



# Aplicaciones para la generación de información agropecuaria mediante inteligencia artificial

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Taller de Innovación y Aplicaciones con Datos Geoespaciales

Banco Central de Chile

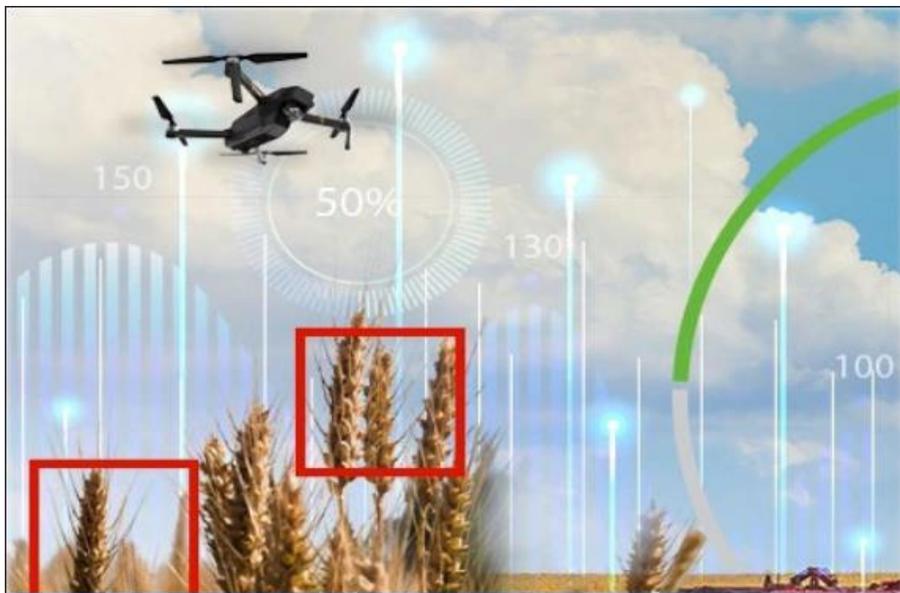
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# Contexto y Relevancia

- IA para la agricultura en Chile:
  - Digitalización y herramientas avanzadas como IA en la agricultura chilena.
  - Mejor monitoreo y respuesta ante eventos climáticos extremos y desastres.
  - Sostenibilidad sectorial y protección de recursos naturales.
- Este taller y su objetivo.

# Aplicaciones para la generación de información agropecuaria mediante inteligencia artificial:

- Inteligencia artificial para la estimación de superficie de trigo a nivel nacional (2023)
- Implementación de un indicador de pérdida de suelo en las zonas de uso agropecuario actual y potencial utilizando imágenes satelitales (2024)
- Inundaciones de Junio (2024)



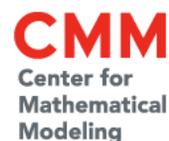
Estudio: Inteligencia artificial para la estimación de superficie de trigo a nivel nacional



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# Inteligencia artificial para la estimación de superficie de trigo a nivel nacional (2023)



# Metodología



# Metodología

Paso 1: Imágenes satelitales y preprocesamiento

Paso 3: Delineación de parcelas

Paso 4: Clasificación de cultivos



Servicios de imágenes satelitales (ej: Sentinel-2)



