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FAIR degree assessment in agriculture datasets using the F-UJI tool

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ABSTRACT

For the agricultural scientific community, data sharing is crucial both for the advancement of the discipline and ability to meet global challenges, such as the target no. 2, i.e., “Zero Hunger,” of the Sustainable Development Goals (SDG 2030). In this context, FAIR (Findable, Accessible, Interoperable and Reusable) principles play an important role, as they guarantee the *findability, accessibility, interoperability*, and *reusability* of shared data. To improve the practice of data sharing, institutions, funders, and publishers are increasingly demanding data be shared as well as be of an acceptable level of quality, including compliance with FAIR principles. Therefore, the objective of this work is twofold: first, this research aims to determine the degree of compliance with the FAIR principles exhibited by a number of datasets; and second, it aims to explore useful and valid methodologies and procedures that can be used to perform this evaluation quickly, automatically, and effectively. For this purpose, the Data Citation Index (DCI) was used to obtain many datasets in the field of agriculture, which were further grouped by repositories and evaluated using the automated assessment tool F-UJI provided by the FAIRsFAIR project. The results indicated that the principle that exhibited the highest scores was “Findable”, while “Reusable” received the lowest scores, as none of the analysed repositories achieved a 50% compliance score in this respect. The datasets published in the Zenodo and Dryad repositories exhibited better overall results in terms of the FAIR principles, and the AG Commons repository was the third best rated repository, representing only one of the first three repositories belonging to the agricultural sector. Regarding the use of F-UJI as an automated assessment tool and DCI as a source for obtaining datasets, we conclude that this methodology is useful, and that although it can be improved, it is easy to use and implement by other scientific groups and agents of interest.

1. Introduction

The use of open data in research and practices has been consolidated and improved over the past two decades in various scientific fields (Quay et al., 2022). In the case of agriculture, data sharing has become increasingly prevalent in response to the needs and demands of the sector (Top et al., 2022). These needs and demands are based on the high complexity of a sector, such as agri-food, the success of which depends on a sustainable supply of healthy and nutritious food for the nine billion people expected to exist in 2050 among other factors, while simultaneously addressing issues, such as climate change and land degradation (Top et al., 2022). In other areas of science, such as genetics (Schatz et al., 2022) and space (Scott et al., 2020), the rapid development of data sharing in agriculture and food systems is key to the digitalisation of knowledge (Laurin et al., 2021; Mey et al., 2019; Restrepo et al., 2022). In addition, the promotion of data sharing in agricultural research is necessary in the broad context of the Sustainable Development Goals, specifically regarding meeting the second goal, i.e., “Zero Hunger”. This goal directly alludes to advances in research and technological development services that can improve agricultural productive capacity in developing countries, particularly in the least developed countries (United Nations, 2022).

The FAIR principles constitute one of the best collective efforts made in recent years to promote the openness and appropriate sharing of research data. These principles, designed in 2016 by a group of researchers, institutions, and publishers, seek to generate a guide for good

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Table 1
Assessment targets within each principle (Devaraju et al., 2020).

Fair principles	Targets
Findable	Object identification
	Descriptive core metadata
	Inclusion of data identifiers and data content descriptors
	Searchable metadata
Accessible	Data accessibility
	Metadata preservation
Interoperable	Semantic interoperability
	Linked related resources
Reusable	Data usage license
	Provenance of data creation
	Community-endorsed metadata
	Community file formats

```
▾ root:
   metric_specification: "https://doi.org/10.5281/zenodo.4081213"
   metric_version: "metrics_v0.4.yaml"
 ▾ request:
     metadata_service_endpoint: null
     metadata_service_type: null
     normalized_object_identifier: "10.5281/ZENODO.4264713"
     oaipmh_endpoint: null
     object_identifier: "http://dx.doi.org/10.5281/ZENODO.4264713"
     test_debug: true
     use_datacite: true
 ▸ results: [] 16 items
   software_version: "1.4.9b"
 ▾ summary:
   ▸ maturity:
   ▸ score_earned:
   ▸ score_percent:
   ▸ score_total:
   ▸ status_passed:
   ▸ status_total:
   test_id: "b0c98b951c3375ea2f4aa68f0f7714a588a9140e"
   timestamp: "2022-06-09T12:55:07Z"
   total_metrics: 16
```


Fig. 1. Example of a JSON file created automatically after evaluation of a dataset using F-UJI.

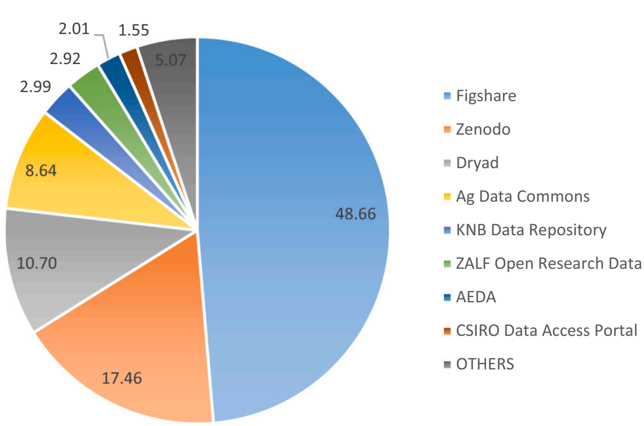

Fig. 2. Percentage of repositories where the datasets were deposited.

practices to ensure that data sharing has real utility (Wilkinson et al., 2016). As their publication in the scientific field, the FAIR principles have served as a breakthrough in open data management, best practices, and the impetus to make digital objects from different sources (such as science, public administration, private sector) available to society (Peters-Von Gehlen et al., 2022). According to Quay et al. (2022), FAIR principles and Open Science are two milestones that are relevant to all disciplines and have revolutionised the concepts of scientific data storage and management. However, FAIR principles are aspirational in the sense that they do not strictly define how to achieve the ideal state of FAIRness, but rather describe a series of instructions, attributes, and behaviours that can help researchers achieve this goal (Wilkinson et al., 2019). These principles are not incremental; some criteria can be satisfied regardless of whether others are satisfied. Despite their rapid acceptance as concepts in the community, it is important to investigate how these principles can be adjusted to a particular domain.

With regard to this adaptation of FAIR principles to concrete realities and specific fields, such as agriculture, various studies have contributed to and provided ideas (Ali and Dahlhaus, 2022; Pommier et al., 2019; Wise et al., 2019). One such contribution is a recently published study by Ali and Dahlhaus (2022), who conducted a systematic review of the role of FAIR principles in sustainable agriculture. This review highlights the advantages of applying these principles to the data generated by the field of agriculture, but also indicates that only a few studies have addressed the practical application of these principles. Among the studies that have attempted to apply FAIR principles in the context of agriculture, a study by Pommier et al. (2019) described application of FAIR principles in the field of plant genomics through the creation and maintenance of the GnpIS repository. This repository was designed to store and disseminate a genomic data archive that complies with FAIR principles in terms of metadata traceability and dataset citability, in accordance with Open Science recommendations. Another example is the work of Wise et al. (2019) on the benefits of FAIR for research and development in the biopharmaceutical industry and other life sciences, such as biomedical, environmental, agricultural, and food sciences. According to these studies, industry investment in following the FAIR principles could be a differentiating factor with respect to how data are exploited both internally and externally by other actors. Additionally, one line of research that promotes the advantages of FAIR principles and highlighted the shortcomings pertaining to their application is the work of Kinkade and Shepherd (2021) on the publication of geoscience data. Among the primary conclusions of these authors are claims that the principles must be reconsidered and the metrics that demonstrate their compliance should be developed to determine the FAIRness of a digital object.

