

Case Study

Livelihood Vulnerability of Dairy Farming Households to Impacts of COVID-19 Pandemic in Kerala

Haritha, K.^{1*} and Gunjan Bhandari²

¹Division of Agricultural Economics, ICAR-Indian Agricultural Research Institute, Pusa Campus, New Delhi, India

²Scientist, Dairy Economics, Statistics and Management, ICAR-National Dairy Research Institute, Karnal, Haryana, India

*Corresponding author: harithakbabu@gmail.com (ORCID ID: 0000-0002-9904-7997)

Received: 11-03-2022

Revised: 24-05-2022

Accepted: 02-06-2022

ABSTRACT

Present study assesses the livelihood vulnerability of dairy farming households to impacts of COVID-19 pandemic by using primary data collected from 200 farmers of Kozhikode district, Kerala. A new index namely, Livelihood Vulnerability Index to Impacts of Pandemic (LVIIP) was developed based on LVI-IPCC approach. Around 22 percent of the total households were found to be highly vulnerable to impacts of pandemic, whereas 41.5 per cent were moderately vulnerable and 36 per cent were less vulnerable. Farmers selling milk to cooperatives were found to have highest mean value of LVIIP (0.08) due to highest exposure (0.23) and lowest adaptive capacity (0.48). Most of the factors responsible for higher sensitivity of farmers selling milk to consumer households and lower adaptive capacity of farmers selling milk to cooperatives were linked to feed and fodder availability. Hence, special provisions for ensuring uninterrupted feed and fodder supply should be included in the rules and regulations formulated during any such future crisis.

HIGHLIGHTS

- A new livelihood vulnerability index to impacts of pandemic (LVIIP) was developed based on the IPCC approach using exposure, sensitivity and adaptive capacity indicators.
- Around 23 per cent sample households were highly vulnerable to impacts of pandemic whereas the percentage of moderately and less vulnerable households were 41.5 per cent and 36 percent, respectively. Issues related to feed and fodder availability were found to be the major reason behind higher sensitivity and lower adaptive capacity of households.

Keywords: Dairy, COVID-19, Vulnerability, LVIIP Index

The COVID-19 which was declared as a global pandemic by World Health organization (WHO) plunged the world into economic recession in 2020, which is the highest recession in the recent past. Like all the other sectors, dairying which is a source of livelihood for millions of rural households in India was severely affected during COVID-19 induced the nation-wide lockdown. Lockdown and restrictions imposed for controlling the spread of COVID-19 pandemic affected the dairy sector primarily due to breakdown of the supply chain and fall in demand (Bhandari *et al.* 2021). Impossibility to immediately adjust production in response to

demand, high perishability, larger (60%) share of unorganized sector, low level of processing, high income elasticity of milk and milk products and large number of farmers with small marketable surplus added to its vulnerability (Bhandari and Ravishankar, 2020; Chandel *et al.* 2020).

India reported its first confirmed case of COVID-19 in Kerala. Moreover, fresh COVID-19 cases are

How to cite this article: Haritha, K. and Bhandari, G. (2022). Livelihood Vulnerability of Dairy Farming Households to Impacts of COVID-19 Pandemic in Kerala. *Econ. Aff.* 67(03): 353-359.

Source of Support: None; **Conflict of Interest:** None



being reported in the state on a consistent basis since 2020, despite a drop of cases in other states. With the aid of dairy cooperatives, the state has also observed a remarkable increase in production of milk over the last five years. Majority of the dairy farmers of the state resides in Malabar region and thus, contribute in making it a milk surplus area (Pillai, 2013). The state also witnessed a sharp fall in sale of milk to as low as 45-50 per cent due to lock down (Business standard, 2020). Due to lack of processing infrastructure, the area is heavily dependent on neighbouring states of Karnataka and Tamil Nadu for converting the surplus milk into milk powder. But during lockdown, Tamil Nadu refused to accept milk from the state citing the large number of Corona virus positive cases in the state. Sale of milk declined mainly due to the closure of HoReCa (Hotel, Restaurants and Cafeteria) sector. Dairy farmers had few or no options for selling their milk or converting it into dairy products as the demand for liquid milk declined (Bhandari *et al.* 2021). Those who were not able to sell it even at lower prices either distributed the milk for free or simply disposed it off. It was estimated that in United States about 5 per cent of the country's milk production in April 2020 was dumped, and this percentage was further higher in May and June 2020 (Yaffe-Bellany and Corkery, 2020). This directly affected the income of dairy farmers who need a continuous cash flow for feeding their animals. From the input supply side, closure of feed and fodder shops coupled with travel restrictions led to their inadequate availability. Moreover, the price hike due to shortage further rendered them unaffordable for the dairy farmers. Milk production was compromised by farmers due to difficulty in purchasing production inputs and increased cost of milk production (Barua, 2021).

