**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

# Insights into Livestock-Induced CO2 Emissions: Nepal's Environmental Challenges

***Omkar Poudel[1], Khom Raj Kharel PhD[2] (Corresponding author), Pradeep Acharya[3], Yadav Mani Upadhyaya PhD[4]***

[1]Assistant Professor of Economics, Birendra Multiple Campus, Tribhuvan University, Chitwan, Nepal. *[(Email: omkar60475@gmail.com) ORCID: https://orcid.org/0009-0008-7873-0237]*

[2]Associate Professor of Economics, Tribhuvan University, Saraswati Multiple Campus, Kathmandu, Nepal. *[(Email: kharelkhom@yahoo.com) ORCID: https://orcid.org/0000-0002-9806-7224]*

[3] Account Specialist at NOWCFO, MBA, Tribhuvan University, Kathmandu, Nepal. *[(Email: pradeep.acharya197@gmail.com) ORCID: https://orcid.org/0000-0001-8055-8757]*

[4]Assistant Professor of Economics, Saraswati Multiple Campus, Tribhuvan University, Kathamndu, Nepal. *[(Email: yadav.upadhyaya@smc.tu.edu.np) ORCID: https://orcid.org/0000-0003-3089-3615)]*

**Article History:** Received 1 Dec. 2023; Reviewed 23 Jan. 2024; Revised 7 March 2024; Accepted 9 June 2024.



## Abstract

*This study investigates cattle-related carbon dioxide emissions, their sources, and their effects on Nepal's environment. This research utilizes descriptive and analytical approaches in a quantitative manner to examine the complex connection between livestock populations and carbon dioxide (CO2) emissions in Nepal. A comprehensive analysis was conducted on the secondary data spanning from 1990 to 2020. Various statistical tests are employed to examine the existence of both short-term and long-term relationships between variables. The findings suggest that past CO2 emissions and the number of pigs has a significant impact on current CO2 emissions, while other factors do not appear to have a statistically significant effect. There is limited evidence available to establish a clear cause-and-effect connection between variables, except for the influence of poultry on cattle and goats, which subsequently impacts poultry. The model diagnostic confirms the suitability of the ARDL model, as stability tests indicate that the model's parameters remain consistent over time. This study explores the intricate relationship between livestock populations and CO2 emissions in Nepal, highlighting the importance of further research and policy interventions to promote sustainable environmental management.*

***Keywords:*** *Climate change, livestock production, ARDL model, CO2 emission, Nepal.*

## Introduction

Carbon emissions from animal husbandry have become a major problem and affect the sustainable expansion of animal husbandry. Additionally, they have a major obstacle to the establishment of a low-carbon and green economy (Zhuang, 2017; Xiong et al., 2016). Overindulgence in carbon emissions intensifies the effects of global warming and declining environmental quality (Bashir et al., 2020; Khalfaoui et al., 2021), obliging people to confront grave dangers like resource scarcity, extreme weather events, economic stagnation, and health harm (Yang et al., 2021; Liu et al., 2019; Rehman et al., 2021).

Animal husbandry is the cause of 9% of human carbon emissions, 37% of human methane emissions, 65% of human nitrous oxide emissions, and 64% of human nitrogen emissions, according to the Food and Agriculture Organization of the United Nations (FAO)

(Steinfeld et al., 2006). Ranching for livestock has long been an essential part of local ecosystems and landscapes, making a substantial contribution to global food supply. It is often known that cattle are essential to human civilizations since they provide them with food, income, employment, nutrition, and insurance against danger (Perry & Sones, 2007; Herrero et al., 2009).

As agriculture affects the worldwide flow of greenhouse gases, it is a significant industry that both causes and is affected by climate change. A few of the greenhouse gases that are contributing to climate change include CO2, CH4, and N2O, which are produced by agricultural practices (such as energy usage, plant and animal production, fertilizer, pesticide use, etc.). (Akalın, 2014; Houghton, 2003). Using the life cycle assessment method, Yao et al. (2017) reveal the evolutionary characteristics of carbon emissions of animal husbandry in China at both temporal and spatial levels, offering a clearer picture for implementing energy conservation and emission reduction at the animal husbandry level. Still, academics are more likely to focus on the finer points of carbon emissions from animal agriculture.

Zhuang & Li (2017) look at the various ways that different animals feed or measure their carbon footprints. Though they are not a direct source of information for developing scientifically sound macro-level strategies to minimize carbon emissions related with animal husbandry, these microstudies are useful in offering a scientific knowledge of carbon emanations associated with animal farming. Furthermore, a number of studies use the emissions factor approach or life cycle method to assess the overall carbon emissions associated with animal husbandry. Regional differences are then examined using descriptive statistics. Nevertheless, the afore mentioned studies merely explain the notable geographical variations in animal husbandry-related carbon emissions. The patterns and causes of the differences, however, have not received much attention. Therefore, studies on the characteristics and factors that contribute to carbon emissions in animal husbandry are beneficial for achieving low-carbon development in this industry and providing useful policy references for examining the reduction of carbon emissions path.

Much of the population of Nepal, an overwhelmingly agricultural nation tucked away in the Himalayas, works in agriculture, with livestock being essential to rural incomes. Numerous livestock species, including cattle, buffaloes, goats, and sheep, are supported by the nation's distinct topography and range of climatic zones. But there are environmental costs associated with this livestock dependence, especially in terms of greenhouse gas emissions. The raising of livestock increases emissions of the powerful greenhouse gasses methane (CH4) and nitrous oxide (N2O), which worsen global warming. Nepal is working to strike a balance between environmental sustainability and economic growth, thus it's critical to comprehend how livestock affects CO2 emissions.

When looking at Nepal's CO2 emissions more broadly, the nation released about 38.3 million metric tons of CO2 in 2021, with a large contribution from agriculture. Enteric fermentation and manure management are the core bases of Nepal's livestock-related greenhouse gas emissions, which make up around 11.3% of the country's overall emissions. It is estimated that livestock-induced emissions account for around 4.3 million metric tons of $CO_2$ equivalent per year, which is a significant amount of the nation's carbon footprint. decreasing emissions associated with livestock can provide a substantial contribution to Nepal's overall goals for decreasing greenhouse gas emissions, hence addressing these emissions is essential to the country's climate mitigation measures. The study aims to investigate the specific contribution of livestock to Nepal's greenhouse gas emissions, focusing on the percentage and volume of $CO_2$ emissions attributed to livestock. This study also examines how these livestock-related emissions impact Nepal's overall greenhouse gas emissions.

