is the expected grain supply in year t; α is the intercept of the linear trend equation; β is the rate of change in the linear trend equation; t is the year; Y_t is production; X_t are imports of the commodity; and P_{t-1} is the lagged price in a cobweb model.

We can then formulate a two-objective linear program that (i) minimizes the cost of storage of that supply; and at the same time (ii) maximizes food security. Thus;

$$S_t = S_{t-1} + Y_t - C_t \quad for\ t = 1, 2, \ldots, n \ldots \tag{18}$$

Where storage at the end of time t (S_t) is equal to storage at the end of the previous period (S_{t-1}) plus production in time t (Y_t), less the consumption of the grain in that period (C_t). Nonetheless, storage at the end of any period must be less than the capacity of the reserve (R);

$$S_t \leq R \quad for\ t = 1, 2, \ldots, n \quad \ldots \tag{19}$$

The level of storage after the final year (S_n) will be defined as equal to the stock volume just before the beginning of the first year (S_0);

$$S_0 = S_n \ldots\ldots \quad (20)$$

The relationship presented in equation (18) is included so that the linear program will neither create grain that has not been produced nor destroy grain that exists. If we add the n constraints of the form equation (20) we will notice that each S_t (except S_0 and S_n) appears once with a positive sign and once with a negative sign. Thus, when S_t are summed over periods t = l, 2, …, n-1, they cancel out. The requirement expressed as equation (20) permits S_0 and S_n to cancel, so that the summation of production and consumption over all periods is given as follows;

$$\sum_{t=1}^{n} Y_t = \sum_{t=1}^{n} C_t \ldots\ldots \quad (21)$$

The consumption level, C_t can be described as a fraction of this expected demand level for any given year;

$$C_t = A_t O_t \quad for\ t = 1, 2, .., n \quad \ldots\ldots \quad (22)$$

Where O_t is the volume of expected demand or production and A_t is the fraction of O_t that is actually consumed. Substituting this in equation (18) gives;

$$S_t = S_{t-1} + Y_t - A_t O_t \quad for\ t = 1, 2, \ldots., n \quad \ldots. \quad (23)$$

Assuming that the fraction of demand met through consumption will always be maintained greater than or equal to some lower bound:

$$A_t \geq B \quad for\ t = 1, 2, \ldots, n \quad \ldots\ldots \quad (24)$$

where B represents the smallest fraction of expected demand met through consumption over a design horizon of n years. Again, all decision variables take non-negative values;

$$S_t, A_t, O_t, Y_t, C_t, B, R \geq 0 \quad for\ t = 1, 2, \ldots., n \quad \ldots\ldots \quad (25)$$

As such, the optimal grain reserve two-objective (minimizing storage costs R and maximizing food security through B) linear problem can be presented as follows;

$$\text{Objective} : Max\ [B, -R] \ldots\ldots \quad (26)$$

Subject to;

$$S_t - S_{t-1} + A_t O_t = Y_t \quad for\ t = 1, 2, \ldots.., n \quad \ldots\ldots \quad (27)$$

$$S_t - R \leq 0 \quad for\ t = 1, 2, \ldots.., n \quad \ldots\ldots \quad (28)$$

$$S_0 - S_n = 0 \quad for\ t = 1, 2, \ldots.., n \quad \ldots\ldots \quad (29)$$

$$A_t - B \geq 0 \quad for\ t = 1, 2, \ldots., n \quad \ldots\ldots \quad (30)$$

$$S_t, A_t, O_t, Y_t, C_t, B, R \geq 0 \quad for\ t = 1, 2, \ldots., n \quad \ldots\ldots \quad (31)$$

2.1.2. Data sources

The study used FAOSTAT (2022) data which includes Food Balance Sheets and Supply Utilization Accounts. The Food and Agriculture Organization of the United Nations collects data on several countries focusing on food security parameters like production, food security and nutrition, food balances, trade, food prices, cost and affordability of healthy diets, population, climate change and many others that are essential in attaining the Sustainable Development Goal (SDG Two) of zero hunger. FAOSTAT further collects data on informal cross-border trade which is essential in the computation of the optimal stocks. The data is easily accessible on https://www.fao.org/faostat/en/#data and is free of charge to all users in the world.

3. Results and discussions

3.1. Descriptive statistics

As earlier pointed out, the study mainly relied on the Food and Agriculture Organization (FAO) Food Balance Sheet data for Malawi captured from 2010 through 2020. Table 1 shows that maize production in the country has been revolving around 2369 (000 MT) in 2016 and 3978 (000 MT) recorded in 2014. Many factors explain the variations in maize production ranging from occurrences of floods and droughts which have been severe in the past decade. The year 2014 received good rains which resulted in the country experiencing good yields which were helped by the Farm Input Subsidy Program (GoM, 2016). Nonetheless, erratic rains in 2016 affected maize production in the country. This is further explained by the 328 (000 MT) of maize that the country ended up importing from Zambia (FEWSNET, 2022). The other crucial thing to note is that FAOSTAT agrees with the findings of FEWSNET (2022) that despite the country imposing an export ban on maize in the last two decades, the country still exports some substantial amounts through informal trade implying that the food security objectives cannot be attained without considering international trade.