Imágenes preprocesadas

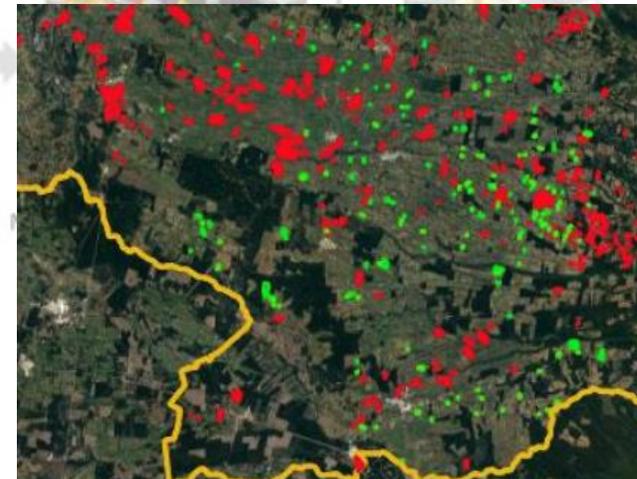
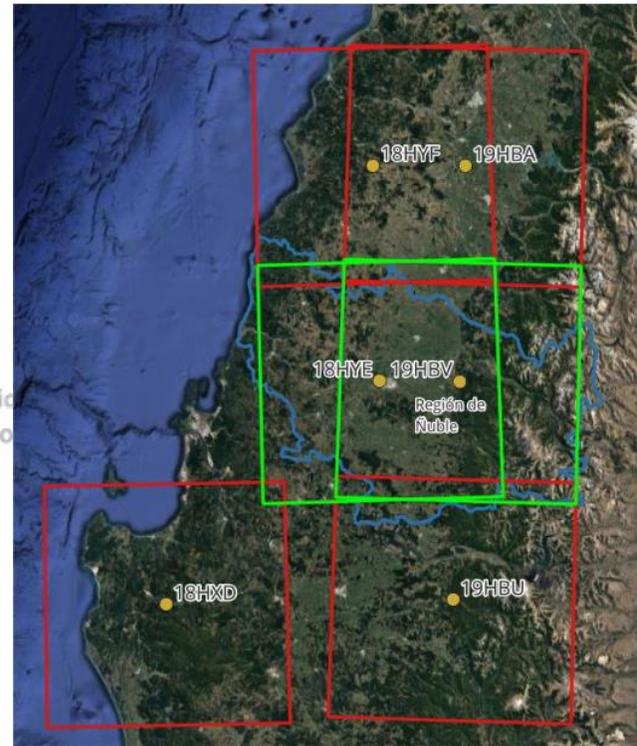


Polígonos etiquetados

Paso 2: Datos etiquetados de cultivos



Mapa de segmentación



- Sentinel-2 L2A (multi-spectral)
- CMM Copernicus Hub
- 2021 - 2022
- Long-time Archive (LTA)
- Bases de procesamiento

- Catastro de Propiedades Rurales – SII/CIREN
- Programa de Seguro Agropecuario
- Programa de Gestión de INDAP
- Catastro Frutícola

# Metodología

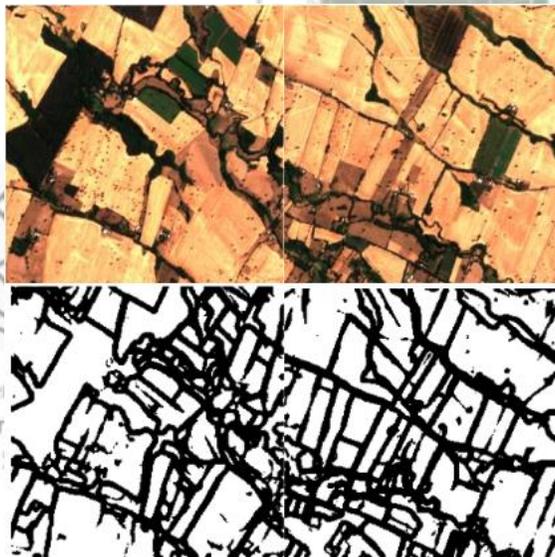
- Pre-procesamiento datos satelitales
- AI4Boundaries<sup>1</sup>
- ResUNet-a e inferencia
- Barriere & Claverie (2022)<sup>2</sup>. El modelo está entrenado de la misma manera que un modelo de lenguaje, i.e., su tarea es predecir cuál es el tipo de cultivo debido a información previa.

Paso 1: Imágenes satelitales y preprocesamiento

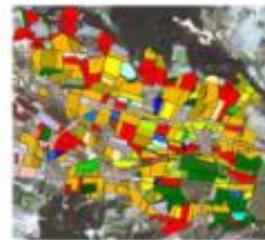
Paso 3: Delineación de parcelas

Paso 4: Clasificación de cultivos

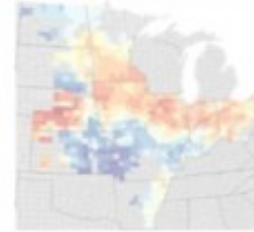
producción



Mapa de segmentación



Mapa de clasificación de cultivo



Mapa de estimación de producción

Paso 2: Datos etiquetados de cultivos

<sup>1</sup><https://github.com/waldnerf/ai4boundaries>

<sup>2</sup><http://arxiv.org/pdf/2208.10838>

## Multimodal Crop Type Classification Fusing Multi-Spectral Satellite Time Series with Farmers Crop Rotations and Local Crop Distribution

