Geospatial data for a better future

Instructions: Click on the link to access each author's presentation.

Chair: Peter Petko

Participants:

Manuel Cuélla Rio: Adoption of GSBPM to manage Geospatial Information Production Process

Abel Coronado: Implementation of the Open Data Cube for Earth Observation in Mexico: Challenges and Prospects in Generating Statistical and Geographical Information

Wlodzimierz Okrasa: The Community and Individual Well-Being Interaction in Alternative Modelling Approaches Using Spatial Data

Ranyart Rodrigo Suarez Ponce de Leon: Assessing desertification and vegetation loss in Natural Protected Areas of northern Mexico

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Adoption of GSBPM to manage Geospatial Information Production Processes

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The disciplines of Statistics and Geography complement each other

INEGI is an autonomous public institution responsible for regulating and coordinating the **National System of Statistical and Geographical Information**, as well as for collecting, analyzing, and disseminating **statistical and geographical information** about Mexico's territory, resources, population, and economy

Old and new ways of producing cartography

Traditional cartographic production

Aerial images

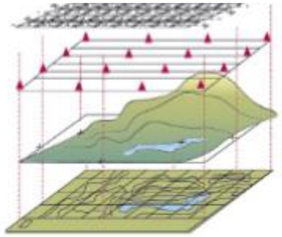
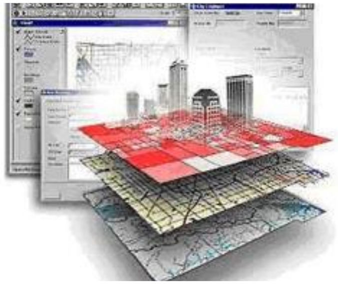
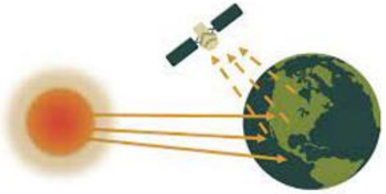


Image correction and processing

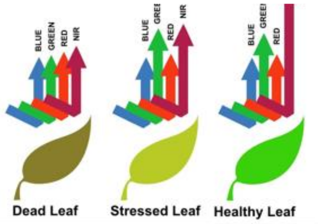


Paper and digital maps

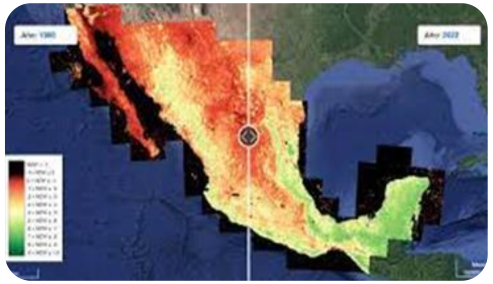
Use of satellite data



Electromagnetic wave detection

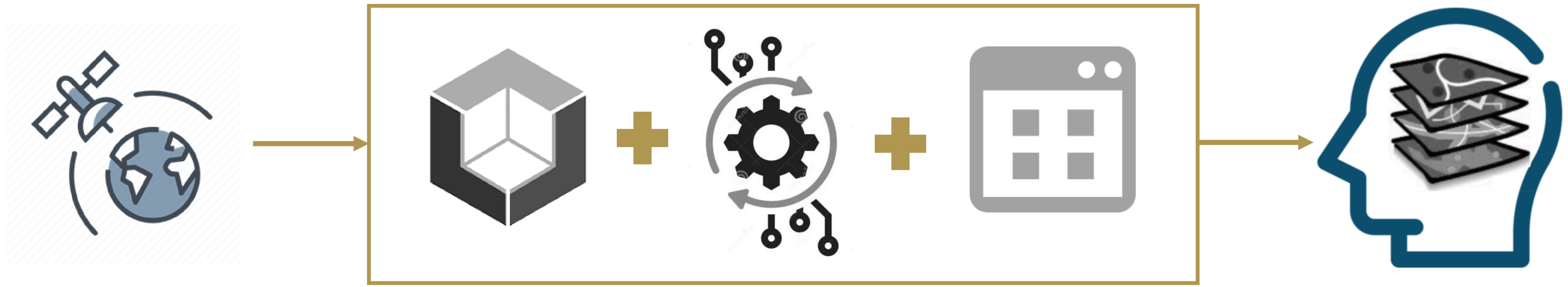


Spectral analysis



Vegetation index

Mexican Geospatial Data Cube (MGDC)



Satellite data | **Open Data Cube** | **Algorithms** | **Apps** | **Informed decision-making**

- LandSat
- Sentinel
- MODIS

The Open Data Cube is an open-source solution for accessing, managing and analyzing large amounts of geographical information systems data, primarily earth observation data

- Health and density of vegetation
- Urbanization
- Illegal mining

From Research Project to Production Process

As a **research project**, the MGDC was a temporary effort with specific goals and outcomes

These results have contributed to **expand** the **data ecosystem.** Now, we needed to streamline it as a **production process**

Transfer the MGDC to the area in charge of **geographical information production**

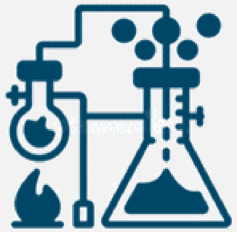
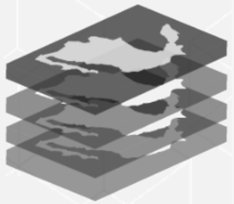
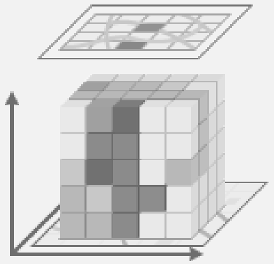
Statistical and Geographical Process Model (MPEG-GSBPM)

MGDC as a Production Process

User needs	Program	Production Process	Products
Recognize the geospatial and time dimensions of environmental, socioeconomic, and demographic events	Satellite image processing	Mexican Geospatial Data Cube	Geomedian Surface Water Classification Index from Space Normalized Difference Vegetation Index
	Objectives, goals, and strategies to satisfy users' needs	Resources, data, activities, and phases used and executed to produce statistical and geographical information	Outputs from the execution of production processes

MGDC's development stages vs. MPEG phases

MGDC's development stages


Product design → Images' acquisition → Preprocessing → Processing → Product creation → Publication

MPEG phases

Specify needs & Design	Build & Collect	Process	Analyze	Disseminate

Management of the MGDC within the MPEG framework

Specify Needs	Design	Build	Collect	Process	Analyze	Disseminate	Evaluate
Activities							
Identify and define information needs	Define concepts, topics, categories, geographical process and products	Technological infrastructure development to manage satellite images	Search, selection, download, and storage of satellite images	Set up and treatment of images indexed into the ODC	Geospatial products' analysis, and whether information needs were met	Publish *Geoviewer*, methodology, and metadata	Geographical process evaluation
Main deliverables							
• User needs analysis • Relevance indicators	• Conceptual design scheme and dissemination products	• Model & tech IT specs • Apps and software services	• Set of images	• Change log • Processed image backup	• Quality report • Images w/ dissemination controls • Metadata	• Dissemination scheme • Product delivery • Press release	• Evaluation report • Action plan

Advantages of aligning MGDC to MPEG

- Establish relationship between objectives, activities, inputs, and outputs
- Organize and describe information production activities based on a standard framework
- Link activities and results in each phase
- Identify roles and responsibilities in each phase
- Promote knowledge transfer, and accountability
- Improve risk management and process replicability

Thank you

Implementation of the Open Data Cube for Earth Observation in Mexico: Challenges and Prospects in Generating Statistical and Geographical Information

Dr. Abel Coronado

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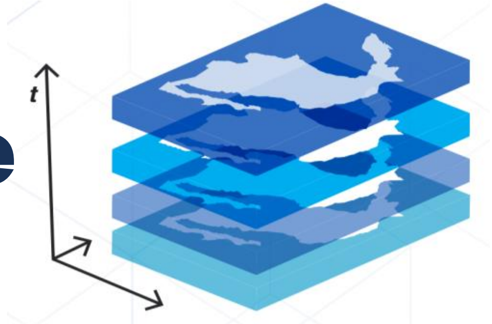
Introduction to the Open Data Cube

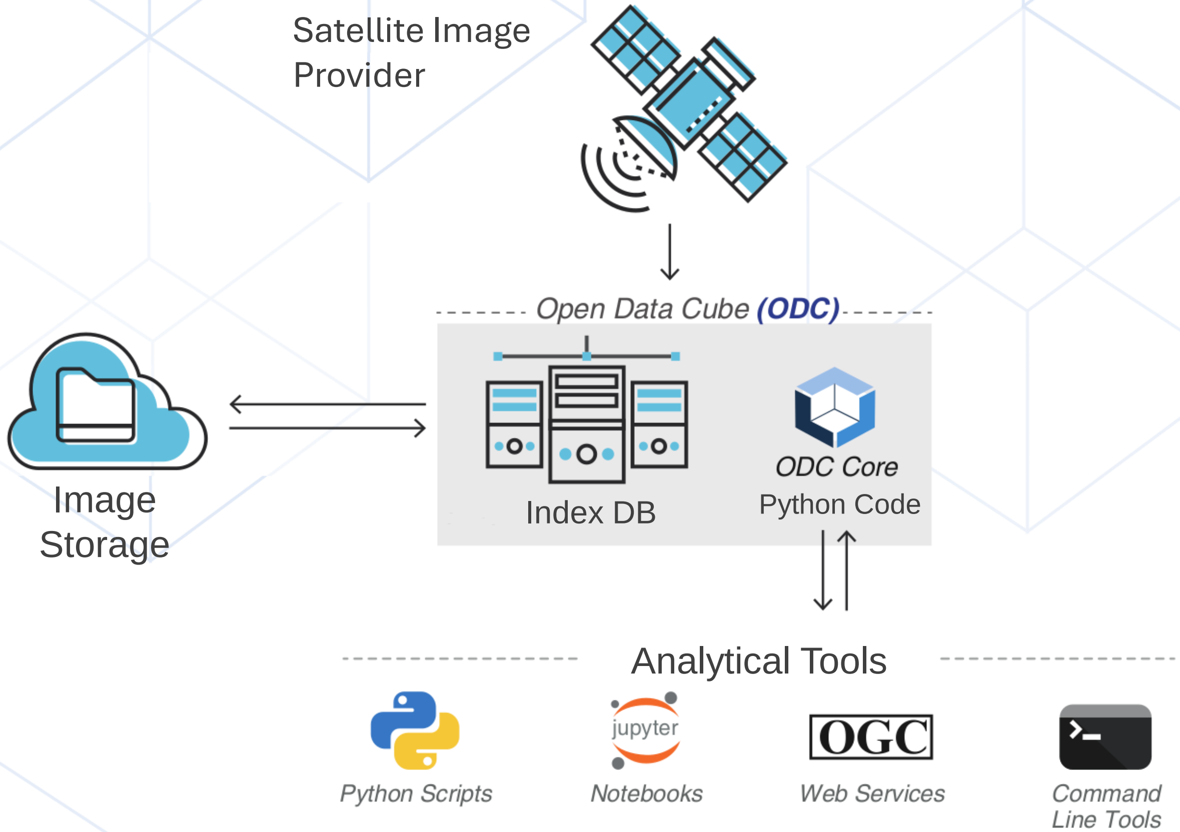


- **What is the Open Data Cube?**
  - The Open Data Cube (ODC) is a freely accessible, open-source software that supports the management, access, and analysis of large volumes of Earth observation data.

- **Importance of Earth Observation Data Management**
  - Managing vast amounts of Earth observation data is crucial for monitoring environmental, socio-economic, and demographic phenomena. The Open Data Cube enables efficient data handling, facilitating advanced analysis and application development .

Open Data Cube (ODC) Architecture Overview

- **Satellite Image Provider**: Primary source of satellite imagery for data analysis.
- **Image Storage**: Local on-premises storage for securing and accessing image data.
- **Index DB**: Database for indexing and managing the stored images efficiently.
- **ODC Core**: Central Python-based component that processes, integrates various data sources, and supports custom scripting within the ODC environment.
- **Analytical Tools**:
    - **Python Scripts**: For automated data processing.
    - **Jupyter Notebooks**: For interactive data analysis and visualization.
    - **Web Services and Command Line Tools**: Interfaces for data access and management.



Ornelas; et al. (2019). *Open Data Cube for Natural Resources Mapping in Mexico*. In Proceedings of the 1st International Conference on Geospatial Information Sciences, Kalpa Publications in Computing, Volume 13, Pages 70–78.

