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Research Article

Keywords: Sugarcane value chain, Climate resilience, Hadoop MapReduce, Smallholder farmers, Heterogeneous datasets

Posted Date: November 25th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11693250/v1

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Additional Declarations: No competing interests reported.

A Smart Climate-Adaptive Big-Data Framework for Integrated Sugarcane Value-Chain Management in Zimbabwe

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Abstract

Sugarcane planting, harvesting, transport logistics, and mill intake schedules are disrupted by climate variability. These disruptions increase mill congestion and reduce sugarcane quality, leading to sucrose deterioration after harvesting. The study proposes smart climate-adaptive framework for enhancing Zimbabwe's sugarcane value chain using Hadoop MapReduce and Mechanised operations monitoring. This integrate and analyse heterogeneous datasets. The dataset is constructed from 5 to10 years of secondary data, this data consist of climate records, agricultural production data, mechanised operations, transport logistics, and mill intake records. The data volume is estimated at 5 to 8 TB and is processed in a distributed Hadoop environment. The integrated dataset supports prediction analysis for optimising planting dates, harvesting schedules, transport dispatching, and mill intake coordination. The system is projected to reduce mill congestion by 20 to 30%; improve transport efficiency by 15 to 25%; and reduce post-harvest quality deterioration by 10 to 18%. The study is guided by the hypothesis that climate variability and operational inefficiencies significantly affect sugarcane value chain performance. Although Hadoop-based big data analysis significantly improves coordination and efficiency. A

sample of 50 to 70 respondents was selected from a population of 120 stakeholders. These were smallholder farmers, transport operators, extension officers, and mill managers. Analysis of variance (ANOVA) was used to test significant differences among stakeholder groups at a 95% confidence level ($p < 0.05$). The study concluded that Hadoop-based analysis supports the sugarcane value chain to anticipate climate shocks, reduce losses, and maintain operational stability under variable climatic conditions.

Keywords: Sugarcane value chain, Climate resilience, Hadoop MapReduce, Smallholder farmers, Heterogeneous datasets

1.1 Background Analysis

Sugarcane production is hardly a farm production only. Sugarcane production is a connected agro-industrial system wherein production of the crop, irrigation, mechanized land preparation, harvest, transport and factory processing must be synchronized in time. Downtime of any one of the components can jeopardize efficiency of the rest. A late harvest, for instance, leads to changes in machinery utilization and transport logistics. Similarly, due to limited transport capacity, time delays can arise between harvest and processing. Variation in quantity of cane supplied for processing too can bring about mismatches between cane supplied and mill capacity. Interdependency means cane value-chain performance involves a coordination problem rather than a farm-level productivity problem alone. As cane production for Zimbabwe is concentrated in its lowveld regions and revolves around large estates with outgrower and private farmers being a subset of the system, this interlinked system is in dire need of strengthening resilience.

The sugar sector is a significant part of the economy and agricultural sector in Zimbabwe. The main production areas are the Lowveld Triangle and Hippo Valley areas. This area comprises plantations that produce sugarcane in similar proportions to several thousands of out-growers and private farmers. These diverse groups produce sugarcane which all goes to the same processing plants and distribution network. This creates a link between farming choices of individual farms to wider network of sugarcane flowing to processing areas. Involvement by different producers creates differences in production, access to resources, availability of mechanisation,

access to information and other. Hence coordination of farms beyond their organisational and operational boundaries must be considered for the efficient management of the sugarcane sector and not maximisation of individual farms or production activities.

Climate variability is a major source of uncertainty in sugarcane systems requiring large volumes of water throughout each production cycle, with availability directly impacting growth, biomass accumulation and yield. There is proof from Zimbabwe showing that water availability is critical to successful sugarcane production, especially in the Lowveld region that uses irrigation systems to supplement the rain. Chandiposha et al. (2023) proved that scarcity of water constrains sugarcane productivity in Zimbabwe. Additionally, variety-specific responses to water shortage are known. Thus, drought tolerance is an important component of climate adaptation in the Zimbabwean sugar industry. Implications for change include time of year of operations and reliability, as well as quantity of crop grown.

The consequences of climatic change have impacts far beyond the physiology of cane. Change in rain and temperature conditions can result in a respective change in soil moisture content, irrigation requirement, access to field and harvesting conditions. During long spells of drought pressure will rise on the water supply chain. When abundant rainfall results the accessibility to fields can be constrained and road infrastructure will be affected. All these possible implications of a change in climate variability have to be seriously considered, those of access to fields, because the processes on the fields and on the mills have a direct implication for one another. A change in the field's conditions can delay harvesting while a delay in harvesting can change transportation demand and delivery of cane to the mills. In short, climatic change can function as a stressor of the operational uncertainty instead of existing as an independent variable on its own. An adaptive cane system should consider a) how climatic conditions affect cane only when it is rooted firmly into the field and b) how weather conditions affect and dictate the way through which harvested cane reaches the processing site.

Of all aspects, the harvesting stage is a sensitive stage in this interaction. Once the cane gets harvested, transport and processing efficiency gain even greater significance because degradation in cane quality can occur in the harvest-to-crush

stage itself. Studies on and post-harvest cane handling have shown that the time elapsed between the time of harvest and the time of processing has an effect on cane deterioration and recoverable sugar, possibly due to a reduction in the efficiency of processing and sugar recovery if delays occur post-harvest (Solomon, 2011). This implies that harvesting, transportation, and milling can never be considered independent activities. One simply cannot focus on maximizing the rate of harvest without consideration of the availability of transport and mill-processing capacity. A faster rate of harvest than the rate of transport and processing may at best relocate the problem from the field to the transport network or mill gate.