3.2. Dynamic optimization results

3.2.1. Results using consumption figures (production, imports & exports)

As a recap of the estimation, consumption is a function of production and net imports (exports – imports) as presented by equation (1). To model the optimal stock, the study first considered estimates of consumption over the years which show and bring out the variations in consumption because of various events that occurred between 2010 and 2020, the period of consideration in this study. However, there exists a possibility of underestimation of a country's expected consumption figures because of the low production of maize and/or lack of financial capability to import enough maize in the country. To that extent, a trend analysis for consumption was considered to model the variations overtime (Fig. 2).

Much as the demand for maize in Malawi can be considered inelastic, consumption transitions are noticed between 2010 and 2018 due to different climatic shocks with an average of 3326 (000 MT). In detail, maize consumption peaked in 2014 and 2020 with 3966 (1000 MT) and 3681(1000 MT), respectively. The lowest consumption levels in the overall trend are observed in 2016 and 2018 with a value of 2667 (1000 MT) and 2676 (1000 MT) respectively. Both 2016 and 2018 experienced climatic shocks (GoM, 2022). Before the maximum jump in 2014, the values in previous years (2010–2013) are within the average of 3326 (1000 MT).

Following the World Bank (2021), the optimal stock is calculated from the difference in the target consumption and supply. As such, the consumption trends are later compared to domestic supply. According to FAO balance sheets, domestic supply is a collective term for production, imports, exports, and changes in stock. The shortfall surplus estimates as shared in Fig. 3.

In a nutshell, the zero (0) - threshold is the determinant of the excess supply and unsatisfied demand. Based on equation (4), above the zero (0) threshold, is the unsatisfied demand while below the threshold (in red) is the excess supply. Holistically, Malawi faces self-sufficiency scenarios if SGRs are properly utilized. The transitions are complementary whereby a year of supply surplus is followed by a year of supply deficit. Nonetheless, the trend analysis indicates that Malawi faces an average of 400 (000 MT) in excess supply. The upper bound in excess supply was experienced in 2018 with a value of 576 (000 MT) and 500 (000 MT) in 2016. The fluctuations in these years were triggered by stock variations which influenced the overall domestic supply. On the other end, the highest fluctuation of unsatisfied demand was noticed in 2014 with 793 (000 MT), followed by 233 (000 MT) in 2013 and 104 (000 MT) in 2017.

Table 1
FAOSTAT food balance sheet for Malawi from 2010 to 2020.

Year	Production (000 MT)	Import Quantity (000 MT)	Export Quantity (000 MT)	Net Imports (000 MT)	Stock variation (000 MT)	Non-food uses (000 MT)	Consumption (000 MT)
2010	3419	16	10	6	138	0	3425
2011	3699	6	366	−360	−105	1	3338
2012	3619	0	24	−24	−1	0	3595
2013	3640	61	2	59	293	0	3699
2014	3978	33	4	29	834	1	4006
2015	2776	105	2	103	−183	0	2879
2016	2369	328	3	325	−473	0	2694
2017	3464	48	6	42	140	1	3505
2018	2698	7	2	5	−549	0	2703
2019	3392	6	2	4	19	0	3396
2020	3692	28	1	27	215	1	3718

Source: FAOSTAT

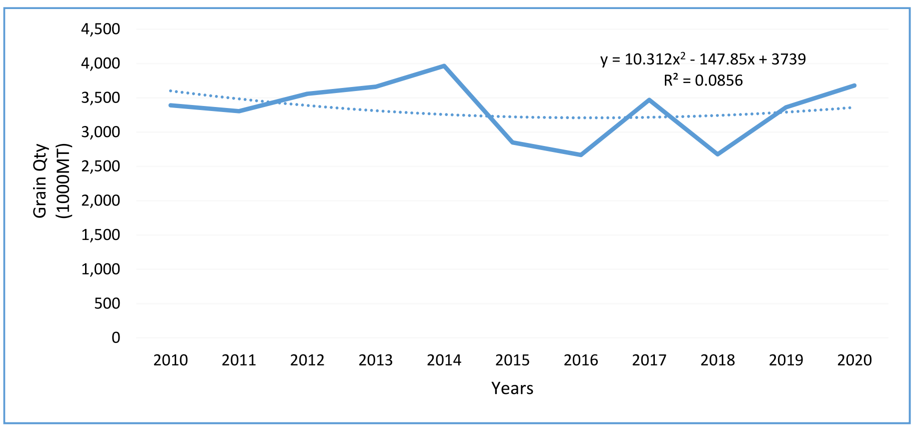

Fig. 2. Target Consumption at 99 % (consumption estimated using equation (1.0))
The Figure computes the proportion of maize output required to feed 99 % of the population in Malawi. It is computed using FAOSTAT data and the National Statistics Office (NSO) data, considering the total supply which is a combination of production and net imports. The dotted line is the regression.
Source: Author Computation

