Measuring sustainable development progress in Peru using a multivariate latent Markov model.

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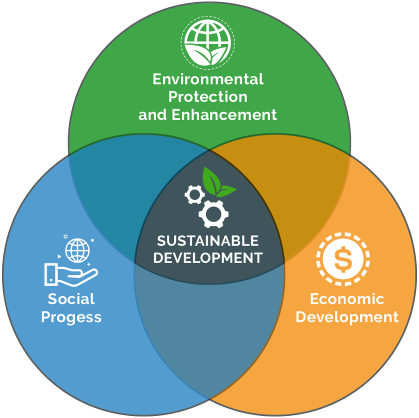
- This implies that the best choices are likely to remain those that meet the needs of society and are **environmentally and economically viable**, **economically and socially equitable** as well as **socially and environmentally bearable** (Porter & Linde, 1995).
- The highlighted complexity clearly shows how **measuring SD remains a challenging task**.

Sustainable Development



Measurement

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- Sustainable Development Goals (UN)

Novelty

- Using a **multivariate latent Markov model** (Bartolucci et al., 2013), we aim at building up an alternative measure of sustainabile development.
- We apply our model to microdata from **Peru 2004-2017**: gdp increased on average by 5% annually (World Bank, 2024), the poverty headcount was reduced from 16.3% to 4.5% and inequality measured by Gini index decreased by 6.6 percentage points (World Bank, 2024) (INEI, 2018).
- The novelty of our approach allows us to address several critics in the literature on composite indicators for the measurement of development by suggesting a different methodological approach with a similar theoretical framework.

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- Using a **multivariate latent Markov model** (Bartolucci et al., 2013), we aim at building up an alternative measure of sustainabile development.
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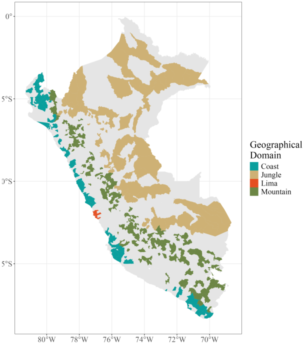
Research Questions

- **Can we measure sustainable development during the considered period using our model?**
- **If so, is our measure correlated with economic development?**

Data Sources

Balanced panel of 528 districts.

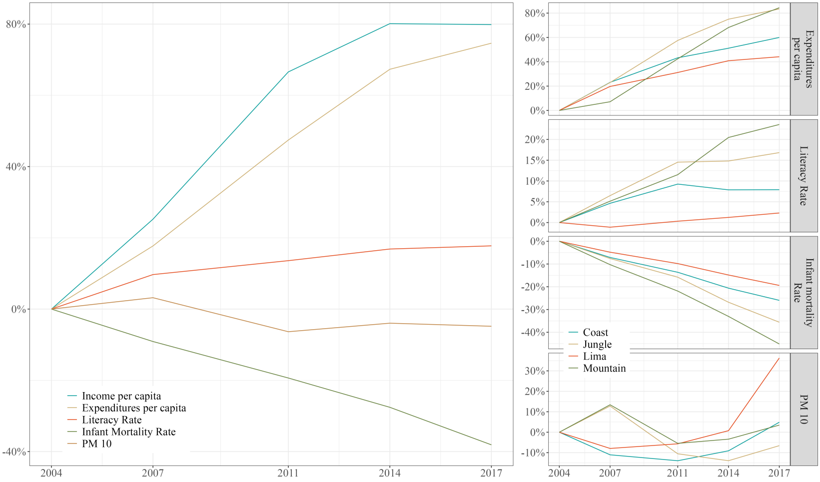
- **Consumption per capita** and **literacy rate**: *Encuesta de Hogares*, cross-sectional data from waves 2004, 2007, 2011, 2014 and 2017.
- **Infant mortality rate at birth** (INEI) by district (2007, 2017).
- **PM_{10} concentration** from the ECMWF Atmospheric Composition Reanalysis 4 (Inness et al., 2019) expressed in $\mu g/m^3$, and normalized by the annual reference average concentration of 15 $\mu g/m^3$ set by the World Health Organization (WHO)(Organization et al., 2021). Resolution of 0.75° x 0.75° (about 27 square kilometers). Air Pollution



Measurement comparison

Name	Measure	Dimension	Weighting	Method	Unit of measure
GDP	GDP	Economic	-	Single indicator	USD
HDI	GNI	Economic	1/3	Composite indicator	Score
	Education Index	Social	1/3		
	Life Expectancy	Social	1/3		
Full model	Income	Economic	Data Driven	LMM	Latent Classes
	Literacy Rate	Social			
	Infant Mortality Rate	Social			
	PM_{10}	Environmental			

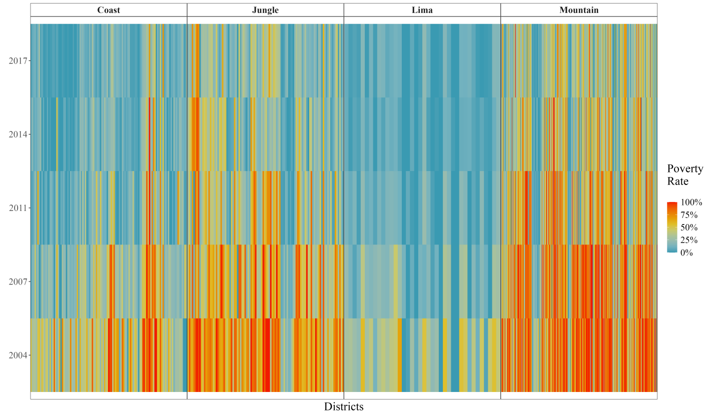
Descriptives statistics



Percentage change in the annual median value of the selected variables with respect to 2004. Left panel at national level; Right panel by geographical domain.