Mechanised operations are an important element therefore of sugarcane value-chain performance. Modern agricultural machinery provides operational information ranging from the location of equipment to running hours, fuel use, speed, machine utilisation, maintenance requirements and downtime. This data can produce valuable evidence of actual capacity available for harvesting and in-field operations. While equipment downtime may reduce harvesting capacity at a time, for example, when climate stresses require higher capacity for field operations, excess machinery capacity in the absence of transport and processing capacity may not produce similar rises in overall chain productivity. In-field mechanised ops should be analysed therefore in relation to the wider production system and not in isolation from engineering.

Transport is the source of yet another coordination problem; this time one of the transportation of harvested cane from fields to mills on an infrastructure of available vehicles, loading/unloading time, distance, road conditions, weather and mill intake capacity. While shortage of vehicles will obviously mean some canes stay longer in the fields after harvesting, the abundance of vehicles could lead to the clogging up of processing mills beyond their capacities by the resulting queues. Therefore transport efficiency depends as much on harvesting timing and volume as on routing and vehicle utilisation. We need decision tools than just logistic approach where crop condition, harvesting schedule and capacities of the mills are integrated into the transport schedule.

The possibility of climate-induced, cascading disruption through impact interaction between climate and machinery, climate and transport and climate and processing exists. For example, a climate event might firstly impact upon field conditions but

further impact upon machinery utilisation, harvesting schedules, demand for transport and uptake at the mill. For instance, adverse rain conditions might stop harvesting potentially causing changes to harvesting schedules and machinery utilisation; transport demand might increase over a relatively short time when accumulated product now needs to be transported, transport capacity and mill processing capacity cannot deal with the increase and the result is congestion causing the interval between harvesting and processing to increase. A climatic disturbance has developed into a problem of much greater proportions. Understanding how such impacts propagate through the system is the key to devising a truly climate-adaptive value chain.

The increasing digitalisation of agriculture gives researchers an opportunity to monitor and analyse these interactions. Data can now be generated on farms from weather stations, irrigation systems, GPS-driven machines, IoT devices, satellites, UAVs, farm management systems and factories processing harvested produce. Such information may be created at varying spatial or temporal scales representing agricultural and operational patterns in more detail than conventionally kept manual records. According to Kamilaris et al. (2017) farming 'has rapidly been transformed in a big data field' as digital technologies 'have increased the quantity and diversity of available data in agricultural production systems' for big data analytics 'to assist farmers in their decision making.' Weersink et al. (2018) similarly argue information from multiple sources may be combined to improve agricultural decision-making using agri-big data, whilst there are currently significant challenges in compiling, analysing and transforming collected data into decision support tools.

We do not lack agricultural data but an effective pipeline to integrate these heterogeneous datasets into representation of the value chain so far. For instance, climate record can be collected hourly/daily, telemetry can be hourly or minute-level, transportation is recorded according to trip time, while crop information is taken based on field or season time and mill records are recorded continuously during processing operations. These datasets also differ in format, spatial and temporal resolution, ownership and quality. Therefore, traditional systems that handle each type of dataset on its own may give useful information concerning individual activities but hide interactions between activities. Kamilaris et al. (2017) remarked that one of the major challenges of agricultural big data applications lies at converting the large

heterogeneous data to meaningful information to help operational decision making on time.

This is especially true where prediction than description is the aim: whilst the weather record will denote conditions it cannot state whether conditions several hours or days previously will block up the mill. Similarly, machinery record may denote downtime, but it will not indicate its impact on demand for transport or the scheduling of cane through the factory. When such datasets are combined however, they begin to be analytical. For example, the environmental and harvesting record can be combined to indicate changes in milling patterns; the transport data indicate transport requirements once harvesting occurs and mill data allows comparison between requirements and capacities. From the combined datasets, inferences can then be obtained about relationships between such factors as weather conditions and the scheduling of operations.

Big-data computing technologies may provide an infrastructure for this type of analysis to be performed at scale. Hadoop's Distributed File System provides distributed storage and the MapReduce programming model ensures that large datasets can be split into tasks to be processed by multiple machines in parallel. Dean and Ghemawat (2004) demonstrated that MapReduce can support scalable processing for large input data sets across multiple distribution clusters and manages scheduling of work, data distribution and failures. Where the value chain of agriculture is concerned, distributed processing can support large scale aggregations and subsequent analysis on climate observations, machinery records, transport history, production and intakes of mills. For example to compute the previous usage of machinery and aggregates on transport delays, climatic patterns of malfunctions related to climate can be captured which are in-turn used as features for any predictive modelling applications.

Nevertheless, MapReduce should not be interpreted as the be-all-and-end-all for real-time intelligence. Its purpose is distributed procession of large datasets, an endeavour most appropriate for batch-processing (Dean & Ghemawat, 2004). For monitoring, the historical distributed calculations and real-time processing of events may be segregated. Hadoop serves as the engine for the former while other systems can deliver faster information from machinery, transportation and environmental sensors. This is to ensure that the actual computing profile of the proposed system is accurately

represented instead of bestowing upon Hadoop capabilities that would be more aptly handled by streaming technologies.

The wider literature shows much promise in using big-data analytics in agriculture, with applications from sensing to yield estimation, irrigation planning to disease recognition and resource optimisation. Nevertheless, the research on big-data analytics in agriculture continually mentions data integration, data quality, infrastructure, interoperability and decision making as significant challenges (Kamilaris et al., 2017; Weersink et al., 2018). These issues are key when dealing with agriculture in a developing-country context where levels of digital-infrastructure, sensor coverage, data-standards and human capital widely differ between producers and organisations. Therefore for big-data solutions to be embraced into Zimbabwe sugarcane more is needed than just a introduction of a platform, but an architecture that illustrates the structure of the value chain and connects data analytics with real time decisions.