## Literature Review

The dietary habits of the populace have changed significantly in tandem with their rising quality of life, and there is a perpetual need for animal products like meat, milk, and eggs. To ensure a continuous increase in the production of livestock products, there will inevitably be an increase in carbon emissions from animal husbandry. However, since raising animals has a higher economic return than planting, more farmers are turning to animal husbandry as a means of boosting their income and fostering the industry's rapid growth. As a result, more people are engaged in animal husbandry, which raises the quantity of $CO_2$ emissions from livestock and animal farming and feeds the world's expanding population. To determine agricultural carbon emissions on a national and international scale, three primary methods are utilized: the life-cycle methodology, the model technique, and the carbon emission coefficient method.

Rehman et al. (2018) used the carbon emission coefficient technique to study Pakistan's agricultural greenhouse gas emissions and found that over half of the country's emissions came from animal agriculture. The main sources of carbon emissions in animal husbandry were large animals like cattle and sheep, according to Xie et al. (2020), who quantified the carbon emissions from animal husbandry in three provinces in Central China using the carbon emission coefficient approach. Utilizing the carbon emission coefficient approach and the IPCC greenhouse gas emission inventory as a point of reference, Luo et al. (2017) investigated China's agricultural carbon emissions from 1997 to 2014. When compared to farming, they found that raising animals resulted in a sizable quantity of carbon emissions.

A systematic assessment of the condition of carbon emissions from animal farming was conducted by Ting Xie et al. (2019). Using simulations utilizing the growth curve, s-curve, and other time series models, the carbon emissions from the cattle sector in Henan province were calculated over the course of the next 10 years. The article's conclusion was that, despite their tiny numbers, big animals create considerable carbon emissions, whereas poultry and pigs produce negligible emissions. The primary contributors are cattle, namely dairy cows, buffaloes, and cows; the carbon emission rate of dairy cows is higher than that of buffaloes and cows. Goats and pigs then follow the emission. In order to successfully lower the carbon emissions rate of farm and dairy animals, the feeding arrangement for livestock might be adjusted.

Tunc et al. (2009) used the Log Mean Divisia Index (LMDI) to study the factors that affect variations in $CO_2$ emissions for the Turkish economy. Agriculture, industry, and services made up the three primary sectors of the Turkish economy. This study looked at the years 1970–2006 to evaluate the ways that changes in industry shares and energy sources brought about by macroeconomic policy affected carbon dioxide emissions. Results showed that Turkey's CO2 emissions were mostly caused by economic activities. The economic structure underwent major changes, but these had little influence on emissions; in contrast, the intensity effect was large. West & Marland (2002) devised an index method for evaluating agricultural carbon emissions based on four factors: seed culture, chemical fertilizers, pesticides, and agricultural irrigation. They used the complete life-cycle approach as an example.

Yao et al. (2017) used the whole life-cycle method to measure the carbon emissions from animal husbandry across 31 provinces and autonomous regions in mainland China between 2000 and 2014. They found that about 80% of the total carbon emissions from animal husbandry were related to intestinal fermentation and manure management. Yao (2017) conducted an extensive study that demonstrated how these two factors significantly raised the total quantity of greenhouse gas emissions in the animal husbandry industry throughout the study period.

The forward and backward relationships between water consumption, agricultural value addition, and carbon dioxide emissions in Iran were examined by Najafi Alamdarlo (2016) using the EKC theory. Using data from Iranian provinces gathered between 2001 and 2013, which were computed using panel data and spatial econometrics, the Kuznets theory was applied to investigate these associations. The correlation between per capita income and water uses and carbon dioxide emissions was shown to be an inverted U. Additionally, a geographical study revealed a strong correlation between these factors in the surrounding areas and the amount of water used and CO2 emitted by the agricultural sector.

Using a random forest model, Liu and Cheng (2024) investigated the factors influencing the carbon emissions from agriculture in Hunan Province. Unit energy carbon emissions in agriculture, unit crop output value, and unit agricultural GDP energy consumption were shown to be the main contributors. These findings were validated by the LDMI approach. Sensitivity analysis showed that agricultural energy consumption, total agricultural output value, forestry, animal husbandry, and fisheries (AFAF), crop yield, and planting area favorably influence carbon emissions, despite a pattern of fluctuation in the non-urban population. Using the LMDI model, Zhao et al. (2018) also examined these factors and found that although labor force size and production efficiency greatly decreased emissions, agriculture economic level and industrial structure significantly raised them.

Huang and Gao (2022) used Kays's constant equation to draw conclusions from their study, which assessed the agricultural carbon emission and looked at its temporal patterns in Jiangxi between 2000 and 2019. The data indicates that Jiangxi's agricultural carbon emissions grew overall between 2000 and 2019, but gradually at a lesser pace. Furthermore, the degree of urbanization and agricultural economic growth had a favorable influence on carbon emissions, but the labor force, industrial structure, and productivity efficiency of the agricultural sector had a negative impact. Using the spatial autocorrelation model and kernel density estimation, Tian Yin's (2022) research determined that the general geographic characteristic of carbon emission intensity was "high in the east and low in the west."

China's carbon emissions from agriculture showed an annual drop with interannual oscillations throughout time. Zhou et al. (2021) estimated China's agricultural carbon emissions using data spanning from 1997 to 2015 and examined the temporal and geographical features of the data. They proposed that the overall carbon emissions had the three characteristics of "fluctuating rise—rapid

Interdisciplinary Journal of Management and Social Sciences (IJMSS)
Vol. 5, No. 2, July 2024. Pages: 134-151
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
DOI: 10.3126/ijmss.v5i2.69452

rise—slow decline," with a conspicuously unequal distribution across space. All the literature and studies available however fail to reveal the dynamic relation between the Livestock based CO2 emissions. Hence this study provide insight into the nexus of Livestock based CO2 emissions in the context of Nepal.

## Methods

This study used a quantitative methodology that combined analytical and descriptive techniques. Numerous factors were measured, and secondary data were used to quantify the effect of independent variables on the dependent variable. To interpret the findings, the EViews statistical tool, version 10, was used to analyze the obtained data.

### Model Specification

Dependent variable: Carbon dioxide emission (in Kt.)

Independent variables: Number of cattle and buffalo, Number of goats and sheep, Number of chickens and duck (in 1000) and Number of Swine/Pig

$$CO_2 = f(CATTLE + GOAT + POULTRY + PIG)$$

The linear relationship among the variables is established by logarithmically transforming both sides of the equation. This transformation enables us to calculate the elasticity of CO2 concerning the explanatory variables.

$$LNCO2 = \beta 0 + \beta 1\ t + \beta 2\ LNCATTLE + \beta 3\ LNGOAT + \beta 4\ LNPOULTRY + \beta 5\ LNPIG + et$$

Where,

LNCO2= Natural Logarithms of carbon-dioxide emission (in Kt.)

