Using crowd-sourced data for real-time monitoring of food prices during the COVID-19 pandemic: Insights from a pilot project in northern Nigeria

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ARTICLE INFO	ABSTRACT
	The COVID-19 pandemic and related lockdown measures have disrupted food supply chains globally and caused threats to food security, especially in Sub-Saharan Africa. Yet detailed, localized, and timely data on food security threats are rarely available to guide targeted policy interventions. Based on real-time evidence from a pilot project in northern Nigeria, where food insecurity is severe, we illustrate how a digital crowdsourcing platform can provide validated real-time, high frequency, and spatially rich information on the evolution of commodity prices. Daily georeferenced price data of major food commodities were submitted by active volunteer citizens through a mobile phone data collection app and filtered through a stepwise quality control algorithm. We analyzed a total of 23,961 spatially distributed datapoints, contributed by 236 active volunteers, on the price of four commodities (local rice, Thailand rice, white maize and yellow maize) to assess the magnitude of price change over eleven weeks (week 20 to week 30) during and after the first COVID-related lockdown (year 2020), relative to the preceding year (2019). Results show that the retail price of maize (yellow and white) and rice (local and Thailand rice) increased on average by respectively 26% and 44% during this COVID-related period, compared to prices reported in the same period in 2019. GPS-tracked data showed that mobility and market access of active volunteers were reduced, travel-distance to market being 54% less in 2020 compared to 2019, and illustrates potential limitations on consumers who often seek lower pricing by accessing broader markets. Combining the price data with a spatial richness index grid derived from UN-FAO, this study shows the viability of a contactless data crowdsourcing system, backed by an automated quality control process, as a decision-support tool for rapid assessment of price-induced food insecurity risks, and to target interventions (e.g. COVID relief support) at the right time and location(s).

1. Introduction

Globally, food systems are susceptible to threats and shocks, which are often trailed by amplified impacts on households and individuals who are living near or below poverty thresholds (Huntingford et al., 2005; Jones and Sanyang, 2008). Potential threats to food systems are diverse, and the severity of their impact can vary, depending on factors including geography, timing, duration, preparedness, economic conditions, and governance. In Africa, periods of high food price inflation are persistent (Alper et al., 2016), seasonal price volatility is high (Gilbert et al., 2017) and shocks to food supply chains due to extreme weather effects, fluctuations in exchange rate or trade policies, or conflicts, often cause additional, unanticipated spikes in food prices in the continent

(Minot, 2014).

The outbreak of the coronavirus (COVID-19) pandemic and related lockdown measures caused a severe disruption of food systems — including restriction of labor availability, interruption of transport, and limitation of input distribution, which has translated into unanticipated fluctuations in commodity prices (Swinnen and McDermott, 2020). As price-takers, poor consumers face harsh difficulty in coping with price increases from sudden food system disruption because their purchasing power often dwindles as their income becomes insufficient to purchase the minimum quantity of food required to meet their household dietary needs. Moreover, household income sources have been severely affected by the COVID-19 crisis, especially in urban environments, because many informal businesses and services were discontinued while many workers

on daily wages were unable to seek or secure employment (ElKadhi et al., 2020; NBS-WB, 2020). According to Laborde et al. (2020), African countries are expected to be hit hard (economically) by the pandemic, and net effects on poverty and food security could be higher than those of the 2008–2009 global financial crisis.

While the disruptive impact of the COVID-19 pandemic on food security are forecasted at country-level based on expert knowledge (e.g. FSIN 2020; Resnick 2020; Devereux et al., 2020), data-driven evidence of the extent, timing, and localization of such impacts is rarely available at the right time or granularity to guide relevant interventions and policy decisions. Data-driven intelligence is critical for decision-support on food security in Africa, especially to mitigate the impact of emerging or current threats, including further waves of the pandemic and associated uncertainties. Observable, real-time changes in the current or actual (nominal) price of food commodities across various locations and market segments is a potent and timely indicator of household-level food security, when combined with relevant socio-economic indicators (De Hoyos and Medvedev; Ogundari, 2017; Devereux et al., 2020). Despite the vulnerability of Sub-Saharan Africa (SSA) market systems and the potential large-scale impact of COVID-19 on food security (Resnick 2020; FSIN 2020), established food price data collection systems in SSA are intrinsically unable to generate actionable data that can unlock insights about rapid changes in food prices in time and space. Several institutions regularly collect information on commodity prices in low-and middle-income countries (e.g. the FAO Food Price Monitoring tool (FAO GIEWS-FPMA, 2020), World Food Programme Vulnerability Analysis and Monitoring (WFP-VAM, 2020), and the IFPRI Food Security Portal). But the resulting price data are often limited in scope, because they monitor prices at specific markets and often at highly coarse spatio-temporal scales (e.g. monthly and at [sub-]national level). Moreover, in most instances of sudden disruptions to the food system, data is typically lagging in time and usually available after threat events, thereby precluding access to relevant contextual insights that can guide rapid and context-specific intervention(s). The proliferation of mobile phones and internet access in recent years has catalyzed the emergence of innovative remote data gathering techniques that show great promise in addressing these problems. Citizen participation via digital tools and platforms has the potential to provide near real-time monitoring of food prices at relatively low cost to complement other data sources while empowering citizens as both providers and users of information. Our recent Food Price Crowdsourcing in Africa (FPCA) project in northern Nigeria, piloted by the European Commission's Joint Research Centre (JRC) and other collaborating institutions, was initially tested and validated in 2019 and then reactivated during the first COVID-19 lockdown in May and June 2020 and finds that maize and rice prices dramatically spiked in the midst of the crisis, threatening food security.

Various approaches to crowdsourcing real-time food price data collection have been tested over the past decade in developing countries with varying levels of success (Seid and Fonteneau, 2017; Zeug et al., 2017; Ochieng and Baulch, 2020). Several of these initiatives faced difficulties in achieving meaningful crowd participation, in the large number of crops included, in the lack of local expertise, or in setting up efficient data processing methods to derive accurate and representative information in a timely manner (Jones and Kondylis, 2016). Under the auspices of the FPCA project, we developed, deployed, and tested a systematized process for crowdsourcing daily prices for a small number of staple foods, and presented the validated data in an open-access web dashboard. Following an initial round of publicity, over 700 volunteers from Kano and Katsina States in northern Nigeria were invited to submit food price data through a mobile app during visits to any type of market for purchase or mere price checking. Aware of the challenges faced by earlier crowdsourcing initiatives, we used several approaches for forming a sufficiently large and motivated crowd, and developed a new method for automated quality control and data validation.