With this back drop, the present study attempts to analyse the livelihood vulnerability of dairy farming households to impacts of pandemic. The study helps in understanding and it plays a vital role in determining how the pandemic and the nationwide lockdown affected the livelihood of the dairy farmers and also will helps to determine the major factors which made the farmers more vulnerable to such crisis so that appropriate coping strategies can be taken to minimize the impact.

MATERIALS AND METHODS

The study was carried out in Kozhikode which is one of the front-line dairy districts among the 6 districts of the Malabar region and houses the headquarters of "Malabar Regional Co-operative Milk Producers Union Ltd." Kozhikode and Kunnamangalam blocks were selected randomly out of the twelve blocks in Kozhikode district. Thereafter, three villages were chosen randomly from each selected block. A random sample of 100 dairy farming households was drawn from the cluster of villages in each block thus, constituting a total sample size of 200 dairy farming households. For the purpose of analysis, post-stratification was done based on the milk marketing channels. On the basis of marketing channels, the sample was divided into following categories- (a) Category-I (DC) consisting of 66 farmers selling milk solely to the dairy cooperatives, (b) Category-II (CH) consisting of 81 farmers selling milk directly to the consumer households and (c) Category-III (Mix) consisting of 53 farmers selling milk partially through both channels.

Primary data was collected from the sample respondents during January- March, 2021 by using pre-tested survey schedule which was then analyzed by using the following analytical tools for achieving the objectives of the study.

Construction of Livelihood Vulnerability Index to Impacts of Pandemic (LVIIP)

An index was constructed to assess livelihood vulnerability of dairy farming households to impacts of pandemic by modifying Livelihood Vulnerability Index (LVI) given by Intergovernmental Panel on Climate Change (IPCC). It is a pragmatic method based on the Livelihood Vulnerability Index (LVI) and the LVI-IPCC approach to assess livelihood vulnerability to climate variability and change (Hahn *et al.* 2009). The indicators used in computing the LVI were modified to suit the requirement of the present study.

Vulnerability is the extent to which a system is prone to or unable to cope with adverse effects of pandemic. It is the function of the character, magnitude and effects of pandemic to which a system is exposed, its sensitivity and adaptive capacity. Exposure is the nature and degree to which

a system is exposed to pandemic. Sensitivity is the degree to which a system is adversely affected by pandemic. Adaptive capacity is the capability of a production system or region to better adjust to the pandemic.

$$\text{Vulnerability} = \frac{(\text{Exposure} + \text{Sensitivity})}{\text{Adaptive Capacity}} \dots(1)$$

In Eq. (1), summation of exposure and sensitivity is called as 'potential impact', which is very much harmful, if the region or production system has a high degree of index score. Hence, vulnerability level of a region is the extent of potential impact over adaptive capacity of that region or production system (Sendhil *et al.* 2018).

Accordingly, Eq. (1) can be rewritten as,

$$\text{Vulnerability} = \frac{\text{Potential impact}}{\text{Adaptive Capacity}} \dots(2)$$

Where,

$$\text{Potential impact} = (\text{Exposure} + \text{Sensitivity}) \dots(3)$$

Steps in vulnerability assessment

The dairy farming households' livelihood vulnerability index to impacts of pandemic was constructed by using the following steps:

1. Identification of household vulnerability indicators

Selection of indicators is critical for any vulnerability assessment study. Suitable indicators were selected by reviewing the published literature and by discussing the same with experts for identifying the hypothesized functional relationship. The indicators of exposure, sensitivity and adaptive capacity are presented in Table 1.

2. Normalization

Normalization of the indicators was done in order to make sure that all the indicators are comparable owing to measurement on different scales for each indicator (Vincent, 2004; Varadan and Kumar, 2015; Kale *et al.*, 2016; Kumar *et al.* 2016; Ponnusamy *et al.* 2016; Mahida and Sendhil, 2017; Sendhil *et al.* 2018).

