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Land use indicators and causes of death patterns in South America: a correlation, PCA and regression analysis

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Abstract
This study explores the link between land use and land cover change (LUCC) and causes of death (CD) in South America from 1990 to 2021. Key LUCC indicators (agricultural land, arable land, hectares per person, and forest area) were analyzed using correlation, principal component analysis (PCA), and linear regression. Findings show that reduced LUCC indicators correlate with higher mortality from cancers, particularly skin melanoma, colon, and pancreatic cancers. PCA revealed that declines in LUCC contribute to environmental pollution and increased cancer risks. Temporal trends showed rising rates of colon cancer and stroke, while leukemia declined. Environmental factors such as pesticide exposure and air pollution were significant contributors. The study emphasizes the need for policies integrating LUCC management with public health strategies to reduce disease risks. Limitations include regional focus and lack of age-specific data, suggesting future research should focus on specific areas and age groups.

Keywords*:* *Land use and land cover change; causes of death, correlations, principal component analysis, linear regression.*

Introduction

Land Use and Land Cover Change (LUCC) refers to the modifications humans make to the Earth's surface, including changes in how land is utilized (e.g., agriculture, urbanization) and the vegetation or features that cover it (e.g., deforestation). These chan-ges can significantly impact both the environment and climate (Ui and Mak, 2021). In South America, LUCC has been particularly pronounced, with non-Amazonian ecosystems losing more vegetation (58%) than the Amazon itself. Between 2000 and 2012, these regions accounted for 45% of the total forest loss in South America, surpassing the Amazon's 42%. Ecosystems such as the Chilean Matorral and the Atlantic Forest have been heavily impacted. Similarly, regions like the Dry Chaco, Cerrado, Temperate Grasslands, and Tropical Dry Forests have undergone major changes, primarily due to agricultural expansion. This transformation has altered temperature patterns and potentially rainfall, although research on the specific effects of these changes remains limited (Salazar et al., 2021). A regional climate model revealed that deforestation exacerbates extreme climate events. Including increased rainfall during the wet season, leading to flooding and crop damage, while simultaneously diminishing rainfall during the dry season worsening drought conditions. These shifts ipose serious risks to human and livestock health, agriculture, and biodiversity (Qin et al., 2025). Moreover, LUCC proofundly influences temperature regulation through its effects on carbon sinks. Both deforestation and afforestation directly impact carbon storage, which in turn affects atmospheric CO_2 levels. An increase in CO_2 accelerates global warming, whereas a decrease can help cool the atmosphere. LUCC also influences soil

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respiration, which affects the release of CO_2 into the atmosphere, further exacerbating the problem (Zhen et al., 2023). As a human-driven process, LUCC is often accelerated by industrial development seeking rapid economic growth. While industrialization has reduced certain diseases such as syphilis, typhus, and the plague, it has also contributed to the rise in others, including ischemic heart disease, diabetes, cancer, and road traffic injuries (Mackenbach, 2021). For instance, Sorya and Buckcherry (2022) demonstrated that the prevalence of malignant bone neoplasms in individuals from the medieval period increased during the industrial era in England. They attributed this rise to exposure to carcinogens, environmental radiation, infections, random genetic mutations, and an increase in population longevity, which led to more cancer cases. Another significant health concern associated with LUCC is the rise in PM2.5 levels. These fine particulate matter particles, smaller than 2.5 micrometers, are harmful due to their ability to penetrate the lungs and bloodstream. PM2.5 originates from sources, such as vehicle emissions, industrial processes, and wildfires (Vieceli et al., 2023). Ying et al. (2022) found that LUCC plays a substantial role in the evolution of PM2.5 concentrations, with urban areas experiencing the highest pollution levels. In addition to its impacts on human health, LUCC increases interactions between humans and wildlife, creating conditions that favor the emergence of zoonotic diseases. Previous molecular characterization by Kan et al. (2005) and Hu et al., 2018) described coronavirus sequences that were unclassified at the time. Only later, Alvarado et al., 2020 revealed that these sequences shared a high identity percentage with SARS-CoV-2, the virus responsible for the recent COVID-19 pandemic. Notably, the viral samples originated from animals primarily wildlife, underscoring the importance of understanding the role of LUCC in facilitating disease transmission. Given these various impacts, this study aims to explore the relationship between LUCC and causes of death (CD) in South America. Through correlation analyses and Principal Component Analysis (PCA), and temporal linear regression the study seeks to better understand how LUCC influences mortality across the region.

