Data Article

Satellite imagery dataset of manure application on pasture fields

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Abstract

Applying manure to pasture fields is a very common method of fertilization. However, rainfall can cause the manure to leach into water bodies near the field, contaminating the water and damaging the environment and the animals living in it, ultimately affecting human life. This paper presents a dataset consisting of images of 30 plots after manure application, verified by on-site investigations. This involved visiting 38 different plots, of which 8 were discarded because they were not suitable, either because of their small size, the lack of a specific manure application date, or the images being too cloudy in that period. The imagery is collected through Google Earth Engine using the satellite Sentinel-2, which offers 13 hyperspectral bands in the range of ultraviolet and near-infrared wavelengths including the visible spectrum. From these 13 bands, the most common hyperspectral indices in the literature for precision agriculture are calculated and added into the images as channels. 51 hyperspectral indices are calculated, summing up to a total of 64 channels per image when adding the raw bands from Sentinel-2. No normalization has been performed on any of the channels. The data can be used for further research of automatic classification of manure application to control its use and prevent contamination.

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Specifications Table

| Subject                          | Agronomy and Crop Science |
|---------------------------------|---------------------------|
| Specific subject area           | Remote sensing for precision agriculture to detect and classify recently manured pasture fields. |
| Type of data                    | Image                     |
| How the data were acquired      | All data is acquired through Google Earth Engine. Plots are manually selected in Google Earth Engine after an on-site investigation. Images are downloaded from the satellite Sentinel-2 using Google Earth Engine. Finally, cloudy images are filtered out manually. |
| Data format                     | Raw, Filtered, Processed  |
| Description of data collection  | The regions of interest with the considered plots in the images are located after careful on-site inspection and verification. When a manured field is found, photographs are taken as validation and the location is indicated by GPS. Then, from Google Earth Engine, the appropriate region is manually selected, and the corresponding Sentinel-2 images are downloaded from the date on which the plot was manured, or the closest possible later date. |
| Data source location            | City/Town/Region: Northern region of Spain |
|                                | Country: Spain            |
|                                | Latitude and longitude: latitude around [43.55, 43.38], and longitude around [−5.50, −4.10]. |
|                                | All images are obtained from the satellite Sentinel-2. |
| Data accessibility              | Repository name: Mendeley Data |
|                                | Data identification number: https://doi.org/10.17632/fbvvvf55kp.1 |
|                                | Direct URL to data: https://data.mendeley.com/datasets/fbvvvf55kp.1 |

Value of the Data

- The development of such a dataset is costly and time-consuming, as on-site investigations are necessary to verify manure application and to accurately select the plot. In addition, clouds and other problems, such as plots that are too small, must be filtered out.
- This dataset can be used to train machine learning models to automatically detect manured fields to analyze illegal fertilization or hot spots. This provides an opportunity for further research on this topic.
- Each plot has multiple images from different dates from before and after manure application. This offers the opportunity to investigate classification methods that benefit from temporal analysis. The differences in terrain depending on its date can be considerable, which adds a substantial amount of information to the status of the plot.
- The imagery contains the most relevant hyperspectral indices in the literature for precision agriculture and provides all 13 Sentinel-2 bands from which more hyperspectral indices can be created if needed.
- There is no other dataset of this type in the literature for this particular problem. Moreover, even if other datasets were created, this data would still be useful, as it belongs to a particular region and crop type which could be used to complete other datasets or to validate results.
1. Data Description

The dataset consists of three folders: the “src” folder, where all the code to generate the dataset is stored; the “groundtruth” folder, which contains an image mask for each plot; and the “imagery” folder which contains images with the satellite imagery raw bands and the calculated hyperspectral indices. The ground truth images are in “.png” format and follow a color code:

- White (255, 255, 255): Plot of interest
- Black (0,0,0): Other

The “imagery” folder contains a folder for each plot. Each plot folder contains another two folders, one for the images from before the application of manure and another one for the images from after manure application. Every image is in “.tif” format and has 64 channels. The order of the channels and how to calculate them can be found in the “Experimental design, materials and methods” section.