Following equation was employed for normalization of indicators having positive functional relationship with their respective index,

Normalization =

$$\frac{\text{Actual value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}} \dots(4)$$

On the other hand, following equation was used for normalization, if negative functional relationship occurs.

Normalization =

$$\frac{\text{Maximum value} - \text{Actual value}}{\text{Maximum value} - \text{Minimum value}} \dots(5)$$

3. Assignment of weights to indicators

After normalization of the indicators, weights were assigned based on their level of effect on vulnerability. Various methods such as equal weights, inverse of variance, expert opinion and Principal Component Analysis (PCA) can be employed to assign weights to the indicators. Each method has its own merits and demerits (Varadan and Kumar, 2015; Sendhil *et al.* 2018). However, PCA is the most extensively used technique to assign weights with the assumption of linear relationship existing among the variables. The PCA based weights assigning method used by several researchers (Kaiser, 1960; Ayyoob *et al.* 2013; Rana *et al.* 2015; Kale *et al.* 2016; Mahida and Sendhil, 2017; Sendhil *et al.* 2018) was adopted in this study. The functional formulation is as follows:

$$X_i = \Lambda_i F_i + e_i \dots(6)$$

Where X_i indicates the N -dimensional vector of variables influencing vulnerability; Λ_i represents the; $r \times 1$ common factor; F_i represents the factor loading; e_i represents the associated idiosyncratic error-term of order $N \times 1$.

The weights obtained from the PCA were calculated using following equation:

$$W_i = \sum |L_{ij}| E_j \dots(7)$$

Where W_i represents the weight of the i^{th} variable; L_{ij} represents the Eigen value of the j^{th} factor; E_j

represents the loading value of the i^{th} variable on j^{th} factor.

4. Estimation of Livelihood Vulnerability Index to Impacts of Pandemic (LVIIP)

Exposure, sensitivity and adaptive capacity indices were computed separately by using their respective indicators along with their respective estimated weights in the following equation (Sendhil *et al.* 2018).

$$\text{Index}_{\text{household}} = \frac{\sum_{i=1}^n X_i W_i}{\sum_{i=1}^n W_i} \dots(8)$$

where, X_i represents the normalized value of i^{th} variable; W_i is the weight of i^{th} variable.

Finally, Livelihood Vulnerability Index to impacts of pandemic (LVIIP) was calculated as per the IPCC approach, using Eq. (1).

$$\text{LVIIP} = (\text{Exposure} + \text{Sensitivity}) - \text{Adaptive Capacity} \dots(9)$$

LVI-IPCC Index is scaled from -1 (least vulnerable) to 1 (most vulnerable) (Hahn *et al.*, 2009). Hence, range of LVIIP is also scaled from -1 (least vulnerable) to + 1 (most vulnerable).

5. Categorization of dairy farming households

Finally, cumulative square root frequency method was used for categorizing the sample dairy farming households as high, moderate and low vulnerable based on the computed LVIIP.

RESULTS AND DISCUSSION

The summary statistics of exposure, sensitivity, adaptive capacity and household vulnerability indices are presented in Table 2. It can be observed that the value of exposure index (0.23) is highest for the households belonging to category I (CH). Households belonging to category II (CH) were found to be most sensitive with a value of 0.39 for the sensitivity index while maximum adaptive capacity was present in the case of category III (Mix) households.

The value of LVIIP was highest for category I (DC) and lowest for category III (Mix) households. The mean value of LVIIP was highest for category I

(DC) (0.08) due to higher value for exposure (0.23) and sensitivity (0.34) indices coupled with lower value of adaptive capacity (0.48). The value of LVIIP for category II (CH) was marginally less than category I (DC). Despite of lower exposure, LVIIP was high for category II (CH) due to high value of sensitivity (0.39). Lowest sensitivity and highest adaptive capacity resulted in lowest value of LVIIP for category III (Mix).

Table 3 shows the distribution of sample households across levels of different indices. Around 41.5 per cent of the households were having moderate value of LVIIP while 36 per cent were having low and 22.5 per cent were having high LVIIP value. Percentage of households with high LVIIP was more in the case of category I (DC) and category II (CH). Majority of the households (54.71%) in category III (Mix) were having low LVIIP value.