Based on the data generated, we analyzed food price changes and assessed the functionality of a systematized crowdsourcing data collection tool, which was envisioned as a decision-support tool for food system monitoring, in the context of a COVID-related shock to the food system in northern Nigeria. We illustrate how crowdsourced price data can provide a timely and spatially disaggregated monitoring of food prices, which is an important input for the assessment of the spatio-temporal relationship between sudden prices increases and purchasing power of citizens.

2. Data and methods

2.1. Study area

This study was conducted in northern Nigeria, where a pilot project to crowdsource food price data in Africa was led by the European Commission's Joint Research Centre (Solano-Hermosilla et al., 2020a, Fig. 1). Nigeria is the most populous country in Africa, and it is projected to be the third most populous country in the world by 2050 (NPC, 2018). The crowdsourcing system was implemented in the two contiguous states (Kano and Katsina) in the North-West geopolitical zone, which share similar geographic, economic, political and educational characteristics (WorldBank, 2019). The region accounts for about 80% of the main staple foods produced in the country (mainly maize, local rice, soybeans and beans) (Ndukwu et al., 2015). The two states cover an approximate land area of 44,000 km², sub-divided into 78 local government areas (LGAs), and inhabited by 20.4 million people. The predominant occupation across both states is farming and commodity trade, and the market price of grains across the country is dependent on the production and trade dynamics in the region.

Despite government's effort to reduce poverty, in 2016 about 42.8% of Nigerians were living under extreme poverty conditions (below the US$ 1.90 day/per capita poverty line) and poverty prevalence rate has been growing since 2011 in the North-West region, accounting for nearly half of all poor in Nigeria (WorldBank, 2019). The majority of the poor people living in this region spend most (up to 70%) of their disposable budget on food, with little buffer to absorb shocks of rising food prices (NBS, 2019).

Since March 2020, the Federal Government of Nigeria introduced several measures to contain the pandemic, including a lockdown of non-essential activities, closure of schools and a ban on international flights (NCDC, 2020). In April 2020, the North-West region was considered a COVID-19 hotspot, and by mid-April (calendar week 16), the state-level governments took further steps to mitigate the spread of the pandemic by imposing stringent lockdown measures, including movement restrictions (KNSG, 2020, Fig. 2). Residents were urged to stay at home, public gatherings were prohibited, shops and markets were closed down, but with exceptions for medical services, some food retail outlets (mainly supermarkets in Kano) and financial service institutions. In the second half of May (week 21) a few relaxations were introduced, followed by a gradual lift of the lockdown starting on June 2 (week 23). The lockdown ended on July 1 (week 27) with the full restoration of "socially-distanced" business operations, and lift of the ban on inter-state travel, while maintaining the 10 p.m. to 4 a.m. curfew (KNSG, 2020).