In line with the requirements highlighted by Kinkade and Shepherd (2021), several tools have been developed based on a series of metrics that can be used to assess the compliance of a dataset with FAIR principles. These tools pursue the same objective of evaluating the degree of FAIRness of a dataset but employ different methodologies. In general, these tools can be divided into three groups as automatic, manual, and hybrid tools (Peters-Von Gehlen et al., 2022; Sun et al., 2022). According to Peters-Von Gehlen et al. (2022), none of the three models are perfect; however, each offers certain advantages. Manual approximations capture contextual approximations that are more subjective, whereas automatic approximations are stricter in terms of the aspects of the analysis conducted by the machine. More difficulties are encountered in the context of automatic evaluation, and the search for alternatives is urgent. One response to this need is the development of automatic tools for the management of datasets and the assessment of compliance with FAIR principles. One such tool is F-UJI, whose acronym includes the components "F" for FAIR and "UJI" for "Test" (in Malay), which was created as part of the FAIRsFAIR project. According to its creators, the goal of the F-UJI is to evaluate FAIRness beyond the level of an object (dataset) itself (Devaraju and Huber, 2021b). For this purpose, it is important that, as in Huber et al. (2021), all components of the data ecosystem (ranging from the datasets to the accompanying metadata and the repositories that host them) are prepared for machine readability, because F-UJI's automated testing relies heavily on the clarity and evaluability of these criteria in computing environments by any person or group. One of the most valuable contributions of the F-UJI is that it has been made available to the scientific community as an open-source tool that can be used to evaluate a large number of datasets

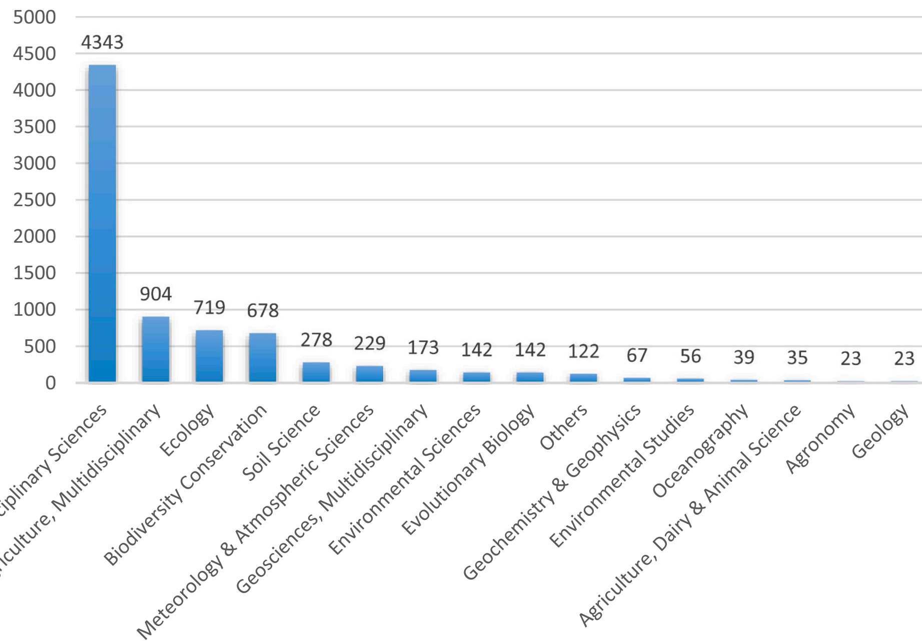

Fig. 3. Number of datasets per top 15 WOS categories.

Table 2
Number of records per content type[a].

Content type	Total	%
Dataset*	3433	54,6
Data study**	2768	44
Software***	87	1,4

[a] A description of the different types of content can be found at https://researchguides.drake.edu/ld.php?content_id=58803678.
[*] Dataset: A single or coherent set of data (or a data file) provided by the repository as part of a collection, data study, or experiment. These can be of multiple file formats such as spreadsheet, video, and audio. Datasets may have cited references or can be citable, but more commonly they inherit metadata of the overall study.
[**] Data study: A description of studies or experiments held in repositories with the associated data used in the data study. These are linked to a repository and may optionally link to a dataset relating to the more granular data files. Data studies can be a citable object in the literature and may have cited references attached in their metadata together with information on such aspects as the principal investigators, funding information, subject terms and geographic coverage.
[***] Software: A single software object provided by the repository, such as a piece of source code, a model, or a complete application. Software may have cited references or can be citable.

simultaneously (Devaraju and Huber, 2021b). This functionality offers interesting possibilities in a context where compliance with FAIR principles is becoming increasingly important (Devaraju et al., 2021). In the near future, the requirements for data sharing by institutions, funders, and publishers will not merely be that the data are shared but that they are minimally findable, accessible, interoperable, and reusable as found in many countries and institutions (Coalition for Advancing Research Assessment (CoARA), 2022; National Institutes of Health, 2023; Sales et al., 2020; Wiseman et al., 2018). In the European context, the "Agreement on Research Assessment Reform" was recently published by the Coalition for the Advancement of Research Assessment (CoARA) at the end of 2022; which was signed by more than four hundred institutions (Coalition for Advancing Research Assessment (CoARA), 2022) and highlights the particular importance of open science in general, open research data in particular, and the FAIR principles as a guarantor of research quality and transparency. Similar trends have also been observed in other contexts such as the new data management and sharing policy of the National Institutes of Health in the United States (National Institutes of Health, 2023), the explicit commitment of the Brazilian government to data science and FAIR principles (Sales et al., 2020), and the Australian government's commitment to integrating FAIR principles into a national agricultural data governance framework (Wiseman et al., 2018).

Regarding the relevance of finding automatic FAIRness evaluation tools that can respond to the needs and demands associated with FAIR research data, we found some studies in which such tools, including the F-UJI, have been used (Peters-Von Gehlen et al., 2022; Sofi-Mahmudi and Raittio, 2022; Sun et al., 2022). In these studies, FAIRness evaluation tools have been used to test a small number of datasets on a specific topic (Sofi-Mahmudi and Raittio, 2022) or at a generic level without focusing on a specific area (Peters-Von Gehlen et al., 2022; Sun et al., 2022). However, the following research gaps have been identified:

1. Studies that have jointly addressed FAIR principles and agriculture or related areas focus on very specific examples are difficult to replicate or extrapolate to other contexts.
2. However, the methodologies of some studies mention the use of tools, such as the F-UJI to analyse datasets drawn from a specific scientific area. These studies employed this approach only for small datasets.

Table 3
Number of records by type of content in the eight major repositories.

Content type	Figshare	Zenodo	Dryad	Ag data commons	KNB data repository	ZALF open research data	AEDA	CSIRO
Dataset	292	1009	674	547	189	185	127	98
Data study	2759	2	3	0	0	1	0	0
Software	0	82	0	0	0	0	0	0