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### Abstract

Accurate, detailed, and timely crop type mapping is a very valuable information for the institutions in order to create accurate policies according to the needs of the citizens. In the last decade, the amount of available data drastically increased, whether it comes from Remote Sensing (e.g., Copernicus Sentinel-2 data) or directly from the farmers (providing in situ crop information throughout the year and information on crop rotation). Nevertheless, the majority of the studies are restricted to the use of one modality (Remote Sensing data or crop rotation and survey data from the Earth Observation data with domain knowledge like crop rotation). Moreover, when they use Earth Observation data they are mostly restricted to one year of data, not taking into account the past years. In this context, we propose to tackle this task via multi-modal crop type classification using three data types, by using a Hierarchical Deep Learning algorithm modeling the crop rotation like a language model, the satellite signals like a speech signal and using the crop distribution as additional context vector. We obtained promising results compared to classical approaches with significant performance, increasing the Accuracy by 5.1 points in a 2-class setting (4.94) and the macro F1 by 4.2 points in a 19-class setting (0.87) using only one set of crop rotation selected by an expert. We finally proposed a data-augmentation technique to allow the model to classify the crop before the end of the season, which works surprisingly well in a multimodal setting.

### Keywords

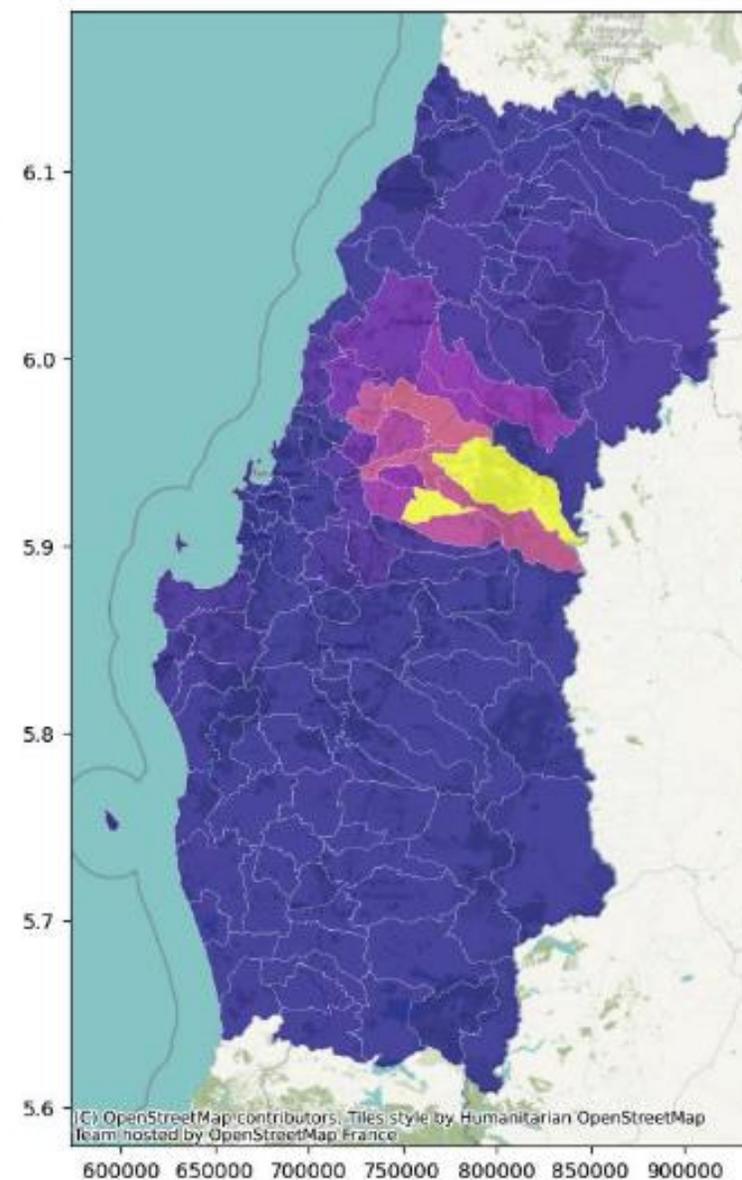
Remote Sensing, Farmer's Rotation, Multimodal System, Hierarchical Model