Materials and Methods

Data considered in this study

The study included twelve South American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, and Venezuela, identified using ISO 3166-1, 2016 two-letter codes: AR, BO, BR, CL, CO, EC, GY, PY, PE, SR, UR, and VE respectively. In this study, parameters such as agricultural land, arable land, hectares per person, and forest area were used as indicators to evaluate LUCC. Data were obtained from the World Development Indicators (2024) and covered the period between 1990 to 2021 for the twelve South American countries (Table 1). Causes of death (CD) were expressed as a rate of deaths per 100,000 population. Data were retrieved from the Institute for Health Metrics and Evaluation (2024) considering the cause of death, the age range of 20–54 years, females (F) and males (M) between 1990 and 2021 for the 12 countries of South America considered in this study (Table 2).

Statistical procedures

A final matrix of 13,824 values comprising 12 countries, 32 years, and 15 CD (for both females and males) and four key LUCC indicators were analyzed. A correlation study explored the linear relationships between variables. Correlation coefficients (CC) were interpreted following Schober et al., 2018: 0.00-0.09 (negligible), 0.10-0.39 (weak), 0.40-0.69 (moderate), 0.70-0.89 (strong), and 0.90-1.00 (very strong correlation). These coefficients represent the strength and direction of re-

Table 1. *Indicator names for LUCC and codes used in this study. Area data was transformed to hectares (Ha) when necessary.*

Original indicator name and Original definition (World Development Indicators, 2024)	Code, this article
Agricultural land (sq. km): Comprises arable land (for temporary crops, meadows, and gardens), land under permanent crops (like cocoa and coffee), and permanent pastures (used for forage for five or more years). Abandoned land and timber forests are excluded.	AGL
Arable land (hectares): Encompasses land used for temporary crops (including double-cropping), temporary meadows, market gardens, and fallow land. It excludes land abandoned due to shifting cultivation practices.	ARL
Arable land (hectares per person): Represents the amount of land available for temporary crops (including double-cropping), meadows, gardens, and fallow periods per capita. Are excluded land abandoned due to shifting cultivation.	HPP
Forest area (sq. km): Includes land with trees at least 5 meters tall, whether used for production or not. It excludes trees in agricultural settings (like orchards and agroforestry systems) and urban areas (parks, gardens).	FA

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Table 2. *Cause of deaths codes used in this study for Female (F) and Male (M) population.*

Original cause of deaths name (Institute for Health Metrics and Evaluation, 2024).	Code, this article
Brain and central nervous system cancer	Brain
Breast cancer	Breast
Colon and rectum cancer	Colon
Diabetes mellitus	Diab
Hypertensive heart disease	Hypt
Kidney cancer	Kidney
Leukemia	Leuk
Lip and oral cavity cancer	Lip
Liver cancer	Liver
Malignant skin melanoma	Melan
Pancreatic cancer	Pancr
Stomach cancer	Stom
Stroke	Stroke
Thyroid cancer	Thyr
Tracheal, bronchus, and lung cancer	Trach

lationships between variable pairs, quantified using Pearson's correlation coefficient (ranging from -1 to +1). Values near +1 indicate positive correlations, whereas those near -1 represent negative correlations (Aggarwal and Ranganathan, 2016). To reduce data dimensionality and identify the primary factors driving LUCC and CD variability, a principal component analysis (PCA) was conducted. Finally, a linear regression covering the 1990-2021 period was applied. All analyses were performed using R version 4.4.2 for Windows (R Core Team, 2023). Statistical graphics were generated with ggplot2 package (Wickham, 2016), correlation matrix heatmaps with pheatmap (Kolde, 2016), data simplification, arrange and reshape was made with dplyr (Wickham et al., 2023) and tidyr (Wickham et al., 2024), temporal data were organized using lubridate (Grolemund and Wickham, 2011) and 3D visualizeations were produced with plotly (Sievert, 2020).

Results and discussions

Correlation coefficients between LUCC indicators and CD

The correlation matrix heatmap revealed strong associations between several LUCC indicators and chronic diseases. Notably, AGL showed a strong correlation with malignant skin melanoma in both MelanF (0.788) and MelanM (0.765), indicating a possible link between agricultural activities and melanoma incidence. The heatmap also highlighted very high correlations between disease pairs such as hypertension (HyptF/HyptM: 0.984), diabetes (DiabF/DiabM: 0.968), and various cancers (ColonF/ColonM, PancrF/PancrM), (suggesting shared underlying factors (Fig. 1). Overall, most correlation values exceeded 0.9. Additionally,