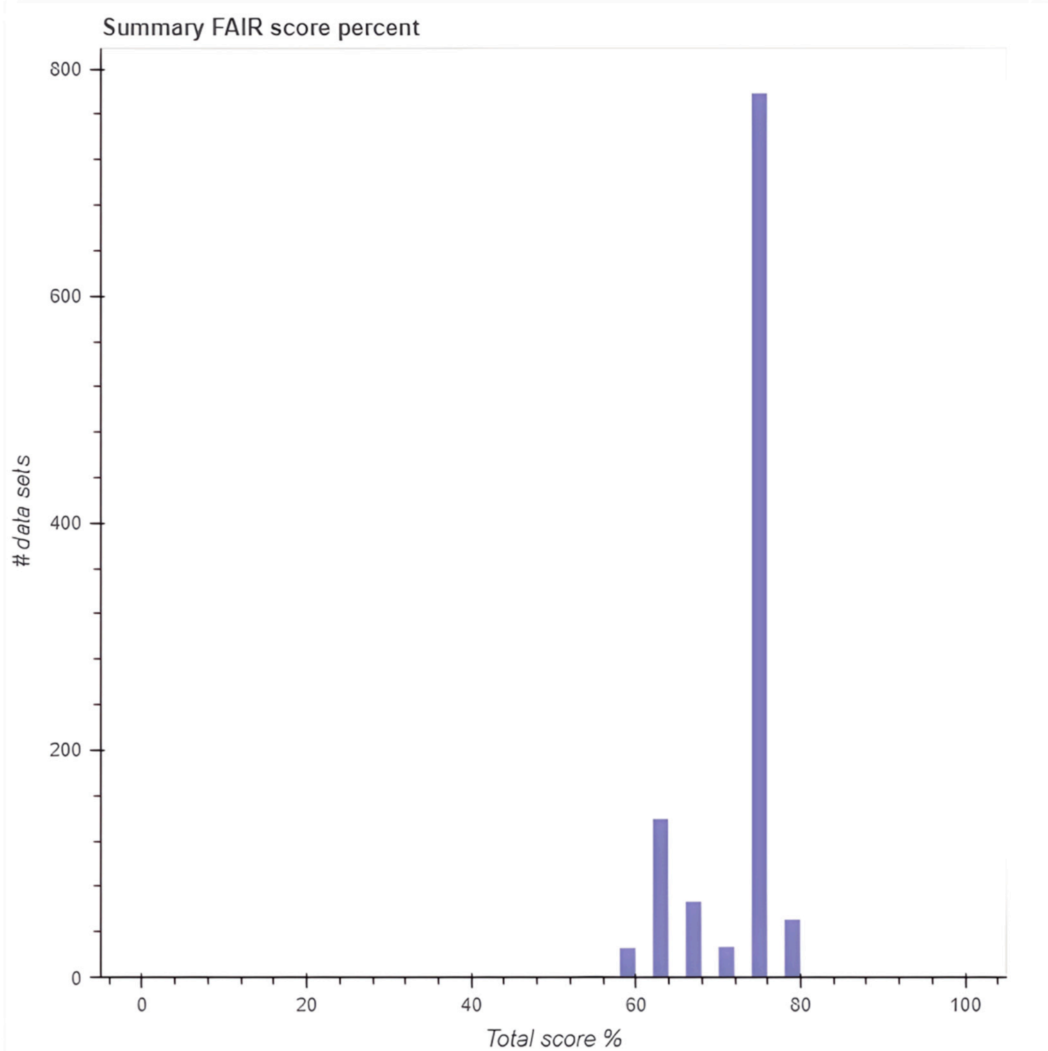

Fig. 4. Percentage of the overall score obtained by Zenodo's datasets.

3. Whether in agriculture or any other specific area, no research has used F-UJI to evaluate compliance with FAIR principles with respect to a large number of datasets or to specify the source of the data.

Therefore, the goal of this study was to analyse the degree to which datasets in the agricultural area comply with FAIR principles using the Data Citation Index of the Web of Science (Clarivate Analytics) for dataset retrieval and F-UJI as an automatic FAIR assessment tool based on the open-source information provided by its creators.

2. Methods

The methodology used in this study consisted of three stages.

2.1. Capture of datasets on agriculture

The datasets were obtained through the Data Citation Index (DCI), a resource offered by the Clarivate company and included in the Web of Science (further WoS) catalogue. The DCI provides access to a large number of descriptive records on datasets obtained through partnerships with repositories, large-scale data, and metadata providers. The DCI provides more than 80 different types of data (i.e., image, sequence data, geoscientific and audio-visual information), all of which were included in our study. The strength of this resource is that it provides an overview that is difficult to achieve when datasets or repositories are viewed in isolation (Clarivate Analytics, 2017).

The following search equation was used to retrieve datasets on agriculture in the DCI:

$$\begin{aligned} \text{TI } (title) &= \text{Agriculture OR AK } (author\ keywords) \\ &= \text{Agriculture OR SU } (subject\ category) = \text{Agriculture} \end{aligned}$$

2.2. Downloading the records

The following variables were imported for each record:1) type of content (dataset, data study, software, or repository), 2) data source (the source from which the data were obtained), and 3) Web of Science category of the data source (i.e. multidisciplinary agriculture, ecology, biodiversity conservation, and environmental sciences).

The bibliographic information collected using the DCI for each record includes authors/creators, year of publication (the collected records were published from 1900 to the present), title of the dataset, publisher (understood as the repository in which the data are deposited or the organisation responsible for making the data available), version, and permanent identifier (e.g. a unique URL, databank accession number, or another permanent identifier such as Handle (hdl) (http://www.handle.net/)).

A total of 7507 records (datasets) were downloaded from the DCI in the .txt format and processed using the Bibliometricos software. Nine

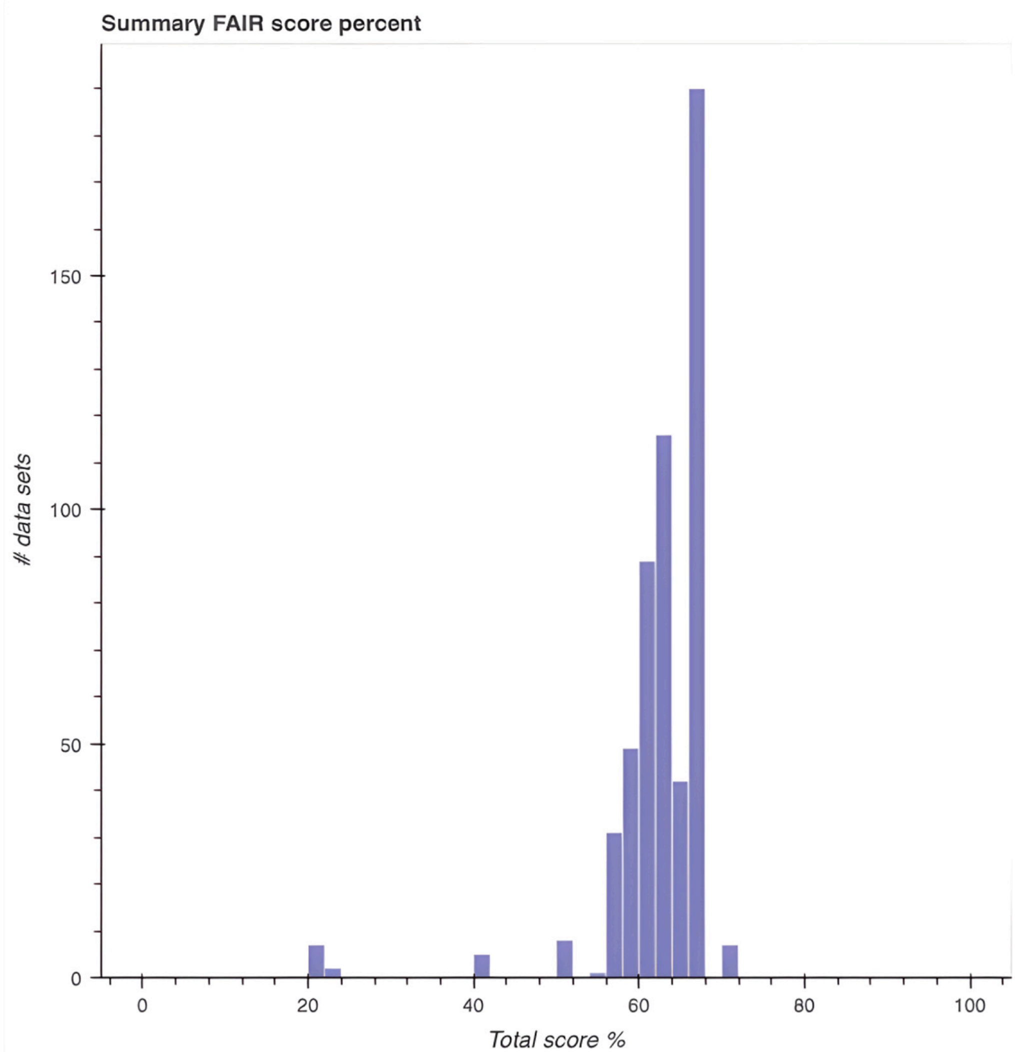

Fig. 5. Percentage of the overall score obtained by Ag Data Commons' datasets.

duplicate records were identified and eliminated, resulting in 7498 records. Subsequently, these 7498 records were transferred to and organised in a relational database.

Of these 7498 records, 1169 did not include a digital object identifier (DOI) as a unique identifier; therefore, they were excluded from the database. The remaining 6288 records were identified as the overall sample referenced in this study (84.4% of the total number of records).