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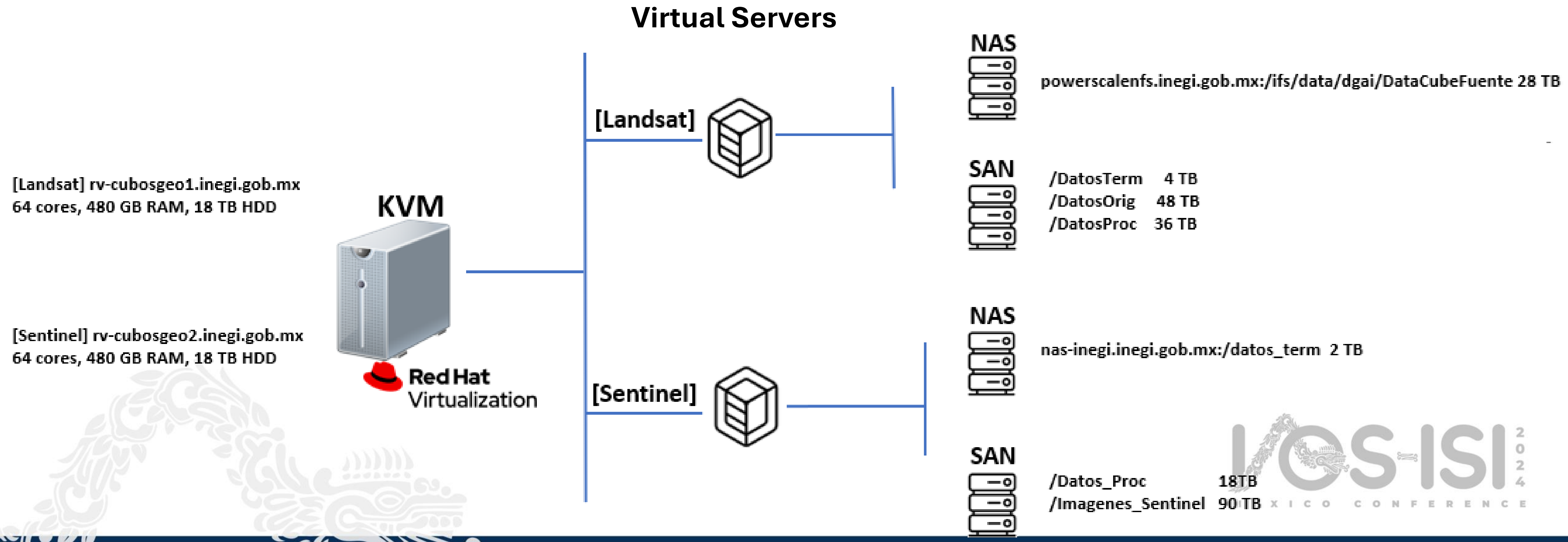
Choosing Between On-Premises Open Data Cube and Cloud-Based Google Earth Engine

- **Open Data Cube (ODC) - On-Premises Solution**
  - **Control and Independence**: Hosted locally for full data control.
  - **Customization**: Open-source and adaptable to specific needs.
  - **Security and Continuity**: Users manage their data with secure, consistent access.
  - **Scalability**: Flexibly expands with resources, avoiding unexpected costs.
- **Google Earth Engine (GEE) - Cloud-Based Solution**
  - **Provider Reliance**: Dependent on a single provider, which may limit flexibility.
  - **Data Access**: Immediate access to extensive datasets and proprietary algorithms.
  - **Cloud Constraints**: Encourages cloud storage, affecting data control; subject to usage quotas.
- **Conclusion: Complementary Use of Both Systems**
  - **Strategic Approach**: Utilize ODC for control over sensitive and large-scale projects, and GEE for its rapid processing and broad dataset availability.

Overcoming Technical Challenges in the Implementation of ODC Mexico (2 Million Square Kilometers)

- **Data Volume Management:** Challenges in storage, processing, and ensuring efficient data access.



Key Milestones in INEGI's Open Data Cube Initiative

2018 - Geoscience Australia Workshop (Canberra, Australia)

- Five INEGI staff members received extensive training in the use and management of the Open Data Cube, with a focus on massive satellite data processing for advanced geospatial analysis.

INEGI's Open Data Cube Milestones

2019 - Landsat Image Acquisition

Thanks to the efforts of Vice President Paloma Meriodio, INEGI received several terabytes of Landsat images from NASA and the USGS, covering all of Mexico from 1984 (nineteen eighty-four) to 2018 (two thousand eighteen). This extensive dataset initiated the production operation of the Open Data Cube in Mexico. Since then, we have regularly downloaded and updated this data to maintain a current and comprehensive archive.

NASA

USGS
science for a changing world

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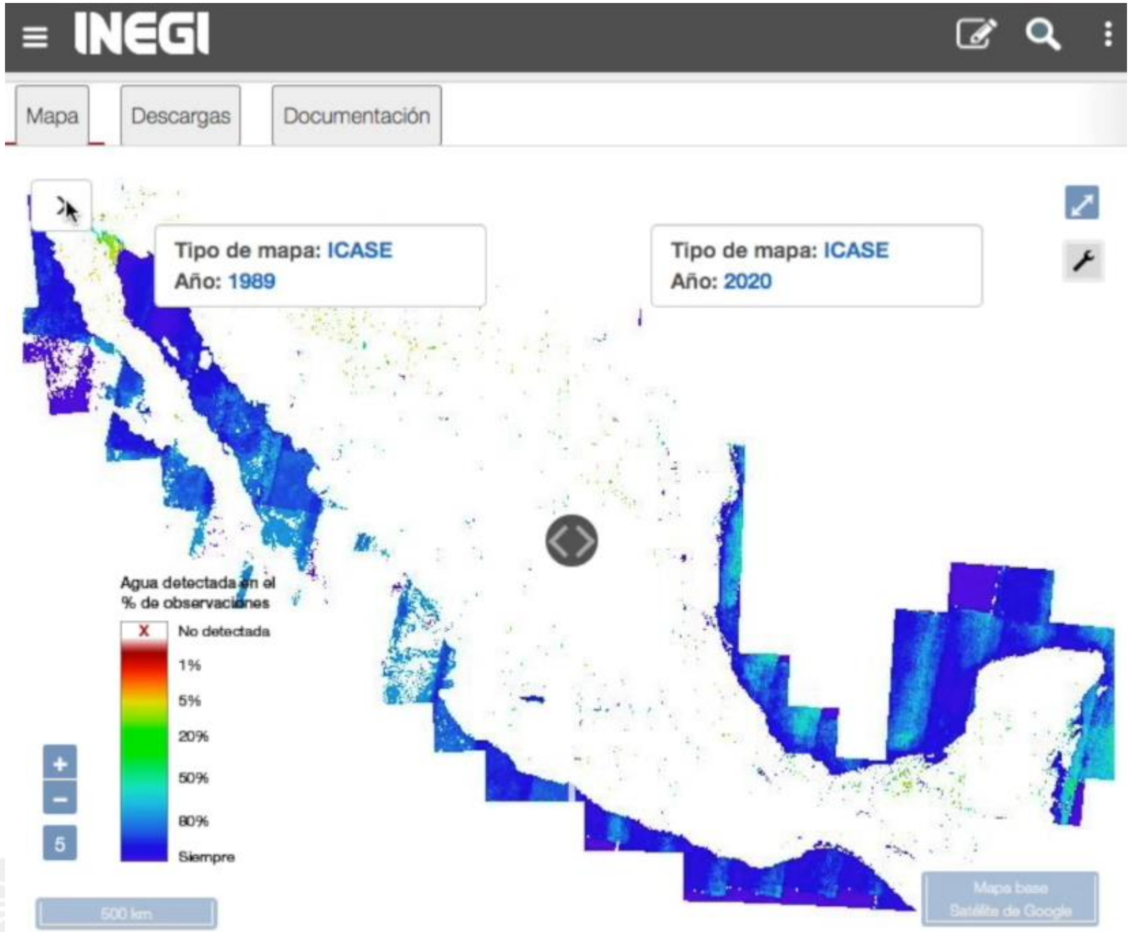
INEGI's Open Data Cube Milestones

- **2020 - Publication of Geomedians**
  - Annual and multi-year geomedians, covering periods with sparse data availability, were published for the years 1984 (nineteen eighty-four) to 2019 (two thousand nineteen). These geomedians are now updated annually to provide continuous insights.
  - A geomedian is a composite image created by taking the geometric median of pixel values over time, ensuring high-quality, cloud-free mosaics. This process combines multiple multiband images, masks clouds and shadows, and produces a consistent and clear view of the land surface.

https://www.inegi.org.mx/investigacion/geomediana

INEGI's Open Data Cube Milestones

- **2021 - ICASE Landsat**
  - Added the Surface Water Classification Index from Space (ICASE) for Landsat to the historical products, updated annually, enhancing water resource management and analysis.

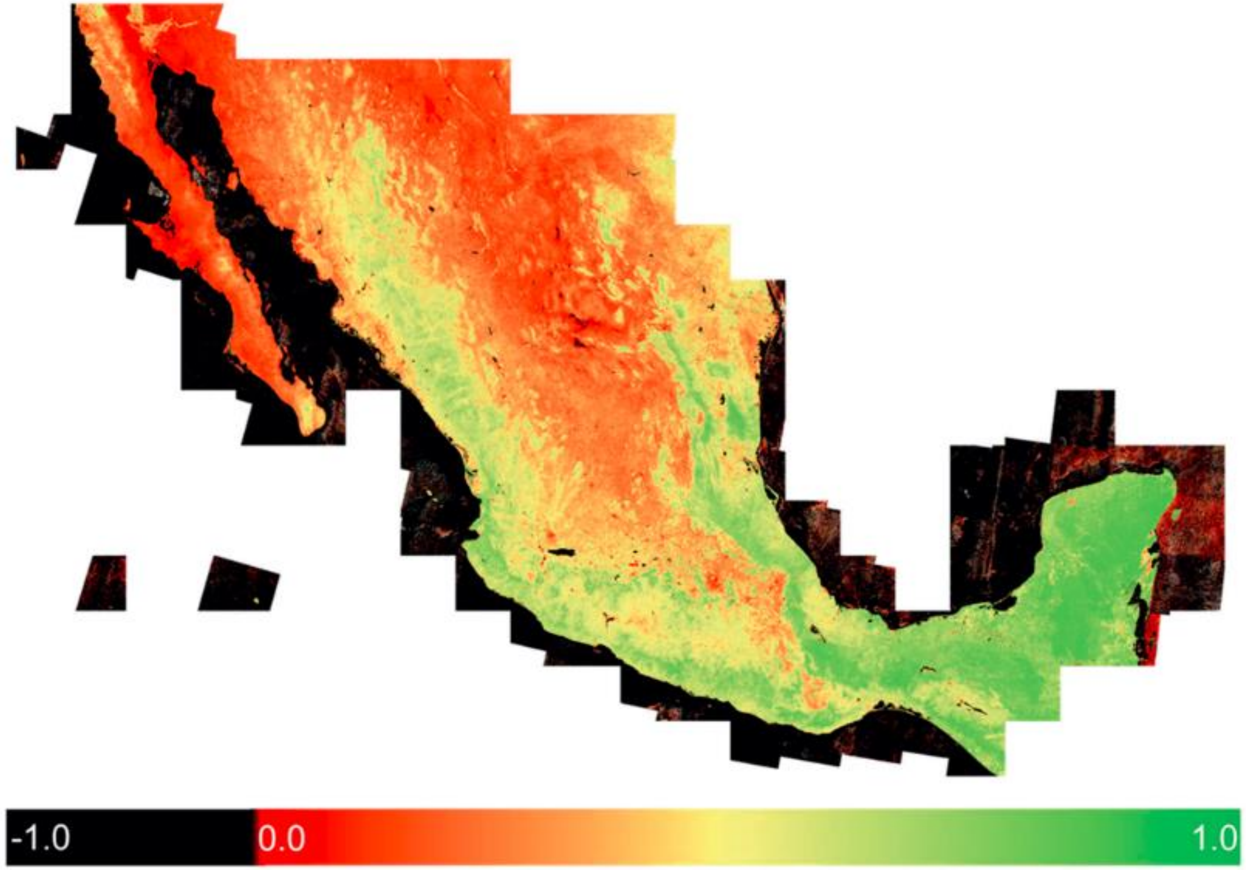


https://www.inegi.org.mx/investigacion/icase/

INEGI's Open Data Cube Milestones

2022 - Publication of Annual NDVI Mosaics

Alongside the geomedians and ICASE, INEGI also started publishing annual NDVI mosaics, covering the period from 1984 (nineteen eighty-four) to 2021 (two thousand twenty-one). The NDVI (Normalized Difference Vegetation Index) mosaics provide a detailed view of vegetation health and density, enhancing our annual data releases.



The color scale ranges from -1.0 to 1.0. Green areas indicate healthy and dense vegetation. Yellow and orange areas show less dense or stressed vegetation. Red areas indicate little to no vegetation

https://www.inegi.org.mx/investigacion/NDVI

INEGI's Open Data Cube Milestones

2024 - Sentinel Image Indexing

Successfully indexed Sentinel images for all of Mexico (October 2022 to 2023), totaling 57TB (fifty-seven terabytes), corrected with Sen2Cor, and integrated into our data cube. Thanks to this, we have started a new project that goes beyond identifying agricultural activity to detecting specific crops using Sentinel-2 time series. This project began in January of this year and aims to enhance our agricultural analysis capabilities with advanced data science techniques.

Landsat 4,5,7,8,9

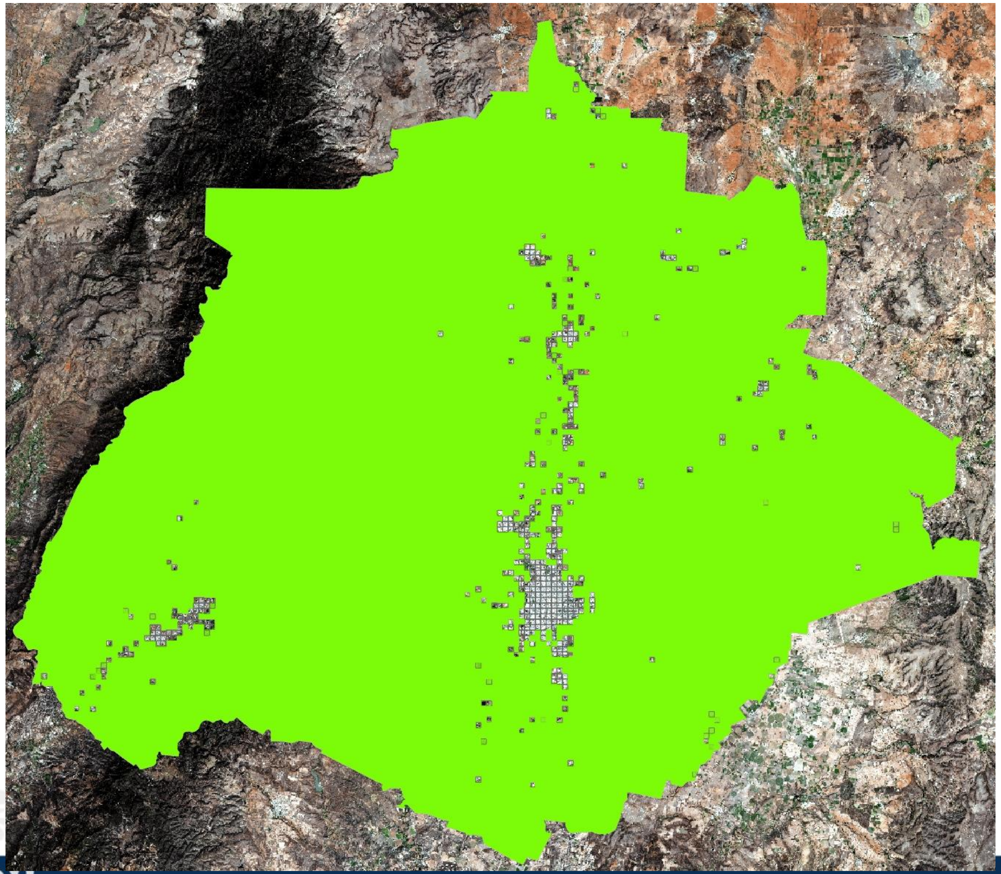
Sentinel 2A, 2B

Practical Applications of the Mexican Geospatial Data Cube (CDGM)

- **Remote Sensing for National Agricultural Boundaries:** Annual estimation of the agricultural frontier using machine learning models on Landsat and Sentinel images, enhancing the frequency and accuracy of agricultural production estimates traditionally based on the National Agricultural Survey and infrequent agricultural censuses.