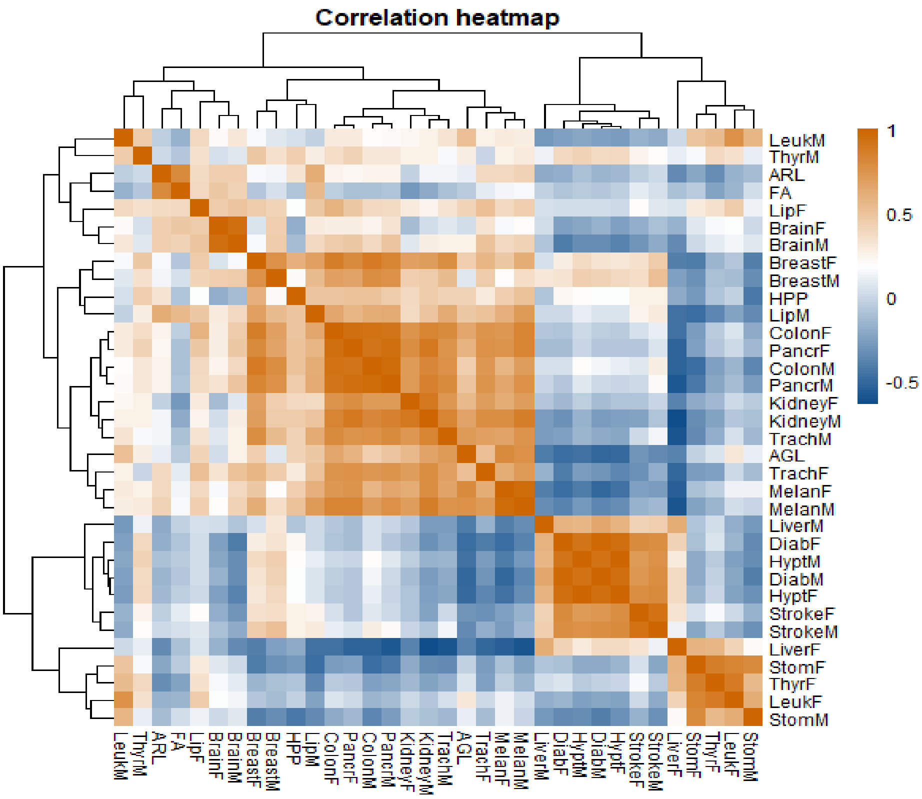

Figure 1
Correlation matrix heatmap of LUCC indicators and CD

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ARL and FA showed a strong association (0.798), reflecting connections between land-use changes and environmental variables. It is worth noting that the correlation matrix heatmap, where variables were grouped into defined clusters, showed patterns similar to those in the PCA. This indicates that the variables shared common underlying factors influencing their behavior.

Principal component analysis

An initial PCA showed that LUCC indicators accounted for most of the variance (data not shown). Therefore, the LUCC data were scaled for compatibility, and a new PCA was conducted. The Cumulative Explained Variance Plot indicated that the first three principal components explained 69.81% of the total variance (Figure 2). This value aligns with the commonly accepted 70%, considered sufficient to retain most of the original information while minimizing the loss of variability (Jolliffe and Cadima, 2016).

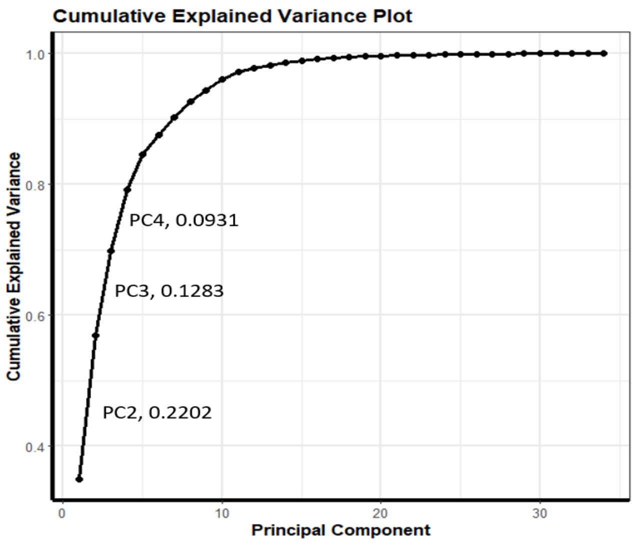

Figure 2. *Cumulative Explained Variance Plot. Proportion of variance explained by each principal component, the first five components collectively account for 69.81 % of the total variance.*

From the interpretation of the contribution of each variable to the PCA, the characteristics of the principal components were grouped as detailed in Table 3.