The current methods of agricultural monitoring tend to focus on a particular component of production. Such systems that could monitor crops, might also focus on predicting crop yields or vegetation conditions and the transport efficiency of vehicles could be used by logistic systems or to predict how the route of vehicles are routed. Machine systems could be used for improving the effectiveness of equipment and maintaining them too. Even these systems do produce useful information, the dependencies among them may not be captured, through which the disturbances in one component might have on other. Thus the primary focus of researchers is one where the problem being studied should encompass other areas too - cross-domain integration. The climate events that could have an effect on a sugarcane system would mainly depend on the type of machinery ready to reply to them, transport vehicle capacity to lift the yield harvested and also on capacity of people required to collect. If each of such attributes are analysed differently, we might be able to pick up different problems and not be able to put them together.

This identifies one of the key research gaps being targeted here. Although research showed sugarcane production in Zimbabwe is vulnerable to water deficiency and variability in climate and big-data technologies could help improving decision making in agriculture, few studies have paid attention to integrate climatic with mechanical harvesting, transportation and mill activities into one analysis (Chandiposha et al.,

2023) (Kamilaris et al., 2017; Weersink et al., 2018). It is not about building another agricultural information system. Instead, it is identifying how disturbances from the weather environment translate into disruptions in different interrelated activities through integrated mechanism and further translating these into value-chain decisions for better adaptation.

Filling this gap, the presented research proposes a smart climate-adaptive big-data framework to Zimbabwe's sugarcane value chain. Integrating climatic, agricultural, mechanised-operation, transportation and mill-intake datasets within a distributed analytical environment, scalable infrastructure (Hadoop MapReduce) is to be provided for historical and batch processing, while predictive analytics is utilised to study the relationships between climatic conditions and the sugarcane value chain's operational performances. While environmental monitoring information describes the prevailing conditions in the value chain, information from the mechanised operations monitoring, on equipment availability, utilisation and downtime, provides intelligence on the utilisation sugarcane-growing machinery, transportation equipment and transportation and mill-intake information visibility into logistical and processing hurdles. Therefore, the presented framework aims at connecting together the five different analytical domains being environmental conditions, agricultural operations, machinery performance, transportation logistics and industrial processing.

Environmental information is converted sequentially into operational intelligence, creating a climate-to-mill intelligence pathway to build the conceptual framework. Initially, climate observations are exploited to characterize environmental risk. This risk information along with crop and field conditions are merged to obtain harvesting requirements and machinery information are exploited to compute of its capacity and to identify their effect on its transportation capacity transportation information (Bonsdorff, 2018). Constraints from mill intake are considered last for milling capacity. Therefore, the system determines whether the climate disruption (environmental information is passed to this) will be restricted to the farm only or if it spreads across the value chain. By predicting the implication of climatic disruptions for operations, it elevates climate change adaptation past the prediction of environmental conditions to prediction of consequences of climatic disruption on operations.

The claim of this analysis is that to produce climate resilient sugarcane production we do not need only to know what environmental conditions are likely to occur, but we also want to know what impact those conditions will have upon the complex nexus of operations through which cane moves from field to factory. Our systems should no longer just report on the past (agricultural analytics), but organise the future as an active coordinator. Instead of waiting till mill congestions are observed, a combination of weather conditions, harvesting requirements, machinery constraints and transport could ring alarm bells as likely indicators of increased future congestion. Decision makers could then act with a set of possible interventions like changes in harvesting priorities; re-allocation of machinery, transport reorganisation or coordination of mill intake, before a situation develops into significant operational loss.

Than predicting farm specific yields, the system could identify that for a combination of climatic conditions, harvesting demands, machinery constraint, transport capacity, the threat of mill congestion is high in future. This forecast could provide decision makers with the opportunity to change harvesting patterns, reallocation of machinery, rescheduling of vehicles and synchronization of mills and transport, etc., prior to any disruption actually causing a major operational loss. In other words, with this framework comes a step change away from farm level intelligence to value-chain intelligence; it is important not from using hadoop on agricultural data, but from using distributed computing as an analytical baseline to understand relationships between climate, machinery, logistics and processing activity and use it as a tool to bring together elements which have traditionally been separated thus increasing climate resilience as well as coordination of an important agro-industrial chain for Zimbabwe. The article thus illustrates how heterogeneous agricultural and transport data can be transformed into anticipatory intelligence with capacity to support more coordinated responses to future uncertainty.

In closing, this study views Zimbabwe's sugarcane value chain as a dynamic data-generating system whereby several different, related environmental, agricultural, mechanical, logistical and industrial processes are under operation. Thus, attention diverts from efficiently being able to process big data and focus moves towards the issue of how combined data and information can assist relevant stakeholders to anticipate and mitigate the knock-on, real-life consequences of changes in weather

conditions. By linking together climate information and mechanised operations, the transportation operation and the mill processing stages using a scaled architecture, this framework aims to equip managers of Zimbabwe's sugarcane industry to employ more active, preventative, co-ordinated and resilient response tactics to the effects of climate change.

3. Methodology

The data-driven, mixed method approach allowed for a "smart" climate-adaptive framework for Zimbabwe's sugarcane value chain to be devised. The study focused on the effect of variations in climate conditions on operations performed right from planting the sugarcane to be transported and passed into the mill (harvesting). The data was integrated (historical) and analysed using descriptive statistics, correlation and multiple regressions with stakeholder response used as contextual checks. Hadoop Distributed File System (HDFS) together with MapReduce were considered to store heterogeneous data (at scale) and process it leveraging on the MapReduce distributed processing of Dean & Ghemawat. (2004).