Practical Applications of the Mexican Geospatial Data Cube (CDGM)

- **Urban Growth and Rural Developments:** Identification of new urban and rural developments through computational learning techniques, providing valuable insights for urban planning and rural development.



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Lessons Learned and Future Directions

- **Inception and Growth:** Initially, CDGM started as an institutional research project involving multiple areas such as technology, geography, and research. It was incubated, addressing challenges related to enabling technology. With the institutional decision to maintain the cube on-premises, significant efforts were made to secure space and servers, highlighting the importance of infrastructure in its development.

- **Transition to Operational Status:** This year, CDGM has evolved from a research status to an official information program. The project has been transferred from the research area to the Geography department, marking its shift to a productive phase driven by the successful outcomes achieved to date.

Thank you

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The Community and Individual Well-Being Interaction in Alternative Modelling Approaches

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IMPROVING OFFICIAL STATISTICS

OUTLINE

INTRO: Background and problem

Measuring complex multidimensional phenomena over time

- rationale for *Multivariate Functional Principal Component Analysis/MFPCA*
  - modelling dynamic phenomenon with MFPCA

Cross-level interaction of well-being measures

- comparison of MFPCA- and classic PCA- approaches
- models of community and individual (macro- / micro-) relationships
  - multilevel modeling in spatial context
  - looking for *causality* - structural modelling

Spatial aspects of cross-level well-being interaction

Conclusions

INTRO

This paper presents an empirical exploration of selected modeling approaches to assess interaction effect between community well-being and individual (household) well-being based on public statistics datasets. It aims to identify best fit for a specific analytical task, given the limitations of the availabile data because of the lack of a multi-source analytical database with a hierarchical (nested) data structure. And the reason is that the asessment of the interaction effect becomes vital from both methodological and (local) development policy standpoints. It is assumed here that clarification of such an entangled issue requires taking into account both temporal and spatial aspects of cross-level dynamics along with the relevant covariates.

The paper (presentation) is structured as follows: The first part is devoted to the the measurement issues with special attention paid to the functional data measurement approach. This approach is employed in the version of Multivariate Functional Principal Component Analysis (MFPCA) to deal with multidimensionality and temporality of community development (deprivation) and of individual   subjective well-being, respectively. The FPCA is an extension of the classic principal component analysis PCA from vector data to functional data (Górecki et al., 2018, 2019) through characterizing units - (local community / commune) or individuals - in terms of many features observed in many time points and after a smoothing process by a vector of continuous functions (Okrasa, Krzyśko, Wołynski, 2020).

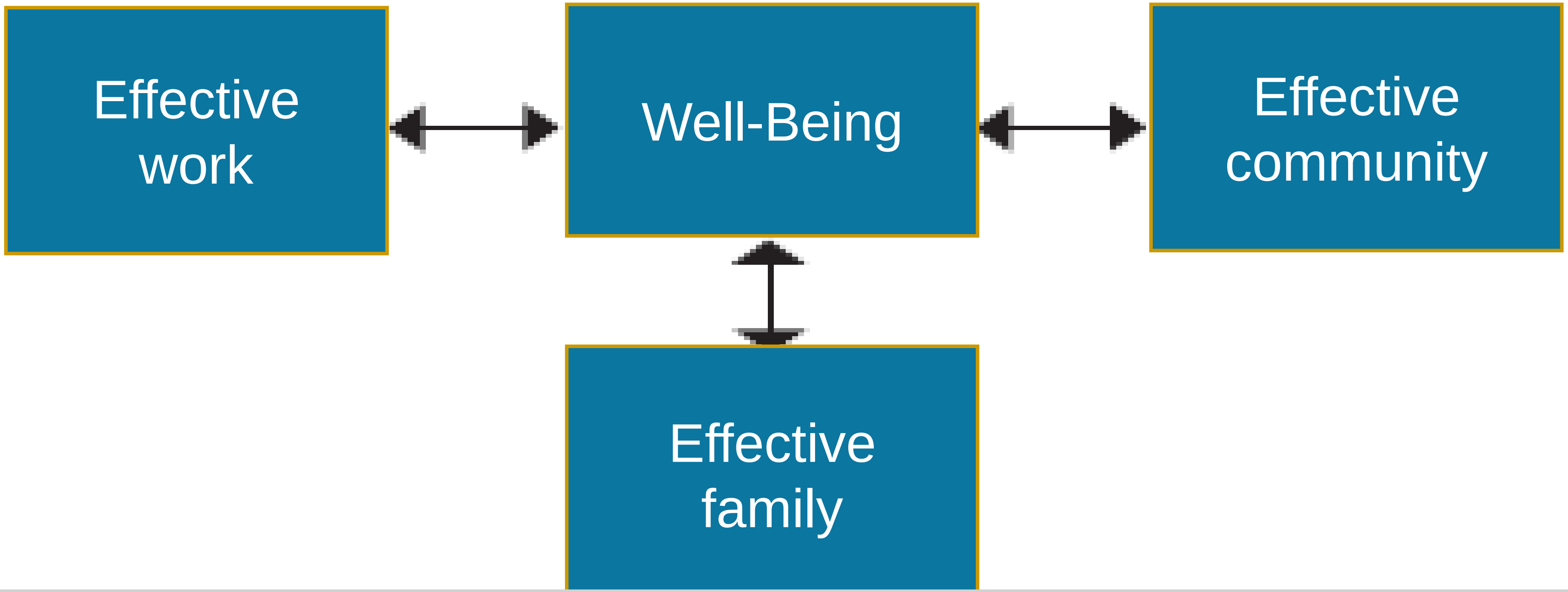
INTRO – cont.

The advantage of the MFPCA over the classic PCA is to obtain a projection of analyzed units into one or two dimensional subspaces using information for the whole period under study, and to divided them into homogenous groups on the basis of the resulting rankings. Having constructed classifications of both local communities (communes) and their residents for a given period of time (2004 – 2014 -2016, and 2009-2015, respectively), the spatial perspective can be involved in the further (third) section of the presentation. This is preceded by the two modeling approaches being employed to cover cross-level operating factors of well-being - the first one includes two-level regression model, and the second uses structural modelling approach in a search for causal-type mediating mechanisms.

The spatial perspective is explicitely involved in the third part of the presentation. The space and place-related effects of the community development (deprivation) on the resulting cross-categorization distribution of individuals are evaluated in terms of spatial patterns (autocorrelation and a tendency to clustering) and spatial dependence / spatial regression (Fischer M.M., Getis 2010; Cressie and Wikle, 2011). Some further extension toward multilevel modelling with spatial effect is considered but not included into the presentation (Okrasa and Rozkrut, 2018). Data used in these analyzes come from both administrative sources (Local Data Bank) and from surveys conducted by Statistics Poland (*Time Use Survey*) and BY an inter-university survey center (*Social Diagnosis*). An integrated Multiple-source Ananlytical Database (MAD) was constructed using geographic code for communes (*gminas*) as an integrator.

Key issues in analyzing the relationship between Community and Personal Well-Being: ***measurement – data – models***

- A **well-being measure** is presumed to be generated not only to satisfy formal requirements but primarily to guide policy, especially about local community development.
  - *Local Community***:** Any configuration of individuals, families, and groups whose values, characteristics, interests, geography, and/or social relations unite them in some way (e.g., Dreher, 2016) → community is defined as **the people living in a place such as a *neighborhood***.



Source: World Economic Forum, 2012. *Global Agenda: Well-being and Global Success* . P.5

Methodological framework for analyzing CWB and PWB:

► accounting for ***micro – macro*** *interdependence*

→ *modelling* ***multilevel relationships***

► bringing ***space*** into the question /equation

→ ***spatial (dependence) analysis.***

- **Modelling multilevel *relationships* –** two types of strategies:
  - cross-level ***interaction-***focused approach:
    - ***decomposition of variance*** into *within* groups/differences among individuals in community (level -1) and *between* groups (level-2) reflecting differences across comunities;

      → models for hierarchically structured data – risk of 'ecological fallacy' (Goldstein, 2003(2010); Subramanian, 2009; Sampson 2003)
  - ***structural modelling*** of *(causal) mediation mechanisms:*
    - ***decomposing total effect*** of the independent ('treatment') variable into the natural *direct* and *indirect* effects (Hong, 2015).

Multidimensional measures of well-being
- dimensionalization / operationalization according to PCA and FD-PCA - some comparisons

- **Multiple-source Analytical Database /ADB**

  Local Deprivation and Subjective Well-Being (SWB)

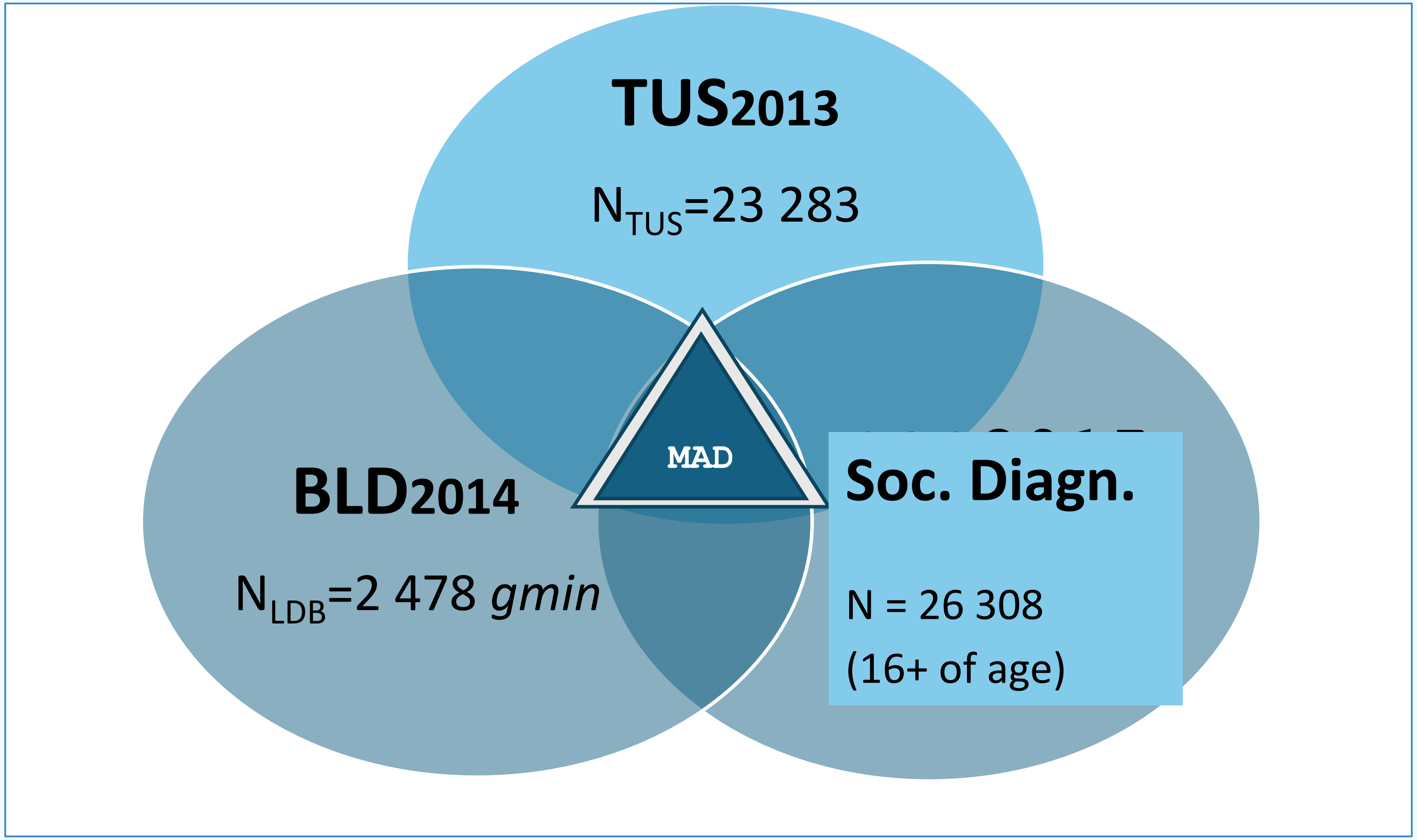
Data from:

(i) measures of local community (communes) development and the relevant covariates are from public statistics***: Local Data Bank /LDB -****Statistics Poland* (years 2004, 2008, 2010, 2012, 2014, 2016); NUTS5/LAU2; (N = 2 478 commues / *gminas*)

(ii) subjective well-being measures base on data from nation-wide surveys:

(a) Social Diagnosis /SD curried out in every other year (2003-2005 -...- 2015) and
(b) Time Use Survey / TUS 2013, Statistics Poland).