Table 3. *Groups defined by the four principal components resulting from this research*

PC	Name
PCA1	Cancer Mortality and Agricultural Development
PCA2	Cardiometabolic, Cancer Mortality and Land Availability
PCA3	Hematological and Glandular Cancer Mortality

As PC4 was mainly influenced by agronomic variables such as AGL, ARL, HPP, and FA. and these variables are not the core to our objective of analyzing the relationship between LUCC and CD, and since PC1, PC2, and PC3 already explain the key relationships, we omitted a detailed discussion of PC4 to focus on the more relevant components.

Cancer mortality and agricultural dDevelopment, PC1 analysis

To illustrate LUCC–CD relationships across countries, a PCA biplot was generated (Figure 3). The vectors represent LUCC indicators and CD projected onto the principal component space, where arrow direction and length indicate each variable’s contribution and points represent country positions. The analysis showed that PC1 is mainly influenced by cancer mortality rates (BrainF: -0.086, BrainM: -0.146, BreastF: -0.229, BreastM: -0.172, ColonF: -0.271, ColonM: -0.256, MelanF: -0.241, MelanM: -0.266, PancrF: -0.270, PancrM: -0.266, TrachF: -0.241, TrachM: -0.251) and by LUCC indicators AGL (-0.207), ARL (-0.111). As AGL and ARL decreases, cancer mortality tends to rise. Additionally, loading values were similar for M and F, showing little sex-related variation. The magnitude of PCA loadings reflects each variable's influence, where larger larger absolute loading values indicate stronger contributions (Jolliffe and Cadima, 2016). Although the loadings are small, they still represent the variable's contribution to PC1. Given these associa-tions, it is essential to examine the biological and environmental origins of the cancers analyzed, and how these may be influenced by LUCC indicators. Cancer results primarily from DNA mutations and is affected by environmental factors (such as exposure to mutage-nic agents) and epigenetic factors that alter the expression of genes regulating cell growth, survival, or senescence. These alterations may be inherited by daughter cells during cell division, thus facilitating the progression of cancer (Kumar et al., 2017). The PC1 analysis indicates that the shift from crop cultivation to industrial or urban development, combined with reduced AGL and ARL may intensify environmental pollution. This shift likely increases exposure to harmful chemicals and mutagenic agents, contributing to higher cancer mortality rates. These results are consistent with prior research showing that prolonged contact with agrochemicals, insecticides and other pollutants can cause both acute and chronic diseases including cancer (Devi et al., 2022). Brain tumors, such as glioblastomas, have been associated with environ-

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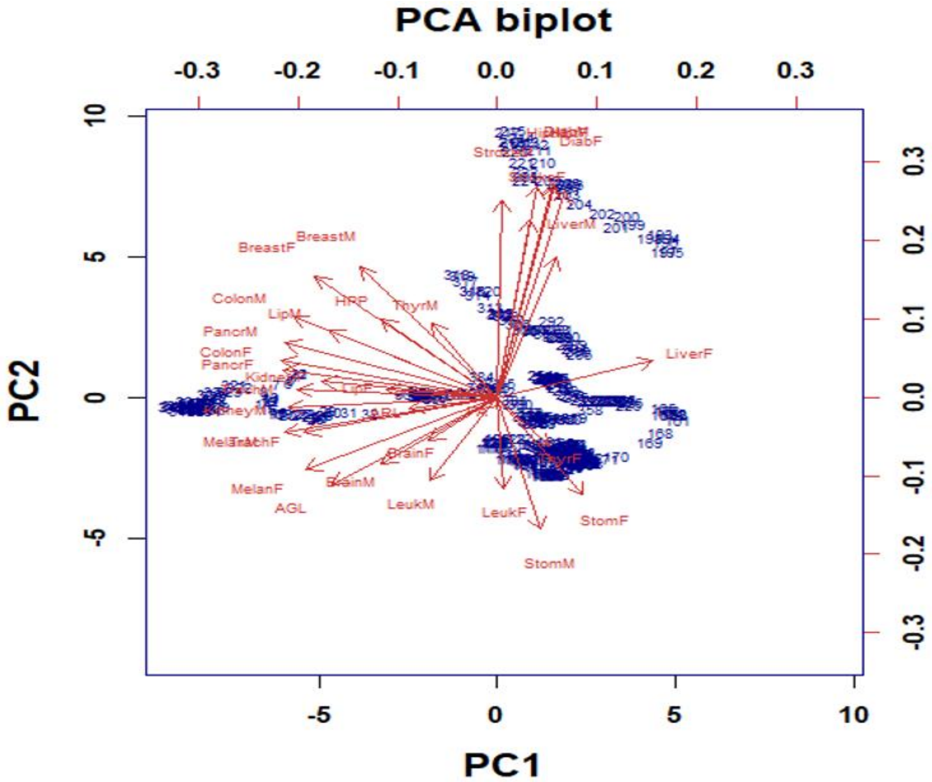