All the plots obtained for this dataset are pastures. This is because pasture is the predominant type of crop in this area of northern Spain. In most cases the grass is mowed prior to manure application. Although in some of the plots the manure is applied directly on the plowed land. This could prevent the trained models from confusing plowed lands and manure. Images of the plots have an area of about 1700 × 1700 m, although the plots inside the images are smaller. A total of 38 plots are studied.

Table 1 summarizes every plot of interest in the dataset, showing the date of manure application, area in square meters, number of available images for each plot from before and after manure application, its suitability for further studies, and its geographical coordinates. The plot identifier is composed of “P-” plus the abbreviation (using only the consonants) of the locality in which the plot is located. The area of the plots is calculated after generating the ground truth mask, where each Sentinel-2 pixel counts as 100 m². The suitability is assessed after studying the Sentinel-2 images of the plot in question. For example, if the region is extremely small, it is discarded.

Table 1
Dataset summary.

| Plot      | Date (YYYY/MM/dd) | Area (m²) | Available images (Before/After) | Suitable (Yes/No) | Geographical Coordinates (Long/Lat) |
|-----------|--------------------|-----------|---------------------------------|-------------------|-------------------------------------|
| P-BLD     | 2022/05/26         | 8900      | 2/1                             | Yes               | −4.2018 43.3973                   |
| P-BLIT1   | 2022/05/16         | 21,200    | 2/2                             | Yes               | −4.0840 43.4309                   |
| P-BLIT2   | 2022/05/26         | 3300      | 2/1                             | Yes               | −4.0840 43.4310                   |
| P-Cardana | 2022/02/24         | 6500      | 8/9                             | Yes               | 8.6580 45.8592                    |
| P-CBRC1   | 2022/05/26         | 6700      | 2/1                             | Yes               | −4.2005 43.3897                   |
| P-CBRC2   | 2022/05/26         | 6400      | 2/1                             | Yes               | −4.2041 43.3847                   |
| P-CLGT    | 2022/05/16         | 17,200    | 3/2                             | Yes               | −4.1096 43.3897                   |
| P-CLMBRS  | 2022/05/26         | 4300      | 3/1                             | Yes               | −4.5447 43.3804                   |
| P-CMNTR   | 2022/05/16         | 2600      | 1/2                             | Yes               | −4.1470 43.4001                   |
| P-DR      | 2022/03/21         | 2500      | 1/5                             | Yes               | −4.1424 43.3967                   |
| P-FNFR    | 2022/05/16         | 10,100    | 2/2                             | Yes               | −4.2657 43.3880                   |
| P-GLS     | 2022/04/30         | 7800      | 2/4                             | No (Clouds)       | −4.1452 43.3996                   |
| P-LLT     | 2022/05/03         | 9600      | 2/1                             | Yes               | −4.1515 43.4001                   |
| P-LNDRS1  | 2022/05/16         | 3200      | 2/2                             | Yes               | −4.2510 43.3880                   |
| P-LNDRS2  | 2022/05/16         | 5400      | 2/2                             | Yes               | −4.2503 43.3880                   |
| P-LNDRS3  | 2022/05/16         | 8500      | 2/2                             | Yes               | −4.2497 43.3872                   |
| P-LNDRS4  | 2022/05/16         | 9100      | 2/2                             | Yes               | −4.2467 43.3877                   |
| P-LNDRS5  | −                  | 5100      | 2/2                             | No (application date unclear) | −4.2435 43.3864 |
| P-MT      | 2022/05/04         | 19,900    | 2/1                             | Yes               | −4.1536 43.3980                   |
| P-NMS     | 2022/02/10         | 5500      | 2/1                             | Yes               | −4.1490 43.4003                   |