LNCATTLE = Natural Logarithms of cattle and buffalo stock number,

LNGOAT = Natural Logarithms of goats and sheep stock number,

LNPOULTRY= Natural Logarithms of chickens and duck stock number (in 1000)

LNPIG= Natural Logarithms of swine/pig stock number

$e_t$= error term

$\beta_i$= constant coefficient

*Table 1:*

**Variables, abbreviations and units used in research**

| Variable names | Symbols | Units | Data sources |
|---|---|---|---|
| Carbon dioxide emission | CO2 | kt | World Bank |
| Cattle and buffalo stock | Cattle | Head | World Bank, FAO |
| Goats and sheep stock | Goat | Head | World Bank, FAO |
| Chickens and duck stock | Poultry | Head | World Bank, FAO |
| Swine/pig stock | Pig | Head | World Bank, FAO |

This research employs both descriptive and analytical methods, relying solely on secondary data. The available literature, including books, journals, and reports from the World Bank, has been utilized to meet the study's objectives. Data from 1990 to 2020 was sourced from the World Bank (2024).

### *Econometric Method*

The study examined the correlation concerning CO2 emissions (in kilotons) and the numbers of cattle, goats, poultry, and pigs in Nepal.

***Stationarity Test:*** Most time series econometric methods operate under the assumption that the variables are stationary. Therefore, the dynamic time series model was tested and estimated using standard methods. A series with a unit root process is characterized as "Integrated to the order one," or I(1), while a stationary process is termed I(0). This common nomenclature is used to categorize time series based on their stationarity characteristics.

***The Autoregressive Distributed Lag (ARDL) Model:*** To investigate the short- and long-term correlations between the quantities of cattle, goats, poultry, and pigs in Nepal and CO2 emissions (in Kt.), the Autoregressive Distributed Lag (ARDL) model was used. It is crucial to establish the sequence of integration for each dependent and independent variable under investigation before utilizing the co-integration approach. The ARDL model cannot be applied to any variable that has an integrated order of I (2) or above.

***ARDL bounds test:*** The ARDL bounds test is employed to identify long-run relationships between independent and dependent variables, offering advantages over traditional co-integration tests (Bahmani-Oskooee & Ng, 2002). This method requires determining whether the data are integrated of order zero, I (0), or order one, I(1). Following this, an error correction model (ECM) is used for further analysis.

***Error Correction Model (ECM):*** The error correction representation of the Autoregressive Distributed Lag (ARDL) model captures the co-integration among variables, which can be assessed through the ECM. The coefficients of the lagged values are used to analyze short-run dynamics.

## Results and Discussion

### Descriptive Statistics

The increase in livestock populations may contribute to higher CO2 emissions, reflecting greater agricultural output and associated activities.

**Table 2:**

*Descriptive Statistics*

| | LNCO2 | LNCATTLE | LNGOAT | LNPOULTRY | LNPIG |
|---|---|---|---|---|---|
| Mean | 8.203212 | 16.22395 | 15.41455 | 10.20676 | 13.74530 |
| Median | 8.046773 | 16.22028 | 15.40438 | 10.06173 | 13.76180 |
| Maximum | 9.625056 | 16.35841 | 15.62504 | 11.32691 | 14.23395 |
| Minimum | 6.844602 | 16.04482 | 15.17773 | 9.510297 | 13.26073 |
| Std. Dev. | 0.768726 | 0.104997 | 0.163124 | 0.593384 | 0.290866 |

**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

| | | | | | |
|---|---|---|---|---|---|
| Skewness | 0.372973 | -0.290330 | -0.002270 | 0.592118 | -0.178348 |
| Kurtosis | 2.355709 | 1.870759 | 1.419938 | 1.994545 | 2.027157 |
| Jarque-Bera | 1.254915 | 2.082620 | 3.224796 | 3.117250 | 1.386805 |
| Probability | 0.533948 | 0.352992 | 0.199409 | 0.210425 | 0.499872 |
| Sum | 254.2996 | 502.9425 | 477.8512 | 316.4097 | 426.1042 |
| Sum Sq. Dev. | 17.72818 | 0.330731 | 0.798288 | 10.56314 | 2.538093 |
| Observations | 31 | 31 | 31 | 31 | 31 |

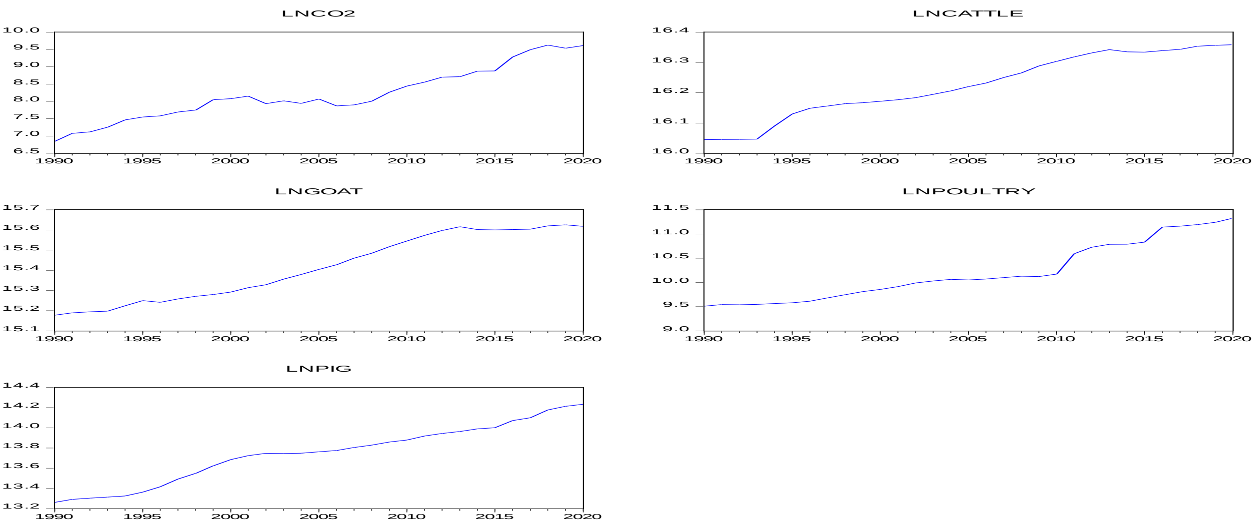
**Source:** Results from data analysis.

This table presents the logarithmic values of CO2 emissions, cattle, goats, poultry, and pig populations over a 31-year period. The close alignment of mean and median values indicates a relatively symmetric distribution. Standard deviations reveal moderate variability, notably for LNCO2 and LNPOULTRY. Skewness values indicate slight asymmetry, with LNCO2 and LNPOULTRY showing positive skewness while the other variables remain nearly symmetric. Kurtosis values below 3 suggest distributions are flatter than a normal distribution. High p-values from the Jarque-Bera test indicate no strong evidence against normality. Overall, the data display moderate variability and approximate normality, making them suitable for further statistical analysis.