### 1. Introduction

Timely and accurate crop type mapping provides valuable information for crop monitoring and production forecast [1]. In-season crop type mapping can serve not only to better estimate the crop areas, but also to improve the yield forecasting by using crop-type specific models. Crop type mapping is thus a major information of the crop monitoring systems focusing to in-season forecast of the crop production. The high-spatial resolution time series enable to determine crop type at a sub-parcel level in most agricultural areas. Most of the remote sensing classification systems relies on supervised techniques, requiring in situ crop identification survey. If the survey data are provided within the season, some systems [2] are designed to predict crop type along the season with a given uncertainty, even if the crop cycle is on-going, such surveys data are expensive because of the need of labels from the current year to train a model, difficult to achieve at large scale and in most cases delivered after the cropping season. There is a high demand for crop type mapping that does not rely on survey data from the on-going season. Such approaches, as the one proposed in this study, are based on model trained with past seasons and applied on the current one, plus we proposed a data-augmentation method to obtain satisfying results earlier in the season. Earth Observation-based crop type mapping. Machine learning classification methods have been widely tested to derive crop type map from remote sensing data. Among the various methods, Random Forest algorithm has proved its capacity to accurately identify crop type, accounting for large and non-parametric data set [3]. Since 2010 and the launch of the first satellite of the Copernicus Sentinel-2 (S2) constellation, the perspective for crop type mapping at large scale has changed. The high spatial and temporal resolution of S2 offers indeed an appropriate data set to distinguish crop type, based on the spatial and temporal signals, at parcel or sub-parcel level in most agricultural region. Taking benefit of this capacity, some operational systems have been expanded [4, 2, 5], combining Earth Observation (EO) data, in situ observations and classifier algorithms to deliver crop type maps at regional, country scale or continental scale [6]. Crop type mapping using Deep Learning methods. The recent progress in deep learning brought the crop type mapping applications. In [7], the authors are classifying crop types at the parcel level, using the data from the French Brittany during the season 2017. The authors have compared a Transformer-Encoder [8] and a Recurrent Neural Network of type Long-Short-Term-Memory

|                                      | precision | recall | f1-score | support |
|--------------------------------------|-----------|--------|----------|---------|
| other crops                          | 0.992     | 0.998  | 0.995    | 1283    |
| unspecified_season_common_soft_wheat | 0.961     | 0.831  | 0.891    | 59      |
| accuracy                             |           |        | 0.991    | 1342    |
| macro avg                            | 0.977     | 0.914  | 0.943    | 1342    |
| weighted avg                         | 0.991     | 0.991  | 0.991    | 1342    |