2.3. FAIR evaluation of datasets using the F-UJI tool

The FAIR evaluation performed using the F-UJI tool was based on aggregated metadata, including metadata embedded in the landing page and metadata retrieved from a PID (Persistent Identifier). F-UJI considers the following schemes to be PIDs: Handle, Persistent Uniform Resource Locator, Archival Resource Key, Permanent Identifier for Web Applications, and DOI (Sun et al., 2022).

The assessment of datasets using the F-UJI focused on several generic cross-domain metadata standards, such as those proposed by Dublin Core, DCAT, DataCite, and Schema.org (Devaraju et al., 2020). The results of these evaluations provided various scores regarding the data and dataset metadata based on 16 metrics distributed across four principles: five metrics for findable, three for accessible, three for interoperable, and five for reusable. Each of these metrics has been described in detail by Devaraju et al. (2020) (Table 1).

F-UJI is a REST (Representational state transfer) API[1] service that uses the OpenAPI specification.[2] The tool is open-source and falls under the MIT License, which makes it possible to install the service by downloading it from GitHub (Devaraju and Huber, 2021a).

As discussed before, F-UJI can be used in two ways:

1. The online application offers an intuitive summary of the FAIR aspects of the evaluated data objects (PID). However, resources can be evaluated manually by inserting only one PID.
2. The tool can be installed locally, and a Python script can be executed to realise API calls in the loop for each PID in the queue. Thus, F-UJI can compile a large number of datasets (the script can be found on GitHub published by the FAIRsFAIR project).

Thus, we used the second approach to perform a massive evaluation featuring many datasets (5967 PIDs).

[1] REST API is a software architectural style that describes the architecture of the Web.

[2] OpenAPI Specification (OAS) defines a standard, programming language-agnostic interface description for HTTP APIs.

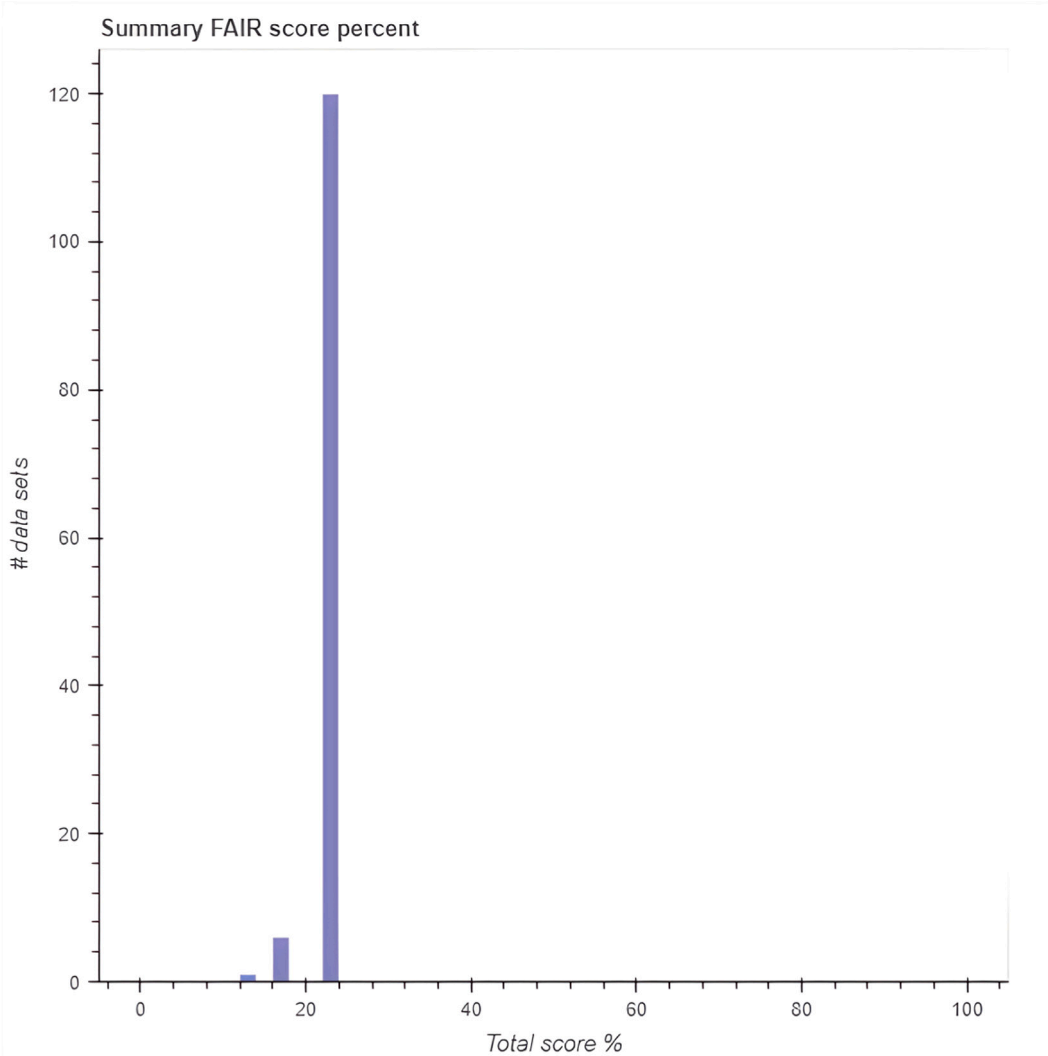

Fig. 6. Percentage of the overall score obtained by AEDA's datasets.

After compilation, the tool produces JSON files for each PID that contain the assessment results. These files include scores, practical tests, inputs/outputs, and assessment contexts for each of the 16 metrics (see the demo of the tool in FAIRsFAIR, 2020).

Fig. 1 shows an extract from a JSON file that includes the identifier number, metric name with results (output), evaluation score, debugging messages, and a summary of all metrics in the evaluation. Finally, to visualize the scores after compiling all the PIDs, we created a report by running a computational notebook (. ipynb document) provided by the FAIRsFAIR team (Devaraju and Huber, 2021a). This notebook provides an overall analysis and visualisation of all PID responses assessed using the F-UJI.

In summary, a) the report reads JSON's responses, b) collects all the total scores for the FAIR metric within a data frame, and c) visualises the metrics and summarises the evaluations (in our case, the datasets associated with each repository). The characteristics of the report are discussed in the Section 3.

For further analysis, two aspects of the findings of this study were considered.

1. The overall repository score considers the results obtained from the datasets for all principles.
2. Scores obtained by each repository with respect to the four principles separately.

3. Results

3.1. Results obtained from the DCI

Of the 6288 valid records included in the sample, 5962 (94.81%) corresponded to the period from 2013 to 2022, with 2014 being the year with the highest productivity. Regarding data sources, 30 different repositories were observed (Fig. 2).

Of the 11,162 distinct authors identified, 11 had more than 100 published datasets, with the most productive author being Ignazio Carbone ($n = 177$), a professor at North Carolina State University working in the areas of evolutionary biology, molecular population genetics, and genomics. In terms of the number of citations received, 3277 records received at least one citation, accounting for 52.1% of the total citations. Of these, 15 received five or more citations. The most frequently cited dataset, i.e., "Dr. Duke's Phytochemical and Ethnobotanical Databases", received 17 citations; this dataset was deposited in the "Ag Data Commons" repository in 2016, was of the type "dataset" and fell within the WoS category "agriculture, multidisciplinary". This dataset can be accessed at the following DOI: https://data.nal.usda.gov/dataset/dr-dukes-phytochemical-and-ethnobotanical-databases.

A total of 41 different subject categories were identified, the most notable of which were "multidisciplinary sciences" (54.47%), "agriculture, multidisciplinary" (11.34%), "ecology" (9.02%), and "biodiversity conservation" (8.5%) (Fig. 3).