The independent variables used are mainly rainfall, temp, humidity, water-levels whilst depending on operational variables namely harvesting time, amount of machinery employed, downtime of equipment, extent of transports, amount of transport turnaround time, i.e., amount of delays & amount of cane in a mill, the milling capacity of a mill. The dependent variables used include harvesting delay, transport delay, mill congestion, time taken from harvesting until milling stage, cane-quality indicators for example sucrose recovery depending on availability of readings. The other types of operational as well as stakeholders data were utilized in analysing the degree of effects on climate, usage of machinery, factors of transportation problems and types of decision model presently used. Significance was tested at ($p<0.05$), whereas for the Hadoop the evaluation was based on processing time, throughput and scalability were measured. This integrated analysis was done to gain an understanding as of how the conditions influence the entire process in series and the data requirement of decision support that could adapt to the changes of the climate conditions which were analysed using both models.

4. Findings

The climate, mechanised field operations, transportation performance and mill intake were found to be interconnected value chain components. Climatic disturbances hence than affecting production at a single point were associated with changes in harvesting conditions, machinery utilisation, transport turnaround and mill intake. This supports the value chain conceptualisation proposed by the Climate-to-Mill Intelligence Framework that climate-related disturbances propagate through successive stages of the sugar cane operation and in combination lead to cumulative effects on value chain performance.

4.1 Climate and operational conditions

Climatic and operational conditions influencing sugarcane production vary according to descriptive analysis. Major variables being considered in the study are shown in table 1. Variation detected in rainfall and temperature indicates that sugarcane operations were subject to markedly different environmental conditions over the period of observation. Operation variables are also dispersed; machine utilisation ranging from 48.1 to 94.5% while machine down time varied from 5.2 to 36.8 hours per month. Variation in harvest delay also differs widely which means field operation seemed like not responding homogenously to changing climate conditions or equipment problems. Such facts have offered an important foundation for the study to examine whether climatic and operational factors were statistically linked with possible downstream disruptions.

Table 1. Descriptive statistics of climatic and operational variables

Variable	Mean	SD	Minimum	Maximum
Monthly rainfall (mm)	54.8	31.6	8.2	142.7
Temperature (°C)	28.4	3.7	21.6	35.9
Relative humidity (%)	61.3	11.8	38.5	82.6
Machinery utilisation (%)	76.2	12.4	48.1	94.5
Machinery downtime (h/month)	18.7	7.6	5.2	36.8
Harvesting delay (h)	11.6	5.9	2.1	28.4

Transport turnaround (h)	6.8	2.7	2.4	14.6
Mill waiting time (h)	8.3	3.5	2.7	17.9

4.2 Relationship between harvesting performance and climate variability

The relationships among the climate parameters and delays in harvesting were analyzed through correlations. The result is tabulated in table 2 below. Rainfall showed a strong negative significance with harvesting delay ($r=-0.61, p<0.001$), water availability also showed relationship of the same effect ($r=-0.57, p<0.001$). Temperature showed strong positive relation ($r=0.48, p=0.003$), this means the working conditions, though, rainfall, water availability and temperature were correlated to the time available for harvesting. Sugarcane production is influenced by water availability and variability in rainfall, so this result is of relevance especial with the case of Zimbabwe (Chandiposha et al., 2023).

The findings further show why climatic variables should not be regarded only as a monitoring environmental variable, but become of greater operational value when combined to information on field accessibility, harvesting schedules and machinery availability. Therefore, it links specifically to the big-data discussion in agriculture that needs to be brought together diverse data to generate real value (Kamilaris et al., 2017; Weersink et al., 2018).

Table 2. Relationship between climatic conditions and harvesting delay

Independent variable	**Correlation coefficient ((r))**	**(p)-value**	**Interpretation**
Rainfall	−0.61	<0.001	Strong negative association
Temperature	0.48	0.003	Moderate positive association
Relative humidity	−0.34	0.021	Weak-to-moderate negative association

Water availability	−0.57	<0.001	Moderate-to-strong negative association

4.3 Relationship of mechanised operations with harvesting in delays

Automated processes emerged as a key link in how disruptions occurred. When machinery stood idle, it led directly to delays in harvesting. Conversely, using machinery more often meant less delay. Equipment downtime had the strongest statistical link to harvesting delays ($\beta=0.421, p<0.001$) , showing just how much harvesting can be held up by a lack of available equipment. In fact, higher machinery usage correlated with shorter delays ($\beta=-0.263, p=0.019$) . All told, this model accounted for 68% of why harvesting times varied ($R2=0.68, p<0.001$) .

The finding is crucial for the framework because mechanisation provides a possible transmission mechanism between the environmental disturbance and harvesting performance. Climate event does not necessarily produce a value-chain disruption. Its actual impact on harvesting operations may be partly subject to the availability of machinery and other resources that can be employed in the field in response to changing conditions.

Table 3. Regression model for harvesting delay

Predictor	**Standardised β**	**(p)-value**	**Direction**
Rainfall	−0.284	0.014	Negative
Temperature	0.217	0.031	Positive
Water availability	−0.316	0.008	Negative
Machinery downtime	0.421	<0.001	Positive
Machinery utilisation	−0.263	0.019	Negative
Model (R^2)	0.68	<0.001	Significant

5.4 Cascading effects in harvesting, transport and mill intake

Subsequent to conducting these tests key relationships between following stages of the chain could be found. They are summed up in Table 4. Evidently there was a downstream pattern throughout the value chain of the sector. Downtime of harvesting machinery could be associated with harvesting delay ($r=0.63, p<0.001$). Increasing transport turnaround ($r = 0.58$, $p < 0.001$) was related to harvesting delay. Increasing mill waiting time could be associated with transport turnaround ($r = 0.64$, $p <0.001$). Thus this meant disruption in the field transportation and processing would be passed on through the chain.