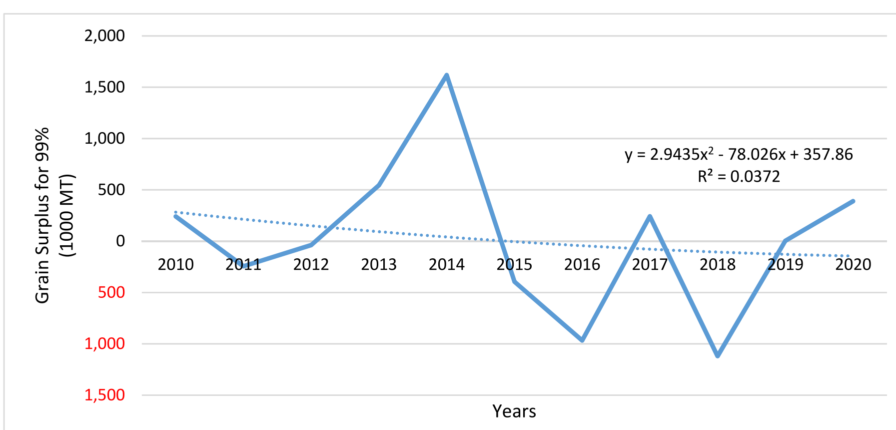

Fig. 3. Surplus for 95 % Target Consumptions (consumptions estimated using equation (1))
The Figure is computed by taking difference between the total supply and target required consumption for 95 % of the population. It uses FAOSAT data and the population of Malawi data from National Statistics Office.
Source: Author

Table 2 presents the optimal stock based on the target level of consumption and in reference to equation (4), the optimal stock considers the maximum value within the trend (2010–2020). However, it is to the understanding that unsatisfied demand is more detrimental than excess supply. The optimal stock was determined based on the unsatisfied demand.

On average, the optimal stock based on the 95 % target level of consumption in 12 months is **632.7 (000 MT)**. With this amount, the country is expected to be able to meet any forthcoming shortfalls in the supply of maize and the consumption needs of the population. Considering the capacity of NFRA and ADMARC, the country can only hold 86.5 percent of the optimal stocks as physical stocks, which calls for the

Table 2
Optimal Stocks for Various Target Levels of Consumption (consumption estimated using equation (4) [a]).

The target level of consumption	Maize (1000 MT)
99 %	792.9
98 %	752.9
97 %	712.8
96 %	672.8
95 %	632.7
94 %	592.6
93 %	552.6
Average	672.8

[a] Optimal stock implies the exact amount of inventory a warehouse/storage needs to hold to satisfy the regular demand without being out of stock.

need to have a virtual reserve to supplement shortfalls in periods where domestic supply fails to meet target consumption.

3.2.2. Optimal capacity of the emergency reserve

According to the World Bank (2021), the capacity of a country's emergency reserve is not measured by the available storage space but by the needs of the population affected by shocks. The principle behind this model is that variations in the long-term consumption trend of previous years should provide constraints rather than the available resources in a country. As such, the optimal capacity of a country is not the physical storage rooms but rather the variations in long-term consumption. The optimal capacity in this context of emergency stock ensures there is a sufficient supply of maize in the distribution system to meet the consumption needs of any emergency. To that extent, the optimal stock allocation towards emergencies is based on the worst-case scenario whereby overall population production circles are affected.

Following HAPA (2022), the optimal capacity of the emergency reserve can be computed using equation (2) of per capita consumption which again provides a more appealing case during emergencies. During this period, a socialist-market is ideal and hence provides an even distribution based on the availability of stocks. At 95 % target consumption, the optimal capacity of the emergency reserve using per capita consumption equations is **2659.5** (000 MT). Since during emergencies food aid programs depend on per capita consumption, an emergency optimal stock of **2659.5 (000 MT)** will be considered (Table 3).

3.2.3. Optimal buffer stock using stock-to -use ratio

Buffer stock is the extra stock that is maintained to mitigate the risk of stock outs due to uncertainties in grain supply (IFPRI, 2020). In detail, buffer stocks maintain price stability, minimize food shortages through safety net transfers and prevent sudden drops in price (Sutopo, 2011). FAOSTAT data for Malawi are used for computations. Relevant parameters contained in the data include production, beginning and ending stocks, imports, and exports.

Much as maize market intervention (export ban for example) is done in Malawi, informal market transactions have eluded the forces of demand and supply to control market prices. During the lean seasons or after specific shocks, the maize prices fluctuate upwards affecting the accessibility component in food security. Similarly, prices are way below the optimal costs during peak seasons and surpluses (i.e., immediately after harvest). Buffer reserve caters for both scenarios and in the estimation, total supply/total consumption is used. The other choice variables are opening stocks and stock variation which are used to estimate the closing stocks.