2.2. Crowdsourcing food price data

The data for this study was collected through the Food Price Crowdsourcing Africa (FPCA) platform, which was launched in September 2018 to collect and disseminate daily price data of various staple food commodities [in real-time] on a web-dashboard, after processing and validation. The FPCA project adopted a digital platform for
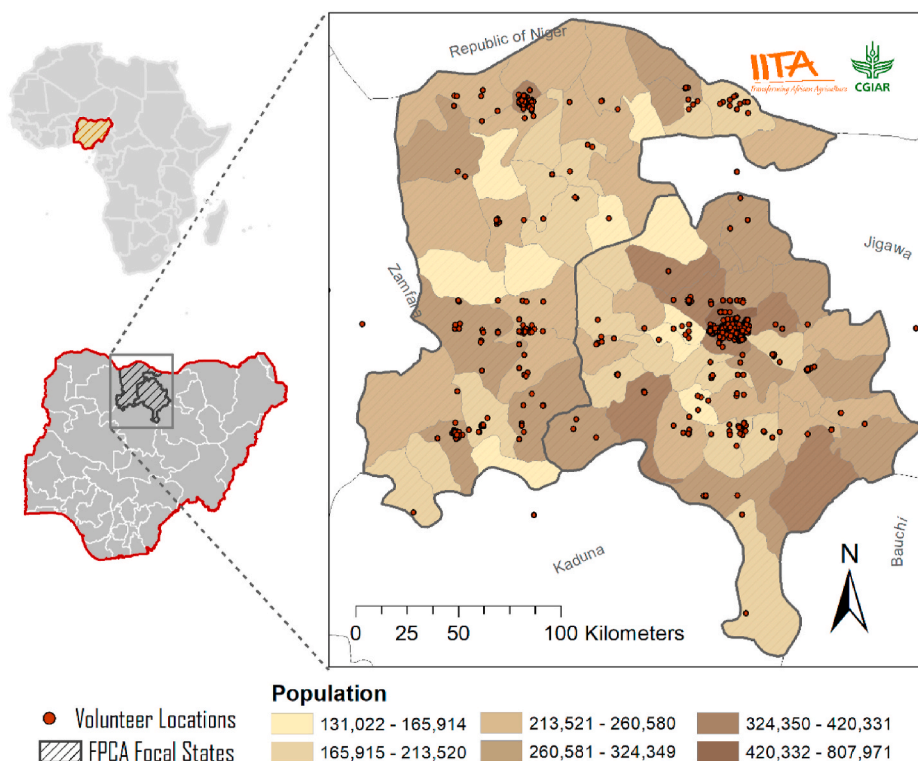
Fig. 1. Map of focal area covered by the FPCA (Food Price Crowdsourcing Africa) pilot project, in Katsina and Kano States (Nigeria), with volunteer locations at the time of registration in the mobile app, and population estimates within each local government area (LGA).
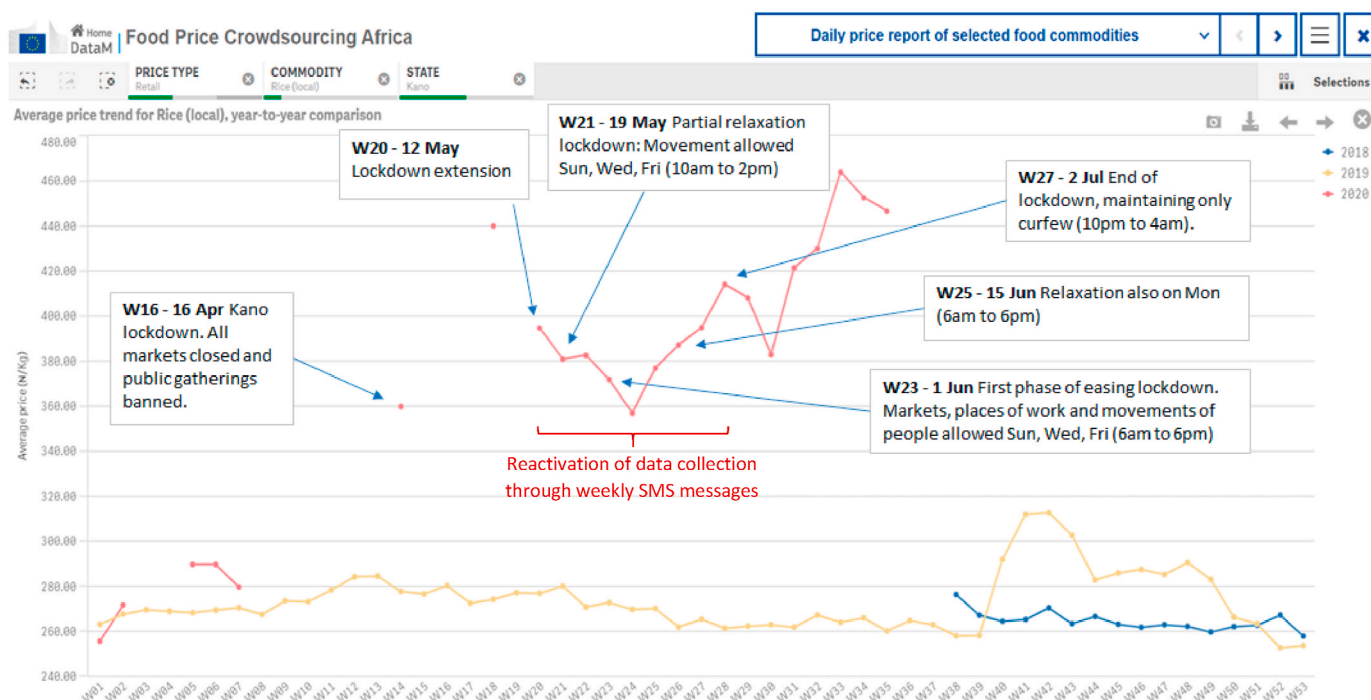
Fig. 2. Illustration of the web dashboard with interactive visualization of the data in [near]real time, here presented for retail prices of local rice (in ₦/Kg) in Kano state from September 2018 to July 2020. COVID-related measures and post-lockdown measures implemented by Kano state are indicated for the corresponding weeks in 2019. Source: FPCA web dashboard (https://datam.jrc.ec.europa.eu/datam/mashup/FP_NGA/index.html) and the Kano State Government (https://www.kanostate.gov.ng/).

crowdsourcing food price data from citizens based on the premise that accessible broadband mobile technology is available in most parts of the study region, and an increasing number of people are using smartphones

within and outside cities (GSMA, 2019). The commodity prices are reported by registered[1] (total enrolled = 737) and unregistered volunteers through a configured mobile app (called, Open Data Kit – ODK, www.opendatakit.org) during their regular purchase or visit to the market. The volunteers were enlisted through an initial promotion campaign (8 weeks) in September 2018, including the use of leaflets, radio advertisement, mini-webpage, and word of mouth. We ensured that the data management process guarantees the anonymity of the participants. The data collection system allows immediate data transmission (when volunteer's device is fully online) or later submission (when offline). The mechanism for real-time data transmission rests on both the tool and structure of the micro-reward/monetary incentive. By operationalizing a daily-threshold (30 valid observations) micro-reward system, volunteers were encouraged to submit data daily and as soon as possible,[2] but also advise to only submit at will, especially during regular visits to the market (as the associated costs of visiting a market are not compensated). Generally, the platform prompts each volunteer to submit price data on local rice, imported rice (Thailand and Indian), maize (white and yellow), beans (white and red) and soybeans. However, our subsequent analyses for this study focuses on white maize, yellow maize, local rice, and Thailand rice which constitutes ~75–85% of daily dietary intake in the region (REACH, 2020a).

The data collection system was initially developed and piloted in the study area with a goal of advancing innovation for seamless and contactless data collection at different points along the value chain (i.e. farm gate, wholesale and retail), covering both urban and rural areas. For the purpose of this paper, we focus only on retail prices (the actual prices paid by consumers at point of purchase), which correspond to 86% of all data contributions. Until June 2019, the data crowdsourcing system was sustained with effective behavioural nudges in the form of motivational messages (intrinsic motivation), and micro-rewards (extrinsic motivation) to increase the willingness of the crowd to participate (for more details see Solano-Hermosilla et al., 2020b). The geographical location of the registered volunteers (Fig. 1) illustrates how the geographical density of registered volunteers corresponds to the population density in the two states. Data quality was maintained by recording the geo-location of data entry, pre-defined thresholds for incentivized submission, automated data checks through a series of algorithms to extract, clean and validate the data values before ingestion into the data aggregation platform, an interactive web-dashboard (https://datam.jrc.ec.europa.eu/datam/mashup/FP_NGA/index.html). Full details on the overall design, implementation, and validation process of the systematized data crowdsourcing system are presented by Solano-Hermosilla et al. (2020a). Following the pilot project, which ran from September 2018 till June 2019, the system functionality and data quality was validated, as explained in more detail in section 2.4. After this, the platform remained active, open for data submissions without the provision of monetary rewards or communication with volunteers, and the data was freely available on the web dashboard as a potential incentive for continued submission, fostering the valuable two-way interaction with citizens as data providers and users. Yet, without behavioural nudges and micro-rewards to motivate or compliment the volunteers, data submissions were found to decline over time. To understand how the COVID-19 pandemic is affecting food prices in Nigeria, the system was reactivated by nudging volunteers with SMS messages to induce data contribution as a public good (intrinsic motivation). From May 12,

2020 to 16 June 2020 (week 20–25)[3] messages were sent, weekly, to the pool of registered volunteers, and resulted in the resurgence of data submissions. Further analysis focused on data collected during the period 12 May till July 26, 2020 (week 20–30), in comparison to the corresponding period in 2019 (during the initial pilot project), to assess the increase in grain prices relative to the previous year.