It can also be observed from Table 3 that the percentage of households having high exposure to the pandemic was highest in category I (DC). Seven (10.66%) out of 66 households in category I (DC) were in high exposure category. On the other hand, only 2.5 and 1.8 per cent of the households respectively, in the case of category II (CH) and category III (Mix) were having high exposure index. Majority of the households (56.79%) in category II (CH) were having low exposure index. Overall, the percentage of households falling under high, medium and low exposure was around 5, 51.5 and 43.5 per cent, respectively.

During the study it was found that number of COVID positive members and quarantine days were more in the case of Category I (DC) households. Moreover, distance to nearest containment zone was comparatively lower for this group and number of days for which there was no milk procurement/sale was higher. These all might be the plausible factors contributed to higher exposure index of Category I (DC).

The mean value of sensitivity index (0.39) was highest for Category II (CH), followed by Category I (DC) (0.34) and Category III (Mix) (0.32). Percentage of households having high sensitivity index was also more in the case of Category II (CH). Around forty-one per cent of the total households in Category II (CH) were highly sensitive while this percentage was almost one-third for the rest two categories.

Table 1: Indicators of exposure, sensitivity and adaptive capacity

Components	Indicators	Sub-indicators	Functional relationship
Exposure	Pandemic and its effects	Number of family members who were tested positive for COVID-19	+
		No of quarantined days	+
		Distance to nearest containment zone (km)	-
		No. of days for which input shops for dairy farming were closed/ out of stock	+
		No of days for which there was no milk procurement	+
Sensitivity	Health and Poverty	Number of members requiring daily care (chronically ill)	+
		Average time to nearest health centre (km)	+
		Distance to nearest veterinary hospital (km)	+
		Dependency ratio	+
		Whether household is BPL	+
		Number of members who lost job due to pandemic	+
	Dependency for inputs	Availability of local substitutes for cattle feed/concentrate	-
		Average time for which fodder stock is available with farmers (in days)	-
		No of irrigation sources	-
		Depend on market for purchasing green fodder	+
Distance to procurement and urban centre	Ratio of hired labour to total labour use in dairying	+	
	Ratio of hired migrant labour to total labour use in dairying	+	
Adaptive Capacity	Assets and ownership	Distance to nearest milk procurement centre (km)	+
		Distance to nearest urban centre (km)	+
		Ownership of vehicle	+
		Number of refrigerators for storing excess milk	+
	Livelihood strategies	Basic things required for making milk product at home	+
		Availability of grazing land	+
		No of sources of income	+
		Any member of the family has savings	+
	Social networks	Total operational land holding (acres)	+
		Livestock units owned by household (SAU)	+
		Membership in dairy cooperatives	+
		Received any kind of help or support from neighbours	+
		Participated in knowledge exchange with others	+
		Access to agricultural research institutions/KVK	+
	Knowledge and skills	Availability of paravets in local areas	+
		Distance to nearest dairy processing facility from home (km)	-
		Dairy farmer who has higher than secondary level of education	+
		Household in which at least one member has taken training in dairying	+
		Dairying experience of the household (years)	+

Overall, majority of the households (40.5%) were moderately sensitive. Percentage of households having high and low sensitivity was 25.5 and 34 per cent, respectively.

The main reasons behind higher sensitivity of households belonging to Category II (CH) were higher mean value of various indicators like

distance of nearest health centre (4.86), distance of nearest veterinary hospital (4.19), ratio of hired labour to total labour use in dairying(0.05), distance to nearest milk procurement centre (1.37), and low mean value of number of irrigation sources (1.07) coupled with more percentage of household dependent on market for purchasing green fodder

Table 2: Summary statistics of exposure, sensitivity, adaptive capacity and household vulnerability indices across marketing channel categories

Marketing channels	Exposure		Sensitivity		Adaptive capacity		LVIIIP*	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range
Category I (DC)	0.23 (0.13)	0.11-0.93	0.34 (0.08)	0.17-0.53	0.48 (0.08)	0.45-0.52	0.08 (0.19)	-0.28-0.94
Category II (CH)	0.19 (0.08)	0.11-0.70	0.39 (0.08)	0.24-0.59	0.51 (0.12)	0.23-0.76	0.07 (0.17)	-0.25-0.89
Category III (Mix)	0.20 (0.05)	0.09-0.30	0.32 (0.08)	0.17-0.57	0.57 (0.11)	0.32-0.81	-0.05 (0.14)	-0.32-0.37
Overall	0.20 (0.10)	0.11-0.93	0.35 (0.09)	0.17-0.53	0.52 (0.11)	0.23-0.81	0.03 (0.18)	-0.32-0.94

Figures in parentheses indicate standard deviation, * LVIIIP: Livelihood Vulnerability Index to Impacts of Pandemic.