Through a regression specified in equation (9), a trend line was fitted using estimates of the carryover stock response towards the total supply in percentages (marginal effects). As an extension, a stock-to-use ratio is also estimated as an emphasis towards price volatility. The stocking parameter defines the carryover stock's response toward supply changes.

A percentage increase in the total demand triggers an increase in the closing stocks by 117.8 % and on average, the closing stock only holds 10.9 % of the total demand. On a different view, the stock-to-use ratio emphasizes the composition of maize as a determinant of livelihoods with 89.1 % of the total supply falling under-utilization (Table 4).

However, the stock-to-use ratio (carryover stock consumed in the next year) objective is mostly determined based on price variations. In this case, a comparative analysis based on the years, and the average price was adopted (Fig. 4). Overall, the stock-to-use ratio was highest in 2014. This is due to the bumper harvest of 2012 and 2013 which resulted in high carry-over stocks in the year 2014 (FEWSNET, 2013; FEWSNET, 2014; FEWSNET, 2017). The variations in the stock-to-use ratio from 2016 to 2020 is a result of the country being hit by cyclones and droughts.

It should be noted that the study considers real prices of maize which are the nominal prices deflated using the CPI. Based on the trend analysis (Figs. 4), 2014 had the highest stock-to-use ratio (0.2736) and it was complemented by the prices (Mk 90.6/Kg in Fig. 5) which were the second lowest after 2012 (Mk 55.4/Kg) (Fig. 5). Between 2012 and 2020, 2016 was the only year with very high maize prices. This was due to the 2015/16 drought (FEWSNET, 2017) which resulted in maize scarcity on the market further bringing in maize inflation. 2021 through 2023 saw rising maize prices due to an increase in cost of production as a result of devaluation of the Malawi Kwacha (GoM, 2023)

3.2.4. Optimal buffer stocks

The dynamic optimization equations follow a two-objective model that intends to maximize the allocation towards food security (fraction of the total production) and minimize the possible storage costs. A two-fold analysis is done that considers two different capacities. First is the availability of the public storage of NFRA and ADMARC which accrues to 547 (000 MT). A second analysis was done with the same equations but considering the storage capacity of the Agricultural Commodity Exchange (ACE) certified privately owned warehouses. However, despite ACE having certified a total of 267 (000 MT) of storage space, less than 20 percent of the storage space is in use for purposes of grain storage under the Warehouse Receipt System among others. This ensured an adjustment of the total storage capacity to 579,800 MT with an inclusion of in-condition ACE certified private warehouse capacity of 32,800 MT.

i) Public Storage Capacity

As earlier alluded to, the estimation of the buffer stocks follows a two-objective function (equation (3.6)) of maximizing food security and

Table 3
Optimal Capacities at different target levels of consumption (consumption estimated using equation (2) and optimal capacity estimated using equation (5)).

The target level of consumption	Maize (1000 MT)
99 %	2771.5
98 %	2743.5
97 %	2715.5
96 %	2687.5
95 %	2659.5
94 %	2631.5
93 %	2603.5
Average	2687.5

Table 4
Stocking parameter and stock-use ratio.

Stocking Parameter (dy/dx)	Stock-to-use Ratio
1.1776	0.1086

Source: Owner's Ordinary Least Squares (OLS) Computation based on equation 9

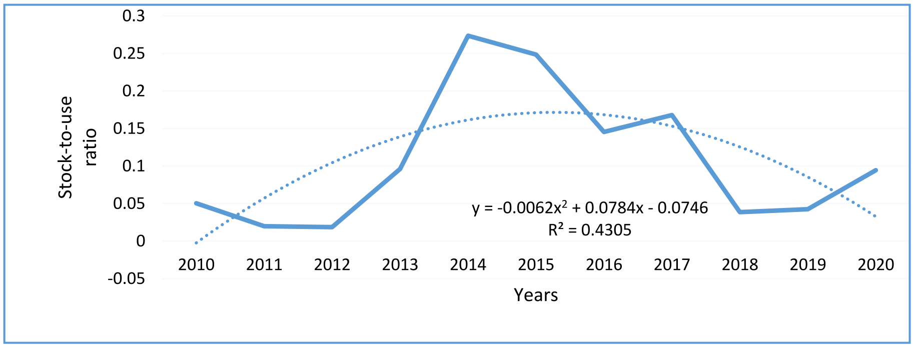

Fig. 4. Stock-to-use ratio over the years (2010–2020)
The Figure is computed by dividing the carryover stock in every year and the total use. It uses FAOSTAT opening and closing stock data, and the total use which includes consumption, animal feed and brewery.
Source: Author's Computation