### *Graphical Analysis of CO2 Emissions and Livestock Populations over a 31-Year Period*

Visual representation of data helps understand CO2 emissions trends and livestock populations over a 31-year period. It enables easy observation of changes, potential correlations, and significant fluctuations. These graphs aid in understanding the relationship between livestock populations and CO2 emissions, identifying long-term trends and potential causal factors.

**Figure 1:** *CO2 emission, cattle stock, sheep stock, poultry stock and pig stock of Nepal by 1990- 2020 years*




From 1990 to 2020, LNCo2 showed a slight increase in carbon dioxide emissions. Cattle population remained stable, while goat population showed modest growth until 2015. Poultry population increased steadily from 2000 to 2020, and pig population slightly increased from 1990 to 2020, indicating incremental growth.

**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

### *The unit root test*

To determine if the data has stationarity, the unit root test is utilized. To be more precise, the stationarity requirement is met or not by using the Augmented Dickey-Fuller (ADF) test (Poudel, 2022). The findings of the unit root test, namely the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, provide light on the stationarity of the time series data for LNCO2, LNCATTLE, LNGOAT, LNPIG, and LNPOULTRY.

**Table 3:**
*Unit Root Test Table (PP)*

| | **At level** | | | | | |
|---|---|---|---|---|---|---|
| | | **LNCO2** | **LNCATTLE** | **LNGOAT** | **LNPIG** | **LNPOULTRY** |
| With Constant | t-Statistic | -0.3780 | -1.3407 | -0.7735 | -0.2707 | 2.2956 |
| | ***Prob.*** | ***0.9008*** | ***0.5973*** | ***0.8122*** | ***0.9181*** | ***0.9999*** |
| With Constant & Trend | t-Statistic | -1.5883 | -1.4364 | -1.2769 | -1.8249 | -1.5820 |
| | ***Prob.*** | ***0.7737*** | ***0.8288*** | ***0.8744*** | ***0.6673*** | ***0.7762*** |
| Without Constant & Trend | t-Statistic | 3.7324 | 5.2685 | 4.0708 | 5.4445 | 3.8400 |
| | ***Prob.*** | ***0.9998*** | ***1.0000*** | ***0.9999*** | ***1.0000*** | ***0.9999*** |
| | **At First Difference** | | | | | |
| | | d(LNCO2) | d(LNCATTLE) | d(LNGOAT) | d(LNPIG) | d(LNPOULTRY) |
| With Constant | t-Statistic | -5.2604 | -2.8712 | -2.8326 | -2.9958 | -4.4951 |
| | ***Prob.*** | ***0.0002**** | ***0.0611**** | ***0.0661**** | ***0.0471**** | ***0.0013**** |
| With Constant & Trend | t-Statistic | -5.1951 | -2.8863 | -2.8250 | -2.9251 | -7.0716 |
| | ***Prob.*** | ***0.0012**** | ***0.1811*** | ***0.2003*** | ***0.1697*** | ***0.0000**** |
| Without Constant & Trend | t-Statistic | -3.8877 | -1.9010 | -1.6350 | -1.4267 | -3.3792 |
| | ***Prob.*** | ***0.0004**** | ***0.0558**** | ***0.0953**** | ***0.1401*** | ***0.0015**** |

**UNIT ROOT TEST TABLE (ADF)**

| | **At Level** | | | | | |
|---|---|---|---|---|---|---|
| | | LNCO2 | LNCATTLE | LNGOAT | LNPIG | LNPOULTRY |
| With Constant | t-Statistic | 0.1284 | -1.7766 | -1.0555 | -1.9989 | 1.0271 |
| | ***Prob.*** | ***0.9621*** | ***0.3840*** | ***0.7193*** | ***0.2855*** | ***0.9958*** |
| With Constant & Trend | t-Statistic | -1.5195 | -2.6187 | -0.9944 | -3.6815 | -1.6938 |
| | ***Prob.*** | ***0.8000*** | ***0.2753*** | ***0.9294*** | ***0.0406*** | ***0.7290*** |
| Without Constant & Trend | t-Statistic | 3.7675 | 2.0669 | 2.0151 | 3.4895 | 3.7668 |
| | ***Prob.*** | ***0.9998*** | ***0.9888*** | ***0.9874*** | ***0.9996*** | ***0.9998*** |
| | **At First Difference** | | | | | |
| | | d(LNCO2) | d(LNCATTLE) | d(LNGOAT) | d(LNPIG) | d(LNPOULTRY) |
| With Constant | t-Statistic | -3.5323 | -2.9166 | -2.8209 | -4.0088 | -4.5561 |
| | ***Prob.*** | ***0.0148**** | ***0.0556**** | ***0.0677**** | ***0.0050**** | ***0.0011**** |
| With Constant & Trend | t-Statistic | -3.4967 | -3.1789 | -2.8626 | -4.3702 | -4.8249 |

Interdisciplinary Journal of Management and Social Sciences (IJMSS)
Vol. 5, No. 2, July 2024. Pages: 134-151
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
DOI: 10.3126/ijmss.v5i2.69452

| | | | | | | |
|---|---|---|---|---|---|---|
| | ***Prob.*** | ***0.0599**** | ***0.1083*** | ***0.1883*** | ***0.0097****** | ***0.0030****** |
| Without Constant & Trend | t-Statistic | -1.6506 | -1.9289 | -1.8736 | -0.8096 | -3.3970 |
| | ***Prob.*** | ***0.0924**** | ***0.0526**** | ***0.0591**** | ***0.3551*** | ***0.0014****** |

Notes: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%.

At a significance level of 5%, the Augmented Dickey-Fuller (ADF) test yields the following results: (I) The null hypothesis, which asserts that each variable's level series has a unit root, is accepted; but, (ii) it is rejected when the variables have their first difference. Given that all series become stationary when they are differentiated once, this argues that all series are integrated in order one. Because the variables are co-integrated, it is feasible that they have a long-term connection (Poudel et al., 2024).

## VAR Lag Order Selection Criteria

Before conducting the co-integration test, it is necessary to determine the appropriate lag length. The table below indicates that most of the criteria recommend selecting 1 lag. Therefore, we proceed with further tests using lag (1).

**Table 4:**

*VAR Lag Order Selection Criteria*

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 155.4131 | NA | 2.15e-11 | -10.37332 | -10.13758 | -10.29949 |
| 1 | 348.7506 | 306.6733* | 2.01e-16* | -21.98280 | -20.56836* | -21.53982* |
| 2 | 373.9046 | 31.22561 | 2.36e-16 | -21.99342* | -19.40027 | -21.18128 |

**Source:** Results from data analysis.

## ARDL Model Result

The Autoregressive Distributed Lag (ARDL) model is used for estimating the long-run and short-run relationships between variables in a time series context (Poudel, 2024).