2.3. Ancillary data

For each instance of data acquisition by volunteers, some ancillary data were saved to the system. Volunteers indicated the package size for which each price was recorded, and also the geo-coordinates of the shop or market were auto-recorded and submitted from the mobile device used. This allowed for the spatial mapping of prices and for calculation of the distance travelled to the market. We use the latter to shed light on how the COVID-19 crises and lockdown measures affected the mobility and purchase behavior of consumers.

Population and richness data were used to contextualize the impact of the recorded food price increase on the number of people impacted and their relative level of economic wellbeing, respectively, within the LGAs where data were reported in both 2019 and 2020. The 2016 population estimates were sourced from UN Humanitarian database (UN-OCHA - https://data.humdata.org/organization/ocha-nigeria). As a proxy for the general level of economic wellbeing in the LGA, the 2010 richness index was sourced from UN-FAO GeoNetwork database (http://www.fao.org/geonetwork/srv/en/main.home). In the absence of more recent data, it was assumed that the distribution of the relative economic wellbeing, as represented by the FAO richness index, has not changed significantly despite the time lapse.

To compare the crowdsourced price data with official reported averages, price data from the 'Selected Food Prices Watch' dataset published monthly by the National Bureau of Statistics (NBS) of Nigeria were used to calculate 2-year average indices of price changes and current (2020) year-to-year indices of price changes for the target commodities within the period (May–July) (NBS 2020).

2.4. Data processing and analysis

We applied the fully automated process for checking and cleaning of submitted commodity price data in real time, that was developed by Arbia et al. (2018) and further enhanced by Arbia et al. (2020) and Solano-Hermosilla et al. (2020a). In brief, the method consists of a series of steps implemented in algorithms (developed in R software) to assess spatial-temporal markets (clusters) of daily commodity prices, filter out spurious data points, and confine price values to reasonable attribute ranges. In the first step, submitted data was spatio-temporally validated (using the auto-recorded time and geo-location) where closer points (in time and space) are expected to yield similar numbers. In a second step, the data was reweighted to ensure reliability, resembling a formal spatial sampling design. Therefore, the quality control process attenuates potential effects of sampling bias inherent to the voluntary nature of crowdsourcing and the non-random distribution of smartphone owners and digital competence, by applying a system of weights in relation to a theoretical formal probabilistic sampling design for the study area. A normalised measure of data representativeness, the crowdsourcing reliability indicator (CRI) (ranging from 0 for low reliability to 1 for the highest reliability) compares the coverage of the entire datapoints compared with the formal probabilistic sampling design. For the data in 2020, a CRI value of 0.85 is obtained, suggesting that the crowdsourced data can be considered reliable, even though it is lower than the value obtained during the pilot phase in 2019 (CRI of 0.96).

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[1] Also non-registered volunteer citizens can contribute data to the system, but account for only 3% of total data submissions, none of these during the COVID-related lockdown period that is the subject of this study.

[2] The submission tool records both the date/time of the data entry start and the date/time of data submission, and submissions that start on one day and are submitted on another would not qualify for the micro-reward. Only the first 30 submitted and verified data contributions are eligible for the daily micro-reward.

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[3] The text of the SMS read as follows: "The FPCA mobile app still accepts data submissions. New insights to improve food price transparency and price fairness to the public are key in time of crisis."

The validated data for the eleven weeks in 2020 (i.e. week 20–30) and corresponding weeks in 2019, were compiled for each commodity and converted to US$/Kg using the exchange rate of ₦360/US$. A weekly price change index was computed for each commodity for the whole study area between the two periods, using equation (1). The price index measures the magnitude of change in weekly prices of the commodity between 2019 and 2020 at the geographic level of interest (e.g. state, LGA and ward) for which sufficient observations become available.

Price Index for commodity j, PI_i (%) = 100 * p_{i2020}/ p_{i2019} (1)

Besides, we illustrate geographical associations by linking the georeferenced price data with socio-economic data, mainly the FAO richness index and population data. The population estimates were spatially joined to the LGA[4] boundary shapefiles, while richness index per LGA was computed with a zonal statistics tool in ArcMap 10.3.1 to derive the average richness index value within each LGA.

3. Results and discussion

3.1. Data submission and volunteer participation

Overall, we collated 23,961 valid price points across the four commodities during a period of eleven weeks (weeks 20–30) in 2020 and 2019, coinciding with the COVID lockdown period (up to week 23), the gradual easing of lockdown measures (weeks 23–27) and the return to "socially-distanced" normal business (week 28–30). A total of 2,134 datapoints were submitted by 65 active volunteers in 2020, compared to 21,827 datapoints submitted by 221 active volunteers in the corresponding period of 2019. It should be noted that the crowdsourcing platform was activated in 2019 with nudges in combination with micro-rewards, which explains the higher number of submissions during that period. Additionally, we expect that COVID-related mobility restrictions in 2020 may have affected the capability or the motivation of volunteers to visit markets and to record and submit data,[5] further exacerbated by the reduced purchasing power reported in relation to COVID crisis (REACH 2020a).

The validated price data are presented in a web-dashboard that allows for interactive visualization of the data in [near]real time, visualization of trends and comparisons across years and seasons (Fig. 2). The boxes collect announcements of the state government of Kano on the lockdown (https://www.kanostate.gov.ng/). Although the active motivation of volunteers ended in June 2019, sufficient data submissions were received to draw reliable inference on commodity prices, up to the first few weeks of 2020. The increased data inflow from week 20 onwards reflects the effectiveness of the 6-week SMS communication campaign to reactivate data submissions through the FPCA data collection platform.