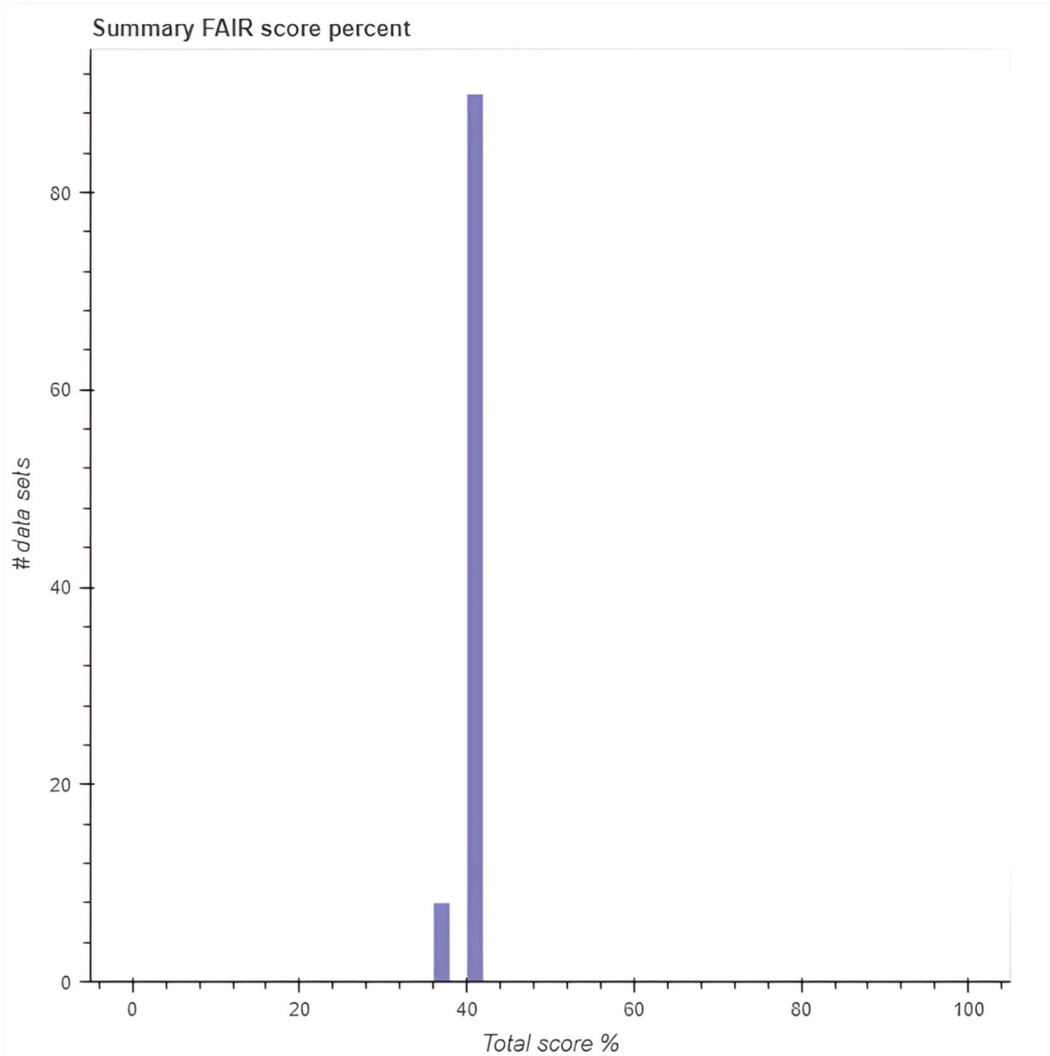

Fig. 7. Percentage of the overall score obtained by CSIRO's datasets.

Three typologies were discovered, of which the most frequent was "dataset" (54.43%) (Table 2).

To evaluate the datasets using F-UJI, the datasets were divided into the top eight repositories based on the number of datasets deposited (Fig. 2). The number of datasets deposited in these eight repositories accounted for 94.9% of the total number of datasets, which was considered sufficiently representative. Of these eight repositories, four were general repositories, i.e., Figshare (https://figshare.com/), Zenodo (https://zenodo.org/), Dryad (https://datadryad.org/stash), and CSIRO (https://data.csiro.au/), and four were thematic repositories, i.e., Ag Data Commons (https://data.nal.usda.gov/), KNB Data Repository (https://knb.ecoinformatics.org/), ZALF Open Research Data (https://open-research-data.zalf.de/default.aspx), and Agricultural and Environmental Data Archive (AEDA) (http://www.environmentdata.org/). The content distributions of the top eight repositories by content type are presented in Table 3.

3.2. Results of the FAIR assessment of the datasets selected by the F-UJI tool

The results obtained using the F-UJI tool were based on the 16 metrics described previously, which were established in the FAIRsFAIR project and distributed among four principles.

Following the analysis of each group of repositories using this tool, we passed the results through a computational notebook report, ultimately obtaining visualisations of the summaries of each FAIR principle for all eight repositories.

The report itself contained two sections:

1. ***"Read jsons responses"*** creates a data frame that includes all scores obtained for each of the 16 metrics,
2. ***"Visualize different FAIR metrics"*** creates a histogram plot of the results that includes visualisations of each principle and the overall FAIR score, as shown below (Figs. 4–11).

Our simulation provided an approximate illustration of the information obtained using automated tools. The charts (Figs. 4–11) obtained from the reports represent the FAIR scores of the 5,967 data objects tested, which were divided primarily by repositories (Table 4).

This study focused on summary scores per principle and the overall FAIR score. However, the information provided in this report is highly complex. Our research dataset is published in the Figshare repository (Petrosyan et al., 2022), from which all research results of the experimental analysis and simulation are available (including the JSON files from F-UJI and files from reports).

The results obtained from each repository based on the aspects analysed are described in detail in (Table 4). Figs. 4–11 show the graphs of the overall scores obtained from each repository. The vertical axis represents the number of objects tested, and the horizontal axis indicates the FAIR scores of the datasets. The FAIR scores ranged from 100%

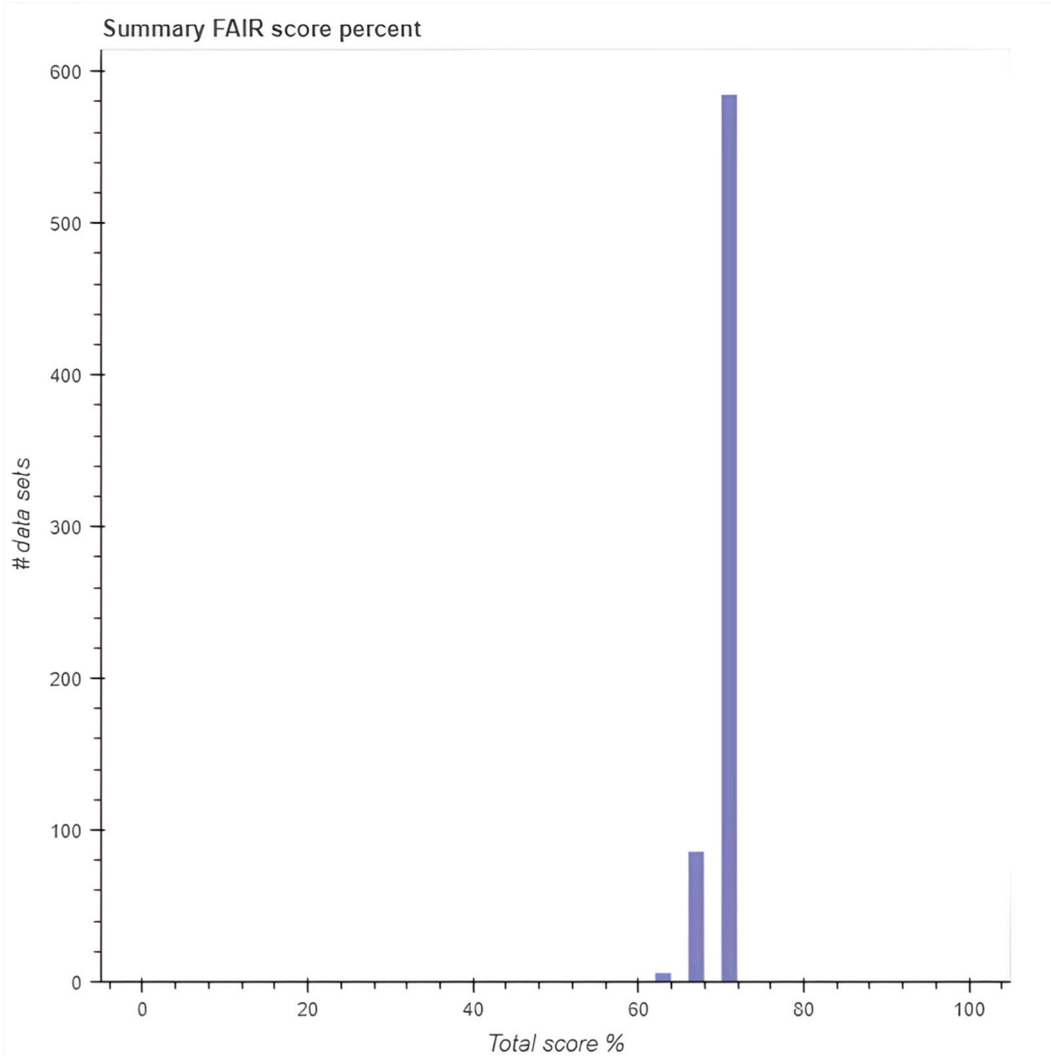

Fig. 8. Percentage of the overall score obtained by Dryad's datasets.