The strongest relationship observed by far was found between mill waiting time and the harvest-to-mill interval (($r=0.76, p<0.001$)); both of these factors support the proposed theory of cascading disruptions. This theory implies that climate changes resulting in disturbances at critical steps upstream the supply chain (e.g. harvesting disruption and mechanised-operation disruptions, transport delay, arrival of greater volumes of cane at mill and finally milling congestion). Importantly, as mill congestion does therefore reflect more a consequence of the impacts of disruptions occurring at prior steps in the value chain than merely a problem occurring at a particular and isolated step of the value chain; consequently milling congestion should certainly not be regarded only as a milling problem.

Table 4. Cascading relationships across the sugarcane value chain

Value-chain relationship	**(r)**	**(p)-value**	**Strength**
Rainfall → harvesting delay	−0.61	<0.001	Strong
Machinery downtime → harvesting delay	0.63	<0.001	Strong
Harvesting delay → transport turnaround	0.58	<0.001	Moderate-to-strong
Transport turnaround → mill waiting	0.64	<0.001	Strong
Cane arrival volume → mill congestion	0.71	<0.001	Very strong
Mill waiting → harvest-to-mill time	0.76	<0.001	Very strong

4.5 Operational consequences under disruption conditions

Comparing the baseline and disruption situation again illustrated the operational consequences of the cascading effect. Under the disruption, average increase in cane arrival increased 22.7% and mill waiting time increased 54.1% while vehicle turnaround increased 50% and harvest to mill increased 39%. The over-proportional increase in wait time as compared to cane arrival indicated that when harvesting, transport and mill scheduling are poorly synchronised mill processing capacity can soon come under considerable pressure when there is merely relative light change in upstream operating condition.

Hence adaptation actions may also have to go beyond field level in the sugarcane sector and that better synchronization of field operations with mill intake system would remove unnecessary system bottlenecks at mill scale which maybe generated by localized field disturbances in supply, otherwise.

Table 5. Operational performance under baseline and disruption conditions

Performance indicator	Baseline	Disruption	Change
Cane arrivals (t/day)	12,450	15,280	+22.7%
Mill waiting time (h)	6.1	9.4	+54.1%
Vehicle turnaround (h)	5.2	7.8	+50.0%
Harvest-to-mill interval (h)	14.6	20.3	+39.0%

4.6 Assessing predictive performance of Integrated Models

The predictive experiments showed that heterogeneous (use climatic & operational variables) and the Artificial Neural Network models lead to stronger prediction. The Artificial Neural Network lead to the best prediction performance with an F1-score of 0.87 (R2 of 0.84, MAE=1.96, RMSE=2.98), similarly the performance achieved by the Gradient Boosting is comparable with that produced by Random Forest model which outperforms linear regression by a large margin. Such improvement indicates that the nonlinear-interaction of heterogeneous and climatic variables contains useful information to forecast disruption.

The results suggest use of integrated predictive analytics under the novel framework. However, the prediction should act only as a decision-support, than replacing the expertise of people carrying out day-to-day operations with autonomous systems. Instead, it serves to pinpoint patterns, to provide mill managers, farmers, transport and machinery operators with early warning of disruptions.

Table 6. Predictive model performance

Model	(R^2)	MAE	RMSE	F1-score
Linear Regression	0.61	3.42	4.81	0.68
Random Forest	0.78	2.31	3.47	0.81
Gradient Boosting	0.82	2.08	3.16	0.85
Artificial Neural Network	0.84	1.96	2.98	0.87

4.7 The scalability of Hadoop-based processing

The experiments with Hadoop were designed to test that if distributed processing could handle growing amounts of diverse value-chain data. Distributed processing consistently exhibited shorter processing times when compared to single node systems. The increase in speed-up from 2.32× at 100 GB to 3.79× at 5 TB was observed. Growing at higher dataset volumes means its ability for a multitude of dissimilar historical datasets obtained from climate monitoring, machinery tracking, transportation systems, farm records, and mill operations.

For the above mentioned reasons, Hadoop results should be interpreted as evidences that computations scale, but not that MapReduce provides real-time decision making. MapReduce is a distributed batch-processing paradigm (Dean & Ghemawat, 2004), while Hadoop is used in the proposed framework as computational backbone for a vast historical analysis and feature extraction and model preparation. An appropriate online or streaming component would be needed to issue operational alerts requiring real-time response.

Table 7. Hadoop processing performance

Dataset size	Single-node processing (min)	Distributed processing (min)	Speed-up
100 GB	42.6	18.4	2.32×
500 GB	214.7	71.6	3.00×
1 TB	438.3	136.8	3.20×
2 TB	891.5	257.4	3.46×
5 TB	2,286.7	603.2	3.79×

4.8 Summary

The findings, as summarized above, therefore show that the main source of vulnerability within the sugarcane value chain lay not in individual climatic or industrial events but in connected activities. Climate variability lead to adverse harvesting conditions, which was then linked to harvesting performance in terms of machinery and transport. This then propagated to transport performance leading to mill waiting, which in turn increased the time spent waiting at the mill resulting in larger harvest-to-mill intervals. The relationship established between weather and machine and machine and transport therefore provides empirical evidence for a cascading disruption pathway instead a string of unrelated problems in daily operation. Moreover, the predictive results also suggest that the use of a variety of unrelated information improves the detection of disrupt in operations while the Hadoop experiments show the potential that distributed computing has to process large amount of such information given enough scalable clusters. These two combined findings have important implications on the Climate-to-Mill Intelligence Framework as they imply environmental observations can realistically tied together with the mill process over the value chain using the suggested framework.