Multiple-source Analytical Database / MAD
– *bottom-up* data integration, with territorial code (KODTERYT) for the commune/municipality (an ‘anchore’)



Measuring local deprivation and personal well-being

- ***Multidimensional Index of Local Deprivation (MILD)***

  (i) Classic version: *Confirmatory* Factor Analysis / PCA (single-factor)

  (ii) *Functional* Principal Component Analysis *(FPCA)*

  Eleven (pre-selected) domains of deprivation - each characterized by a number of original items: *ecology – finance – economy – infrastructure – municipal utilities – culture – housing – social assistance – labour market – education – health* [altogether 67 items]

- ***Personal Subjective Well-being***/*SWB* and ***Community Subjective Well-being*** *CSWB*

  – SWB: individual subjective measure based on *Social Diagnosis,* using FPCA

  – SWB: individual quasi-objective - *Time Use Survey* (one-off survey data) *;*

  – CSWB: compositional - subjective*:* self-reported satisfaction with selected aspects of life (*Social Diagnosis*)

Functional Data version of the Principal Component Analyzis

- The employed functional data measurement approach – in the version of the ***Multivariate Functional Principal Component Analysis (MFPCA)*** - is an extension of the classic principal component analysis PCA from vector data to functional data (Gorecki et al., 2018, 2019) with the procedure of representing data by function or curves (see Ramsay and Silverman, 2005) developed on the Besse's (1979) theoretical idea of multivariate data – where random variables take values in general Hilbert space - and its further important developments in different contexts. Of special interest here is an application to factorial methods - principal component analysis, canonical analysis - by Saporta (1981), and by Jacques and Preda (2014), who demonstrated usefulness of combining the MFPCA with **cluster analysis**.

  - The advantage of the FPCA over the classic PCA is to obtain a projection of analyzed units into one or two dimensional subspaces using information for the **whole period under study**, and to divide them into **homogenous groups** on the basis of the resulting rankings.

    - Having constructed classifications of both local communities (communes) and their residents for a given period of time (2004 – 2014, 2016, and 2009-2015, respectively), the spatial perspective is involved in the second part of the presentation (Okrasa, Krzyśko, Wołynski, 2020).

MFPCA – cont

We assume that the analyzed objects characterized by variables are observed in many time points (years, months, days). Therefore, an appropriate model describing the examined objects will be *p*- dimensional random process

$$\mathbf{X}(t) = (X_1(t), \ldots, X_p(t))^\top \quad t \in I$$

Assume also that $\mathbf{X}(t) \in L_2^p(I)$ where $L_2(I)$ is a Hilbert space of integrable functions with a square on the interval *I*, and that the expected value of the process

$$\mathrm{E}(\mathbf{X}(t)) = \mathbf{0} \quad t \in I$$

From the above it follows that each component of the process can be represented in the following form:

$$X_k(t) = \sum_{b=0}^{\infty} \alpha_{kb}\varphi_b(t), \; t \in I,$$

where in the functions $\varphi_1, \varphi_2, \cdots$ form a base in space $L_2(I)$

FPCA – *cont.*

The above representation of the process requires knowledge of an infinite number of coefficients. We use an approximate representation that uses only a finite number of the first base functions. Assume that the k-th component of the process has the following representation:

$$X_k(t) = \sum_{b=0}^{B_k} \alpha_{kb}\varphi_b(t), \quad t \in I,$$

where the number B_k determines the degree of smoothness of the function $X_k(t)$ (the smaller the value B_k, the greater the degree of smoothing). Similarly to the classical case, we are looking for a random variable (the first functional component) *U* of the form:

$$U = \langle \boldsymbol{u}, \boldsymbol{X} \rangle = \int_I \boldsymbol{u}(t)^\top \boldsymbol{X}(t)dt$$

having the maximum variance for all $\boldsymbol{u}(t) \in L_2^p(I)$; (u, u)=1**.**

In general, the k-th functional main component fulfills the conditions:

$$\lambda_k = \sup_{\mathbf{u} \in L_2^p(I)} \mathrm{Var}(\langle \mathbf{u}, \mathbf{X} \rangle) = \mathrm{Var}(\langle \mathbf{u}_k, \mathbf{X} \rangle), \quad \langle \mathbf{u}_{\kappa_1}, \mathbf{u}_{\kappa_2} \rangle = \delta_{\kappa_1\kappa_2}, \quad \kappa_1, \kappa_2 = 1, 2, \ldots, k.$$

In the functional case, we have:

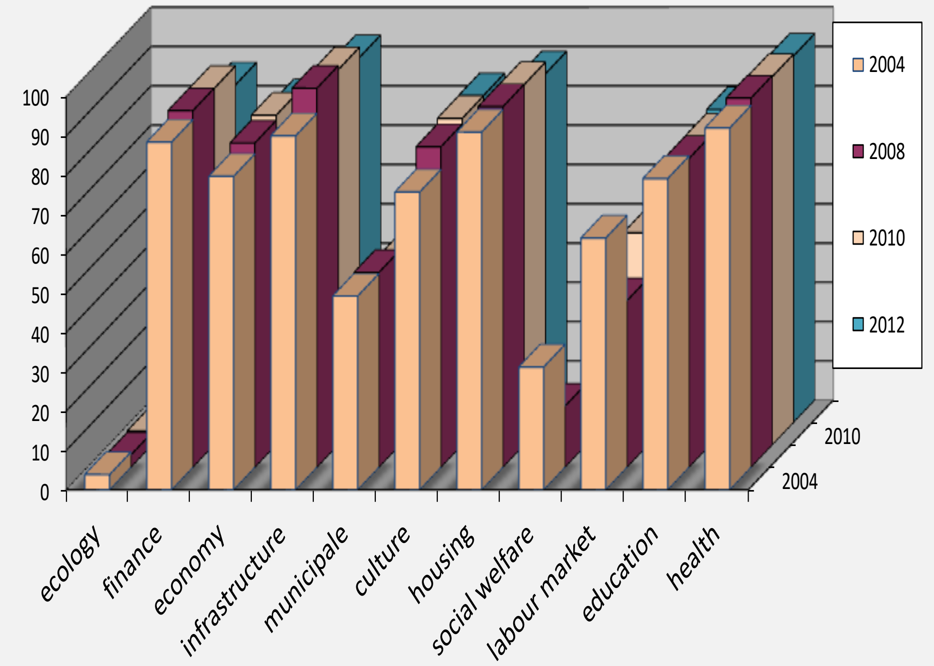
$$\langle \mathbf{u}_k, \mathbf{u}_k \rangle = \int_I u_{k1}^2(t) + u_{k2}^2(t) + \cdots + u_{kp}^2(t)dt = 1.$$

Thus, the quantity $\int_I |u_{kj}(t)|dt$ is a measure of the contribution of *j-th* component of the random process to the construction *k-th* functional principal component**.**

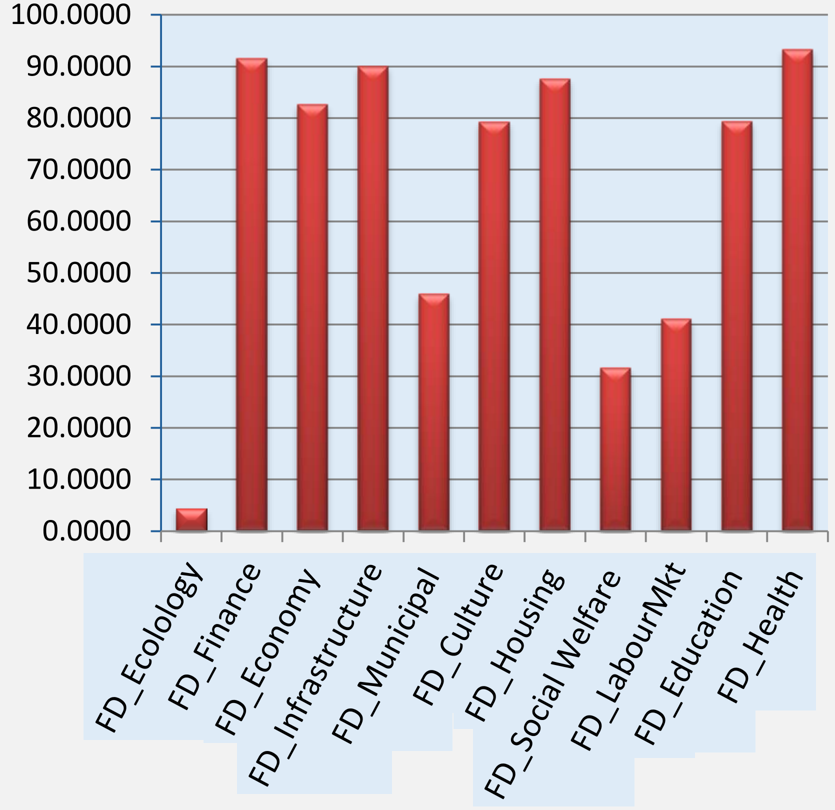
Since this process is only observed in a finite number of time moments, it is necessary to transform (smooth) discrete data into functional data (for details, see Ramsay and Silverman (2005); Gorecki, Krzysko, Wolynski (2019).

Comparison of local deprivation measures according to by classic PCA and the FPCA

Multidimensional Index of Local Deprivation /MILD – by domains (2004-08-10-14)



FD_Index of Local Deprivation/FD_MILD by domains (2004-2016)



Influence of ***local risk*** associated with particular domains of local deprivation on selected measures of *satisfaction with …*

The *synthetic measure of satisfaction (SMS)* – as an indicator of overll subjective well-being attributed to commune as a place of residents ('compositional' variable: percentage of 'satsfied' or 'very satisfied' on each scale) - is composed of the following five separate scales:

(i) satisfaction with ***living conditions,***

(ii) satisfaction with ***living environment ,***

(iii)satisfaction with ***social and family relations,***

(iv) satisfaction with ***personal situation,*** and

(v) ***disappproval of antisocial*** behavior.

- **Local Risk** is defined as a product of a FD-scale of local deprivation in a domain and the respective fraction of the commune population (P_k) defined through the ratio of the domain deprivation (ILD_d –Index of Local Deprivatio) to the total size of deprivation (MILD):

RiskFD_(domain) = FD-deprivation (d-domain) x (P_k * (ILD_d / MILD)).

Individual (subjective/quasi-objective) **well-being:** *Time Use Survey* data-based measures

- Social indicators approach – attempts to exploit TUS data (Juster; and others. e.g. Andrews 80s.); in economics (macro-indicators, Becker 1965; Nordhaus, 2009; micro-level: Kahneman and Krueger, 2006); (also used in poverty research – eg., gender effect).
    - Survey research (day reconstruction method/DRM –Statistics Poland: TUS_2013 ; N=23 000)
- Econometric research and econometric/psychometric combined approaches – Krueger and Khaneman et al.. (2008) – indicator of emotion / negative /positive affects associated with a performed activity / ‘time of unpleasant state’ - U-index :

$$\mathbf{U_i = \Sigma_j \, \mathit{I_{ij} h_{ij}} / \Sigma_j \mathit{h_{ij}}} \qquad (\mathrm{TUS_{2013}}: \mathrm{I} = -1.\ 0.\ +1)$$

and $\mathbf{U = \Sigma_i(\Sigma_j \, \mathit{I_{ij} h_{ij}} / \Sigma_j \mathit{h_{ij}}) / N}$ for N-persons / group in population ;

For U-binary (-1 & 0 vs. +1), odds of U [chance of other than ‘pleasant’ or non-positive state vs. ‘pleasant’]:

Odds (U) :: $\mathbf{U_i / (1- U_i)}$ → Odds U by the community level FD-measures of deprivation/development and by its selected characteristics

Effects of *local deprivation* and of *risk associated* with local deprivation (selected domains) **- in** Fnctional Data version) - **and of the local community characterisitcs for *individual well-being* (odds of U-'unpleasant')**
(average for a commune's residents in the TUS sample; min. 10 pers. per comm.)

Model	Unstandardized Coefficients		Standard. Coeff.	t	Sig.
	B	Std. Error	Beta		
• (Constant)	0,494	0,209		2,364	0,018
• FD_Local Deprivation (development) (2004_16)	0,000	0,000	-0,092	-2,204	0,028
• Risk assoc. w/depr. labor market	-0,073	0,021	-0,211	-3,542	0,000
• Risk assoc. w/depr. loc.economy	0,080	0,027	0,214	2,987	0,003
• Temporarily absent (from home / per 1000 pers)	0,004	0,002	0,071	1,979	0,048
• Proportion of 'employed' to 'not-employed'	-0,054	0,010	-0,175	-5,631	0,000
• Number of NGOs per 1000 pers	-0,017	0,011	-0,049	-1,534	0,125
• Local authority active in revitalization	0,069	0,026	0,085	2,715	0,007
F (7, 1012) = 9,7.842; p<0,000					

Models type I:

Cross-level operating factors of individual and community well-being:

macro - micro influence

Assessing cross-level interaction between personal and community well-being – a basic model (e.g., Subramanian. 2010)

- $\boldsymbol{y_{ij}}$; well-being of *i* individual in *j*th commune/gmin ;
- $\boldsymbol{x_{1ij}}$ predictor of indywidual (level-1) – such as: income, age, education, or satisfaction (e.g., with life in a community, family life , etc.
- predictor of level-2 / (macro-level): *Multideminsonal Index of Local Deprivation* for *j*th commune (gmina) /MILD_j

Model for level-1:

$$\boxed{y_{ij} = \beta_{0j} + \beta_l\, x_{1ij} + e_{0ij}}$$

where: β_{0j} – refers to x_{0ij} average score on a well-being scale in j-th commune/gmina (eg., . 'less affluent' or 'low-income', < Me, x_{0ij} =1);

β_l – average differentiation of individual well-being associated with individual material status , (x_{1ij}), across all communes; e_{0ij} – residual term for the level-1.