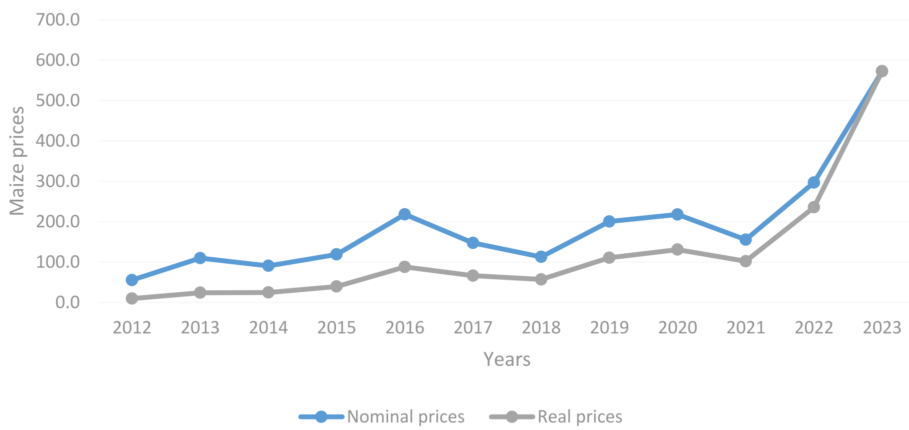

Fig. 5. Deflated Price Trend of Maize in Malawi (base year 2012).
Source: Author's Computation

minimizing storage costs. The constraints are given as equations (27)–(31). In this regard, the food security objective of maximizing consumption, i.e. utilization of the domestic supply given as a fraction of supply consumed, is constrained by the public storage capacity of 547 (000 MT). Through a dynamic program in python using Numpy and GEKKO libralies, the maximized utilization or consumption fraction (B) in equation (26) which presents the food security objective was found to be 0.8. Again, the optimal opening stocks (S_{t-1}) and closing stocks (S_t) as presented in equation (29) are 353.1 (000 MT) and 146.1 (000 MT), respectively. Constraining the dynamic program to its constraints including the public capacity gives an optimal stock value of **499.2** (000 MT) without considering the stock variations.

ii) Public-Private Sector Partnership

The second dimension of the analysis attempted to address the lower capacities owned by the public sector. This shifts the capacity constraint to 579.8 (1000 MT). The same dynamic programming model is estimated as above, with just a change in the capacity constraint. The optimal food security objective (B) remains 0.8 with an optimal opening stock of 127.5 (1000 MT) and a closing stock of 418.1 (1000 MT). The dynamic program in this second scenario gives an optimal stock of **545.7** (1000 MT).

iii) Unconstrained Storage Capacity

Following HAPA (2022), physical space is not a constraint enough to limit a country's food security objective. Virtual reserves can help in storing some of the grain. To relax the assumption of the capacity, the current study makes the following assumptions: (a) the buffer stock without a capacity constraint must be greater than or equal to the buffer stock with limited capacity; (b) the optimal stock is the minimum stock held with unlimited capacity.

Table 5 provides buffer stock optimal capacity estimation from 2010 to 2020 with unconstrained storage capacity. Parameters of end-year stock (S_t), expected demand (O_t), Utilization (C_t) and the fraction of expected utilization (A_t) as computed from equations (23) and (24). Sticking to an expected utilization fraction of 0.8, only 2015 with the optimal stock of 1012 (000 MT) and 2016 with an optimal stock of 539 (000 MT) satisfy the prerequisite conditions (HAPA, 2022). Since the

Table 5
Buffer stock capacity estimation (2010–2020)[a].

Year	End-year stock	Expected demand	Utilization	Fraction of Expected utilized
2010	174	3287	2220	0.7
2011	69	3445	2305	0.7
2012	68	3596	2469	0.7
2013	361	3407	2334	0.7
2014	1195	3173	2222	0.7
2015	1012	3063	2334	0.8
2016	539	3167	2450	0.8
2017	679	3366	2348	0.7
2018	130	3252	2451	0.8
2019	150	3377	2736	0.8
2020	365	3504	2800	0.8

[a] Buffer Stocks are stocks for stabilizing prices.

2016 value of 539 (000 MT) is below the optimal stock (545.7 (000 MT)) for the combined capacity of the public and private sector, the 2015 value of **1012 (000 MT)** is the optimal stock for the unconstrained buffer (Table 5).

To further contrast with the stock-to–use ratio estimates which consider 2014 end-year stock as the optimal buffer stock; the fraction of utilization indicates that the end-year stock of 2014 was due to a compromise in consumption (World Bank, 2021). This can be attributed to the factor of the prices whereby most stocks were held in storage with the anticipation of better future prices, an indication of the essentiality of the considered constraints and the robustness of the results in the dynamic optimization model.

Having estimated the optimal stock levels, it is crucial to note that SGR is not meant for the whole population but rather a vulnerable segment of the population. In this case, the vulnerability calculations are based on World Bank poverty headcount percentages and poverty ratios based on different poverty lines (World Bank, 2021). Fig. 6 provides the percentage of the total population that is living below the different poverty lines as stipulated by the World Bank. As of 2021, 50.7 percent of the population were living below the poverty line, indicating a need for cushioning food reserves for more than half the population.