(continued on next page)
Table 1 (continued)

| Plot  | Date (YYYY/MM/dd) | Area (m²) | Available images (Before/After) | Suitable (Yes/No) | Geographical Coordinates (Long/Lat) |
|-------|-------------------|-----------|---------------------------------|-------------------|-------------------------------------|
| P-PQN | 2022/02/27        | 5300      | -/2                             | No. (Clouds)      | -4.1495 43.3991                     |
| P-PSG | 2022/04/06        | 5400      | 3/2                             | No. (Too narrow, partly fertilized) | -4.1411 43.3970                     |
| P-QNTLS1 | -              | 13,600   | 7/3                             | No (application date unclear) | -5.5830 43.5463                     |
| P-QNTLS2 | 2022/05/16      | 8500      | 7/3                             | Yes               | -5.5840 43.5458                     |
| P-SNTLLN | 2022/03/17      | 14,200    | 2/4                             | Yes               | -4.1170 43.3935                     |
| P-SNVCNT1 | 2022/05/16      | 6700      | 2/2                             | Yes               | -4.4048 43.3939                     |
| P-SNVCNT2 | 2022/05/16      | 29,200    | 2/2                             | Yes               | -4.4001 43.3945                     |
| P-STBN | 2022/05/04        | 11,300    | 3/1                             | Yes               | -4.1366 43.3960                     |
| P-TGL1 | -                | 28,000    | 2/1                             | No (application date unclear) | -4.0695 43.4216                     |
| P-TGL2 | 2022/05/16        | 12,300    | 2/2                             | Yes               | -4.0701 43.4276                     |
| P-TMSN | 2022/02/10        | 4700      | -                               | No (Clouds)       | -4.1519 43.3996                     |
| P-TNNS1 | 2022/05/26       | 19,500    | 2/1                             | Yes               | -4.1871 43.3999                     |
| P-TNNS2 | 2022/05/06        | 11,100    | 1/2                             | Yes               | -4.1918 43.3987                     |
| P-TPRN | 2022/04/06        | 1800      | 3/3                             | No. (Too narrow)  | -4.1390 43.3965                     |
| P-VG1  | 2022/04/09        | 12,200    | 3/6                             | Yes               | -5.4866 43.4699                     |
| P-VG2  | 2022/04/13        | 4900      | 4/5                             | Yes               | -5.4801 43.4693                     |
| P-VLDMR | 2022/02/07        | 17,500    | 2/2                             | Yes               | -4.1561 43.4056                     |
| P-VNS  | 2022/04/23        | 16,600    | 3/2                             | Yes               | -4.1504 43.4042                     |

The complete dataset consists of 31.48 ha for the plots of interest. Each pixel is 0.01 ha.

2. Experimental Design, Materials and Methods

The first indications of a newly manured plot are given by people living in the area or by Sentinel-2 imagery surveys. To label the plots, first, an on-site investigation is carried out to confirm that the plot has been fertilized with manure and to observe the real dimensions of the fertilization in the plot. Then, using Google Earth Engine, the plot is annotated according to the observed dimensions. An example of this process is shown in Fig. 1.

Google Earth Engine is also used to download the imagery with the script “download_imagery.js”. The plots are then exported as KML files and used to generate ground truth masks by taking advantage of the georeferenced Sentinel-2 imagery, as shown in Fig. 2. The script used to generate the ground truth masks from the KML files is called “generate_groundtruth.py”.

To generate the images of the dataset, the first 13 channels are obtained directly from the 13 bands of the Sentinel-2 images. Sentinel-2 has two satellites in its orbit (Sentinel-2A and Sentinel2B), where each one has an orbit of 10 days. Their orbits are at the greatest distance from each other, which is why the acquisition time of the images for the same region is around 5 days. Table 2 shows the wavelengths and bandwidths for each band in μm for S-2A and S-2B separately.

The remaining 51 channels of the images from the dataset are hyperspectral indices which are calculated as different combinations of the 13 Sentinel-2 raw bands. To obtain these hyperspectral indices, the general literature of precision agriculture for fertilizers using satellite imagery has been studied [1–9] and the most relevant hyperspectral indices have been obtained. The script necessary to generate the hyperspectral indices is called “calculate_indices.py”. Table 3 shows how to calculate each hyperspectral index and its channel number in the images.
Fig. 1. On-site investigation (left). Plot annotated in Google Earth Engine (right).