Treating β_{0j} as random variable: $(\beta_{0j} - \beta_0) + u_{0j}$, where u_{0j} is locally-specific associated with average value of β_0) for a specified group (eg. less satisfied with a community) and grouping them into fixed and random components (e_{0ij} + u_{0j}) we obtain *variance component model* or *random-intercept* model:

$$\boxed{y_{ij} = \beta_0 + \beta_l\, x_{1ij} + (e_{0ij} + u_{0j})}$$

Modeling *fixed-effect* we include a level-2 predictor – MILD -(index of local deprivation) along with individual characteristics, including *interaction* term between the two levels :

$$\boxed{\beta_{0j} = \beta_0 + \alpha_1 MILD_{1j} + u_{0j} \quad \text{and} \quad \beta_{1j} = \beta_1 + \alpha_2 MILD_{1j} + u_{1j}}$$

Accordingly, a two-level model can be specified as below:

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \alpha_1 w_{1j} + \alpha_2 w_{1j} x_{1ij} + (u_{0j} + u_{1j} x_{1ij} + e_{1ij} x_{1ij} + e_{2ij} x_{2ij})$$

- where w_{1j} is a 2-level predictor. i.e. the index of local deprivation. $MILD_{1j}$.

The following model was calculated using data from *Time Use Survey* 2013 (22 695):

$$IWB(U\text{-}iincome_{ij} + \boldsymbol{\alpha}_1 MILD_j + \boldsymbol{\alpha}_{11} education_{ij} * MILD_j + \boldsymbol{\alpha}_{21} income_{ij} * MILD_j + u_{1j} education_{ij} + u_{2j} income + ndex)_{ij} = \boldsymbol{\beta}_{00} + \boldsymbol{\beta}_{10} education_{ij} + \boldsymbol{\beta}_{20} u_{0j} + e_{ij}$$

[It is assumed that] Such a specification of cross-level (between individual and community/gmina measures of well-being) with *interaction* effect should ensure robust estimation (e.g.. Subramanian. op. cit.. p. 521; Hox et al.. 2018).

→ Preliminary results

Multilevel regression of personal well-being – *U-index* (all activities) – on individual and commune charactersitics with cross-level interaction term; comparison of ***Functional Data***-based and ***classic PCA*** approaches

Model with FDPCA-measures (MILDevelopment)	**Std Beta**	**t**	Model with classic PCA-measures (MILDeprivation)	**Std Beta**	**t**
Constant		13,258	Constant		5,096
Income	0,056**	6,901	Income	0,027**	4,050
Education (years of schooling)	0,075**	4,728	Education (years of schooling)	-0,045	-0,610
FD_Community Development 2004-2014	0,082*	2,304	Community Deprivation 2004-2014	-0,062*	-2,133
FD_Education *Community Development	-0,111**	-2,737	Education*Community Deprivation	0,123*	1,668
FD_Comm. Dvpt * Income	0,152**	17,778	Comm. Depriv.* Income	0,091**	13,547

$F(5,15086) = 100\ 418$ ($p<.001$) $F(5,22690) = 87\ 196$ ($p<.001$)

**. significant at $p < 0.01$ and * at $p < 0.05$.

Strong similarity of results obtained with FDPCA and PCA, respectively – with a more clear pattern of dependences in the first case – confirms the (expected) dvantage of the former mainly for interpretation and result presentation purposes.

Models type II:

Structural modelling approach - *causal* mediating mechanisms:
local deprivation as a factor modifying effect of an individual commune's attribute on the residences' well-being according to U-index

- Hhld Income - indpendent var. / 'treatment'
- Local deprivation / MILD – *mediating* factor

Hypothesis: The level of deprivation of a commune (gmina) affects the influence of the residents‘ subjective well-being by their material status (income) [structural modeling (e.g. G. Hong. 2015)]:

Y - U-index (individual well-being)

Z – source of influence: HH income (average in a commune/gmina)

M - *mediator*: level of local deprivation /MILD_2014

$$M = \gamma_0 + aZ + \varepsilon_M$$

$$Y = \beta_0 + bM + cZ + \varepsilon_M$$

Substituting for M → *reduced-form* model:

$$Y = (\ldots) = \beta'_0 + c'Z + \varepsilon'_Y$$

Estimation of diffrences between coefficients of ifluence c’ – c (with local deprivation/MILD as a mediator) allows to assess indirect effect (of MILD) in estimating influence of Hhld income on individual well-being (U)

Structural (*causal*-type) modelling:
quality of living environment(*ILD*-selected domains) as a moderating factor in assessing influence of respondents' income on subjective well-being

Model / predictors	Standardized Coefficients		Difference
	Beta	**t-statistics**	**(c'- c)**
Dependent Var: U-index for all activities			
M I: ILD_economy	-.054	-1.565	0.304
Monthly income/ Mi (c’)	.072 *	2.070	
ILD_economy on Mi (c)	-.358 **	-11.807	
M II: ILD_social assistance	-.091 **	-2.824	0.013
Monthly income /Mi (c’)	-.111 **	-3.439	
ILD_soc asst. on Mi (c)	-.104 **	-3.214	
M III: ILD_labor market	-.089 **	-2.725	0.065
Monthly income /Mi	-.061 *	-1.850	
ILD_labor market on Mi (c)	-.154 **	-4.802	
M IV: ILD_health	.054	1.638	0.108
Monthly income /Mi (c’)	-.070 *	-2.137	
ILD_health on Mi (c)	-.178 **	-5.583	

The level of repondent income modifies the impact of local deprivation(MILD) - selected domains/ILD - on individual (subjective) well-being significanty.

Spatial aspects of between-level relationship (spatial heterogeneity)

- Two-step spatial analysis:

(1) Checking a tendency to clustering among 'spatial units' (communes/gminas) with respect to selected measures – subjective and objective – using Moran' I (global):

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

where: x_i. x_j - values of a measure at each location; ***W*** is the spatial weights matrix.

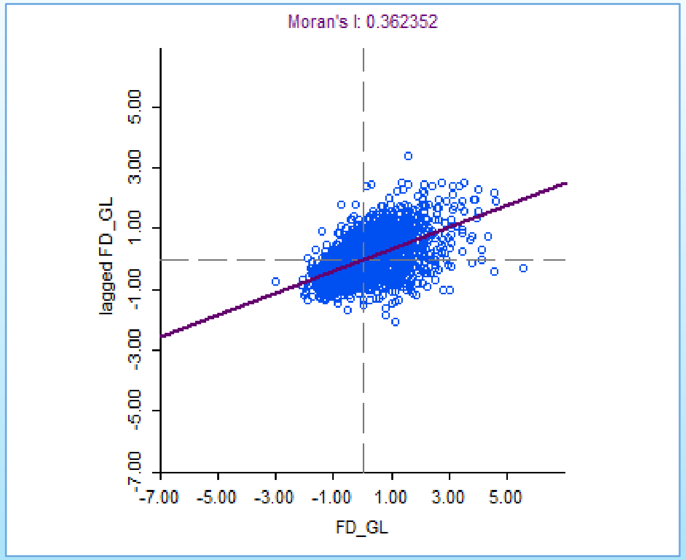
(2) Estimation of the spatial regression model parameters: (notation for individual/commune observation *i*):

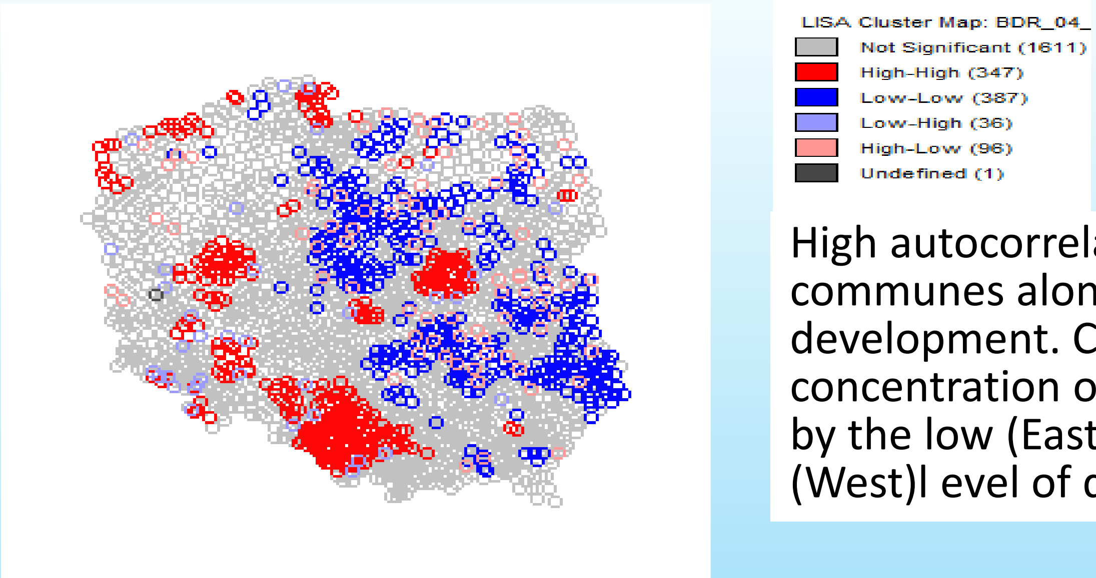
$$y_i = \rho \sum_{j=1}^{n} W_{ij}\, y_j + \sum_{r=1}^{k} X_{ir}\, \beta_r + \varepsilon_i$$

where: y_i – the dependent variable for observation *i*; X_{ir} *k* – explanatory variables r = 1. …. k with associated coefficient β_r ; ***W*** matrix; ρ is parameter of the strength of the average association between the dependent variable for region /observations and the average of them for their neighbours; ε_i is the disturbance term – it might be assumed that ε_i is meant as either the ***spatially lagged*** term or ***spatial error*** formulation ((eg.. LeSage and Pace. 2010).

(LISA:) Scatter plots and cluster maps of local deprivation acc. to:
(a) $FD\_MILD_{2004-2016}$ (M's I: 0.36); and (b) $MILD_{2016}$ (M's i: 0.39) - comparison

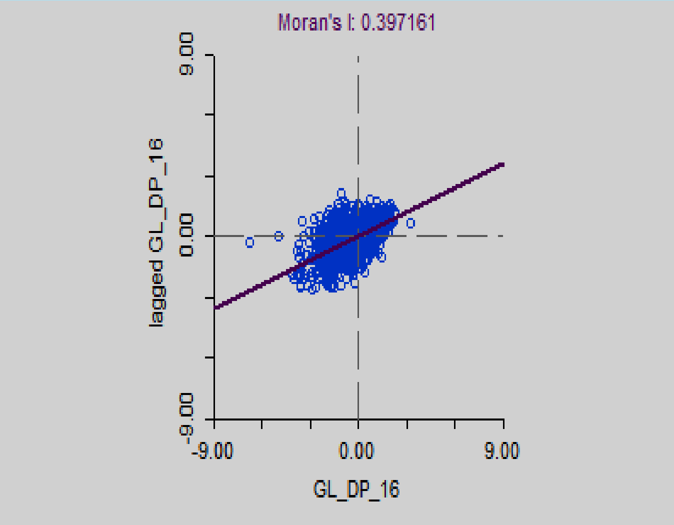
(a)

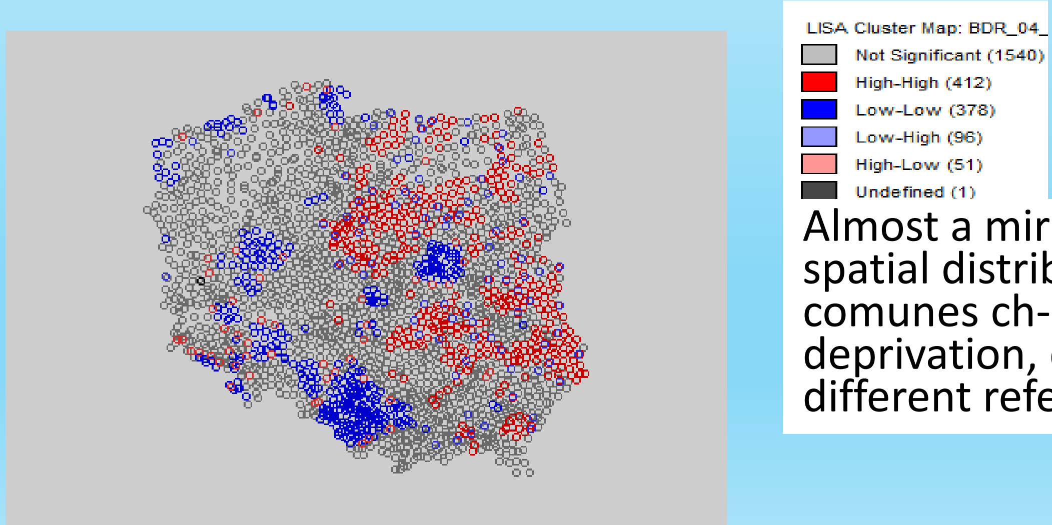




High autocorrelation of communes along the level of development. Clear pattern of concentration of clusters ch-d by the low (East) vs. high (West)l evel of development .

(b)

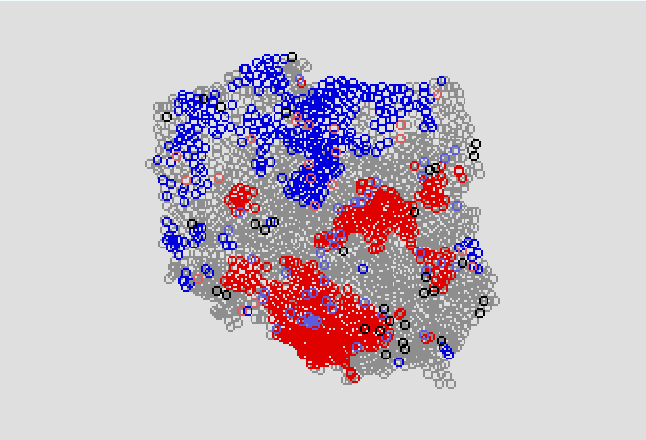


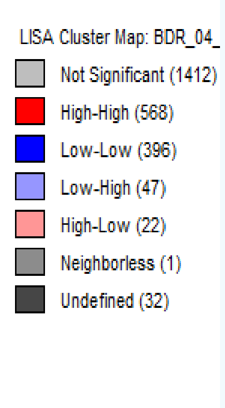


Almost a mirror pattern of the spatial distribution of comunes ch-d by the level of deprivation, despite the different reference period

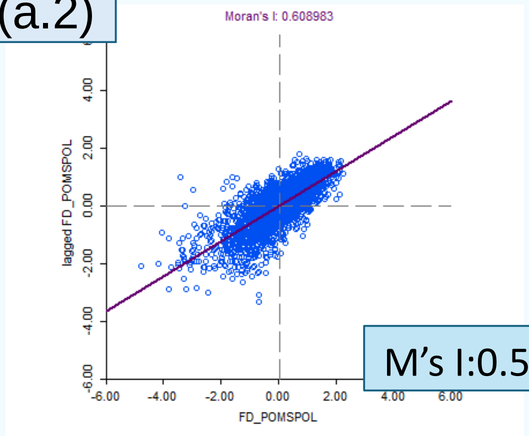
Cluster maps and scatter plots of deprivation / 'development' in the domains of (a) *local social welfare* by FD-measure (2004-16) and FA-classic and (b) *local labour market by* FD-measure and FA.