Based on World Bank statistics, most Malawians are currently consuming below $6.85 a day as the trend lines are almost at par with the overall population of 17,914,500 (Fig. 7). The second class comprises $3.65 a day with an average of 15,961,819 individuals. The National poverty line and $2.15 are the closest representatives of vulnerabilities to be used with an average population of 9,082,651 and 12,558,064 individuals, respectively.

Table 6 hence presents the optimal stock computed from dynamic optimization and aligned to the vulnerabilities based on World Bank statistics. The annual (12 months) optimal stock is **632,700 MT (95 % level of consumption)**, the emergency stock reserve at 95 % level of consumption is **2,659,500 MT** and the Buffer Stock based on public-private sector partnership in warehouses (ADMARC, NFPRA & ACE) is **545,700 MT**. However, as an extension to the availability of storage space from private traders and on-farm accounted from the trend lines, the buffer stock extends to **1,012,000 MT** (Table 6). In estimating the stock distribution based on vulnerabilities, the focus was however put on the current national line and the $2.15-a-day threshold.

The large-scale warehouses (NFRA, ADMARC, ACE) buffer stock capacity covers only 86.2 % of the optimal stock which indicates that the warehouse capacity remains low even with public-private partnerships. This calls for a virtual reserve that can supplement the physical stocks.

Table 6 clearly shows that the country's storage capacity of 579.8 (000 MT) held by NFRA, ADMARC and ACE is inadequate to meet the optimal stock of **632,700** MT which entails the maximum possible supply shortfall needed to meet target consumption demand in 12 months. However, expanding the storage space is not an option as it will increase maintenance costs of the SGR. As such, the country should consider the establishment of a virtual reserve. However, common practice in estimating optimal stocks of SGRs is to hold stocks for 3 months which are mostly for the lean months' response. As such, from Table 6 the recommended stock levels to be held in **3 months** with another 3 months lead time to mobilize grains are as follows: (i) Optimal stock level of **316,350** MT to offset historical shortfalls in supply; (ii) Optimal capacity of emergency reserve of **674,178 MT** for the vulnerable population (50.7 % of the population); and (iii) Buffer Stocks with a Capacity of **191,267.9** MT under ADMARC, NFRA, and ACE; for minimum food security requirements of the 70.1 % of the population living below $2.15 a day.

3.2.5. *Integrating dry-chain technology into the SGR*

Malawi's SGR has long served as the government's principal safeguard against seasonal shortages, price spikes, and humanitarian crises. Yet the system remains under stress: stocks must be rotated frequently because of quality deterioration, and the National Food Reserve Agency (NFRA) often finds itself replenishing volumes through imports at a significant fiscal cost. Dry-chain technology, defined as a management continuum that dries grain to safe moisture thresholds immediately after harvest and then maintains that dryness hermetically, improving reserve performance while cutting national losses (Alliance Bioversity and CIAT, 2023).

Maize in Malawi is typically harvested at 18–22 % moisture content which is well above the 13 % threshold at which mold, aflatoxin, and insect activity are suppressed. Traditional sun-drying on tarpaulins or bare ground rarely achieves uniform dryness, and once grain is bagged in woven polypropylene, ambient humidity can be re-absorbed. Consequently, quality depreciation accelerates, shortening the useful life of stocks to fewer than nine months in silo and little more than three months in village stores. Dry-chain protocols interrupt this cycle. By combining rapid drying via mechanical dryers, maize cribs, or solar bubble dryers with hermetic storage (e.g., PICS bags, Super Grain bags, or metal silos) the chain effectively "locks in" safe moisture conditions throughout transport, aggregation, and reserve warehousing (Alliance Bioversity and CIAT, 2023). Evidence from Northern China shows that feed maize stored in hermetic conditions near Beijing retained protein, starch, and amino-acid profiles for four consecutive years with no fumigation (Li et al., 2017). Such stability dramatically lengthens rotation intervals and reduces re-conditioning costs.

The Government of Malawi has already moved toward a blended

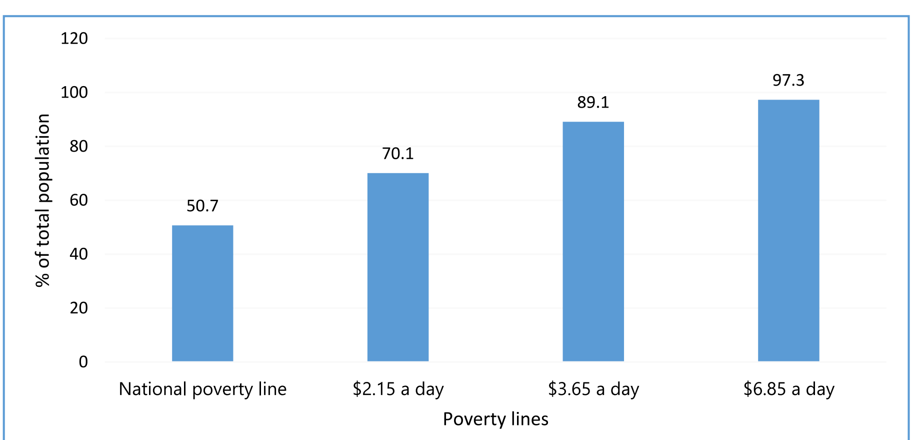

Fig. 6. Percentage of population under different poverty lines
The Figure shows the poverty lines in Malawi as computed by the World Bank.
Source: World Bank (2021)