Figure 3
PCA biplot where arrows show the direction and strength of LUCC indicators and CD contributions, and points represent countries' positions within the principal component space.

mental pollutants like air pollution, pesticides, heavy metals, and ionizing radiation. Fine particulate matter (PM2.5) can penetrate the blood-brain barrier, increasing the risk of tumors by causing oxidative stress, DNA damage, and inflammation, thereby promoting tumor formation, particularly in vulnerable groups like children (Pagano et al., 2023). In particular, regarding breast cancer, o,p'-dichlorodiphenyltrichloroethane (o,p'-DDT) continues to be used for malaria vector control in South America and Its derivatives have been linked to breast cancer cell activation in women (Pestana et al., 2015). Male breast cancer, though less common, shows higher mortality and lower survival rates (Konduri et al., 2020) and appears influenced by the same factors affecting PC1. The association between agrichemicals and colorectal cancer remains under investigation, though some studies suggest that compounds like chlorpyrifos and aldicarb may increas colorectal cancer risk (Sabarwal et al., 2018). Melanoma, a highly lethal skin cancer primarily results from UV-induced DNA mutations (Kumar et al., 2017). Environmental factors such as climate change, rising temperatures rural and occupational exposures, and air pollution increase melanoma risk. Urban planning strategies, such as the construction of taller buildings, may reduce sun exposure and help mitigate the risk for vulnerable populations (Yuval et al., 2022; Watson et al., 2024).

Similarly, pancreatic cancer (Pancr) arises from hereditary and acquired mutations in critical genes such as KRAS, CDKN2A/p16, SMAD4, and TP53, along with the presence of PanIN (pancreatic intraepithelial neoplasias) lesions and telomere shortening in epithelial cells (Kumar et al., 2017). Beyond smoking and alcohol, environmental toxins, lifestyle factors, and obesity contribute to its development, emphasizing the need for preventive measures (Zanini et al., 2021). Globally, lung cancer mortality rose from 1990 to 2019, especially in Oceania, Asia, and Sub-Saharan Africa, with men more affected, though rates among women are increasing due to smoking and pollution (Ji et al., 2023). Overall, the decline in agricultural land, environmental factors and exposure to pollutants, combined with lifestyle factors like smoking and obesity, significantly contribute CD of these cancers.

Cardiometabolic, Cancer mortality and land availability, PC2 analysis

Principal Component 2 is primarily defined by positive loadings from metabolic disease mortality rates DiabF (0.328), DiabM (0.340), HyptF (0.338), HyptM (0.336) followed by StrokeF (0.282), StrokeM (0.314), BreastF (0.192), BreastM (0.207) and finally HPP (0.124). Therefore, all mortality rates and HPP increase simultaneously. Conversely, stomach cancer mortality