(a.1)



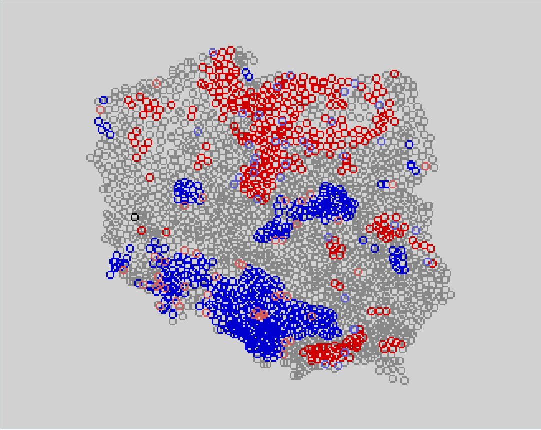


(a.2)

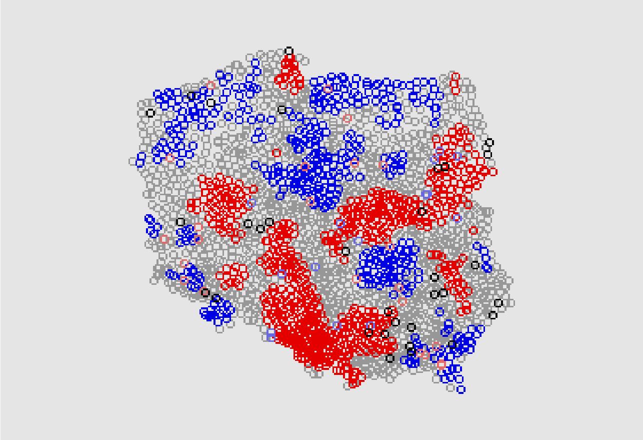


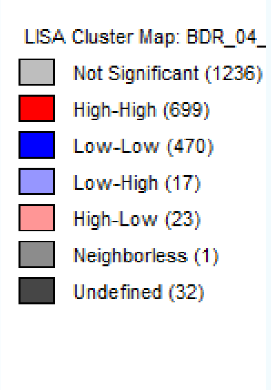
M's I:0.56

(a.3)

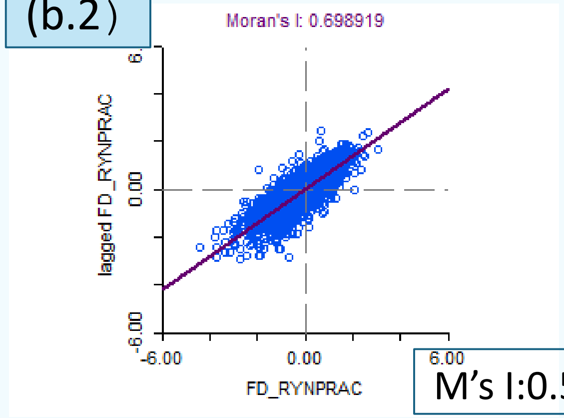


(b.1)



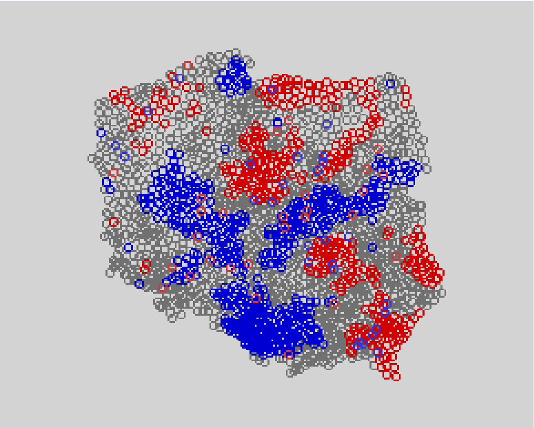


(b.2)



M's I:0.56

(b.3)



Strong autocorrelation and clear pattern of spatial clusters in each of the two domains – local social welfare and labour market – provide case for interpretation of the above relationships between risk associated with FDPCA-measure and 'classic' PCA measure, (a.1&a.3, and b1&b.3, respectively): the patterns are similar (but inverted values suggests different interpetation - 'development' ('1') vs. deprivation ('3').

SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION (FD-measures)

Dependent -- Subjective well-being

All scales – SMS/*Synthetic Measure of Satisfaction (N 352)*

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	6.58928	4.69413	1.40373	0.16040
RiskFD_LabMkt	1.05379	0.470991	2.2374	0.02526
RiskFD_Economy	-1.4603	0.542753	-2.69055	0.00713
Subsidies FD_2016pc	0.000735	0.001080	0.68092	0.49592
NGOs per 1000_2016	-0.46272	0.2308	-2.00488	0.04498
Comm. w/revitalization	0.18080	0.381625	0.473771	0.63566
Migration_balance	0.04184	0.041461	1.00924	0.31286
LAMBDA	**0.16678**	0.0560501	2.97569	0.00292

DIAGNOSTICS FOR HETEROSKEDASTICITY

TEST	DF	VALUE	PROB
Breusch-Pagan test	6	36.8021	0.00000

SPATIAL ERROR DEPENDENCE FOR WEIGHT MATRIX : BDR_04_16_Juneo5_2019

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	8.4296	0.00369

SPATIAL ERROR MODEL - MAXIMUM LIKELIHOOD ESTIMATION (FD-measures)

Dependent: *Satisfaction with personal situation* (N 352)

Variable	Coefficient	Std.Error	z-value	Probability
CONSTANT	2.90449	3.33088	0.87198	0.38321
RiskFD_LabMkt	0.630598	0.329713	1.91256	0.05580
RiskFD_Economy	-0.747787	0.381996	-1.95758	0.05028
Subsidies FD_2016pc	1.7133e-05	0.0007664	0.022345	0.98217
NGOs per 1000_2016	-0.262531	0.16303	-1.61032	0.10733
Comm. w/revitalization	0.009240	0.26974	0.03425	0.97267
Migration_balance	-0.008147	0.029267	-0.27837	0.78072
LAMBDA	**0.132998**	0.056856	2.3392	0.01933

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS

TEST	DF	VALUE	PROB
Breusch-Pagan test	6	30.3470	0.00003

TEST	DF	VALUE	PROB
Likelihood Ratio Test	1	4.9045	0.02679

CONCLUSIONS

Following the conceptualization of the triadic interdependence of data, measurement, and model, some observations seem worth mentioning in light of the presented empirical results:

► Bottom-up, data-driven approach to constructing Analytical Data Base encompassing individual and group/commune variables, seems to provide an alternative to the lacking appropriate (nested) data structure in analyzing cross-level relationship between the respective (development and well-being measures), within a multidimensional framework.

► Functional Data approach to multidimensional measurement of community well-being (i.e., switching from PCA to FPCA), as well as to selected measures of subjective well-being, allows on the one side, to utilize information on long-term process of local development and, on the other, to expand the analysis towards employing a spatio-temporal frameworek, while clarifying the between individual (micro) and commune (macro) level relationsips.

► In consequence of involving dynamic aspect of the local development process (due to using FD-approach) in the analysis of its influence on the residents' personal well-being both planning and resource allocation policies become better informed and, expectedly, more effective (for instance, a given level of individual well-being can be achieved at a lower level of input with such an additional information than otherwise).

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Thank you

IOS-ISI 2024
MEXICO CONFERENCE

ASSESSING DESERTIFICATION AND VEGETATION LOSS IN NATURAL PROTECTED AREAS OF NORTHERN MEXICO

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INEGI
International Statistical Institute
IAOS IMPROVING OFFICIAL STATISTICS

Introduction

Importance

- The importance of quantifying the undeniable changes present in the environment (global warming)
- The need to develop strategies that provide solutions to the United Nations Sustainable Development Goals SDG (15.3.1)
- The opportunity to evaluate established public policies for environmental protection (i.e., Natural Protected Areas)

Goals

Asses vegetation loss for northern Mexico using Natural Protected Areas as the study regions.

- Integrate different sources of geospatial information to enhance the analysis.
- Generate information to aid in tracking progress on SDG 15.3.1 and improve decision-making.
- Evaluate human impact on the environment.

Data Sources

IOS-ISI 2024

MEXICO CONFERENCE

Data

ESA-CCI

TEXT 1

Land Cover data provided by the ESA and mapped to UNCCD

INEGI SERIES

TEXT 1

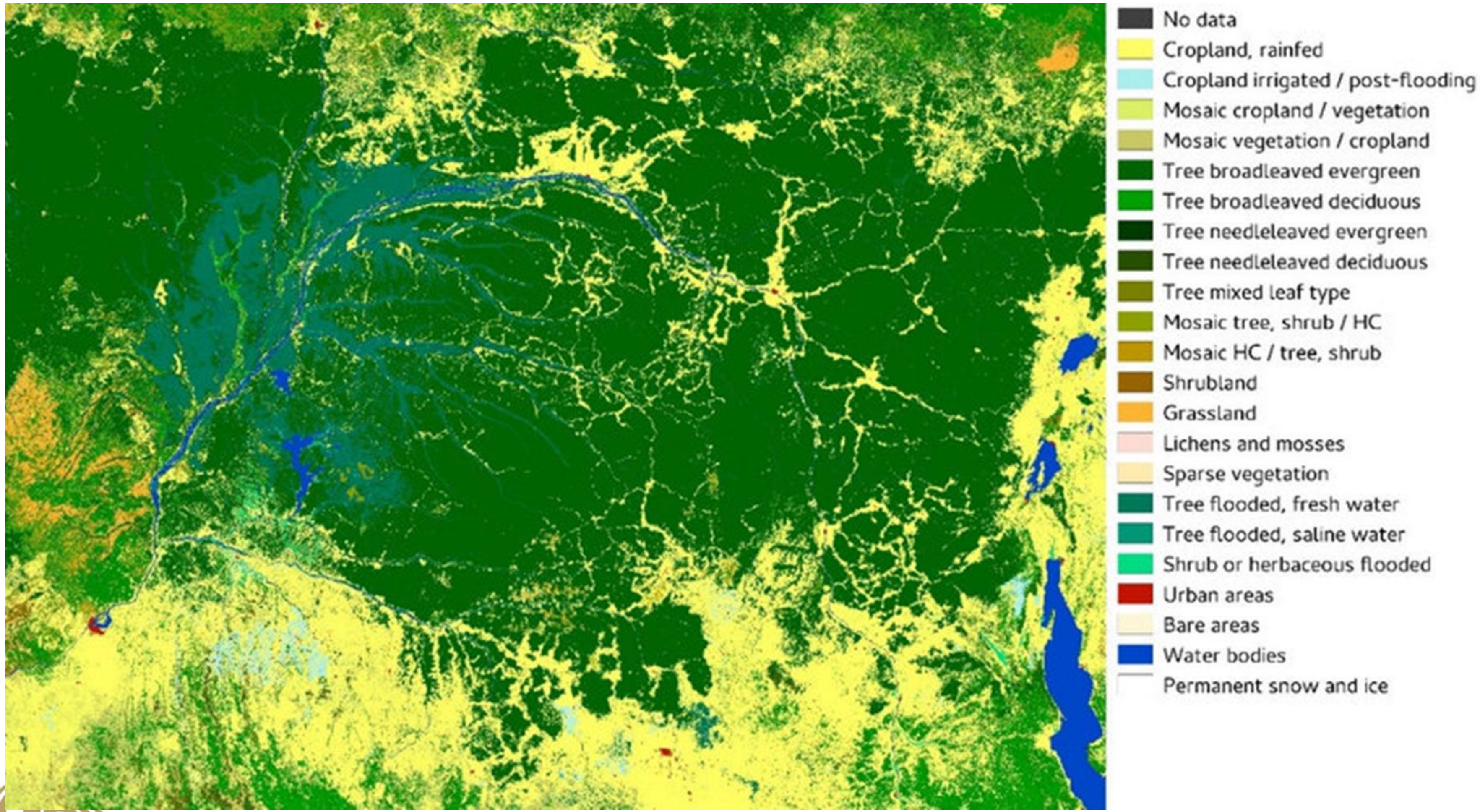
INEGI’s vegetation data rasterized and mapped to UNCCD