Variability

Income Poverty



Share of household income poor by district and year in Peru. The shade is the poverty rate in each district as defined by INEI. On the horizontal axes, there are districts clustered by geographical domain; on the vertical axes, the years considered. A change in color from red to cyan in the vertical direction for a given district implies reduction of the poverty rate in that district.

The model

$$E[Y_{itj}|U_{it} = c, X_{it}] = \alpha_{cj} + \beta_j X_{it}$$

- We assume that the results are independent of each other and of the past conditionally on a discrete latent variable U_{it} that can take values from 1 to $\boldsymbol{k}$.
- We also have a column vector of covariates X_{it} for each district on each occasion of time (time dummies).

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- We also have a column vector of covariates X_{it} for each district on each occasion of time (time dummies).
- Let Y_{itj} denote the j-th Gaussian response, for household $i = 1, \ldots, n$ at time $t = 1, \ldots, T_i$.
- Y_{it1} to denote expenditures per capita (logs).
- Y_{it2} for literacy rate (logs of the odds ratio).
- Y_{it3} for infant mortality rate (logs of the odds ratio).
- Y_{it4} for PM_{10} (logs).

HDI model

Class	Expenditures Per Capita	Literacy Rate	Infant Mortality Rate
1	23.3***	0.56***	0.34***
2	**68.49*** **	**2.21*** **	**0.16*** **
3	47.47***	1.29***	0.29***
4	**26.8*** **	**0.71*** **	**0.56*** **

Table: Intercept parameters in the HDI model. Expenditures per capita are expressed in *Peruvian Soles*, literacy rate and infant mortality rate can be instead interpreted as relative risks. In red we hilighted what we consider the "worse" class, and in cyan, the "best" class. ., * , ** , *** Significance at the 10, 5, 1and 0,1% levels, respectively.

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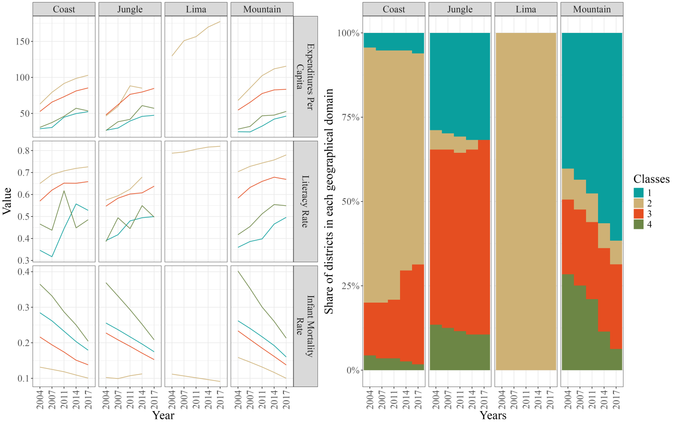

Figure: Left panel: average value of the considered variables by HDI model class, year and geographical domain. Right panel: the share of districts present in each HDI model class by geographical domain.

Full model

Class	Expenditures Per Capita	Literacy Rate	Infant Mortality Rate	PM_{10}
1	59.51***	1.93***	0.2***	0.68***
2	27.01***	0.76***	0.44***	0.56***
3	**68.17*****	**2.08*****	**0.19*****	**1.5*****
4	**28.3*****	**0.67*****	**0.35*****	**0.98.**

Table: Intercept parameters in the full model. To each class corresponds a value in each response variable. Income is expressed in *Peruvian Soles*; literacy rate and infant mortality in odds ratio; PM_{10} is normalized by the reference value of $15\mu g/m^3$. In red we highlighted what we consider the "worse" class, and in cyan, the "best" class. ., * , ** , *** Significance at the 10, 5, 1and 0,1% levels, respectively.

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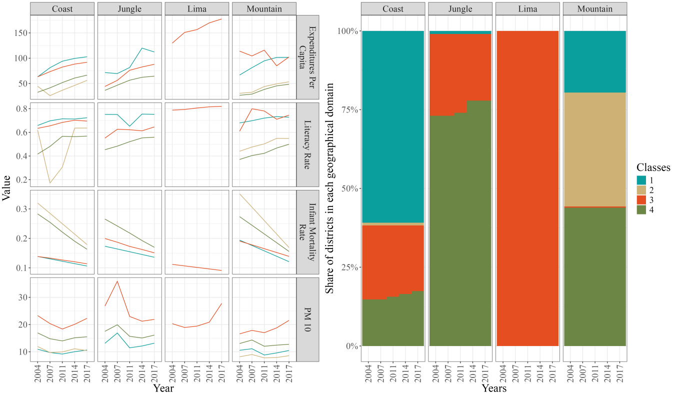

Figure: Left panel: average value of the considered variables by full model class, year and geographical domain. Right panel: the share of districts present in each full model class by geographical domain.