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StomF (-0.155), StomM (-0.210) exhibits negative loadings. Once again, the loading values displayed minimal differences between females and males. The endocrine system, composed of widely distributed glands, regulates metabolic balance by secreting hormones that travel through the blood to target cells. These hormones are released in response to specific hormonal signals, and their production is controlled by negative feedback to maintain homeostasis (Kumar et al., 2017). Any alteration in endocrine function can lead to disease. Endocrine-disrupting chemicals (EDCs), which are external substances that interfere with hormonal activity, increase the risk of adverse outcomes, such as cancer, reproductive dysfunction, cognitive impairments, and obesity (La Merril et al., 2020). Diabetes mellitus is a metabolic disorder characterized by hyperglycemia due to defects in insulin secretion, action, or both. Hypertension is commonly linked to metabolic syndrome (Kumar et al., 2017). Our results indicate that the expansion of agricultural lands may heighten pesticide use, increasing exposure through contaminated products and occupational contact. Some pesticides such as Polychlorinated Biphenyls (PCBs) and cadmium (present in pesticides and fertilizers), are recognized as EDCs. These substances disrupt hormonal processes and are directly associated with higher risk of diseases, including breast cancer, particularly among postmenopausal women due to their estrogenic properties, which disrupt the delicate balance of hormone signaling (Silva et al., 2021). Occupational factors such as pesticide exposure, physical strain, and stress, along with lifestyle factors including older age, male sex, smoking, hypertension, and diabetes, significantly increase stroke risk in farmers (0.863 per 1000 person-years) compared to the general population (0.271) with male farmers being particularly vulnerable (Lee et al., 2020). Environmental factors such as air, water, and soil pollution, along with radiation, altitude, and climate, significantly influence gastric cancer risk. Long-term exposure to pollutants like particulate matter, nitrates, and heavy metals increases the risk, while poor water quality and certain agricultural practices also contribute. Dietary factors like high intake of meat, fat, and salt, along with infections from H. pylori and viruses like EBV, are additional major risks. Preventative measures, lifestyle changes, and further research are key to reducing gastric cancer incidence (He et al., 2025). Interestingly noise exposure, particularly from residential source, was linked to higher stroke risk, with a 10 dBA increase raising stroke risk by 6%, especially for ischemic stroke (Yankoty et al., 2022). Road traffic. noise and air pollution (from PM2.5) independently increase stroke risk while green space shows only a weak association once pollution and noise are considered (Poulsen et al., 2023). Hectares per person, a key indicator of the land required to sustain an individual's lifestyle, is known as the ecological footprint (Bouma, 2010). A recent study predicts that by 2030, this will rise, especially in Asia, where consumption will exceed biocapacity, while regions like South America and Europe will show more balanced resource use (Moros-Ochoa et al., 2022). Notably, the value of HPP found in the present study, suggests that greater hectares per person availability may result from the replacement of greenspaces. The reduction in greenspaces limits opportunities for outdoor physical activity and encourages practices such as the use of agrichemicals, monoculture farming, and the consumption of calorie-dense foods, all of which contribute to obesity, diabetes, hypertension, and stroke. In contrast, exposure to greenspaces has been linked to lower disease risks and improved blood pressure (Bu et al., 2023; Zhang et al., 2024). In summary environmental factors like urbanization, pesticide exposure, and pollution, combined with metabolic diseases (e.g., diabetes, hypertension), increase cancer and stroke risks. Endocrine-disrupting chemicals worsen hormonal balance. Occupational factors, like farming, also elevate stroke risk. Reduced green spaces limit physical activity, promoting obesity and metabolic diseases, while green spaces improve health.

Hematological and glandular cancer mortality, PC3 analysis

This component is primarily influenced by leukemia mortality rates LeukF (0.415), LeukM (0.334), along with stomach and thyroid cancer mortalities StomF (0.366), StomM (0.257), ThyrF (0.426), and ThyrM (0.292). Therefore, the mortality rates of these cancers tend to increase together. To visualize the temporal evolution of variables, a 3D plot was created (Figure 4) offering a dynamic and comprehensive view of how these factors evolve and interact. Temporal trends (such as the observed increases in cancer mortality rates over time), will be further explored in the upcoming analysis of the linear models, which consider the influence of the years and the changes over time captured in PC3. Figure 4 shows that PC1 and PC2 capture the primary sources of variance within the dataset, defining the position of countries over time. PC1 reflects a strong relationship between general cancer mortality (including colon, pancreatic, and breast

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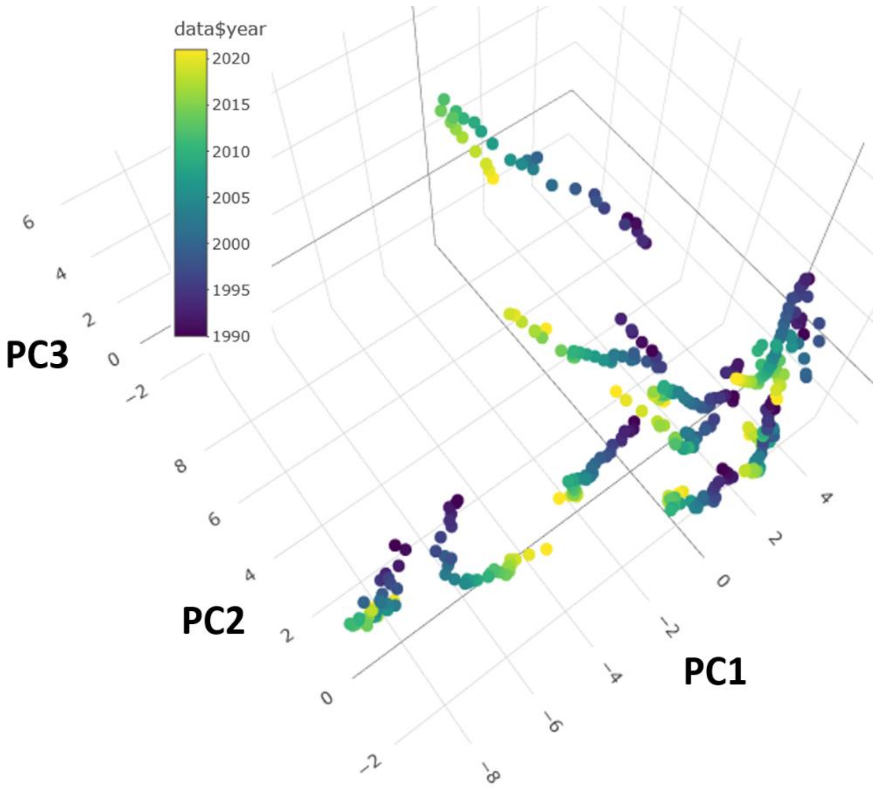