**Table 5:**

*ARDL Model Results*

| Selected Model: ARDL (1, 0, 0, 0, 1) | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **t-Statistic** | **Prob.*** |
| LNCO2(-1) | 0.569377 | 0.175426 | 3.245687 | 0.0036 |
| LNCATTLE | 0.202104 | 1.978264 | 0.102162 | 0.9195 |
| LNGOAT | 0.037973 | 1.331110 | 0.028527 | 0.9775 |
| LNPOULTRY | 0.458999 | 0.226440 | 2.027024 | 0.0544 |
| LNPIG | 2.890976 | 1.316629 | 2.195740 | 0.0385 |
| LNPIG (-1) | -2.833393 | 1.196462 | -2.368144 | 0.0267 |
| C | -5.841117 | 13.56060 | -0.430742 | 0.6707 |
| R-squared | 0.983003 | Mean dependent var | | 8.248499 |

**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.978569 | S.D. dependent var | 0.738611 |
| S.E. of regression | 0.108129 | Akaike info criterion | -1.410026 |
| Sum squared resid | 0.268912 | Schwarz criterion | -1.083080 |
| Log likelihood | 28.15039 | Hannan-Quinn criter. | -1.305433 |
| F-statistic | 221.6925 | Durbin-Watson stat | 2.075457 |
| Prob(F-statistic) | 0.000000 | | |

**Source:** Results from data analysis.

The chosen model, ARDL (1, 0, 0, 0, 1), signifies an Autoregressive Distributed Lag (ARDL) model, with lag orders specified for each variable. Within this model framework, the coefficient for LNCO2(-1) stands at 0.569377, indicating a positive impact of the lagged LNCO2 value on the current one, statistically significant at the 0.05 level ($p = 0.0036$), implying the influence of past LNCO2 levels on present ones. However, coefficients for LNCATTLE, LNGOAT, and LNPOULTRY (0.202104, 0.037973, and 0.458999, respectively) lack statistical significance ($p > 0.05$), suggesting no significant effects of their past values on their current states. LNPIG's coefficient of 2.890976 signifies a positive relationship with its lagged value, statistically significant at the 0.05 level ($p = 0.0385$), while LNPIG (-1) with a coefficient of -2.833393 indicates a negative relationship, significant at the 0.05 level ($p = 0.0267$), implying a reversal effect from the previous period on the current LNPIG value.

### *Co-integrating Equation in ARDL Model*

In the framework of an ARDL model, the co-integrating equation delineates the long-term relationship among the variables under examination. This equation is formulated when evidence of co-integration is present among the variables, indicating a shared stochastic trend (Poudel, 2023). The hypotheses for the co-integration test are stated as follows: $H_0$: There is no co-integrating equation, and $H_1$: There is a co-integrating equation. Additionally, the ARDL Long Run Form and Bounds Test are conducted to further analyze the long-term relationships between the variables.

**Table 6:**

*ARDL Long Run Form and Bounds Test*

| Null Hypothesis: No levels relationship | Value of Statistics |
|---|---|
| Computed F- Statistics | 2.636399 |
| 5% Critical Value | |
| Value in Lower Bound | 2.56 |
| Value in Upper Bound | 3.49 |

**Source:** Results from data analysis.

The F-statistic (2.6364) falls within the 10% significance level bounds for both asymptotic and actual sample size, indicating inconclusive evidence for a cointegrating relationship. This suggests a weak long-run equilibrium relationship or further investigation with larger sample sizes or alternative cointegration tests.

**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

### *ECM Model*

Error correction model (ECM) was used to find the short and long run relationship among variables in time series regression model. The finding of ECM is shown as:

**Table 7:**

*Estimated Long-run Coefficient: ARDL (1, 0, 0, 0, 1) Selected by Schwarz Bayesian Criterion-ECM*

| Variable | Coefficient | Std.Error | t-statistic | p-value |
|---|---|---|---|---|
| **ECM** | -0.430623 | 0.098130 | -4.388300 | <0.001 |

**Source:** Results from data analysis.

Table 7 indicates that the error correction coefficient is -0.954827, significant at both the 1% and 5% levels with a p-value of less than 0.001. This finding suggests a rapid convergence towards equilibrium, highlighting the robustness of the model's adjustment process.

### *Granger Causality Test*

Within the ARDL framework, the Granger Causality Test serves as a standard tool for evaluating causal relationships among the model's variables. A significant outcome in this test indicates that past values of the purported predictor variable offer valuable information for predicting the dependent variable (Poudel et al., 2023).

**Table 8:**

*Granger Causality Test Results*

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| LNCATTLE does not Granger Cause LNCO2 | 30 | 1.56810 | 0.2212 |
| LNCO2 does not Granger Cause LNCATTLE | | 0.48553 | 0.4919 |
| LNGOAT does not Granger Cause LNCO2 | 30 | 2.75792 | 0.1083 |
| LNCO2 does not Granger Cause LNGOAT | | 2.91348 | 0.0993 |
| LNPOULTRY does not Granger Cause LNCO2 | 30 | 4.26201 | 0.0487 |
| LNCO2 does not Granger Cause LNPOULTRY | | 2.35904 | 0.1362 |
| LNPIG does not Granger Cause LNCO2 | 30 | 0.01726 | 0.8965 |
| LNCO2 does not Granger Cause LNPIG | | 8.40363 | 0.0074 |
| LNGOAT does not Granger Cause LNCATTLE | 30 | 0.54893 | 0.4652 |
| LNCATTLE does not Granger Cause LNGOAT | | 0.19183 | 0.6649 |
| LNPOULTRY does not Granger Cause LNCATTLE | 30 | 1.39232 | 0.2483 |
| LNCATTLE does not Granger Cause LNPOULTRY | | 4.78950 | 0.0375 |
| LNPIG does not Granger Cause LNCATTLE | 30 | 0.42446 | 0.5202 |
| LNCATTLE does not Granger Cause LNPIG | | 5.06518 | 0.0328 |
| LNPOULTRY does not Granger Cause LNGOAT | 30 | 8.97162 | 0.0058 |
| LNGOAT does not Granger Cause LNPOULTRY | | 5.07447 | 0.0326 |

Interdisciplinary Journal of Management and Social Sciences (IJMSS)
Vol. 5, No. 2, July 2024. Pages: 134-151
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
DOI: 10.3126/ijmss.v5i2.69452

| | | | |
|---|---|---|---|
| LNPIG does not Granger Cause LNGOAT | 30 | 0.49339 | 0.4884 |
| LNGOAT does not Granger Cause LNPIG | | 0.01287 | 0.9105 |
| LNPIG does not Granger Cause LNPOULTRY | 30 | 1.69020 | 0.2046 |
| LNPOULTRY does not Granger Cause LNPIG | | 0.51858 | 0.4776 |

**Source:** Results from data analysis.

The results show limited evidence for past values of one livestock population variable directly causing changes in another (except for poultry influencing cattle and goats influencing poultry). However, past poultry population seems to be a useful predictor for future CO2 emissions, suggesting a potential long-term impact. Overall, the relationships between livestock populations and CO2 emissions require further investigation.