WEATHER STATIONS

TEXT 1

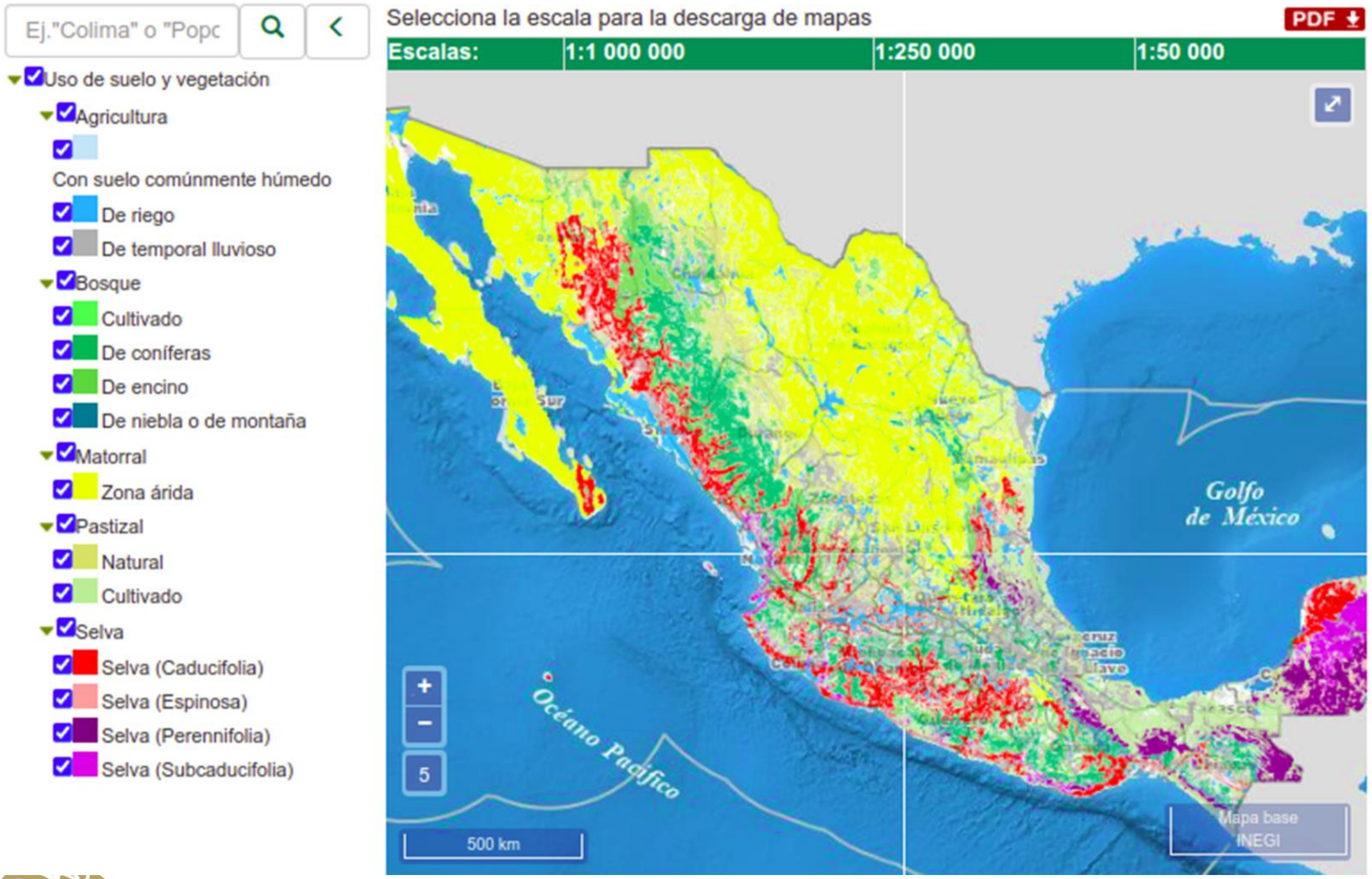
Precipitation data gathererd by weather stations

ESA-CCI LC



- 22 classes

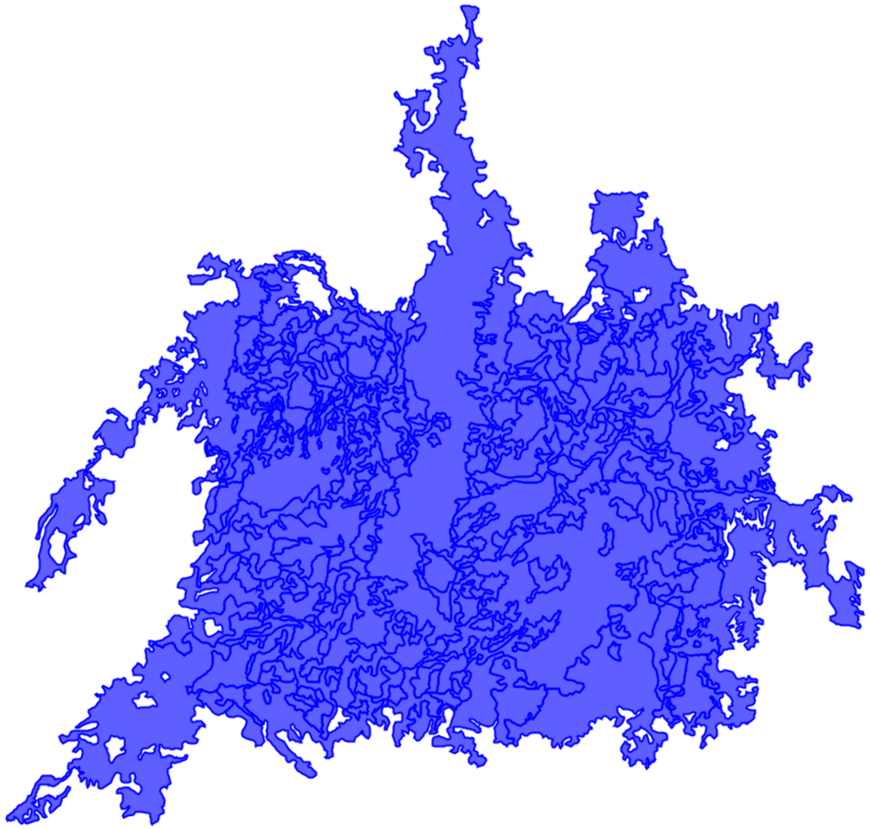
INEGI vegetation series

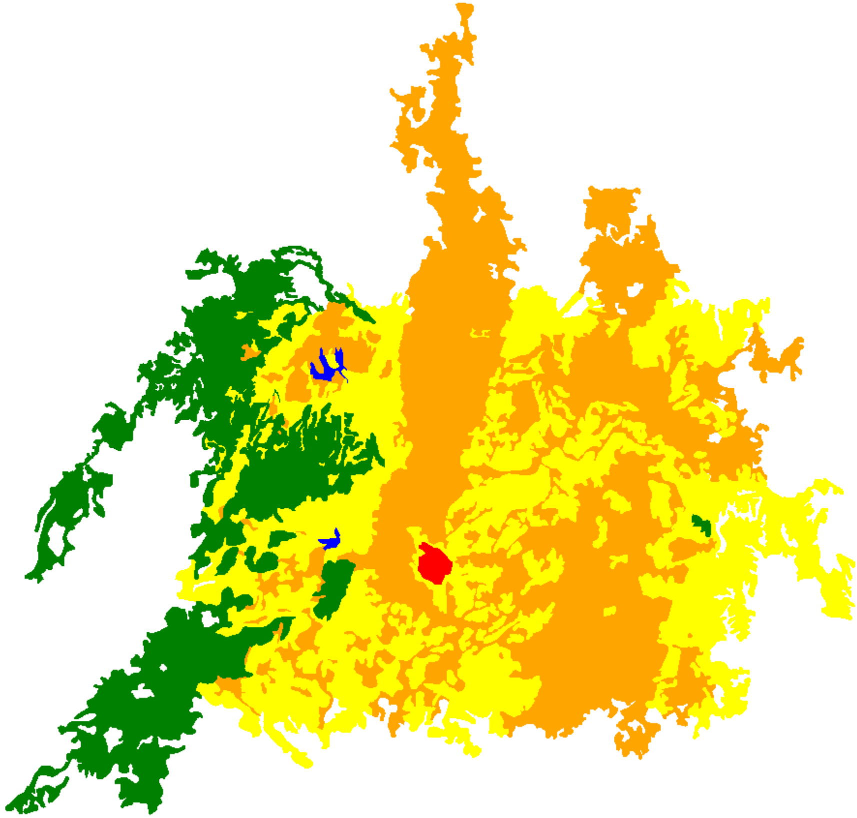


- Series I (1992) 9 classes
- Series VII (2018) 189 classes

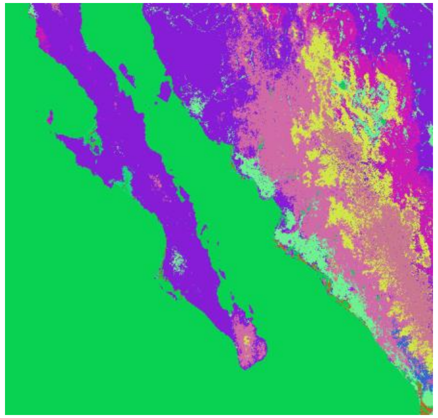
Methodology

Rasterization

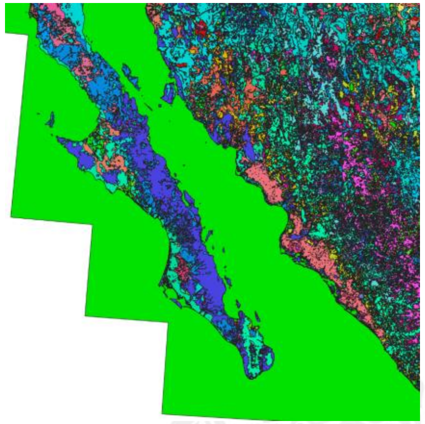




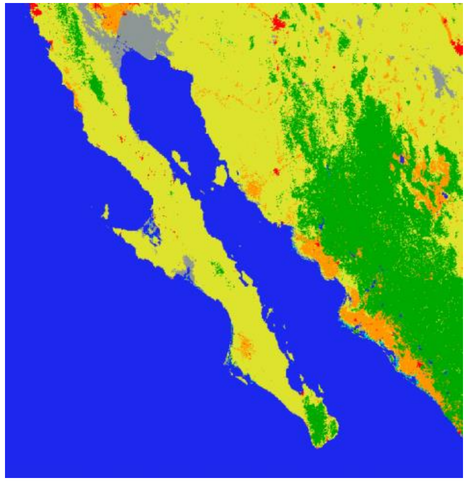
Land Cover Mapping



ESA-CCI 22 Classes



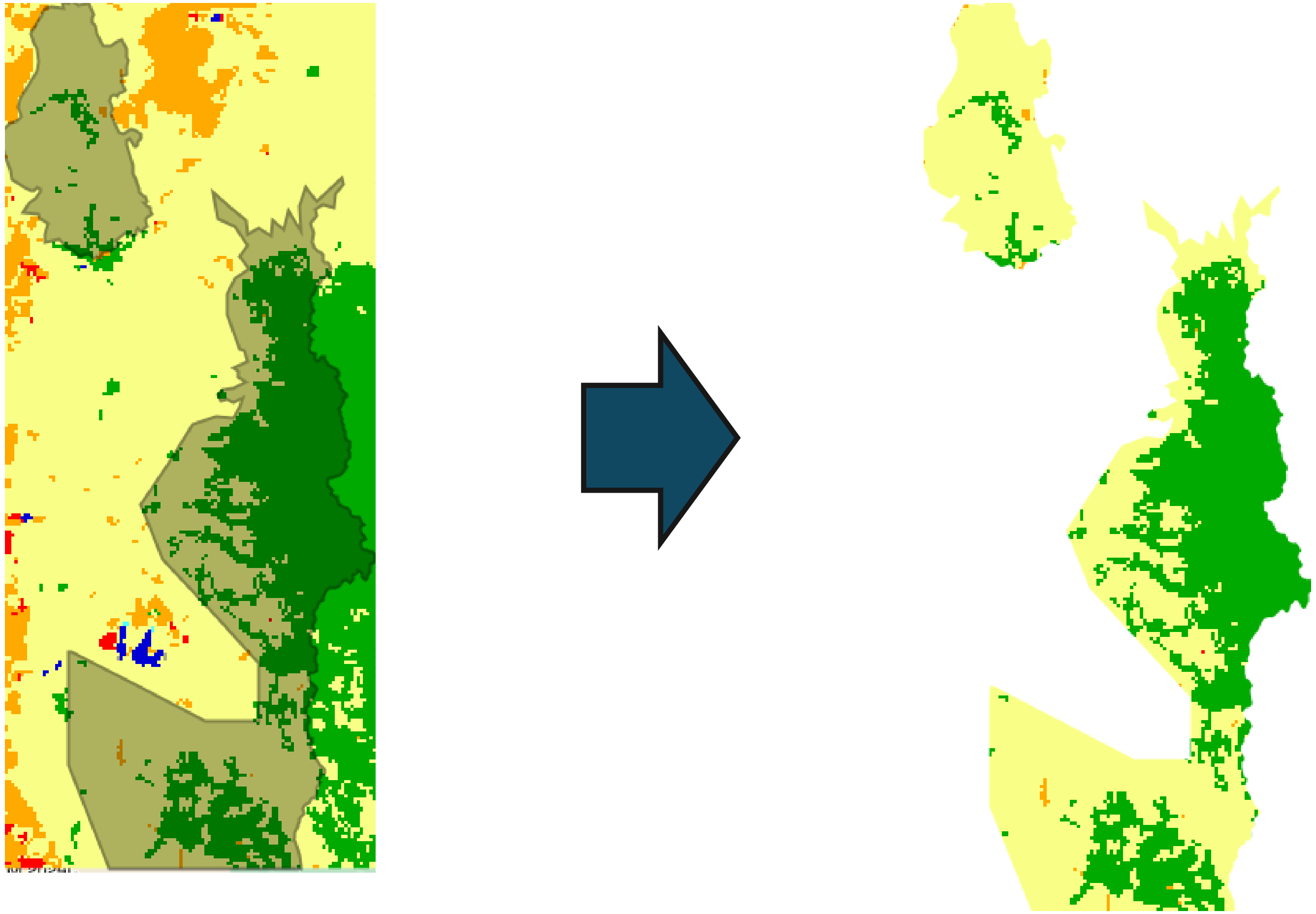
INEGI series 9-189 Classes



UNCCD 7 Classes

```
var lc_type = lc.map(function(feat){
  var entidad = feat.get('ENTIDAD')
  var entidad_tipo = ee.Algorithms.If(ee.String(entidad).equals('AREA AGRICOLA'), 3,
    ee.Algorithms.If(ee.String(entidad).equals('AREA SIN VEGETACION'),6,
      ee.Algorithms.If(ee.String(entidad).equals('BOSQUE'),1,
        ee.Algorithms.If(ee.String(entidad).equals('CUERPO DE AGUA'),7,
          ee.Algorithms.If(ee.String(entidad).equals('LOCALIDAD'),5,
            ee.Algorithms.If(ee.String(entidad).equals('MATORRAL'),2,
              ee.Algorithms.If(ee.String(entidad).equals('OTROS TIPOS DE VEGETACION'),2,
                ee.Algorithms.If(ee.String(entidad).equals('PASTIZAL'),2,
                  ee.Algorithms.If(ee.String(entidad).equals('SELVA'),1,0))))))))) 
  return feat.set({ENTIDAD_NUM:entidad_tipo})
})
```