Figure 4
Screenshot of the interactive 3D PCA plot generated with Plotly Sievert (2020).

cancer rates) and agricultural development indicators (such as arable land and pesticide use), suggesting that land use intensification drives mortality variance. PC2, on the other hand, represents a combination of cardiometabolic mortality (such as stroke) and land availability, capturing variation that distinguishes countries by lifestyle-related health risk and population density. Together with PC3, these components offer a three-dimensional view of how land use indicators and mortality patterns are correlated and have evolved in South America from 1990 to 2021. Leukemia is a cancer of hematopoietic cells that leads to uncontrolled proliferation of immature cells, replacing normal bone marrow. It may be triggered by toxins, radiation, or chemotherapy, often causing chromosomal abnormallities (Papadakis et al., 2024). Recent research on acute myeloid leukemia (AML) intriguingly found that exposure to electrical power, such as living near high-voltage transmission lines, increases the risk 3.22 times of developing AML. Other factors include family cancer history, mental health disorders, and prior use of cytotoxic drugs. No significant associations were found with chemical exposure, smoking, or radiation therapy (Brabant et al., 2022). Stomach cancer is third leading cause of cancer deaths worldwide. Major risk factors include older age, male sex, non-White ethnicity, smoking, and Helicobacter pylori infection, whose chronic gastritis increases relative risk 3.5 to 20 times (Papadakis et al., 2024). Similar environmental influences have been reported in thyroid cancer where a 5 $\mu g/m^3$ increase in PM2.5 levels over a two year period substantially raises the risk of developing the disease, particularly among smokers (Karzai et al., 2022). Furthermore, Zeng et al. (2021) demonstrated that exposure to outdoor temperature significantly affects thyroid hormone levels (modulation of TSH, FT3, and FT4) that play pivotal roles in metabolism, growth, and development. Our analysis concludes that leukemia, stomach, and thyroid cancers exhibit shared mortality trends, driven by environmental factors such as toxins, radiation, and PM2.5 exposure. Key risk factors include age, ethnicity, smoking, H. pylori infection, and family history.

Temporal analysis

Linear regression of variables across twelve South American countries over 32 years showed that 14 variables, including agronomic indicators AGL, ARL, FA, and HPP were not statistically significant, indicating no strong temporal relationship with the time variable (year). In contrast, 20 variables displayed statistical signifycance ($p\text{-value} \leq 0.05$). Among them, Leukemia in females (LeukF) and Tracheal, bronchus, and lung cancer in males (TrachM) exhibited a decreasing trend. In

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addition, Stomach Cancer (StomF/StomM) and stroke (StrokeF/StrokeM) also decreased, regardless of sex (Table 4). From the analysis above, a strong temporal relationship was observed for Colon and rectum cancer in both males and females (ColonM/ColonF), showing a consistent increase across all South American countries, followed by Brain and central nervous system cancer (BrainM/BrainF). Diabetes mellitus in males (DiabM) and Breast cancer in females (BreastF) had high slopes but weaker statistical significance. These trends likely reflect environmental factors, such as pollution, contamination, diet, and sedentary life-styles, which influence the rising incidence of these conditions over time across South American countries. More specifically, each country exhibits different patterns over the years. For example, AR showed the highest mortality rates for ColonF and ColonM between 1998 and 2006, with these rates remaining consistently high. In contrast, EC experienced an exponential increase in mortality rates for ColonF and ColonM during the same period, although its mortality rates remained lower than those of AR (data not shown). It is worth mentioning that another factor not considered in this study is epigenetics. Epigenetics involves heritable changes in gene expression that do not alter the DNA sequence. Environmental factors, such as lifestyle choices and pollutants, influence epigenetic processes like DNA methylation and histone modifi-cations, contributing to diseases such as CVD, obesity, and cancer (Arizala-Quinto and Idrovo-Espín, 2020; Bi et al., 2024), another example are EDCs which induce epigenetic changes that affect health across generations (Bi et al., 2024; Cortez-Ramirez et al., 2024). As final remarks, this study emphasizes the correlations between LUCC and CD rates, revealing patterns and relationships within the data. While various influencing factors were identified, the comple-xity of these connections calls for further in-depth research. South America is facing significant environ-mental challenges, particularly those related to LUCC as climate change. Hartinger et al., 2023 determined that climate change is intensifying public health concerns in South America, including heatwaves, wild-fires, food insecurity, and infectious diseases, particu-larly affecting vulnerable populations. Moreover, climate change is impacting agricultural yields, threa-tening food security and the livelihoods of those dependent on farming.