### *Long Run Causality*

In assessing long-run causality within the ARDL framework, the methodology entails scrutinizing the coefficients linked with lagged variables in the model. Prior to delving into long-run causality, it becomes imperative to conduct tests for co-integration among the variables. Co-integration signifies the existence of a stable, enduring relationship between variables. Confirmation of co-integration suggests a substantive and persistent link between the variables, indicating their concerted movement over the long term.

### *Short run causality*

ARDL models include lagged values of variables to capture short-term dynamics. These lagged terms represent the effects of past values of variables on their current values.

**Table 9:**

*Wald Test Results*

| Null Hypothesis: C (2) =0, C(3)=0,C(4)=0,C(5)=0,C(6)=0 | | | |
|---|---|---|---|
| **Test Statistic** | **Value** | **df** | **Probability** |
| F-statistic | 3.977183 | (5, 23) | 0.0096 |
| Chi-square | 19.88592 | 5 | 0.0013 |

**Source:** Results from data analysis.

The Wald test examines if all seven coefficients (C (2) to C(6)) are jointly zero. F-statistic (3.977183) and Chi-square statistic (19.88592) are very significant (p-value of <1% for both). This strong evidence leads us to reject the null hypothesis. At least one of the lagged independent variables (D(LNCATTLE), D(LNPOULTRY), D(LNGOAT), D(LNPIG) has a statistically significant impact on the current change in CO2 emission. This suggests that past values of these variables help explain short-run changes in CO2 emission.

## Model Diagnosis

Model diagnosis is a continuous process, and researchers may need to revisit and improve their models based on diagnostic results. It is essential to guarantee that the selected model accurately reflects the underlying economic relationships in the data.

**Interdisciplinary Journal of Management and Social Sciences (IJMSS)**
**Vol. 5, No. 2, July 2024. Pages: 134-151**
**ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)**
**DOI: 10.3126/ijmss.v5i2.69452**

### *F-Test*

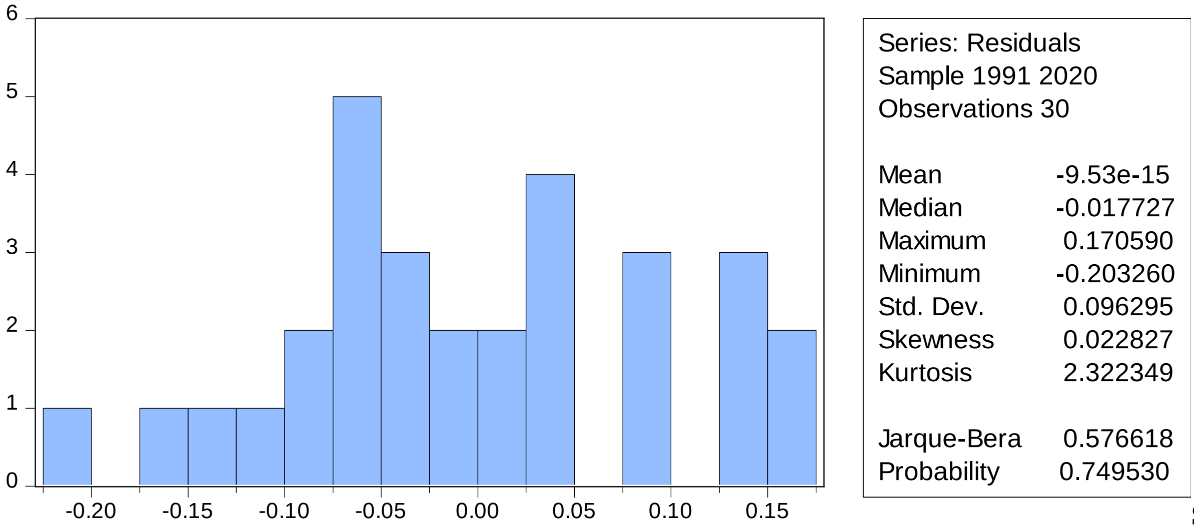
Our model is deemed well-fitted with an R-squared value of 98.30 percent and an F-statistic p-value of less than 1 percent. When evaluating the overall model fit, the F-statistic p-value is statistically significant since it falls under the 1 percent threshold.

### *Normality Test*

To determine if the model's variable distribution satisfies the normality assumption, apply the Jarque-Bera test. Because it implies that the variables follow a normal distribution, this test is significant. Here are the test results:

**Figure 2:**

*Jarque-Bera Normality Test*




**So**
**urce:** Results from data analysis.

Given that the probability value (0.74953) is more than the 5% significance level, the Jarque-Bera test result supports the null hypothesis. This implies a normal distribution for the residuals of the model.

### *Heteroskedasticity Test*

The Breusch-Pagan-Godfrey test, designed to detect heteroskedasticity in econometric regression analysis, is summarized in the table below.

**Table 10:**

*Heteroskedasticity Test: Breusch-Pagan-Godfrey*

| Heteroskedasticity Test: Breusch-Pagan-Godfrey | | | |
|---|---|---|---|
| F-statistic | 1.299700 | Prob. F (6,23) | 0.2967 |
| Obs*R-squared | 7.596094 | Prob. Chi-Square (6) | 0.2692 |
| Scaled explained SS | 2.952023 | Prob. Chi-Square (6) | 0.8148 |

**Source:** Results from data analysis.

Interdisciplinary Journal of Management and Social Sciences (IJMSS)
Vol. 5, No. 2, July 2024. Pages: 134-151
ISSN: 2738-9758 (Print), ISSN: 2738-9766 (Online)
DOI: 10.3126/ijmss.v5i2.69452

The results of the heteroskedasticity test are displayed in Table 10, which reveals that there is no heteroskedasticity since the homoscedasticity null hypothesis was not rejected at the 5% significant level. The observed R-squared has a p-value greater than 5%, indicating homoscedasticity.

### *Autocorrelation Test*

Null hypothesis: The residuals show no evidence of serial correlation.

Alternative hypothesis: The residuals show evidence of serial correlation.