3.2. Temporal evolution of commodity prices during the COVID-19 period

The daily price data submissions, averaged over all georeferenced locations in the study area, show consistently higher grain prices in 2020, compared to the preceding year (Fig. 3). Throughout the eleven weeks data collection period, retail prices of maize (white and yellow) and rice (local and imported) were, in average, respectively 26% and

44% higher in 2020 than in 2019 (Fig. 4). The upward trajectory of the price index is observed since week 24 (2 weeks before the full easing of lockdown restrictions) for all commodities. The price index for maize sustained an exponential rise after the easing of lockdown, which may be due to the confounding impact of new government ban on importation of maize to support local production (NairaMetrics, 2020), notwithstanding the likely effect on already hiked prices associated with COVID disruption. During crisis period, locally produced grains (such as maize) often become life-line commodities for most of the citizens, and can become increasingly expensive as in-country production capacity wanes or the supply to cities dwindles due to logistics constraints (Agwu et al., 2011). Arguably, this COVID-related impact on maize prices may moreover have been amplified by the import ban. The more stable price index for rice may be related to the lifting (from May 2020) of the export ban by major rice producers in Asia, considering that Nigeria imports 46% of its rice consumption (Arouna et al., 2020), which may have relaxed further pressure on the markets, where local and imported rice often compete. Nevertheless, after the withdrawal of the lockdown measures, local rice was still sold at 50% higher price levels, compared to the previous year.

Crowdsourced prices, averaged on weekly basis, were slightly higher than the prices reported by the National Bureau of Statistics[6] (NBS, 2020), which usually lags by about two weeks and provides only a monthly average. Yet, the trend of price indices is mostly similar, with deviations (up to a maximum of 25% difference) in the later period of June for both white and yellow maize (Fig. 4). This supports the notion that crowdsourced data are inherently reliable to assess overall price trends when proper quality measures are built into the data submission system (Arbia et al., 2020; Solano-Hermosilla et al., 2020a).

3.3. Spatial price variation during the COVID-19 period

The crowdsourcing system generated multi-locational data that shows the underlying spatial variability of commodity prices and areas where hotspots of high prices were identified (Fig. 5). Higher prices observed during the period of May–July 2020 (yellow to red dots) were mostly associated with relatively rich (green-blue shaded), and mostly urbanized areas. Further, it is noteworthy that the spatial variability of prices during the COVID period (in 2020) is higher, compared to 2019. The price range for local rice (i.e. the difference in price between the LGAs with the highest and lowest average price) in 2020, exceeded double-folds of the price range in 2019. Hotspots of high prices during the COVID-19 period in 2020 were mainly observed in urban areas (such as Kano city) where mobility restrictions were likely more enforced, compared to remote locations, where enforcement of restriction was either relaxed or non-existent. However, rural areas, where poverty rates typically exceed 70%, were hard-hit as well, considering that average price increases of 22% were observed for maize and 42% for rice.

The dynamics of food prices, affordability, and net impact of the COVID-19 pandemic in urban areas is complex. Generally, average level of richness in urban areas (especially around major cities) is higher than in rural areas, suggesting that urban households may be better positioned to absorb such steep but temporary price increase, for example by reducing non-food expenditures or altering consumption patterns (as recently reported for Ethiopia by Hirvonen et al., 2020). But Nigeria's urban areas are also characterized by high income inequality with a narrow middle-income class and a large number of citizens who are

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[4] The LGA's level of aggregation corresponds to the Second Administrative Level Boundaries, developed by the United Nations (UN, 2001) to promote the availability of reliable geospatial information for sustainable development and food security (i.e. policy-making, programming and planning operations) and the sharing of knowledge and information.

[5] According to Google mobility data for Nigeria (2020), COVID-related restrictions account for up to fifty percent reduction in movement (Google LLC, 2020).

[6] Typically crowdsourcing exercises could have biases towards wealthier volunteers, which may be purchasing higher product qualities, resulting in slightly higher prices. In addition, crowdsourcing exercises usually include data submissions from more remote markets, compared to the main markets of central price collection records, also resulting potentially in higher average prices.
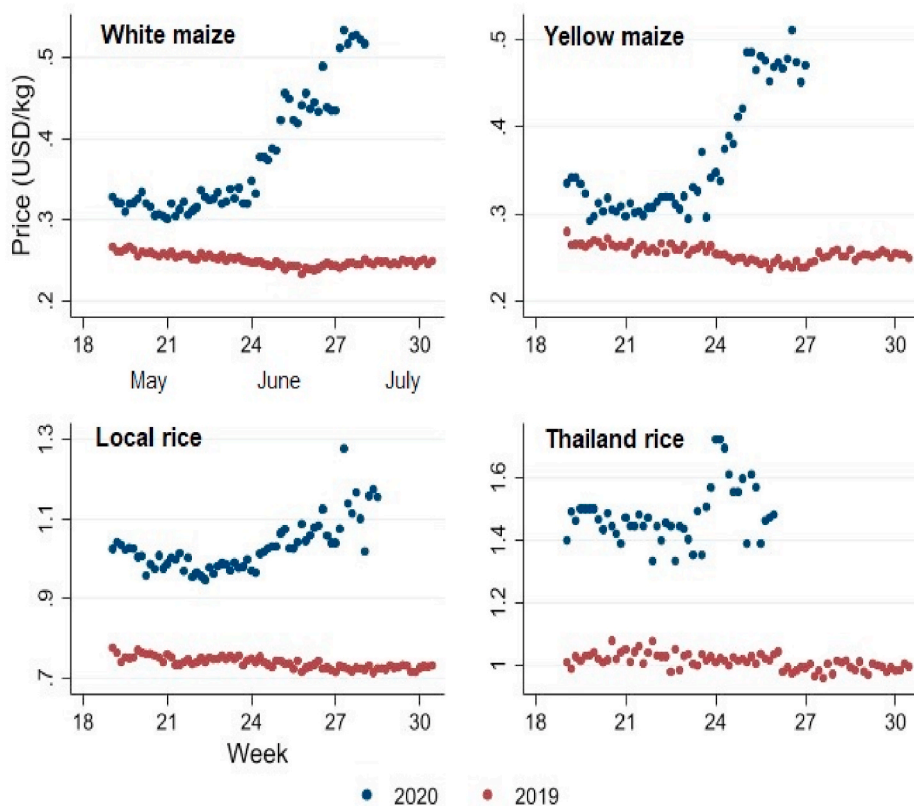
Fig. 3. Average daily price of major grain commodities during weeks of COVID-related period in 2020, and preceding year (2019), as submitted by volunteers located across Kano and Katsina States in Nigeria.
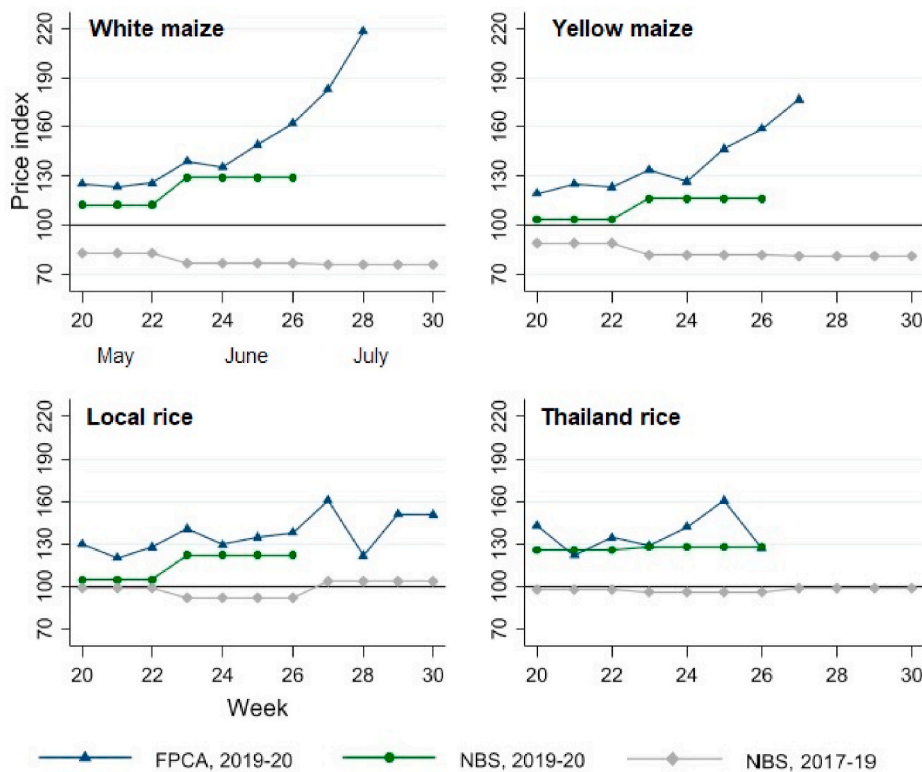