Fig. 2. Sentinel-2 georeferenced image (left). Generated ground truth (right).

To get an idea of the final images, an example of a visualization of one of the plots is shown. Fig. 3 shows at the left the total area of the image in RGB, and at the right, an enlarged version. Fig. 4 shows each of the 64 channels in a black and white color scale. To better visualize the plot, an enlarged version is shown in Fig. 5.
Table 2
Sentinel-2 bands (Sentinel2A and Sentinel2B).

| #  | Band                        | Central Wavelength (μm) | Bandwidth (μm) | Spatial resolution (m) |
|----|---------------------------|-------------------------|----------------|------------------------|
|    |                           | S-2A                    | S-2B           | S-2A                   | S-2B                   |                   |
| 0  | B01 Coastal aerosol       | 0.4427                  | 0.4422         | 0.021                  | 0.021                  | 60                |
| 1  | B02 Blue                  | 0.4924                  | 0.4921         | 0.066                  | 0.066                  | 10                |
| 2  | B03 Green                 | 0.5598                  | 0.5590         | 0.036                  | 0.036                  | 10                |
| 3  | B04 Red                   | 0.6646                  | 0.6649         | 0.031                  | 0.031                  | 10                |
| 4  | B05 VRE                   | 0.7041                  | 0.7038         | 0.015                  | 0.016                  | 20                |
| 5  | B06 VRE                   | 0.7405                  | 0.7391         | 0.015                  | 0.015                  | 20                |
| 6  | B07 VRE                   | 0.7828                  | 0.7797         | 0.020                  | 0.020                  | 20                |
| 7  | B08 NIR                   | 0.8328                  | 0.8329         | 0.106                  | 0.106                  | 10                |
| 8  | B08A Narrow Nir           | 0.8647                  | 0.8640         | 0.021                  | 0.022                  | 20                |
| 9  | B09 Water vapor           | 0.9451                  | 0.9432         | 0.020                  | 0.021                  | 60                |
| 10 | B10 SWIR Cirrus           | 1.3735                  | 1.3769         | 0.031                  | 0.030                  | 60                |
| 11 | B11 WIR                   | 1.6137                  | 1.6104         | 0.091                  | 0.094                  | 20                |
| 12 | B12 SWIR                  | 2.2024                  | 2.1857         | 0.175                  | 0.185                  | 20                |

Table 3
Hyperspectral indices.