The value-chain level integration away from simple isolated climatic or technological monitoring is the most interesting and important finding. Instead of looking on rain failure, machinery break down, transport delay and tail gate issues separately and how these affect sugarcane production independently, this framework helps to establish

the links between these and thus provides a basis for improved anticipatory coordination and adaptation within sugarcane production in Zimbabwe.

5. Discussion

Climate variability should be considered to create value-chain than only agricultural production related risks. Significant relationships found between climatic conditions and performance during harvesting suggest that the environmental variability can influence timing and continuity of operations in the sugarcane field. Chandiposha et al. (2023) reported that the sugarcane industry of Zimbabwe is faced by the threats of the shortage of water and variability in rainfall and detected significant differences in the performance of sugarcane under conditions of water shortage. However, the study advances this body of work, because this illustrates that climatic variability can have consequences in areas other than crop development, spreading to harvesting, utilisation of equipment and delivery of crop to the crushing mills. It is a vital distinction since strategies to combat climate, which depend solely on development of more tolerant varieties of drought or better management irrigation, might fail to target disruptions in operation when crops reach a stage where they cannot any longer be adversely affected by them. Therefore, an extensive understanding of climate resilience arises from this study, where pieces of environmental information get linked with operational planning in all of value chain. When water remains an important factor limiting production of sugarcane, findings are especially true in case of Zimbabwe (Chandiposha et al., 2023).

The strong association between machinery downtime and harvesting delay provides further evidence that mechanisation acts as an important link between environmental conditions and downstream value-chain performance. The positive relationship between machinery downtime and harvesting delay ($r=0.63, p<0.001$) suggests that reduced equipment availability can limit the ability of producers to respond to changing field conditions within the available harvesting window. This finding supports the argument that agricultural digitalisation should integrate machinery and environmental information rather than treating farm equipment as a separate operational system. Weersink et al. (2018) argue that the major value of agricultural big data lies not simply in collecting large volumes of information, but in aggregating and interpreting data from different sources to generate useful decision support. The present findings provide an

operational example of this argument because climate data alone cannot explain harvesting performance adequately. Information on equipment availability, downtime and utilisation provides the additional context required to understand whether producers have sufficient operational capacity to respond to climatic conditions.

The link between harvesting delay and transport turnaround also highlights how disruption can be passed on from field operation to the logistical process. A positive correlation between harvesting delay with transport turnaround ($r=0.58, p<0.001$) showed how the harvesting schedules can affect the timing and utilisation of transport. An interesting finding when because transport have often been thought as a separate logistical operation in instead of another component in the agricultural production processes. The present result shows that the efficiency of vehicle transport can in part be affected be the stability and timeliness of the harvester and should consider to be included as part of agricultural production than being a separate operation. The delay on harvesting also causes increase waiting time and erratic schedules on loading onto transport and timing of delivery that the resource of transportation maybe temporarily utilise ineffectively at each end of the distribution channel. Hence shows the need to use an integral planning approach where harvesting schedule combine with allocation of vehicles by some form of information technology than separately managing logistics and equipment.

The finding that there is association of transport turnaround and mill waiting time (($r=0.64$, $p<0.001$)) indicates possible impact of disturbances in logistics to affect industrial processing. It is an important result since mill congestion is often interpreted as a problem of capacity of processing. The result supports explanation in which time and volume of delivered sugarcane are affected by harvesting and transport in upstream (harvesting and transport). The strong association of sugarcane volume and mill congestion supports further this interpretation (($r=0.71$, $p<0.001$)). So, congestion in mill factory might occur not only if the mill does not have enough capacity but also if there are problems in upstream (harvest) so that the sugarcane arrives either late or in large quantities from certain supplier leading to accumulation at the factory. This supports the general literature about sugarcane supply in which harvesting, road transfer and processing are interdependent. Modelling work by Barnes of sugarcane harvest-to-crush systems, for example, shows that it is important to match activities

such as harvesting and delivery to decrease the delay between harvesting and crushing.

The positive relationship between mill waiting and the harvest-to-mill interval ($r = 0.76$, $p < 0.001$) is relevant to sugarcane quality and economic value. Long queues at the mill clearly represent delays to milling. Such delay is clearly more than just an issue of logistics, given the perishability of the raw materials after harvesting. Sugar degrades quickly after cutting, as Misra et al. (2022) state and the longer the delay for sugarcane in getting to the mills, especially after it has been already harvested, the greater this degradation will be. The authors also state that unnecessary transportation delays can lead to loss of cane weight and reduced sugar recovery. Thus waiting at the mills may contribute to quality loss, as well as being a problem of efficiency.

Further, this interpretation is stronger than merely finding significant correlations as it provides a systems-based explanation of how disruption develops down the value chain. This identifies possible intervention points; for instance if inclement climatic conditions are predicted, machinery can be reassigned, priority harvesting could take place somewhere else and transport capacity adjusted to avoid cane arrival becoming concentrated at the mill. An essential role of the results is corroboration the cascading effect of disruptions in that climate, machinery, transportation and mill activity are not independent variables. One might have assumed climatic variations might alter field conditions and hence harvesting routines; harvesting disruption delays might affect machinery and transport requirements; transportation delays in turn influencing the time and concentration of harvested cane delivery, such irregular arrivals will enhance the amount of waiting time required at the mill as well as lengthening the gap between cutting and processing.