Fig. 4. Price index illustrating the relative change relative to last year's price for the COVID-19 period in Kano and Katsina, based on FPCA 2019-20 data in Nigeria, contrasted with the price data reported by the National Bureau of Statistics (NBS) of Nigeria. For comparison, the light grey line (NBS, 2017-19) illustrates the average price index of change for the past two years (i.e. 2019 -2018 and 2018–2017), based on the NBS data. For the period 2019–20, the index for rice was relatively stable, however, it follows an upward trajectory for maize presumably due to government's restriction of maize importation which resulted in steep increase of maize prices.
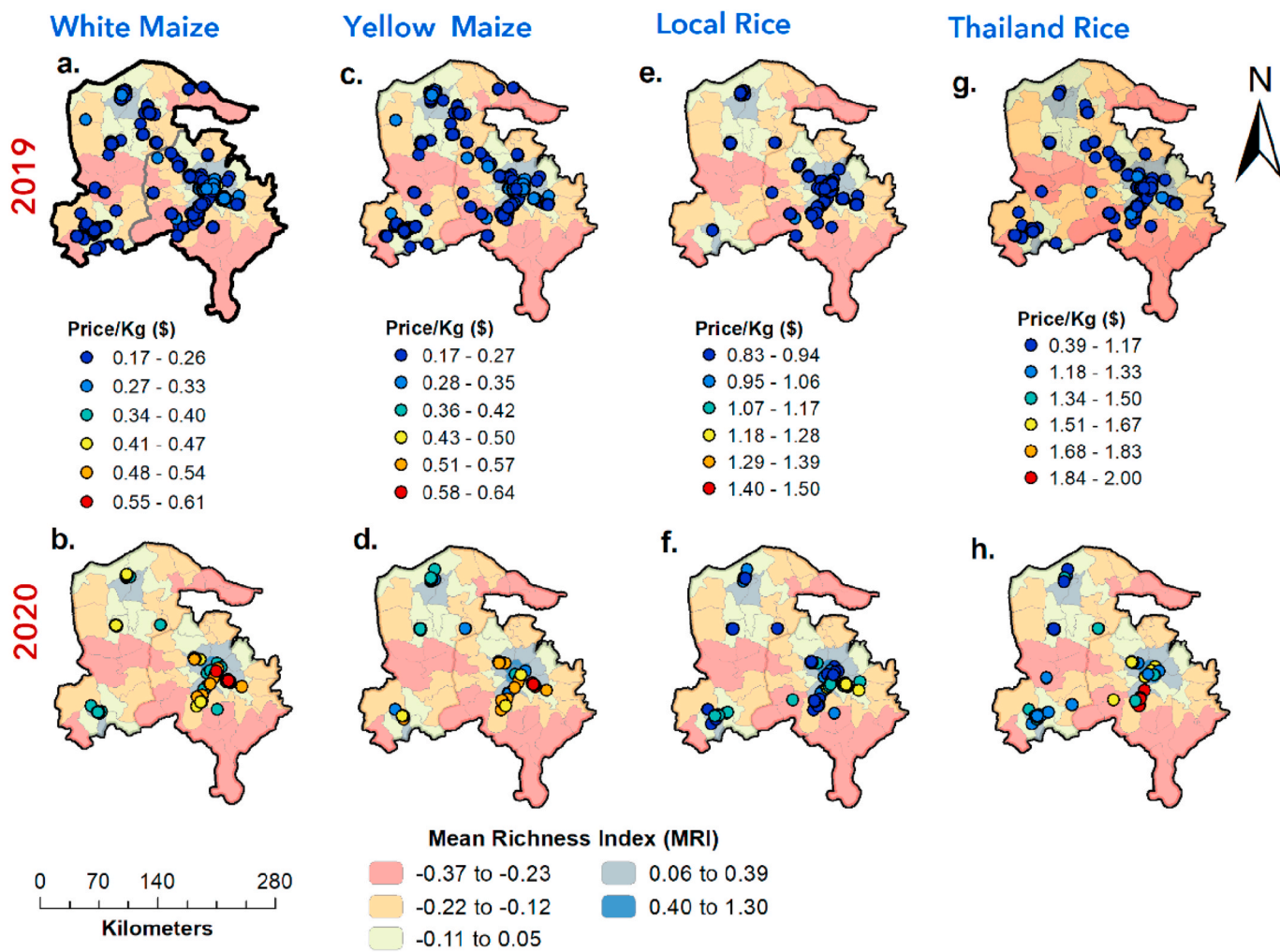
Fig. 5. Spatial distribution of levels of crowdsourced prices of maize and rice in 2019 (top) and 2020 (bottom), relative to mean richness index (MRI) in Kano and Katsina, Nigeria. Colored dots indicate crowd-sourced local commodity prices, ranging from blue (low prices) to red (high prices). The color of each local government area (LGA) indicates the relative level of richness, going from poor (light red) to richer (light blue) than average. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