The Breusch-Godfrey LM test is used to determine whether serial correlation exists in the model. The test's findings are shown below:

**Table 11:**

*Breusch-Godfrey Serial Correlation LM Test*

| Breusch-Godfrey Serial Correlation LM Test: | | | |
|---|---|---|---|
| F-statistic | 0.071218 | Prob. F (1,22) | 0.7921 |
| Obs*R-squared | 0.096802 | Prob. Chi-Square (1) | 0.7557 |

**Source:** Results from data analysis.

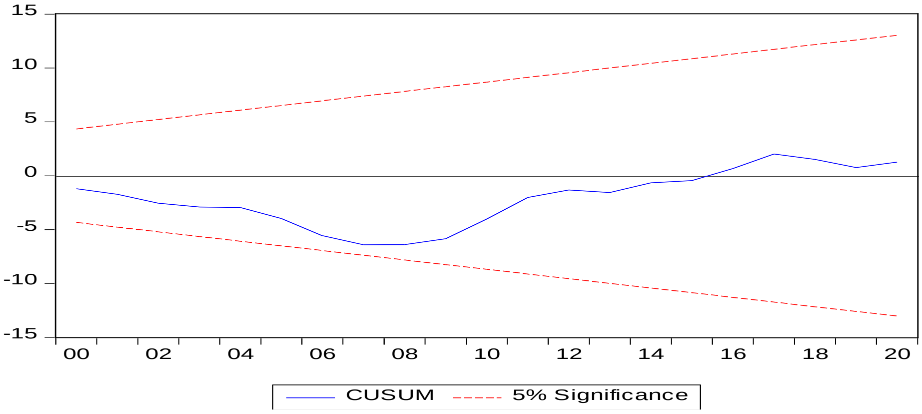
The Breusch-Godfrey Serial Correlation LM Test's overall significance is evaluated using the F-statistic. Prob. F (1,22) p-value evaluates the F-statistic's significance. Other measures of serial correlation include the Obs*R-squared statistic and the Prob. Chi-Square (1) p-value. The null hypothesis that there is no serial correlation in the residuals is not strongly supported in this instance, as indicated by the high p-values for the Chi-Square test and the F-statistic. Since it shows that the residuals do not show a regular pattern over time, this is frequently regarded as desirable. There is no serial auto connection in this case since the chi-square p value is more than 5%.

### *Stability Test in ARDL Model*

A stability test in an ARDL model is a crucial step to verify whether the estimated relationships remain valid over time. It helps researchers and analysts assess the reliability of the model's predictions and identify potential issues with parameter stability. The CUSUM test involves examining the cumulative sum of the differences between the estimated coefficients and a reference value.

**Figure 3:**

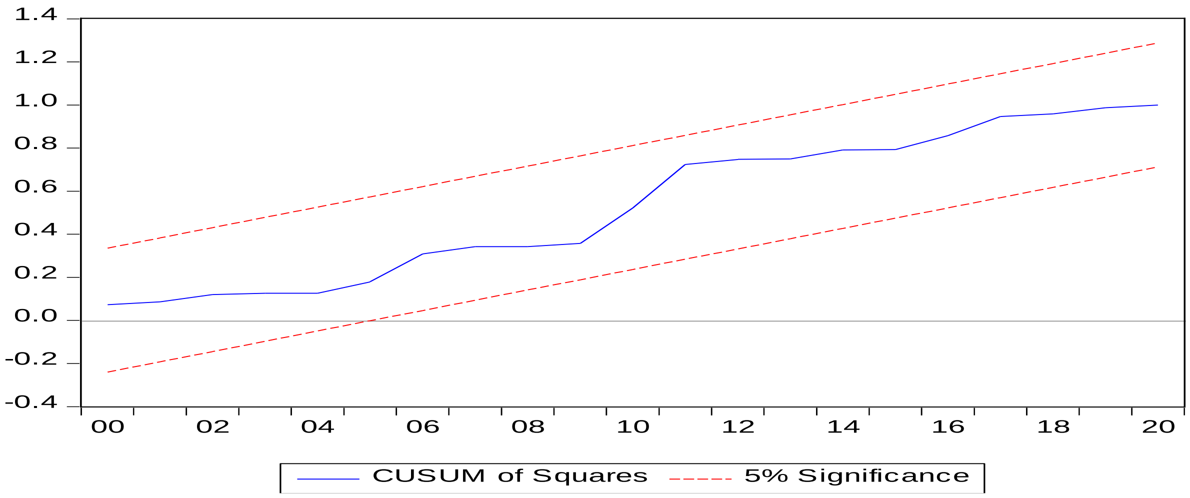
*CUSUM Test*



The two red lines represent the upper and lower bounds of the 5% confidence interval for the CUSUM statistic. The blue line represents the actual CUSUM statistic. Here the blue line remains within the red bounds throughout the time series; it suggests that the model's parameters are stable.

**Figure 4:**

*CUSUM Squares Test*




The two red lines represent the upper and lower bounds of the 5% confidence interval for the CUSUM statistic. The blue line represents the actual CUSUM of squares statistic. Here the blue line remains within the red bounds throughout the time series; it suggests that the model's parameters are stable.

## Conclusions

This study employed a quantitative methodology to investigate the relationship between the carbon dioxide (CO2) emissions of Nepal and the cattle population. This is accomplished by utilizing a combination of descriptive and analytical methods. The research employed an Autoregressive Distributed Lag (ARDL) model to examine the relationships between variables in both the short and long term. The analysis relies on secondary data collected from 1990 to 2020. Additional analysis includes the utilization of co-integration tests, ARDL bounds tests, and error correction models (ECM).

The results suggest that past CO2 emissions and the pig population have a significant impact on current CO2 emissions, while other factors do not demonstrate any statistical significance. There is limited evidence indicating a potential relationship between variables, particularly the influence of poultry on cattle and goats, which subsequently impacts poultry. The model diagnostic confirms the suitability of the ARDL model, as stability tests indicate that the model's parameters remain consistent over time. The findings underscore the intricate relationship between livestock population and CO2 emissions in Nepal, underscoring the necessity for additional research.

## References

Akalın, M. (2014). The climate change impacts on agriculture: adaptation and mitigation strategies for these impacts. *Hitit University Journal of Social Sciences Institute, 7*(2), 351-377. https://ispecjournal.com/index.php/ispecjas/article/view/361

Bahmani-Oskooee, M., & Ng, R. C. W. (2002). Long-run demand for money in Hong Kong: an application of the ARDL model. International journal of business and economics, 1(2), 147-155. Retrieved from https://econpapers.repec.org/RePEc:ijb:journl:v:1:y:2002:i:2:p:147-155

Bashir, M. A., Sheng, B., Dogan, B., Sarwar, S., & Shahzad, U. (2020). Export product diversification and energy efficiency: empirical evidence from OECD countries. *Structural Change and Economic Dynamics*, *55*, 232–243. https://doi.org/10.1016/j.strueco.2020.09.002

Herrero, M., Thornton, P. K., Gerber, P., & Reid, R. S. (2009). Livestock, livelihoods, and the environment: understanding the trade-offs. *Current Opinion in Environmental Sustainability*, *1*, 111–120. https://doi.org/10.1016/j.cosust.2009.10.003

Houghton, R. A. (2003). Why are estimates of the terrestrial carbon balance so different? *Global Change Biology*, *9*, 500-509. https://doi.org/10.1046/j.1365-2486.2003.00620.x