Clipping to ROIs

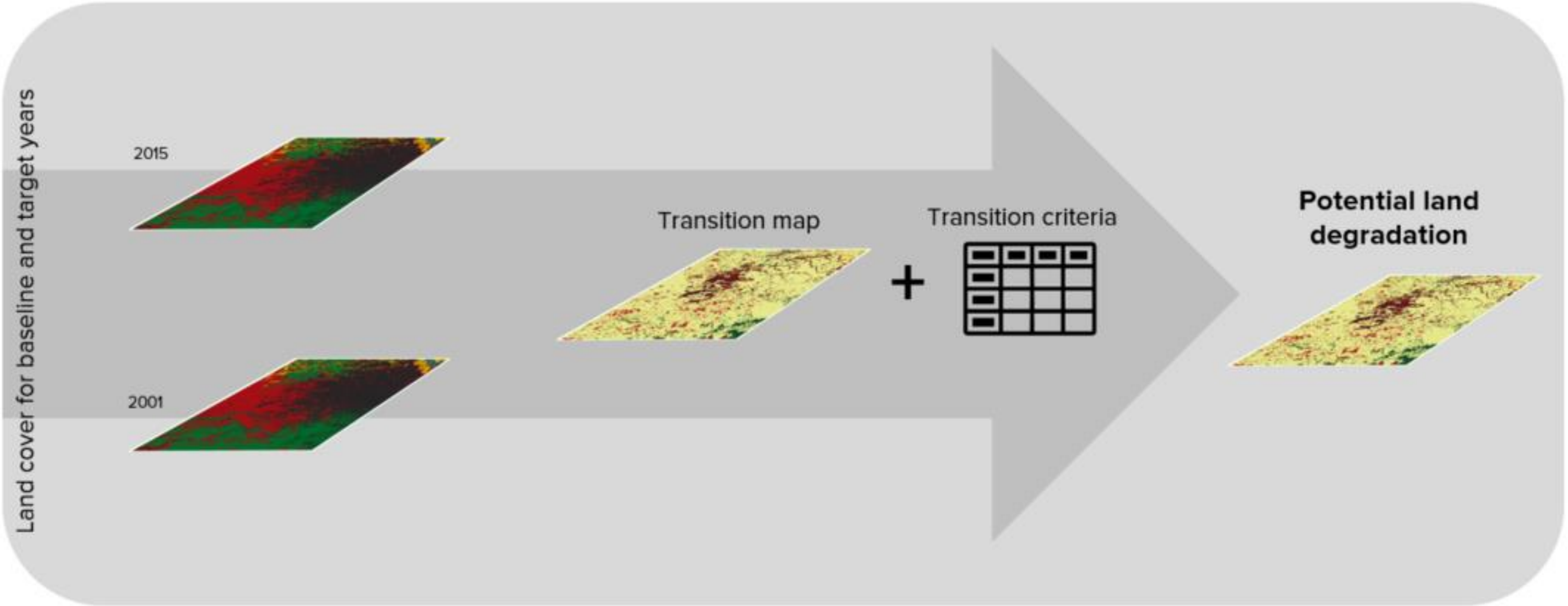


Trends.Earth

- Trends.Earth is a platform to monitor land cover and land use change using earth observations
- Open source and installs by plugin for Qgis
- Uses data from European Spatial Agency (ESA) and cloud computing in Google Earth Engine (GEE)
- Developed to help developing countries meet UN 2030 agenda (SDGs)

Trends.Earth

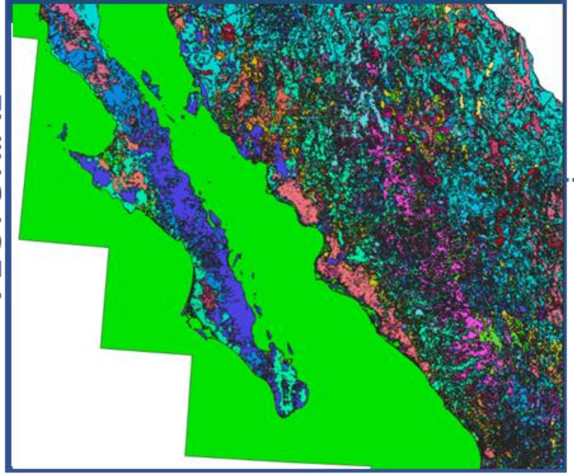
TRENDS.EARTH
tracking land change
from Conservation International



Data	Data Pre-processing	Trends.Earth LC change	Results

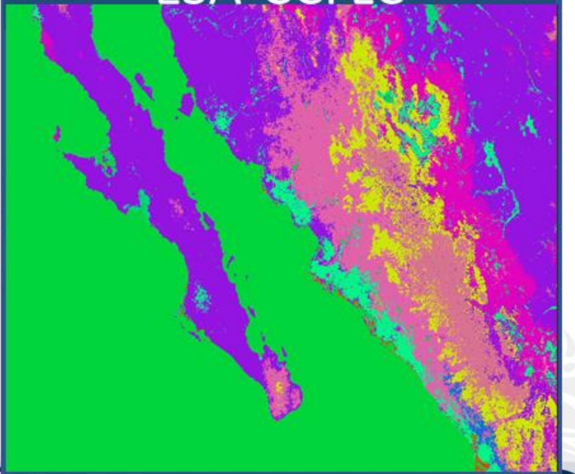
VECTORIAL

INEGI SERIE I Y VII

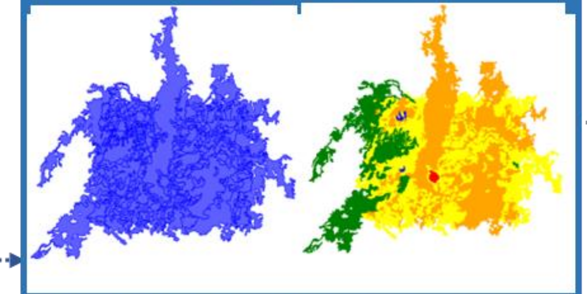


RASTER

ESA-CCI LC



RASTERIZING

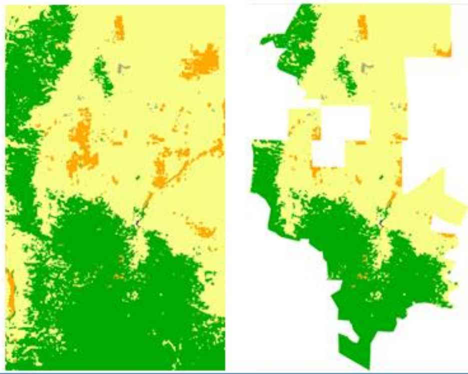


Resolución: 300, 30 y 10m

LC MAPPING

UNCCD CODE	UNCCD LABEL	ESA CCI_CODE	ESA CCI_LABEL
1	TREEE-COVERED AREAS	50	Tree cover, broadleaved, evergreen, closed to open (>15%)
		60	Tree cover, broadleaved, deciduous, closed to open (>15%)
		61	Tree cover, broadleaved, deciduous, closed (>40%)
		62	Tree cover, broadleaved, deciduous, open (15-40%)
		70	Tree cover, needleleaved, evergreen, closed to open (>15%)
		71	Tree cover, needleleaved, evergreen, closed (>40%)
		72	Tree cover, needleleaved, evergreen, open (15-40%)
		80	Tree cover, needleleaved, deciduous, closed to open (>15%)
		81	Tree cover, needleleaved, deciduous, closed (>40%)
		82	Tree cover, needleleaved, deciduous, open (15-40%)
		90	Tree cover, mixed leaf type (broadleaved and needleleaved)
		100	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
2	GRASSLAND	110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
		120	Shrubland
		121	Shrubland evergreen
		122	Shrubland deciduous
		130	Grassland
		140	Lichens and mosses
		151	Sparse trees (<15%)
		152	Sparse shrub (<15%)
		153	Sparse herbaceous cover (<15%)

CLIP TO ROI



TRANSITIONS

Land cover in target year

Land cover in initial year

	Tree-covered	Grassland	Cropland	Wetland	Artificial	Bare land	Water body
Tree-covered	[illegible]	-	-	-	-	-	0
Grassland	+	0	+	-	-	-	0
Cropland	+	-	0	-	-	-	0
Wetland	-	-	-	0	-	-	0
Artificial	+	+	+	+	0	+	0
Bare land	+	+	+	+	-	0	0
Water body	0	0	0	0	0	0	0

TIME GAP

- 1992-2018

TRENDS.EARTH LC CHANGE

TRENDS.EARTH
tracking land change
from Conservation International

Google Earth Engine

RESULTS

Land cover change by cover class

	Baseline area (sq. km)	Target area (sq. km)	Change in area (sq. km)	Change in area (percent)
Tree-covered areas	2.08	5.58	3.51	168.99%
Grasslands	24,760.25	24,156.70	-603.55	-2.44%
Croplands	41.00	67.02	26.02	63.47%
Wetlands	0.00	0.00	0.00	#¡DIV/0!
Artificial areas	0.00	5.06	5.06	#¡DIV/0!
Other lands	61.59	867.69	806.11	1308.93%
Water bodies	244.83	7.69	-237.15	-96.86%

RESULTS

Summary of change in land cover

	Area (sq km)	Percent of total land area
Total land area:	24,858.2	100.00%
Land area with improved land cover:	35.8	0.14%
Land area with stable land cover:	23,913.7	96.20%
Land area with degraded land cover:	908.8	3.66%
Land area with no data for land cover:	0.0	0.00%

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Results

Regions of Interest

Área Natural Protegida (ANP)
Cuatrociénegas
Gran Desierto de Altar
Alto Golfo de California
Janos
Maderas del Carmen
Médanos de Samalayuca
Pabellón de Arteaga
San Pedro
Santa Elena
Sierra la Laguna
Valle de los Cirios
El Vizcaíno

Comparison between ESA and INEGI

	Resolución					
	ESA-CII 300m			INEGI-Serie 300m		
ANP	Mejorando	Estable	Degradación	Mejorando	Estable	Degradación
Alto Golfo de California	0.02 %	96.73 %	2.11 %	2.01 %	72.91 %	24.09 %
Cuatrociénegas	3.27 %	95.41 %	0.20 %	0.82 %	90.43 %	7.48 %
Desierto de Altar	0.63 %	98.46 %	0.87 %	0.0 %	46.83 %	53.07 %
El Vizcaíno	0.02 %	99.17 %	0.46 %	1.12 %	80.46 %	18.07 %
Janos	0.32 %	97.04 %	2.28 %	4.94 %	87.76 %	7.01 %
Maderas del Carmen	2.49 %	95.86 %	1.05 %	20.39 %	76.23 %	2.97 %
Médanos de Samalayuca	0 %	99.06 %	0.20 %	0.0 %	36.66 %	62.6 %
Pabellón	0.32 %	95.96 %	1.88 %	13.12 %	64.21 %	21.31 %
San Pedro	0.18 %	97.64 %	0.70 %	7.39 %	82.3 %	8.96 %
Santa Elena	0.26 %	99.19 %	0.03 %	1.15 %	94.9 %	3.46 %
Sierra la Laguna	5.36 %	93.68 %	0.13 %	12.27 %	84.47 %	2.51 %
Valle de los Cirios	0.07 %	99.31 %	0.42 %	0.16 %	95.46 %	4.19 %

INEGI data sources

	Resolución								
	300m			30m (LandSat)			10m (Sentinel)		
ANP	Mejorando	Estable	Degradación	Mejorando	Estable	Degradación	Mejorando	Estable	Degradación
Alto Golfo de California	2.01 %	72.91 %	24.09 %	2.66 %	75.63 %	21.71 %	2.67 %	75.64 %	21.69 %
Cuatrociénegas	0.82 %	90.43 %	7.48 %	0.96 %	92.51 %	6.53 %	0.97 %	92.58 %	6.45 %
Desierto de Altar	0.0 %	46.83 %	53.07 %	0.03 %	47.67 %	52.28 %	0.03 %	47.73 %	52.24 %
El Vizcaíno	1.12 %	80.46 %	18.07 %	1.05 %	82.03 %	16.89 %	1.05 %	82.15 %	16.8 %
Janos	4.94 %	87.76 % %	7.01 %	5.24 %	86.53 %	8.23 %	5.27 %	86.42 %	8.31 %
Maderas del Carmen	20.39 %	76.23 %	2.97 %	24.03 %	73.99 %	1.94 %	24.34 %	73.78 %	1.86 %
Médanos de Samalayuca	0.0 %	36.66 %	62.6 %	0.0 %	42.5 %	57.5 %	0.0 %	42.92 %	57.08 %
Pabellón	13.12 %	64.21 %	21.31 %	17.43 %	64.13 %	18.28 %	17.77 %	64.15 %	18.07 %
San Pedro	7.39 %	82.3 %	8.96 %	8.69 %	81.34 %	9.94 %	8.67 %	81.41 %	9.92 %
Santa Elena	1.15 %	94.9 %	3.46 %	1.19 %	95.46 %	3.28 %	1.2 %	95.53 %	3.27 %
Sierra la Laguna	12.27 %	84.47 %	2.51 %	12.36 %	85.92 %	1.64 %	12.39 %	86.02 %	1.59 %
Valle de los Cirios	0.16 %	95.46 %	4.19 %	0.14 %	96.15 %	3.7 %	0.14 %	96.2 %	3.66 %

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Conclusions

- Degradation/Desertification found for some ANP
- Results vary greatly depending on the data source used
- Spatial resolution can be changed for INEGI data source
- Comparability and replicability is assured using trends.earth
- INEGI data source can be extendend with experts in LC definitions

Thank you