living below the poverty line (WB, 2019). Thus, substantial price spikes (e.g. the observed >50% increase in price of rice across several urban areas) in combination with job and income losses (NBS-WB, 2020) has important implication for vulnerable citizens in urban areas who are living below or at the fringes of the poverty line. This strongly supports the notion that the COVID-19 crisis threatens food security for low- and middle-income earners in urban areas, in addition to the rural poor (Elkadhi et al., 2020).

The spatial richness of reported price data is valuable to understand price evolution relative to other spatio-temporally varying factors, including socio-economic and environmental indicators. Yet, the spatial distribution/coverage of datapoints in this study precludes in-depth assessment of the relationship between commodity price changes and demographics or socio-economic variables within LGAs. Indicatively, the highest increases in rice and maize prices during the COVID-period were predominantly associated with LGAs where richness index (Fig. 5) and population density (see Fig. 1) are above average. In conventional price monitoring systems, the broader implication of spatially varying price changes is usually masked by the representation of commodity prices based on administrative boundaries and less frequent data collection. As spatially-rich data on food price becomes more available, the impact of changes on food affordability and security can become more evident and support contextual assessment of such impacts within and beyond administrative boundaries.

In addition, while some rural communities may be buffered against short-term impacts of food price increase because of local farm production, the major population of low and middle-income earners in urban areas are likely more vulnerable to food insecurity due to the interplay of job and income losses and food price increases, resulting in a diminished purchasing power. This reduced purchasing power of urban consumers has lingered despite the easing of the lockdown because the share of urban respondents who are employed has remained considerably lower than reported before the outbreak (NBS-WB, 2020; World Bank, 2020), and prices have not returned to pre-COVID levels, resulting in many households experiencing food insecurity and cutting back on food consumption (NBS-WB, 2020; REACH 2020a). According to recent data (REACH, 2020b) 54% of food vendors reported decreased purchases by consumers, while 28% reported that the communities where they trade food commodities are struggling with low purchasing power. Finally, it is relevant to note that data submission in the less densely populated and most economically disadvantaged regions was very terse or non-existent during the COVID-19 period, and this underscores the need to improve the inclusiveness of the crowdsourcing outreach to represent contextual realities of economically disadvantaged populations.

3.4. Food purchasing behavior during COVID-19 period

Besides the collection of price data on the FPCA platform, some additional information collected through the mobile app, provides insights into the impact of the COVID-19 pandemic on consumer purchase behavior. The restrictions of the lockdown and increased costs of public transport (NBS-WB, 2020), likely contributed to a lower number of active volunteers and their frequency of market visits, but the geo-locational information of data submissions also reveal that the mean distance travelled to shops and retail markets reduced by 54% during the period (Table 1 and Fig. 6a). Restrictions in mobility and the closure of preferred markets, may have resulted in shifts to closer, and potentially more expensive food outlets (such as supermarkets) and in limited food access and reduced diet quality of vulnerable consumers (Devereux et al. 2020). Contrastingly, the distance travelled by urban data contributors increased sharply (above the 2019 distance) in weeks 23–24, when the first relaxation of lockdown restrictions took place. Rural consumers seemed to continue buying closer to home, also during the second part of the data period covered.

Fig. 6b illustrates a similar trend in the size of food packages that was purchased over the course of the eleven weeks. Most data submissions during the lockdown period were limited to small packages (less than 25 kg, but typically about 2 kg). As soon as the lockdown was partially relaxed, prices reported for large package purchases (25 kg or more) increased considerably, mostly associated with urban consumers: more than half of data submissions during weeks 25–30 in urban areas was for large packages of rice or maize, compared to only 13% in the previous year.

The increase in distance travelled to the market and the tendency to buy larger packages as soon as lockdown restrictions were relaxed likely reflects a catching up on postponed market visits and food purchases. Such a concentration of postponed demand may help explain the continued higher food prices observed across all commodities during gradual easing of lockdown restrictions (weeks 24–27).

4. Conclusion

The COVID-19 pandemic, and related lockdown measures to slow down the spread of the virus, is disruptive for demand and supply of commodity value chains and has translated into food price hikes. Based on the understanding that food markets in Sub-Saharan Africa are vulnerable to frequent and severe disruptions, observed (and unabated) increase in commodity prices can severely exacerbate food insecurity among the most vulnerable population. We successfully implemented and reactivated a [pilot] crowdsourcing platform for the collection of real-time and spatially-rich price data, processing and visualization in an interactive web dashboard, in the core northern States of Nigeria and show the immediate and lasting impact of COVID-related measures on food prices, and how such changes differ across locations and evolved through time.
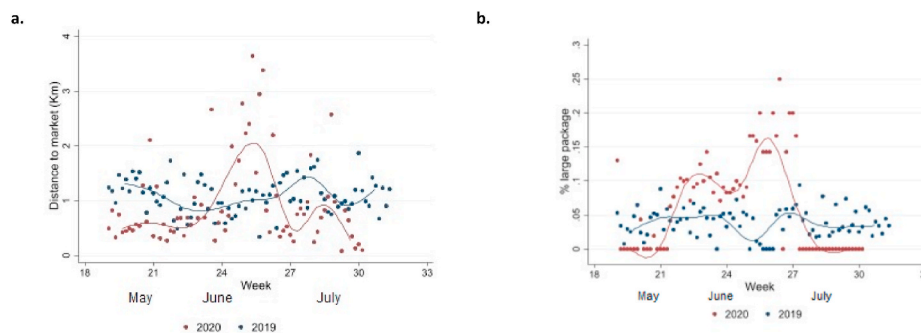
This brief study illustrates the potential of engaging citizens through a mobile app, to ensure the timely acquisition of spatially and temporally rich crowdsourced data, and the possibility for this tool to be activated remotely for an immediate and real-time monitoring of price evolution in the wake of sudden shocks to the food system, even despite limiting circumstances, such as the COVID-19-pandemic.