Conclusions

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- The capital city, **Lima, is not transitioning** in any specification of the model.
- Our results suggest that if we embrace the concept of sustainable development, this implies that poverty reduction must **also** involve improvements in the environmental sphere.
- **We do not have a causal inference scheme**; thus, our conclusions are descriptive of the observed phenomenon.

Robustness

- We compute the **subnational HDI** using the data available to us and we confront it with the results by Smits and Permanyer, 2019. We find levels with a different magnitude, but similar trends.

- The results of the full model are robust to the use of: **income per capita** instead of expenditures per capita, $PM_{2.5}$ instead of PM_{10}, NDVI instead of PM_{10}.

Thank you.

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Appendix

Air pollution

- PM2.5 are universally considered as a **main cause for haze formation due to both natural and anthropogenic factors**. PM2.5 is closely related to human activities within the atmospheric boundary layer. PM2.5 reduces visibility and participates in chemical reactions in the atmosphere to generate new pollutants and severely affects human health.
- The results of various scholars suggest that **industrial emissions**, **car exhaust** (Ji et al., 2018), **urban dust** (Han et al., 2016), **population concentration** (Lou et al., 2016), and **biomass and coal burning** (S. Wang et al., 2018) are the main sources of PM2.5 pollution.
- Other studies have found that **meteorological elements** such as air temperature and pressure (Tunno et al., 2016), wind speed and direction (Z.-b. Wang & Fang, 2016), and precipitation and humidity (San Martini et al., 2015) are important in determining the spatial patterns of PM2.5.
- **Environmental elements** such as altitude, landscapes, and vegetation cover also have a significant impact on PM2.5 pollution (Hao & Liu, 2016).
- Additionally, numerous recent medical studies have demonstrated that P**M2.5 is highly correlated with morbidity and mortality**, and exposed individuals are at increased risk of developing lung cancer, cardiovascular disease, and other respiratory diseases (Wu et al., 2023).

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PM_{10} and ENSO

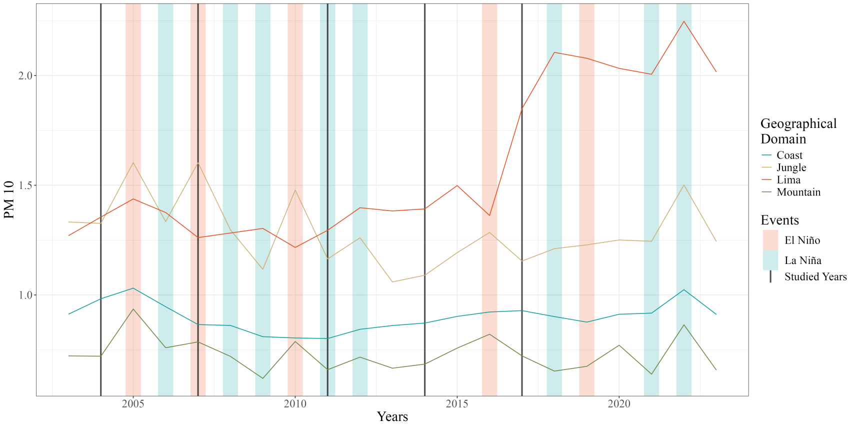

Figure: Trend in PM_{10} normalized by the WHO standard of 15 $\mu g/m^3$ by geographical domain. In red El Niño, in blue La Niña. The black line represents the years considered for our analysis.

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Variability

Table: Descriptive statistics per year of the considered variables. The coefficient of variation (CV) is computed dividing the standard deviation (SD) by the mean value. The Median Average Deviation (MAD) considers the variables after transformation.

Year	**Mean**	**SD**	**CV**	**MAD**
	Expenditures per capita			
2004	48.35	39.21	0.81	0.72
2007	57.47	46.00	0.80	0.78
2011	68.32	43.83	0.64	0.70
2014	74.84	46.42	0.62	0.56
2017	78.22	46.20	0.59	0.55
	Literacy Rate			
2004	0.52	0.19	0.37	0.90
2007	0.55	0.19	0.34	0.85
2011	0.58	0.18	0.31	0.87
2014	0.60	0.16	0.27	0.78
2017	0.61	0.15	0.25	0.67

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Year	Mean	SD	CV	MAD
	Infant Mortality Rate			
2004	0.24	0.10	0.42	0.56
2007	0.22	0.08	0.38	0.52
2011	0.19	0.06	0.33	0.46
2014	0.17	0.05	0.28	0.37
2017	0.14	0.04	0.25	0.25
	PM_{10}			
2004	14.14	5.91	0.42	0.42
2007	14.98	7.36	0.49	0.43
2011	12.53	4.96	0.40	0.42
2014	12.84	4.72	0.37	0.37
2017	14.00	5.87	0.42	0.37

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