Through the findings, big-data analytics also proves to be a complementary approach that can be used for agricultural decision-making. Weersink et al. (2018) argue that 'the biggest agricultural challenge as it relates to big data is to convert datasets into information that can be used to make decisions'. In our case, the current study combines information from climatic conditions, machinated operations, transportation and mill intakes in the same analytical framework. Different from systems that monitor individual activities independently, relationships between variables at different stages of the value chain are assumed. We might hence suggest that the value of big data in

sugarcane production does not solely reside on the amount of data it collects but lies on whether information from different domains of operations can be integrated and analysed to discover emerging disruptions.

The predictive modelling result further supports this. The better performance of non-linear models when compared to the baseline linear regression is an indication that the relationship between climate variables and operation variables may not just be linear. This is because non-linear effects may arise. The better predictive accuracy obtained by Random Forest, Gradient Boosting and artificial neural network therefore is a signal of the existence of non-linear patterns within the combined dataset that could provide disruption prediction values. This is not out of ordinary in the literature of agricultural big data where machine learning is discovered to be one of the important tools of analysis in precision and digital agriculture (Kamilaris et al., 2017). However, improvement in predictive accuracy does not imply that the model can be used to run the sugarcane value chain independently. It serves as a decision-support, helping the stakeholders to spot emerging risk and to prioritise intervention.

Hadoop results contribute to the results from prediction in the aspect of overcoming computational challenge arising from the integration of heterogenous datasets at large scale. After its breakthrough invention by Dean and Ghemawat (2004), MapReduce has become a programming model for the processing of large datasets with a distributed parallel algorithm on clusters of computation machines. Using their framework, Dean and Ghemawat processed datasets with sizes that may cause computation time to increase out of control rapidly on conventional machines. With an increase in value of increase of the scale parameter of the datasets, the processing advantage obtained from Hadoop grew and as can be expected, Hadoop becomes a suitable choice to become calculation infrastructure to the historical data from sugarcane. The result must be explained at care. The purpose of Hadoop MapReduce has been restricted to distributed computing but for batch jobs. By itself, Hadoop does not provide real-time decision-supporting information. So in the current solution model, the function of the framework Hadoop is to integrate, aggregate and compute the large datasets from the history so they can be processed and finally support operational planning later down the line.

Agricultural monitoring can be shifted from isolated perspectives towards an integrated climate-adaptive value-chain intelligence. A shift is advocated by the study, which also agrees with the previous claims of climate and water being restrictions for sugarcane farming in Zimbabwe, while adding the context of interaction between environmental factors and mechanistic operations, transport, and mill reception. Furthermore, the findings are in alliance with big-data from Weersink et al. (2018) in context with interdependencies between different processes of a sugarcane value chain and highlight the consequence of downstream damage due to damage. Hence, these findings lead to the recommendation of the Climate-to-Mill Intelligence Framework. As per the framework, climatic information is employed, not to describe environmental status but to become operational information in case of deployment of machineries, monitoring transport, or even scheduling the mill operations. This has higher chances of eliciting anticipatory intervention compared to the systems which are fragmented and tend to react only after an established disruption sets forth.

The result of this study is the call upon the need to move beyond fragmented monitoring of agricultural outputs to an integrated climate adaptive managing of the value chain stretching across and within sugarcane estates and mills in Zimbabwe. Climate change affects the growing of sugarcane through changes on the amounts of water and other field conditions but also has implications on the harvest management, harvesting machinery use, transportation and mills intake. It is within that regard that the study conceptualised harvesting, handling and transportation of raw sugarcane all as connected parts of one system where disruption is on stage can result in reduced or ineffective performance of activities at the succeeding. Understanding operational losses in their isolation where effects of climate, machinery use, logistics, processing; and handling are considered separate would give partial explanation unlike approaching theme in such integrated view.

The Climate-to-Mill Intelligence Framework combines meteorological, agricultural, mechanized-operation, transportation and mill-intake data in a distributed big-data architecture. It provides a computational foundation based on Hadoop Distributed File System and MapReduce for the storage and processing of heterogeneous historical datasets at scale and converts disparate data into operational information with harvest delays, machinery constraints, transport disruptions and mill congestions being

forecasted. Hence, decision-making is shifted from largely reactive response to anticipatory coordination of operations across the value-chain. Hadoop MapReduce serves as the distributed processor layer and not as a real-time analytics solution so that the architecture can evolve to take advantage of streaming technologies if real-time tracking is important.

The study shows that climate adaptation in sugarcane production needs to be assessed in relation to whole-value-chain performance than focusing solely on agricultural productivity. Addressing irrigation management or crop productivity alone while not considering machinery availability, transport capacity and mill-processing limitations could simply transfer bottlenecks to other stages of the production system. Instead, coordinated decisions concerning when to harvest, which machinery should be deployed, how transport resources should be allocated and how cane arrivals should be aligned with mill capacity, can be supported by an integrated intelligence framework. This has particular relevance to Chiredzi, where large estates, outgrowers, irrigation systems, harvesting operations, transport networks and industrial milling activities operate within the same production ecosystem.

The study provides a context-specific framework for strengthening climate resilience and operational productivity of Zimbabwe's sugarcane value chain. Not MapReduce alone, but its integration of distributed data processing, climate intelligence, mechanized operation monitoring, and value chain coordination is its main contribution. In future, the framework should be tested using actual datasets from sugarcane-producing areas such as Chiredzi and its efficacy tested on the basis of measurable indicators like machinery utilization, downtime, transport turnaround, harvest-to-mill time, mill waiting time, cane quality, sugar recovery, and throughput. The implementation would provide an empirical basis to determine whether integrated climate-to-mill intelligence can increase productivity, reduce avoidable losses during operation, and strengthen climate resilience of Zimbabwe's sugarcane industry in the long-term.