| #  | Abb. | Name                                               | Description |
|----|------|----------------------------------------------------|-------------|
| 13 | NDVI | Normalized Difference Vegetation Index             | R08 − R04 \( \times 1.428 \) |
| 14 | NSNDVI | NIR-SWIR Normalized Difference Vegetation Index | \( \frac{\text{B11} - \text{B07}}{\text{B11} + \text{B07}} \) |
| 15 | SDI  | Swir Difference Index                              | B08 − B12  |
| 16 | GNDVI | Green Normalized Difference Vegetation Index       | \( \frac{\text{B08} - \text{B03}}{\text{B08} + \text{B03}} \) |
| 17 | SAVI | Soil Adjusted Vegetation Index                     | \( \frac{\text{B08} - \text{B04}}{\text{B08} + \text{B04} + 0.428 \times 1.428} \) |
| 18 | OSAVI | Optimized Soil Adjusted Vegetation Index           | \( \frac{\text{B08} - \text{B04}}{\text{B08} + \text{B04} + 0.428 \times 1.428} \) |
| 19 | EOMI1 | Exogenous Organic Matter Index 1                   | \( \frac{\text{B11} - \text{B08}}{\text{B11} + \text{B08}} \) |
| 20 | EOMI2 | Exogenous Organic Matter Index 2                   | \( \frac{\text{B12} - \text{B04}}{\text{B12} + \text{B04}} \) |
| 21 | EOMI3 | Exogenous Organic Matter Index 3                   | \( \frac{\text{B08} - \text{B12}}{\text{B08} + \text{B12}} \) |
| 22 | EOMI4 | Exogenous Organic Matter Index 4                   | \( \frac{\text{B11} - \text{B04}}{\text{B11} + \text{B04}} \) |
| 23 | BNR2 | Normalized Burn Ratio 2                            | \( \frac{\text{B08} - \text{B12}}{\text{B08} + \text{B12}} \) |
| 24 | RVI  | Ratio Vegetation Index                             | \( \frac{\text{B08} - \text{B04}}{\text{B08} + \text{B04}} \) |
| 25 | DVI  | Difference Vegetation Index                        | \( \frac{\text{B08} - \text{B04}}{\text{B08} + \text{B04}} \) |
| 26 | RENDVI1 | Red Edge Normalized Difference Vegetation Index | \( \frac{\text{B08} - \text{B04}}{\text{B08} + \text{B04}} \) |
| 27 | RENDVI2 | Red Edge Normalized Difference Vegetation Index | Same as RENDVI1, but uses B06 instead of B05 |
| 28 | RENDVI3 | Red Edge Normalized Difference Vegetation Index | Same as RENDVI1, but uses B07 instead of B05 |
| 29 | C11 | Chlorophyll Index                                 | \( \frac{\text{B08}}{\text{B08} + 1} \) |
| 30 | C12 | Chlorophyll Index                                 | Same as C11, but uses B06 instead of B05 |
| 31 | C13 | Chlorophyll Index                                 | Same as C11, but uses B07 instead of B05 |
| 32 | NDRE | Normalized Difference Red Edge                    | \( \frac{\text{B08} - \text{B05}}{\text{B08} + \text{B05}} \) |