# Metodología



# Beneficios y aplicaciones

1. Mayor precisión
2. Ahorro de recursos
3. Diseño de políticas agrícolas y ambientales



# Desafíos y Limitaciones Identificadas

1. Disponibilidad de datos
2. Condiciones climáticas variables
3. Validación en terreno
- 4. Generalización del modelo**



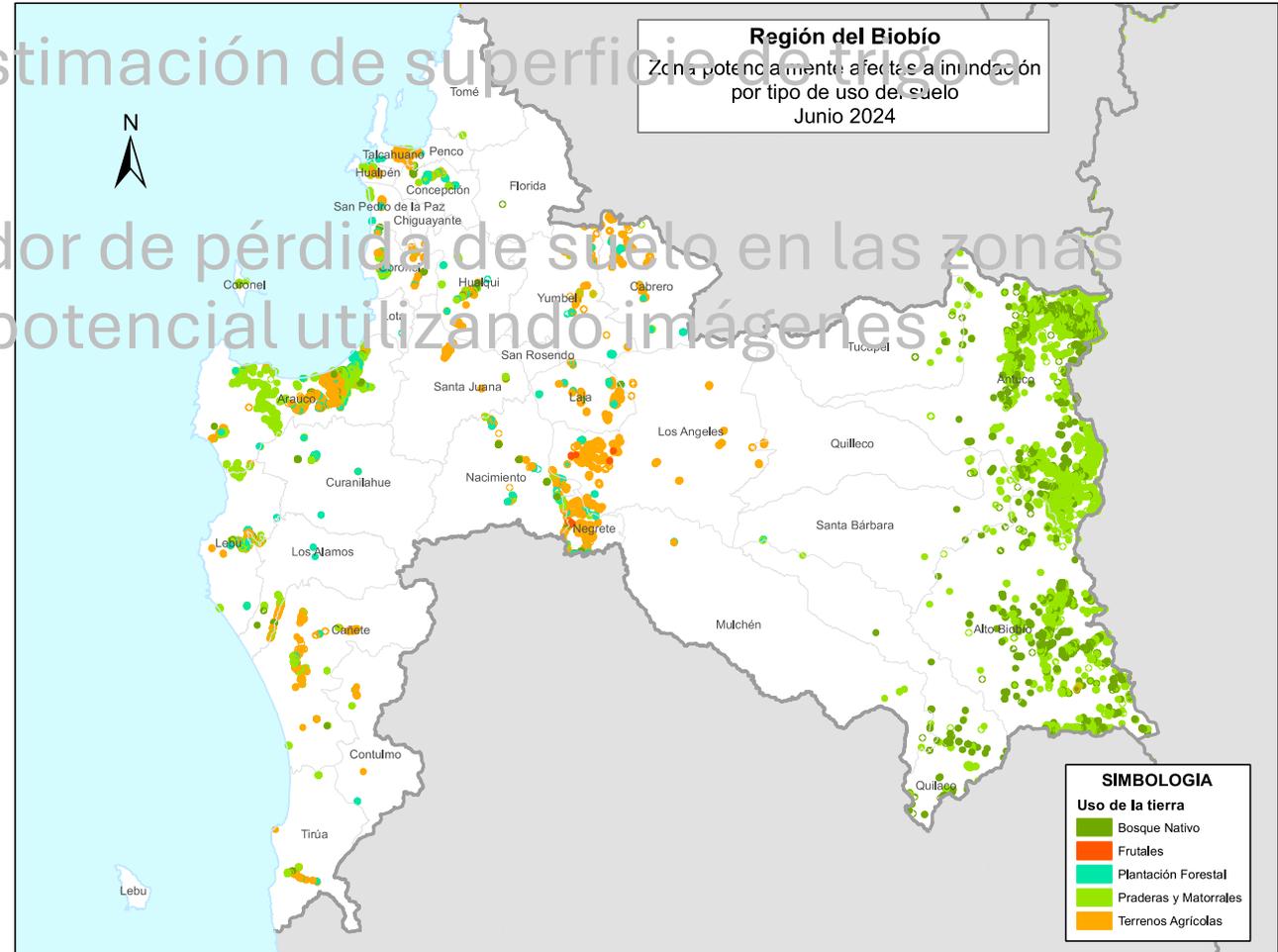
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Superficie en hectáreas potencialmente afectada por inundación

| Regiones      | Superficie en hectáreas potencialmente afectada por inundación |               |            |                       |               |                     |
|---------------|--|---------------|------------|-----------------------|---------------|---------------------|
|               | Total  | Agrícolas     | Frutales   | Praderas y matorrales | Bosque Nativo | Plantación Forestal |
| Valparaíso    | 53   | 15            | 6          | 25                    | 4             | 2                   |
| Metropolitana | 684  | 247           | 12         | 392                   | 32            | 0                   |
| O'Higgins     | 1.407  | 889           | 42         | 420                   | 52            | 4                   |
| Maule         | 5.193  | 2.090         | 10         | 2.796                 | 260           | 37                  |
| Ñuble         | 3.513  | 2.388         | 18         | 700                   | 289           | 119                 |
| Biobío        | 11.232   | 4.129         | 5          | 6.083                 | 705           | 309                 |
| Araucanía     | 15.873   | 2.836         | 10         | 11.107                | 1.680         | 239                 |
| <b>Total</b>  | <b>37.953</b>  | <b>12.594</b> | <b>103</b> | <b>21.523</b>         | <b>3.022</b>  | <b>711</b>          |

# Aplicaciones para la generación de información agropecuaria mediante inteligencia artificial

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