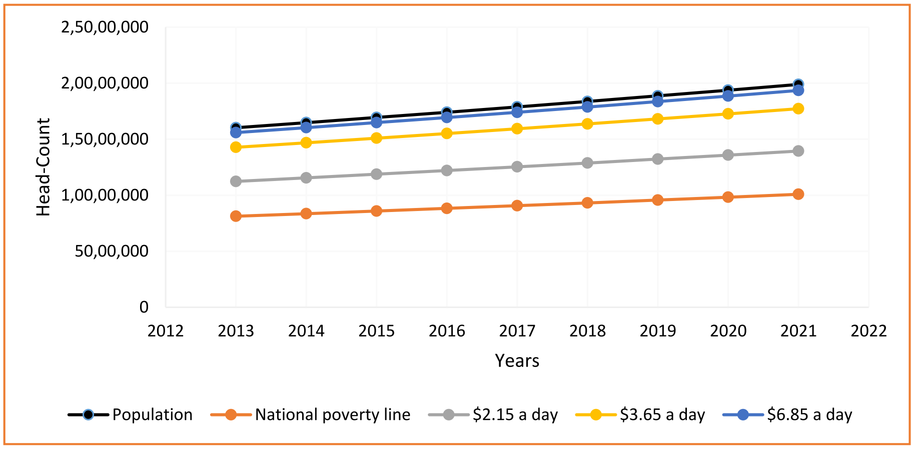

Fig. 7. Absolute population trends based on the poverty lines
The Figure shows the number of people living below the different poverty lines as defined by the World Bank.
Source: World Bank (2021)

storage architecture, contracting private silos under management leases to augment NFRA capacity (Chilenga and Mangisoni, 2023). Dry-chain solutions merge neatly with this arrangement for three reasons. First, private operators can adopt hermetic liners inside existing silos at modest capital cost, extending shelf life and deferring the need for costly aeration systems. Second, decentralized assemblers and farmer organizations can supply grain that is already dry-chain compliant, easing NFRA's quality-verification burden on intake. Third, the presence of a reliable on-farm storage option releases pressure on NFRA to purchase immediately after harvest, allowing farmers to hold grain for later sale, further smoothing seasonal price troughs.

Moving forward, to effectively hold the optimum stock, the SGR needs to incorporate dry-chain technology as a structural solution that aligns with on-farm resilience in attaining national food-security mandates. By minimizing moisture-driven losses, the country can conserve substantial volumes currently relinquished to spoilage, extend reserve longevity (up to 4 years), and reduce reliance on volatile import markets. The encouraging results from ongoing PICS trials, corroborated by multi-year storage studies abroad, provide a robust empirical foundation. With targeted policy tweaks, modest financing, and coordinated capacity building, Malawi can position dry-chain management as the backbone of a modern, cost-effective SGR, turning today's post-harvest losses into tomorrow's strategic buffer.

4. Conclusions and recommendations

Given the widespread food insecurity in the country, the need for a revision of the SGR stocking levels cannot be overemphasized. The current study employed dynamic optimization grain sizing techniques to model optimal stock levels for the Malawian Strategic Grain Reserve to meet its objectives of having buffer stocks, emergency response and price stabilization. The findings reveal the need for the reserves holding optimal stocks of 316,350 MT to be able to offset any historical shortfalls in supply if they were to occur again. However, the country still needs additional stocks to respond to any emergency (674,178 MT) and price stabilization (191,267.9 MT). The study highlights that, to determine optimal reserve levels, one must explicitly incorporate dynamic factors such as population growth, alongside the mounting volatility from climate-related shocks. Nonetheless, the physical capacity for holding stocks remains an area for review with the current ADMARC, NFRA and ACE capacity not achieving half of the optimal stock quantity on an annual basis.

As such, the current study recommends the need for the SGR in holding futures contracts for some of the stocks like emergency reserve where the contract can be triggered once the country faces an emergency. Another way is through holding virtual stocks. This can further be done through grain banks, which are a sub-component of virtual reserves that involve commitments with other countries on quantities of grain to be accessed during a crisis. This involves acquiring contingent contracts consisting of grain loans during emergency responses that are repaid with achieved surplus grain sales. The virtual reserves complement efforts toward open-trade recommendations, emphasizing that exporting is an alternative in years of surplus. Nonetheless, Malawi is a net importer, and unregulated virtual reserves only create a demand for more imports while overshadowing the domestic market. In that regard, the contingency contracts are to be functional when the demand cannot be offset by domestic production and typical levels of imports, and the contingency contracts are to be considered as transitional and only applicable during emergencies. Nonetheless, for a virtual reserve to suffice, the country should consider being flexible in its trade policies, especially on export restrictions; and investing in a dynamic forecasting system that determines maize supply variations from fundamental levels. Lastly, to strengthen national food security and safeguard the SGR against climate related shocks, the SGR should diversify its portfolio beyond maize by gradually incorporating drought tolerant staples like cassava and pulses.