Table 3: Distribution of sample households across different levels of exposure, sensitivity, adaptive capacity and household vulnerability

Particulars	Category	Marketing channels			Overall
		Category I (DC)	Category II (CH)	Category III (Mix)	
Exposure	High	7 (10.60)	2 (2.46)	1 (1.88)	10 (5.00)
	Moderate	35 (53.03)	33 (40.74)	35 (66.03)	103 (51.50)
	Low	24 (36.36)	46 (56.79)	17 (32.07)	87 (43.50)
Sensitivity	High	10 (15.15)	33 (40.74)	8 (15.09)	51 (25.50)
	Moderate	30 (45.45)	34 (41.97)	17 (32.07)	81 (40.50)
	Low	26 (39.39)	14 (17.28)	28 (52.83)	68 (34.00)
Adaptive Capacity	High	11 (16.66)	19 (23.45)	25 (47.16)	55 (27.50)
	Moderate	28 (42.42)	38 (46.91)	19 (35.84)	85 (42.50)
	Low	27 (40.90)	34 (41.97)	9 (16.98)	60 (30.00)
LVIIIP	High	17 (25.75)	24 (29.62)	4 (7.54)	45 (22.50)
	Moderate	29 (43.93)	34 (41.97)	20 (37.73)	83 (41.50)
	Low	30 (30.30)	23 (28.39)	29 (54.71)	72 (36.00)

Figures in parentheses indicate per cent.

(4%) and higher share of households belonging to BPL (Below Poverty Line) category (26 %).

The Category III (Mix) has least value of sensitivity index indicating that households were least sensitive to impacts of pandemic. Distance to the nearest veterinary hospital (3.98) and milk procurement centre (1.21) was comparatively lower in category III (Mix) while the fodder stock was available for longer time which leads to its lower sensitivity index.

The highest mean value of adaptive capacity index was noticed in category III (Mix) (0.57), followed by category II (CH) (0.51) and category I (DC) (0.48). The overall mean value and SD were 0.52 and 0.11, respectively. Maximum value of adaptive capacity index was observed for a household in category III (Mix) (0.81), while a household in category II

(CH) (0.23) was having the minimum index value. Majority of the households (42.5%) were having moderate adaptive capacity (Table 3).

On comparing different categories, it can be observed that the percentage of households having high adaptive capacity was highest in the case of category III (Mix). Around 47 per cent of the households in category III (Mix) were having high adaptive capacity while this value was only 23.45 per cent for category II (CH) and even less (16.66 %) for category I (DC). Percentage of households having low adaptive capacity was higher for category I (DC) (40.90%) and category II (CH) (41.97) in comparison to category III (Mix) (16.98%).

The higher adaptive capacity of category III (Mix) was because of the effect of higher mean value of indicators such as ownership of vehicle (1.43),

number of refrigerators for storing surplus milk (1.08), total operational land holding (1.39), dairy experience of the farmers (23.60), percentage of household with sufficient savings (68%), access to agricultural research stations (20%) and household who got the service of paravets during lockdown (6%).

CONCLUSION AND POLICY IMPLICATIONS

Most of the factors responsible for higher sensitivity of category II(CH) and lower adaptive capacity in category I(DC) were linked to feed and fodder availability. Comparatively smaller land holding size, less availability of grazing land, lower stock of fodder available with the households, higher dependence on market for purchasing green fodder and less availability of local substitutes for cattle feed increased their vulnerability. Thus, vulnerability can be reduced by increasing the area under fodder by utilizing wastelands and reducing the dependence on markets. Establishment of local fodder bank and promoting the usage of silage can also prove helpful. PSEs such as Kerala Feeds Ltd and MILMA Feeds can be encouraged and supported to extend their production footprint in the region, which will aid in halting the abrupt surge in prices during such a crisis and, thus resultant loss. Special provisions for ensuring uninterrupted feed and fodder supply chain should be made in the rules and regulations formulated during any such future crisis.