Huang, X., & Gao, S. (2022). Temporal characteristics and influencing factors of agricultural carbon emission in Jiangxi province of China. *Environmental Research Communications*, *4*. https://doi.org/10.1088/2515-7620/ac6380

Khalfaoui, R., Baumöhl, E., Sarwar, S., & Výrost, T. (2021). Connectedness between energy and nonenergy commodity markets: evidence from quantile coherency networks. *Resources Policy*, *74*, 102318. https://doi.org/10.1016/j.resourpol.2021.102318

Liu, D., Guo, X., & Xiao, B. (2019). What causes growth of global greenhouse gas emissions? Evidence from 40 countries. *Science of the Total Environment*, *661*, 750–766. https://doi.org/10.1016/j.scitotenv.2019.01.197

Liu, L., & Cheng, H. (2024). A study on the influence factors of agricultural carbon emissions in Hunan Province based on Random Forest Model. *E3S Web of Conferences*, *520*, 02032. https://doi.org/10.1051/e3sconf/202452002032

Luo, Y., Long, X., Wu, C., & Zhang, J. (2017). Decoupling CO2 emissions from economic growth in agricultural sector across 30 Chinese provinces from 1997 to 2014. *Journal of Cleaner Production*, *159*, 220–228. https://doi.org/10.1016/j.jclepro.2017.05.076

Ministry of Forests and Environment. (2021). *Nepal's Third National Communication to the United Nations Framework Convention on Climate Change (UNFCCC)*. Kathmandu: Government of Nepal. Retrieved from https://unfccc.int/sites/default/files/resource/TNC%20Nepal_Final_v2.pdf

Najafi Alamdarlo, H. (2016). Water consumption, agriculture value added and carbon dioxide emission in Iran, environmental Kuznets curve hypothesis. *International Journal of Environmental Science and Technology*, *13*, 2079–2090. https://doi.org/10.1007/s13762-016-1005-4

Perry, B., & Sones, K. (2007). Poverty reduction through animal health. *Science*, *315*, 333–334. https://doi.org/10.1126/science.1138614

Poudel, O. (2023). Relationship between defense expenditure and economic growth in Nepal. *Unity Journal*, *4*(01), 208-226. https://doi.org/10.3126/unityj.v4i01.52242

Poudel, O., Kharel, K. R., Acharya, P., Simkhada, D., & Kafle, S. C. (2024). ARIMA modeling and forecasting of national consumer price index in Nepal. *Interdisciplinary Journal of Management and Social Sciences*, *5*(1), 105-118. https://doi.org/10.3126/ijmss.v5i1.62666

Rehman, A., Ma, H., Ahmad, M., Ozturk, I., & Chishti, M. Z. (2021). How do climatic change, cereal crops and livestock production interact with carbon emissions? Updated evidence from China. *Environmental Science and Pollution Research International, 28*, 30702–30713. https://doi.org/10.1007/s11356-021-12948-0

Rehman, A., Ma, H., Ozturk, I., & Ahmad, M. I. (2022). Examining the carbon emissions and climate impacts on main agricultural crops production and land use: Updated evidence from Pakistan. *Environmental Science and Pollution Research International, 29*, 868–882. https://doi.org/10.1007/s11356-021-15481-2

Steinfeld, H., Gerber, P., Wassenaar, T. D., Castel, V., Rosales, M., & de Haan, C. (2006). *Livestock's long shadow: environmental issues and options*. Food and Agriculture Organization. Retrieved from https://www.researchgate.net/publication/239524071_Livestock's_Long_Shadow_Environmental_Issues_and_Options

Tian, Y., & Yin, M. H. (2022). Re-measurement of agricultural carbon emissions in China: Basic situation, dynamic evolution and spatial spillover effects. *China Rural Economy*, *3*, 104–127. Retrieved from https://www.cabidigitallibrary.org/doi/abs/10.5555/20220209317

Tunc, G. I., & Turut-Asik, S. (2009). A decomposition analysis of CO2 emissions from energy use: Turkish case. *Energy Policy, 37*, 4689–4699. https://doi.org/10.1016/j.enpol.2009.06.019

West, T. O., & Marland, G. (2002). A synthesis of carbon sequestration, carbon emissions, and net carbon flux in agriculture: Comparing tillage practices in the United States. *Agriculture, Ecosystems & Environment*, *91*, 217–232. 01. Insights into Livestock-Induced CO2 Emissions. (1).docx

World Bank. (2024). *World Development Indicators* [online database]. Washington, DC: World Bank. Retrived from: https://databank.worldbank.org/

Xie, T., Liu, B., & Chen, J. (2019). Characteristics, and prediction of greenhouse gas emission from livestock industry in Central China. *IOP Conference Series: Earth and Environmental Science, 300*, 032091. https://doi.org/10.1088/1755-1315/300/3/032091

Xie, T., Zhang, H., He, J. J., Liu, Y., Huang, K. W., & Song, M. W. (2020). Characteristics and prediction of greenhouse gas emission from livestock industry in Central China. *China Environmental Science, 40*, 564-572. Retrieved from http://www.zghjkx.com.cn/EN/volumn/volumn_1456.shtml

Xiong, C., Yang, D., & Huo, J. (2016). Spatial-temporal characteristics, and LMDI-based impact factor decomposition of agricultural carbon emissions in Hotan Prefecture, China. *Sustainability*. https://doi.org/10.3390/su8030262

Yang, X., Su, X., Ran, Q., Ren, S., Chen, B., Wang, W., & Wang, X. (2021). Assessing the impact of energy internet and energy misallocation on carbon emissions: new insights from China. *Environmental Science and Pollution Research, 28*(21), 1–25. https://doi.org/10.1007/s11356-021-17217-8

Yao, C., Qian, S., Mao, Y., & Li, Z. (2017). Decomposition of impacting factors of animal husbandry carbon emissions change and its spatial differences in China. *Transactions of the Chinese*

*Society of Agricultural Engineering*, *33*(12), 10–19. https://doi.org/10.11975/j.issn.1002-6819.2017.12.002

Zhao, X. C., Song, L. M., & Tan, S. J. (2018). Research on influential factors of agricultural carbon emissions in Hunan Province based on LMDI model. *Environmental Science & Technology*, *41(1)*, 177-183. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9690071

Zhuang, M., & Li, W. (2017). Greenhouse gas emission of pastoralism is lower than combined extensive/intensive livestock husbandry: a case study on the Qinghai-Tibet Plateau of China. *Journal of Cleaner Production*, *147*, 514–522. https://doi.org/10.1016/j.jclepro.2017.01.126

Zhou,Y.,Wang,T., Peng,R. & Hu,H. (2021). Spatial and temporal characteristics and factors of agricultural carbon emissions in the best and road region of China. *Political Journal of Environmental Studies*, *30*(3), 2445-2457. https://doi.org/10.15244/pjoes/127414