Ideally, food price monitoring systems should be continuously functional to track nuanced dynamics of price changes prior to, during, and after the occurrence of disruptive events that can impact markets or market actors. This crowdsourced data collection system demonstrates the invaluable positioning of consumers as data volunteers and digital citizens who are immediately responsive to the need for real-time price monitoring, especially under conditions of reduced mobility or severe market disruptions (e.g. following extreme weather events or conflicts) when rapid assessment of markets and prices in both space and time is crucial, thereby transcending traditional data collection methods. Considering the rapidly growing affordability and accessibility of mobile phones and internet (Alliance for Affordable Internet, 2020) globally, our successful crowdsourcing of data through volunteers' smartphone suggests that more citizens can be enlisted as volunteers to submit current and useable data at will, subject to the deployment of appropriate nudge or/and incentive to continuously generate timely insights on food price change in space and time (Solano-Hermosilla et al., 2020b; Minot, 2014; Sunstein, 2014).

Moreover, while the geo-locations of submitted data supports the understanding of the spatial variation in prices, it also supports the possibility of linking the price data to spatially-explicit data on biophysical indicators, and the socio-economic vulnerability of the population. We anticipate that this will unlock actionable insights on causes and indicators of food insecurity at varying geographic and time scales when linked with spatially-varying socio-economic and biophysical indicators. This analysis is only based on the data of a pilot project, and the non-monetary activation of the tool in the context of the COVID-pandemic. Yet, we believe that the full potential of this tool can be realized when scaled to broader areas by enlisting more volunteers and testing additional activation measures, such as those tested and described in Solano-Hermosilla et al. (2020b). Additionally, future scaling of the tool and crowdsourcing method that was deployed in this study should include consideration of potential factors that may influence prices, such as a government subsidy or distribution centers providing grains at lower costs. While this was not a concern within the study area, it may be relevant for other areas in the country where government-led interventions are being implemented to ensure food affordability in crisis-affected areas in the north-eastern region of the country.

However, a number of potential concerns remain: This includes the need to explore options to ensure that citizens-focused data initiatives are more inclusive and representative of contextual demographics. For

Table 1

Average distance travelled to the market and the package size (large vs. small) of purchases made by contributing volunteers[a] during the COVID-19 lockdown period (weeks 20–24) and lockdown easing (weeks 25–30) in 2020, and the corresponding weeks in 2019, for the full sample, and by rural/urban location.

	Period	All		Rural		Urban	
		2019	2020	2019	2020	2019	2020
Distance travelled to market (km)	Weeks 20–24	1.18	0.54***	1.33	0.66***	0.91	0.39***
	Weeks 25–30	1.20	1.65***	0.95	0.50***	1.36	1.91***
Large package (%)	Weeks 20–24	0.053	0.073***	0.02	0.008	0.097	0.16 ***
	Weeks 25–30	0.058	0.12***	0.008	0.008	0.13	0.52***
Nr of data SUBmISSIOns	Weeks 20–24	4586	2183	2772	1259	1814	924
	Weeks 25–30	6696	1302	3961	1031	2735	271

*, **, *** indicate the average values for 2019 and 2020 to be statistically different at the 10, 5 and 1% level respectively. Distance travelled to the market refers to the geographical distance between the geo-located points in which the data were collected and the (home) location of registration of the volunteer. Large package refers to packages of 25 kg or more, small packages refer to all packages of less than 25 kg, but in the majority of cases refer to packages of about 2 kg of grains.

[a] For comparison purposes, we restrict the data for the year 2019 to those volunteers having contributed in 2020 as well, to avoid that differences in locations, types of markets and package size derive from a different set of volunteers in both periods.

Fig. 6. a. Daily average of distance travelled by volunteers to acquire price data, based on actual GPS location data, during weeks of COVID-related restriction in 2020 and preceding year (2019). **b.** Daily share of data submissions for large packages (25 kg or more) of grains during weeks of COVID-related restriction in 2020 and preceding year (2019).

instance, educated males living in urban areas were over-represented in the pilot project due to the cultural dominance of male (as head of households) in the study area. Additional efforts are needed to boost the participation of more vulnerable populations, and improve the coverage of remote, less-populated and often highly food-insecure areas. Also, sustaining data contributions to such platforms over time may be challenging if nudges and/or micro-rewards are no longer available to consistently engage volunteers. Our study showed that the crowd could be reactivated easily and successfully and at relatively low cost in an emergency situation, but the effect of an initial nudge can easily wane with time. Thus, a regular or continuous renewal of the pool of volunteers may also be needed to sustain sufficient data submissions, which is critical for robust aggregation and validation of data, and to maintain the reliability of the crowd, but will require modest investment of time and resources. Additionally, a complementary approach to be explored to sustain volunteer engagement can include introduction of a referral system that rewards existing volunteers for successful referral of new volunteers to grow the pool of volunteers, although challenges such as the independence of observations would have to be considered.

Overall, our findings suggest that smartphone- and citizen-driven price data collection can complement traditional price data collection systems in terms of timeliness, geographical granularity and responsiveness to market disruptions—not only from the COVID-19 pandemic, but also conflicts, climate shocks, and other emerging or future threats or disruptions to the food system. This approach can also provide longer-term monitoring of trouble spots to catch incipient price spikes. More generally, policy makers and national institutes should focus on developing ways to integrate rapid, localized data gathering into their responses. In a world in the grips of rapid systems change, crowdsourcing and other emerging tools will be increasingly necessary for providing timely, well-targeted policy responses.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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