Table 4
Summary of variables with statistical significance

Variable	Intercept	year	Pr(>|t|)	p-value
BrainF	-47.2304	0.0243	1.94×10^{-13} ***	1.936×10^{-13}
BrainM	-58.8886	0.0304	7.66×10^{-12} ***	7.658×10^{-12}
BreastF	-89.3236	0.0503	0.0237 *	0.0236
BreastM	-2.4789	0.0013	7.88×10^{-5} ***	0.0001
ColonF	-60.0876	0.0316	1.41×10^{-6} ***	1-407 $\times10^{-6}$
ColonM	-88.25665	0.0458	1.79×10^{-6} ***	7.495×10^{-7}
DiabM	-132.2235	0.0698	0.0388 *	0.0388
Kidney M	-24.3029	0.0127	0.0048 **	0.0048
LeukF	15.3333	-0.0064	0.0372 *	0.0372
LipF	-1.9641	0.0011	0.0069 **	0.0069
LiverM	-12.1898	0.0064	1.1×10^{-5} ***	1.102×10^{-5}
PancrF	-30.0407	0.0156	2.26×10^{-9} ***	2.257×10^{-9}
PancrM	-41.6604	0.0216	9.03×10^{-6} ***	9.03×10^{-6}
StomF	84.7870	-0.0403	0.0001 ***	0.0010
StomM	144.5271	-0.0691	7.10×10^{-11} ***	7.099×10^{-11}
StrokeF	696.7842	-0.3397	$<2\times10^{-16}$ ***	2.2×10^{-16}
StrokeF	705.5258	-0.3425	1.75×10^{-11} ***	1.753×10^{-11}
ThyrM	-2.9702	0.0016	1.08×10^{-8} ***	1.075×10^{-8}
TrachF	-43.5634	0.0232	0.0001 ***	0.0001

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Conclusions

This research explores the correlations between agronomic variables and causes of death, indicating that changes in land use and environmental factors, reflected by AGL, ARL, HPP, and FA, may influence the prevalence of certain cancers and diseases. Principal component analysis (PCA) reveals a complex relationship between LUCC and CD. Specifically, the analysis identifies certain cancer types as the main drivers of high CD rates, with the PCA loadings for these cancer types being nearly identical across both sexes. Additionally, the results from PC1 analysis suggest that as AGL and ARL decrease (both AGL and ARL were established as indicators to evaluate LUCC), cancer mortality rates tend to increase, indicating a link between LUCC and higher CD rates, particularly for various cancer types. The study also examines the broader impacts of land-use changes, deforestation, and agricultural expansion on health and the environment. While increasing agricultural land can enhance food production, it also leads to greater agrochemical use, pollution, and climate change, which contribute to respiratory diseases and cancers. On the other hand, greenspaces may provide health benefits by regulating temperature, improving water quality, reducing air pollution, and enhancing nutrition, although further research is needed. The temporal analysis found that some diseases are increasing in South American countries, while others are decreasing, showing varying prevalence patterns. Notably, diabetes in men and breast cancer in women show the highest growth in the 20-54 age group, which could affect the region's economy due to its impact on economically productive age groups. This study has limitations, as correlations reveal simultaneous associations between variables, and PCA identifies patterns, but neither establishes causal relationships. Further data and detailed analysis are needed to understand the link between land use change and mortality rates. The study also uses general regional data, lacking geographic specificity, and categorizes data by age intervals rather than specific ages. In summary, the findings presented here, could offer valuable insights for guiding future research and public health policies, highlighting the importance of preventive strategies, early detection, and interventions to reduce mortality in South America, while emphasizing the complex relationship between metabolic and environmental factors and the need for continued research.

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Conflict of interest statement

The authors declare no conflicts of interest.

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