(highest) to zero (lowest). According to Devaraju and Huber (2021a), when analysing the results, a score of 50% or above is considered to indicate an average level of FAIRness, whereas a score of 80% or above is considered exceptional.

It is important to note that the results for each repository, both overall and for each FAIR principle, were averages of the evaluation of each repository's datasets.

Overall, of the eight repositories analysed, four were above 50% overall compliance with the FAIR principles, and four were below. Of these, two were of the generalist type (Zenodo and Dryad) and two were of the specific type (Ag Data Commons and ZALF Open Research Data). Of those scoring lower, one was a generalist (Figshare) and one was specific to agricultural areas (AEDA).

When the data were considered in principle, Dryad, Zenodo, Ag Data Commons, and ZALF Open Research Data (in that order) also obtained the best scores in findability, with Dryad, Zenodo, and Ag Data Commons scoring over 90. All repositories had approximately 50% compliance with this principle, which had the highest scores in the overall calculation.

Regarding the principle of accessibility, Zenodo, Ag Data Commons, and Dryad stood out once again, with the latter obtaining 100%, the only perfect score of all the percentages collected. However, none of the other five repositories obtained more than 50% scores for this principle, and the scores did not exceed 35% in any case.

Regarding the principle of interoperability, Zenodo, Ag Data Commons and Dryad achieved more than 50% compliance, followed by CSIRO Data Access Portal, which scores 47.95%. This was the first principle in which two repositories achieved less than 10% compliance.

The reusability principle is the only one of the four in which no repository exceeds 50% compliance, and only Zenodo could achieve 49%. It is also the only principle by which two repositories failed to reach 1%, with one (AEDA) achieving 0%.

Several observations related to the types of DOIs belonging to Figshare were detected during testing with F-UJI. In this case, it was necessary to split the database into three parts because, when testing the database, the F-UJI server was blocked by a large number of REST requests (3051). Thus, it was observed that within Figshare, there are several types of DOIs that belong to third parties, that is, data deposited in Figshare, but with a DOI indicating another origin. FigShare contains 63 datasets (or DOIs) of its own origin and 2988 datasets of different origins. Among these different origins, 2939 have a DOI referring to the journal PLOS ONE. Considering these peculiarities, the 63 datasets belonging to Figshare showed much higher FAIRness scores, both globally and for each principle, than those of the third parties (Table 5).

4. Discussion

This study made it possible to obtain many datasets for agricultural

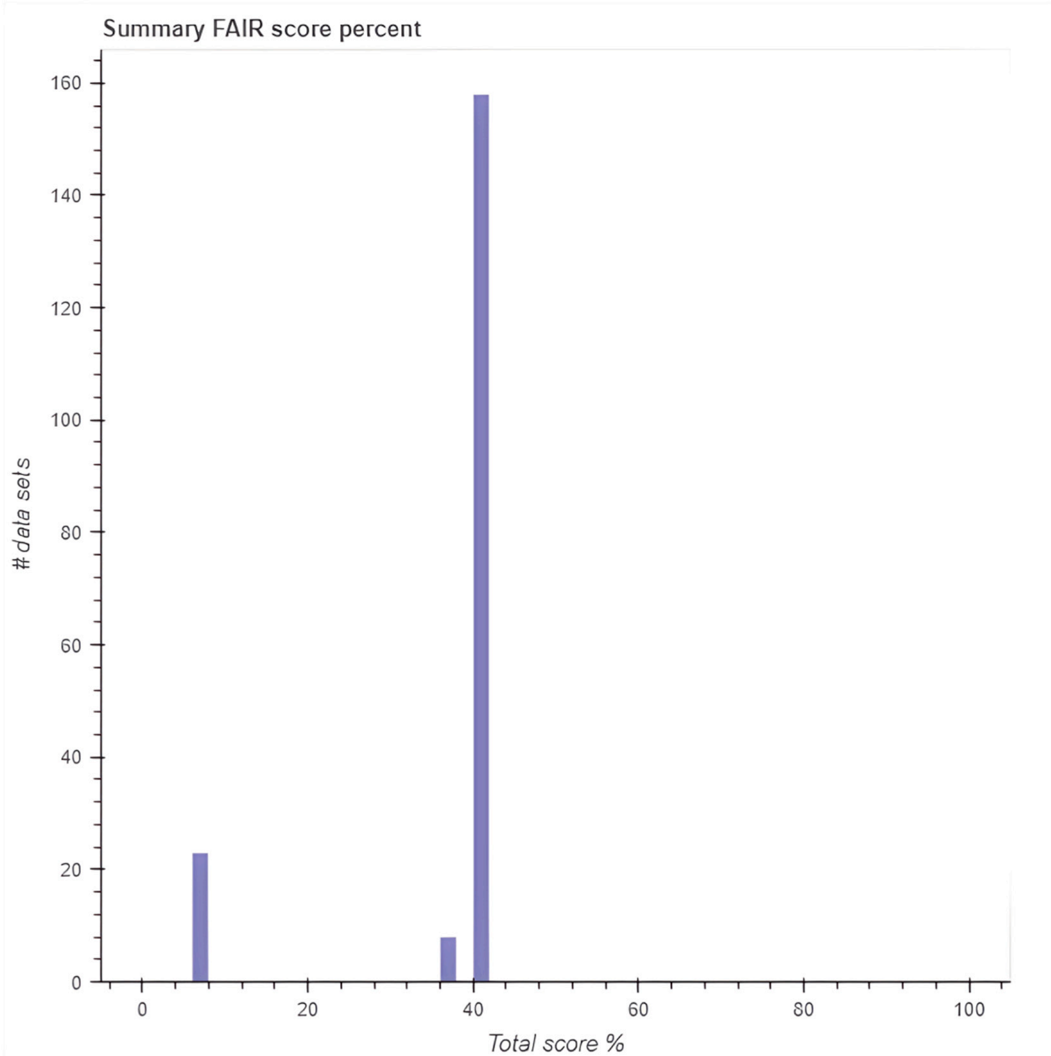

Fig. 9. Percentage of the overall score obtained by KNB's datasets.

areas, which could then be analysed using the F-UJI tool to assess their FAIRness through a unique identifier.

The results of this study allowed for an approximation of the possibilities of the DCI to obtain information on the characteristics of data in agricultural areas. These characteristics provided information on topics such as the origins of the data (the sources), disciplines from which they came, most productive authors, typologies, and degrees of FAIRness. For analysis, the results were divided into two parts: 1) primary characteristics of the datasets obtained through the search equation in the DCI, and 2) the FAIRness analysis of these datasets using the F-UJI tool. Similar differentiation has been used for the discussion.