5. Limitations of the study

This study acknowledges the data uncertainties that exist in recording informal trade with neighboring countries. Much as we ought to minimize data gaps by triangulating multiple sources, several uncertainties persist particularly around informal cross-border maize flows that are only partially reflected in official records. First, although we incorporated FAOSTAT trade matrices which apply mirror-statistics and partner-reporting adjustments that capture a share of unrecorded transactions, these estimates remain indirect, calling for a need for direct observation of Malawi's porous southern frontier. Second, the research team convened two data-validation workshops with technocrats from the National Statistical Office, the National Food Reserve Agency, and the Ministry of Trade to reconcile discrepancies between FAOSTAT, customs ASYCUDA downloads, and border-monitor counts provided by FEWSNET and WFP. While these consultations improved concordance for formal trade figures, the validation acknowledged that district officers often lack incentives, or staffing to document head-loaded or bicycle-hauled grain entering through ungazetted routes.

Again, limitations exist in the accuracy of the crop production estimates provided by the governments through the Agricultural Production Estimates Survey (APES). As such, the estimation system employed is constrained on three fronts: methodological design, resource capacity,

Table 6
Estimates of the sizes of optimal stocks and emergency reserves and buffer stocks.[a]

Item	2013–2021 average estimate of Malawi's Population (17,914,500)		2013–2021 average estimates of vulnerable populations based on the national poverty line (10,084,099)	2013–2021 average estimates for vulnerable populations based on the $2.15 per day threshold (13,942,709)
Optimal Stocks (MT) – using consumption figures estimated from production, import and export data	632,700		–	–
Suggested six months stock figures (MT)	3 months requirements plus, another 3 months' lead time to mobilize additional grain supplies	632,700/2 = 316,350	–	–
Optimal Capacity of Emergency Reserve (MT) – using consumption figures estimated from production, import and export data		**2,659,500**	**1,348,356**	**1,864,309**
Suggested six months stock figures (MT)	3 months requirements plus, another 3 months' lead time to mobilize additional grain supplies	2,659,500/2 = 1,329,750	1,348,356/2 = 674,178	1,864,309/2 = 932,155
Buffer Stocks; ADMARC, NFRA & ACE Capacity (MT)		**545,700**	**276,669.9**	**382,535.7**
Suggested six months stock figures (MT)	3 months requirements plus, another 3 months' lead time to mobilize additional grain supplies	545,700/2 = 272,850	276,669.9/2 = 138,3345.0	382,535.7/2 = 191,267.9
Buffer Stocks; ADMARC, NFRA & ACE, On-farm & Private traders Capacity (MT) i.e. unlimited capacity buffer		**1,012,000**	**513,084**	**709,412**
Suggested six months stock figures (MT)	3 months requirements plus, another 3 months' lead time to mobilize additional grain supplies	1,012,000/2 = 506,000	513,084/2 = 256,542	709,412/2 = 354,706

[a] Findings from the equations on optimal stocks.

and political economy, each eroding data quality and, by extension, the credibility of food-security analysis. Methodologically, APES employs non-probability sampling at Extension Planning Area (EPA) level and relies on farmer recall for both area planted and yields. Plot-size "eye estimates" introduce systematic bias (tending to overstate small plots and understate large ones), while crop-cut verification is conducted on fewer than 2 % of sampled fields, well below FAO's 10 % best-practice benchmark. Remote-sensing cross-checks are ad-hoc because high-resolution imagery must be purchased externally, limiting annual consistency. Financial and human-resource constraints compound these weaknesses. District Agriculture Offices report vacancy rates exceeding 35 %, leaving vast enumeration zones unvisited during peak data-collection periods.

As such, future work would benefit from: (i) strengthening sampling methodology; (ii) funding continuous crop-cut surveys; and (iii) institutionalizing third-party validations. Again, continuous border-sensor monitoring, GPS-enabled trader diaries, and greater regional data-sharing to tighten confidence intervals around unofficial grain movements could reduce the uncertainty in the informal trade data.

CRediT authorship contribution statement

Wisdom Richard Mgomezulu: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mthakati Alexander R. Phiri:** Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Conceptualization. **Davis Muthini:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Paul Thangata:** Writing – original draft, Project administration, Methodology, Investigation, Formal analysis.

Declaration of competing interest

We hereby declare that the information in this article is correct, and that there exist no potential or apparent conflict of interest.

Data availability

Data will be made available on request.

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