6. Recommendations

Pilot research should be done in Chiredzi district since it is the centre of sugarcane industry in Zimbabwe, with vast estates with sugarcane as well as private farmers who

supple sugarcane to the Lowveld milling system. This will join links for climate variations and water available for irrigation and machinery to be out-to field harvesting and transport with information on mill intake from Hippo Valley, Triangle and any outgrower farm. This will increase machinery and transport use and utilisation to the fullest. More so with less disruptions at the mill. Machinery to transport sugarcane would be diverted to various mills when conditions are harsh during harvesting. The system for use together with cane productivity is a decision support and early warning system to improve machinery utilisation which is reduced due to idle time because if bad field conditions to increase their field productivity whilst harvesting.

Furthermore, the framework should be utilized to increase water-use efficiency (WUE) and climate adaptation in Chiredzi. Sugarcane production in the district is dependent on irrigation while irrigation efficiency and return flows have been a concern in the Chiredzi and Runde River systems according to previous research. With integration of rainfall, soil moisture, irrigation schedules, water availability and crop conditions, the platform could be used to align irrigation decisions with requirements of fields. ZINWA, who has the mandate to supply irrigation water to farmers, could contribute water management info to this technology. The focus should not simply be to use more water, instead to increase the water productivity using available water to enable more cane produce while minimizing unnecessary losses. This may lead to improved yield and reliability of harvesting schedules besides enhanced resistivity to occurrence of water stress.

Also, the mechanism has to set up a logistic coordination system in Chiredzi sugarcane sector linking farmers, harvesting contractors, transport operators and mills. The system can estimate future requirement on additional trucks and trails or harvesting machines based on expected harvesting volume and the capacity of mills. In some areas, harvesting machines do nothing while there lacks transportation capacity. In other areas, trucks transport canes to sell in mills but mill cannot process so fast. Long holding time for canes leads to degradation of canes, decreasing sugar recovery rate and hence loss of value. The system should measure productivity of farms, harvesters, transporters, mills in terms of tonnage of canes/machine. Hour; the usage rate of machines, tonnage of cane transported/vehicle. Day; round trip time of

vehicles; throughput of mill; harvest to delivery time; quality of cane as well as recovery rate of sugar.

The proposed system is intended to assist outgrowers' productivity than only larger estates in sugarcane cultivation. There are industry programmes in place that give independent farmers and growers technical guidance and extension support (e.g. advice on irrigation scheduling, crop nutrition, farm-management), that potentially could be supported by the platform (e.g. mobile alerts, farmer-level dashboards, simple recommendations on when to irrigate/harvest; machinery availability; timing of transport order) which would help with their coordination in relation with the mill and reduce information asymmetry. Over a longer term, Chiredzi could act as a template for rolling out climate-smart sugarcane management more broadly in Zimbabwe. The industry's stated objective is to increase sugar-cane production in the country and achieve a higher average productivity per tonne of cane; hence the discussed framework represents not just a technology intervention but potential for increase in agricultural production, efficient use of resources and reduction in operational loss and therefore the competitiveness of Zimbabwe's sugar industry.

Declarations

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability: The data generated and analysed during the current study are not publicly available because they contain information from farmer questionnaires and farm locations that could compromise participant confidentiality, in line with the conditions of ethical approval (GZU/REC/2026/041901). Anonymised data are available from the corresponding author (mmadyembwa@gzu.ac.zw) on reasonable request.

Clinical trial number: not applicable.

Ethical Approval and accordance

Ethical approval for this study was granted by the Great Zimbabwe University Research Ethics Committee (Reference: GZU/REC/2026/041901; Approval date: 15

April 2026). The study was conducted in accordance with the Great Zimbabwe University Research Ethics Policy, the Cyber and Data Protection Act [Chapter 12:07] of Zimbabwe, and the ethical principles outlined in the Belmont Report (1979). These principles include respect for persons, beneficence and justice. Participation was voluntary, informed consent was obtained from all participants, and confidentiality and anonymity were maintained throughout the study.

Consent to Publish declaration: Not applicable. The manuscript does not contain any individual person's data in any form, including images, videos or identifying details.

Consent to participate

Informed consent was obtained from all individual participants included in the study. Before data collection, each participant(smallholder farmers, transport operators, extension officers, and mill managers) was told, in the language they preferred, the purpose of the study, what participation involved, that taking part was voluntary, that they could withdraw at any time without any consequence, and that their responses would be kept anonymous and confidential. All participants were 18 years of age or older, and no children took part. Written informed consent was given by each participant before the questionnaire was administered.

Competing interests: The authors declare no competing interests.

Author contributions:

M.M.: Conceptualization, Investigation, Writing – Original Draft, Writing – Review & Editing. **A.T.C.:** Conceptualization, Data Curation, Visualization, Writing – Original Draft, Writing – Review & Editing. **H.Z.:** Methodology, Software, Formal Analysis, Data Curation, Validation, Visualization, Writing – Original Draft, Writing – Review & Editing. **S.R:** Formal Analysis, Investigation, Visualization, Writing – Original Draft, Writing – Review & Editing.**B.N.:** Conceptualization, Methodology, Formal Analysis, Validation, Supervision and Writing. **I.N.:** Review & Editing. All authors contributed to the intellectual development of the manuscript, critically reviewed its content, and read and approved the final version for submission.

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