In the first part, we obtained an overview of the data published in the agricultural sector over the considered period, with the most productive period being from 2013 to 2022. The fact that this was the most productive period may provide a double explanation. On the one hand, it has been in the last decade that the practice of data sharing has gained the most momentum, with important milestones occurring, such as the publication of the FAIR principles in 2016 (Wilkinson et al., 2016) and creation of the DCI in 2012 in response to the growing demand for tools to facilitate data and metadata management (Clarivate Analytics, 2017). Specifically in the field of agriculture, it was in 2013 that the GODAN initiative was announced at the Open Government Partnership Conference, following the 2012 G8 discussions, where the leaders in attendance committed to the New Alliance for Food Security and Nutrition (Global Open Data for Agriculture and Nutrition, 2019). Among GODAN's major objectives is the precise promotion of a data ecosystem within the agri-food sector that reflects the needs and complexities of all stakeholders, from the farmer to the final consumer, and provides information that can support decision-making. According to this organisation, 14 types of data, including geographic, meteorological, and market data, are required by the agricultural sector. These types of data were grouped into the following sections: 1) legislation and administration data; 2) data on natural resources, land, and the environment; 3) agronomic and agricultural technology data; and 4) socioeconomic data (Global Open Data for Agriculture and Nutrition, 2019).

Regarding the WOS categories to which the data belong, with the exception of "multidisciplinary sciences" because of its broad coverage, the second category in terms of the amount of data is "agriculture, multidisciplinary", which is directly related to the field of agriculture. If we focus on the following categories, the most common are those that are traditionally identified with the practice of data sharing, such as those related to ecology and the environment or meteorology (Berghmans et al., 2017; Nature Communications, 2018; Sieber, 2015).

Regarding the sources of data, of the 30 repositories detected, the most frequent were Figshare, Zenodo, and Dryad, all of which were considered multidisciplinary or generalist. There are several possible explanations for this observation. Within the context of data sharing, these three repositories have a long history, making them more

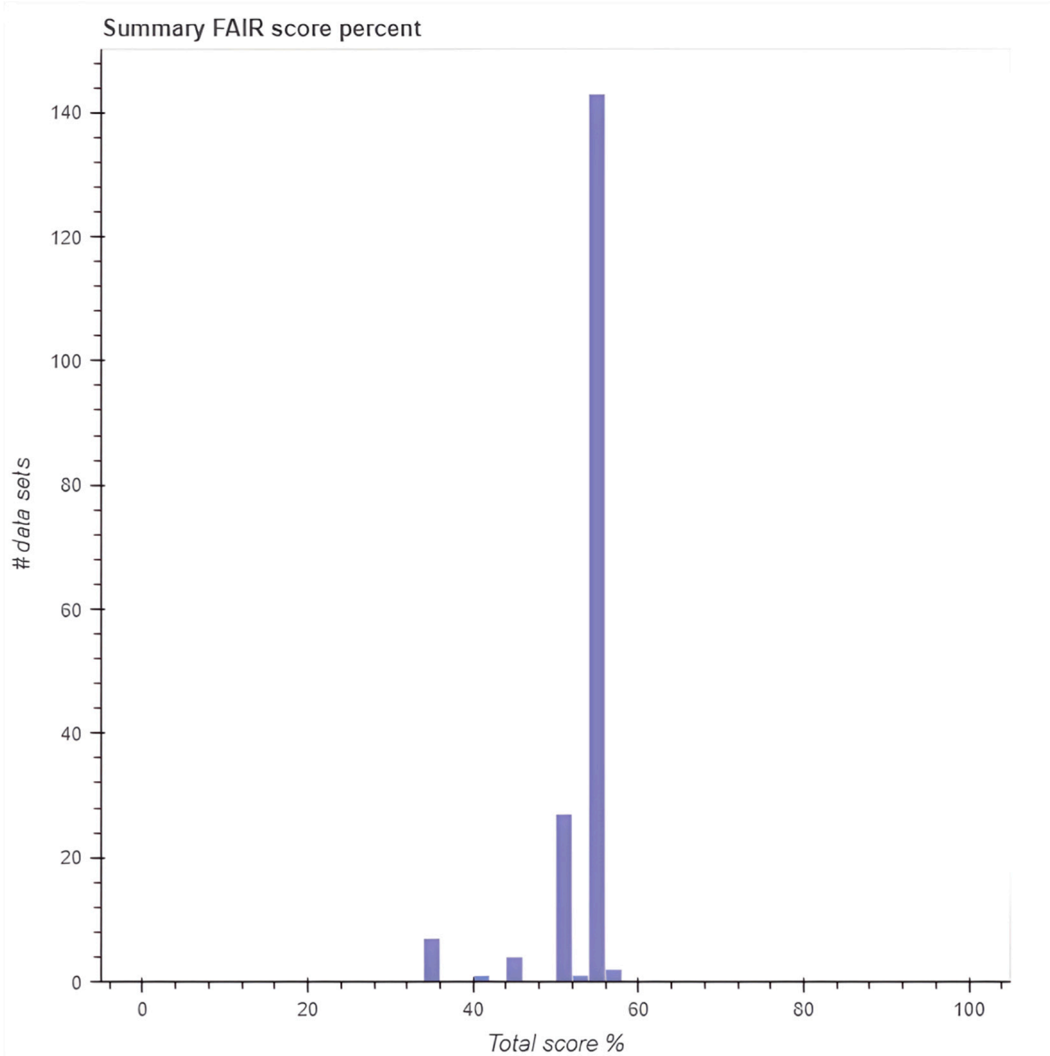

Fig. 10. Percentage of the overall score obtained by ZALF's datasets.

accessible and recognisable (Enis, 2013; Hansson and Dahlgren, 2022; He and Han, 2017; Sicilia et al., 2017). All three are open access, and in the case of Figshare and Zenodo, they are free to both readers and authors who deposit their data. Zenodo is also the reference repository of the European Union, supported by the OpenAIRE initiative, and a reference for numerous projects in the European context (Sicilia et al., 2017). Figshare and Dryad have important partnerships with publishers, institutions, and other organisations. Dryad is also the only repository among the top 8 that includes a data curation service prior to publication through a system called "Dryad's Data Publishing Charges (DPCs)" (Dryad, 2023). The top eight repositories selected by the authors to deposit their data were thematic or institutional. Of these, the one with the largest representation was the Ag Data Commons, an institutional data repository belonging to the United States Department of Agriculture, which was created to support the agricultural research community in sharing and discovering data (United States Departament of Agriculture, 2023). Among thematic repositories, the most frequent of the top eight was the Knowledge Network for Biocomplexity (KNB), an international repository aimed at facilitating ecological and environmental research. There are different opinions in the literature regarding the usefulness of using generalist, thematic, or institutional repositories and the advantages of one or the other.

Generally, while the thematic repositories have the positive aspect of focusing on a specific area and potentially limit the entry of data that do not correspond to that area, the generalist repositories are better known and have much wider coverage (Abadal, 2012). On the other hand, a report by the FAIRsharing initiative, which published a series of recommendations that repositories must meet to be considered a valid infrastructure for hosting and disseminating research data, focused only on generalist and discipline-specific data repositories, excluding institutional repositories because they are less global in nature (Sansone et al., 2020). However, this report was harshly criticised by the Confederation of Open Access Repositories (COAR) because, among other reasons, institutional repositories were left out and claimed that globality was being prioritised and local quality initiatives were being left out (Confederation of Open Access Repositories, 2021).

Regarding the FAIRness analysis of the datasets, these were "packaged" in the eight most frequently used repositories to be analysed in F-UJI. In other words, the results were differentiated by the repository. The generalist repositories, Zenodo and Dryad, were not only among the most frequently used but also those that obtained the best scores at a general level. Next, to obtain an overall score above 50%, the institutional repository Ag Data Commons and thematic repository ZALF Open Research Data were identified as two repositories worth highlighting in the agricultural area, at least in terms of FAIRness.