REFERENCES

- Ayyoob, K.C., Krishnadas, M. and Kaeel, C.M.H. 2013. Intra-Regional Disparities in Agricultural Development in Kerala. *Agric. Update*, 8(1): 103-106.
- Barua, P. 2021. Corona virus Disease (COVID-19) and livelihood: Impact on Dairy Farmers of Kamrup District, Assam, India. *The NEHU J.*, 19(1): 65-72.
- Bhandari, G. and Ravishankar, K.M. 2020. Implications of COVID-19 for Indian Dairy Sector. *Food and Scientific Report*, pp. 43-46.
- Bhandari, G., Lal, P., Chaudhary, U., Haritha, K., Malhotra, R. and Chandel, B.S. 2021. Assessing snowball effect of COVID-19 pandemic on Indian dairy sector. *Indian J. Anim. Sci.*, 91(12): 1011-1017
- Chandel, B.S., Dixit, A.K., Singh, A. and Devi, A. 2020. Economic Analysis of the Impact of COVID-19 Lockdown on Indian Dairy Sector. *Agriculture Situation in India*, 78(8): 21-27.
- Hahn, M.B., Riederer, A.M. and Foster, S.O. 2009. The Livelihood Vulnerability Index: A Pragmatic Approach to Assessing Risks from Climate Variability and Change- A Case Study in Mozambique. *Glob. Environ. Change*, 19(1): 74-88.
- Kaiser, H.F. 1960. The Application of Electronic Computers to Factor Analysis, *Educ. Psychol. Meas.*, 20(1): 141-151.
- Kale, R.B., Ponnusamy, K., Chakravarty, A.K., Sendhil, R. and Mohammad, A. 2016. Assessing Resource and Infrastructure Disparities to Strengthen Indian Dairy Sector. *Indian J. Anim. Sci.*, 86(6): 720-725.
- Kumar, S., Raizada, A., Biswas, H., Srinivas, S. and Biswajit, M. 2016. Application of Indicators for Identifying Climate Change Vulnerable Areas in Semi-Arid Regions of India. *Ecol. Indic.*, 70: 507-517.
- Mahida, D. and Sendhil, R. 2017. Principal Component Analysis (PCA) based Indexing. In: Sendhil et al. (eds.) Data Analysis Tools and Approaches (DATA) in Agricultural Sciences, ICAR-IIWBR, Karnal, India, ISBN No. 978-93-5300-510-8.
- Ponnusamy, K., Sendhil, R. and Krishnan, M. 2016. Socio-Economic Development of Fishers in Andhra Pradesh and Telangana states in India. *Indian J. Fish.*, 63(3): 157-161.
- PTI. 2020. Dairy farmers find the going tough as procurement is stopped. Business standard. April 1, 2020. Available at: <https://www.business-standard.com/article/pti-stories/dairy-farmers-find-the-going-tough-as-procurement-is-stopped> (Last Accessed on 3rd March, 2022).
- Ramabhadran, Pillai, R. 2013. Malabar dairy farming takes a progressive turn. Hindu, Kochi, 14th November 2014.
- Rana, V., Ram, S., Sendhil, R., Nehra, K. and Sharma, I. 2015. Physiological, Biochemical and Morphological Study in Wheat (*Triticum aestivum* L.) RILs Population for Salinity Tolerance. *J. Agric. Sci.*, 7: 119-128.
- Sendhil, R., Jha, A., Kumar, A. and Singh, S. 2018. Extent of Vulnerability in Wheat Producing Agro-Ecologies of India: Tracking from Indicators of Cross-Section and Multi-Dimension Data, *Ecol. Indic.*, 89: 771-780.
- Varadan, R.J. and Kumar, P. 2015. Mapping Agricultural Vulnerability of Tamil Nadu, India to Climate Change: A Dynamic Approach to take Forward the Vulnerability Assessment Methodology. *Climatic Change*, 129: 159-181.
- Vincent, K. 2004. Creating an Index of Social Vulnerability for Africa. Working Paper 56, Tyndall Centre for Climate Change Research, University of East Anglia, Norwich, UK.
- Yaffe-Bellay, D. and Corkery, M. 2020. Dumped milk, smashed eggs, plowed vegetables: Food waste of the pandemic. The New York Times. April 11, 2020.