(continued on next page)
| #  | Abb.   | Name                                                                 | Description                                                                                     |
|----|--------|----------------------------------------------------------------------|-------------------------------------------------------------------------------------------------|
| 33 | MCARI  | Modified Chlorophyll Absorption in Reflectance Index                 | $(B05 - B04) - 0.2 \times (B05 - B03) \times \frac{B05}{B04}$                                  |
| 34 | MCARI1 | Modified Chlorophyll Absorption in Reflectance Index 1               | $1.2 \times (2.5 \times (B08 - B04) - 1.3 \times (B08 - B03))$                                 |
| 35 | MCARI2 | Modified Chlorophyll Absorption in Reflectance Index 2               | $1.5 \times \sqrt{2.5 \times (B08 - B04) - 1.3 \times (B08 - B03)} - 6 \times B08 - 5 \times \sqrt{B04} - 0.5$ |
| 36 | MTVI1  | Modified Triangular Vegetation Index 1                               | $1.2 \times (B08 - B03) - 2.5 \times (B04 - B03)$                                              |
| 37 | MTVI2  | Modified Triangular Vegetation Index 2                               | $1.5 \times \sqrt{2.5 \times (B08 - B04) - 1.3 \times (B08 - B03)} - 6 \times B08 - 5 \times \sqrt{B04} - 0.5$ |
| 38 | EVI    | Enhanced Vegetation Index                                           | $(B08 * (1 - B04)) \times (B08 - B04)$                                                        |
| 39 | AVI    | Advanced Vegetation Index                                           | $(B08 * (1 - B04)) \times (B08 - B04)^{1/3}$                                                   |
| 40 | GCI    | Green Coverage Index                                                | $\frac{B09}{B10} - 1$                                                                        |
| 41 | BSI    | Bare Soil Index                                                     | $B11 + B04 + \frac{B08 + B02}{B11 + B04} + B08 + B02$                                         |
| 42 | NBR1   | Normalized Burned Ratio Index                                        | $\frac{B08 - B17}{B08 + B17}$                                                                 |
| 43 | NDRE1  | Normalized Difference Red Edge                                      | Same as NDRE1, but uses B06 instead of B05                                                     |
| 44 | NDRE2  | Normalized Difference Red Edge                                      | Same as NDRE1, but uses B07 instead of B05                                                     |
| 45 | NDRE3  | Normalized Difference Red Edge                                      | $\frac{(2.0 \times B08 + 1 - \sqrt{120.0 \times B08 + 10.0^2} - 8 \times (B08 - B04))}{2}$ |
| 46 | MSAVI  | Modified Soil Adjusted Vegetation Index                              | $\frac{B08 + B04 - 0.069 \times (B04 - B02)}{B04 - B04 - 0.069 \times (B04 - B02)}$            |
| 47 | WDRVI  | Wide Dynamic Range Vegetation Index                                  | $0.1 \times B08 - B04$                                                                         |
| 48 | ARVI1  | Atmospherically Resistant Vegetation Index 1                         | $0.01 \times B08 - B04$                                                                        |
| 49 | ARVI2  | Atmospherically Resistant Vegetation Index 2                         | $0.00 \times B08 - B04$                                                                        |
| 50 | TSAVI  | Transformed Soil Adjusted Vegetation Index                           | $\frac{0.421 + (B08 - 0.421 \times B04 - 0.824)}{B08 - 0.421 \times (B08 - 0.824) + 0.14 + \sqrt{1 + 0.421^2}}$ |
| 51 | CARI1  | Chlorophyll Absorption Ratio Index 1                                 | $(B05 - B03) / 150 + B04 + 0.486 \times B03) / (B05 / B04)$                                    |
| 52 | CARI2  | Chlorophyll Absorption Ratio Index 2                                 | $(B05 - B03) / 150 + B04 + 0.486 \times B03) / (B05 / B04)$                                    |
| 53 | CVI    | Chlorophyll Vegetation Index                                         | $\frac{B08 + B04}{B04}$                                                                       |
| 54 | EVI1   | Enhanced Vegetation Index 1                                          | $2.5 \times (B08 - B04)$                                                                       |
| 55 | EVI2   | Enhanced Vegetation Index 2                                          | $2.4 \times \frac{B08 + B04}{B08 + B04} + B04$                                              |
| 56 | EVI3   | Enhanced Vegetation Index 3                                          | $2.5 \times \frac{B08 + B04}{B08 + B04} + B04$                                              |
| 57 | SCI    | Soil Composition Index                                              | $\frac{(B11 - B09)}{B11 + B09}$                                                                |
| 58 | GRNDVI | Green-Red Normalized Difference Vegetation Index                     | $\frac{B08 - B03 (B04)}{B08 + B03 + B04}$                                                     |
| 59 | GBNDVI | Green-Blue Normalized Difference Vegetation Index                    | $\frac{B08 - B03 (B02)}{B08 + B03 + B02}$                                                     |
| 60 | GLI    | Green Leaf Index                                                     | $\frac{2 \times B03 - B04 - B02}{(B08 - B04) - 0.03}$                                          |
| 61 | ATSAVI | Adjusted Transformed Soil-Adjusted Vegetation Index                  | $\frac{(B08 - B03) / (B04 + B03))}{0.5}$                                                       |
| 62 | ALTERATION | Alteration Index                                      | $\frac{B08 - B04}{B08 + B04} \times 0.5$                                                      |
| 63 | CTVI   | Corrected Transformed Vegetation Index                               | $\frac{B08 - B04}{B08 + B04} \times 0.5$                                                      |
**Fig. 3.** Sentinel-2 image of a manured plot. Total area of the image plot (left). Enlarged plot (right).

**Fig. 4.** Example of the 64 channels, including raw band and computed indices.
Fig. 5. Example of the 64 channels, including raw bands and computed indices. (Enlarged plot).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Satellite imagery dataset of manure application on pasture fields (Original data) (Mendeley Data).

CRediT Author Statement

Oscar D. Pedrayes: Conceptualization, Methodology, Software, Visualization, Investigation, Writing – original draft; Rubén Usamentiaga: Data curation, Supervision, Validation, Writing – review & editing.
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