Regarding the scores per principle and considering the document published by FAIRsFAIR (Devaraju et al., 2020) which specifies what exactly is evaluated in the metrics, the level of compliance in the content of the eight selected repositories was similar to the alphabetical order of the principles themselves, with findable being the most compliant and

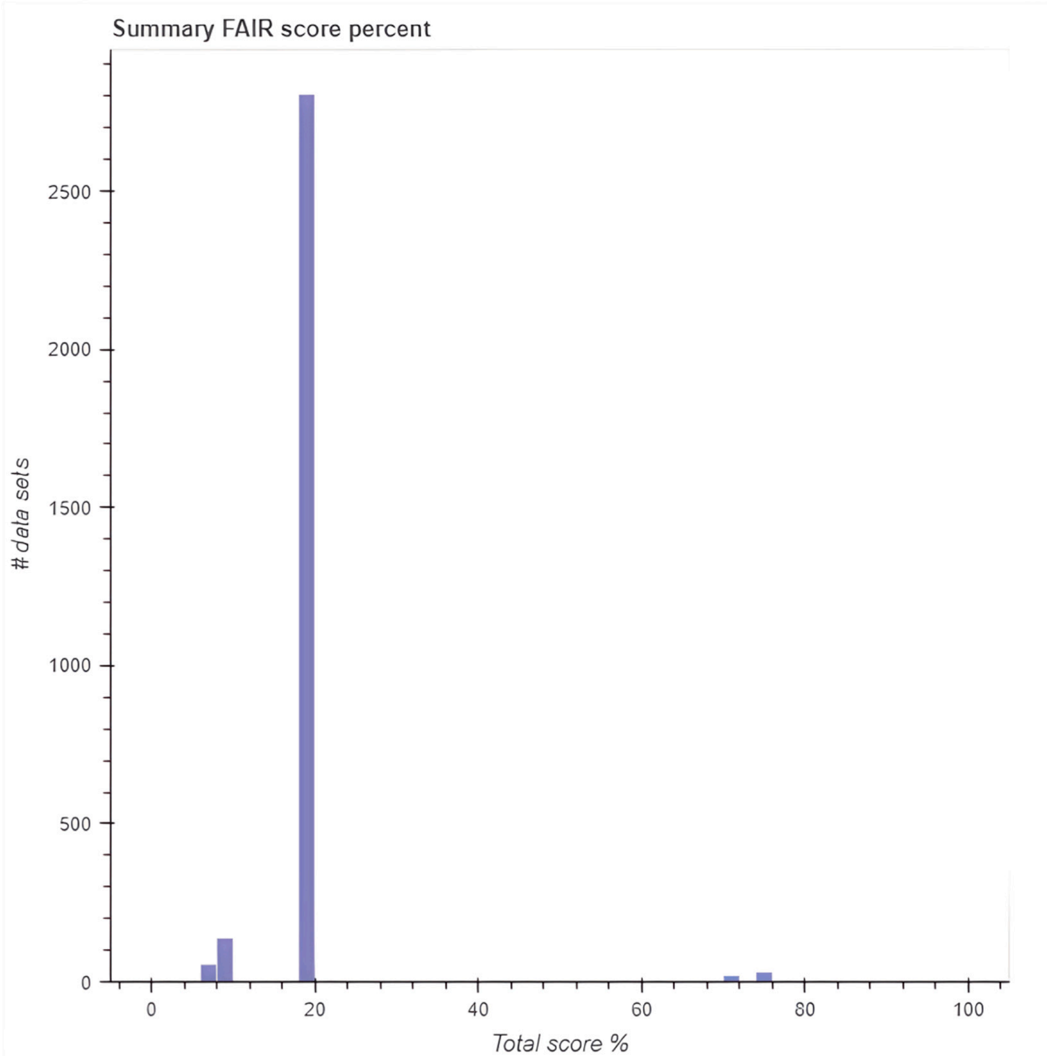

Fig. 11. Percentage of the overall score obtained by Figshare's datasets, including third parties.

Table 4
List of all repositories tested by F-UJI and their results for each FAIR principle and overall.

Repositories	Analized DOIS (num)	Total fair %	F	A	I	R
FIGSHARE	3051	18,96	49,35	31,77	1,18	0,96
ZENODO	1093	72,5	96,12	92,74	74,7	49
DRYAD	677	70,22	99,6	100	71,97	40
AG DATA COMMONS	547	62,1	91,7	64,7	52,4	44,35
KNB Data Repository	189	37,18	77,2	29,27	22,08	17,56
ZALF Open Research Data	185	52,61	83,81	33,6	45	40
AEDA	127	22,54	49,6	31	9,92	0
CSIRO Data Access Portal	98	41,32	71,4	33,3	47,95	20

Table 5
Figshare repository results: the datasets were divided into two groups because of a huge FAIR rating gap by F-UJI

Figshare	Analized DOIS (num)	Total fair %	F	A	I	R
PLOS ONE & other resources	2939	18,1	48,6	31,31	0	0
Figshare	63	60,6	85,03	54	57,53	46,7

reusable the least compliant. Although for each principle there were also repositories that scored higher than others, with Zenodo, Dryad, and Ag Data Commons again the best scorers, the degradation observed from findable to reusable was observed in all repositories. Translated to the content metrics, while data and metadata reached a minimum level of identifiable and basic descriptive elements (creator, title, data identifier, publisher), it was challenging to ensure that data and metadata were accessible through a standardised protocol or that metadata continued to be available even when the data were no longer available.

Regarding interoperability, there is a huge potential for improvement, such as representing metadata using a formal knowledge representation language, using semantic resources, or establishing links between data and related entities. Finally, the principle of reusability deserves special mention, as no repository reached 50%. Suggesting that considering the sample analysed, we are still far from adequately addressing aspects such as whether the metadata truly specify the content of the data, whether they include information on licences, or whether both the data and metadata use standards and formats recommended by the scientific discipline to which they belong.

The results obtained in relation to the four FAIR principles agreed with the study conducted by Huber et al. (2021), with the goal of analysing the state-of-the-art integration and data analysis approaches implemented by world-leading research infrastructures in the earth system and environmental sciences, including some of the repositories analysed in our work. They concluded that, although data repositories have generally made the deposited data searchable by researchers, it is particularly difficult for machines with the current resources offered by these platforms. In general, they stated that although the data were often persistently identified, as we also observed, the way to proceed with them was designed for navigation and manual processing, which is typically challenging or impossible for machines. This fact is particularly relevant regarding interoperability and, above all, reusability in areas such as agriculture and related fields, where integrated data from one or more sources must be transferred to a computational environment that is suitable for analysis.

Another aspect is the type of content, according to the differentiation made by the DCI between the dataset, data study, and software. In general, most records are classified as either data studies or datasets, with software being much more residual. Although the top eight repositories contained few records that were not datasets, the case of Figshare was different. In this repository, which was also the most used, 90.52% of the records were of the data study type. Subsequently, when analysing the DOI of each repository through F-UJI, we found that the vast majority of the data study records belonged to papers published in this journal (PLOS One, 2019). In the subsequent F-UJI analysis, Figshare obtained very low scores when PLOS ONE DOI was isolated from the remainder. This phenomenon illustrates the need to understand the differences between the different typologies of materials that can exist in the DCI and in the repositories to which it connects. The definition of the DCI itself states that the resource "provides a single point of access to quality research data from global repositories across disciplines" (Clarivate Analytics, 2022). While it is true that research data take many forms, are handled in many ways, use many approaches, and are often difficult to interpret once removed from their initial context, it is also true that, in theory, their ultimate purpose when shared is to allow research to be replicated or verified and to allow others to ask new questions about existing data (Borgman, 2012). However, Figshare records from PLOS ONE, which are considered data studies, scored so low on the F-UJI that one might suspect that they are not research data, but other types of supplementary materials that are not intended to meet FAIR principles.

5. Limitations

This study had certain limitations. First, DCI, a useful resource that provides access to more than 400 repositories and several million datasets, data studies, and software, was used to capture information on agricultural data. However, it is not a source that covers the entire universe of currently published agricultural data. Additionally, some repositories were not integrated into the DCI and may have been excluded from the analysis. Additionally, we used only the unique identifiers of the data object in the DOI format, excluding other unique identifiers. Although it is true that identifiers in the DOI format comprised the majority (84.4%), in future studies, we could consider including other identifiers and checking how the F-UJI responds to them.

6. Conclusions

From a general perspective, the implications of this study are relevant to any field of science, particularly agriculture and ecology, both of which are highly interrelated. In the spirit of coming to a full circle, we began the introduction to this paper by discussing the importance of data and the practice of sharing it to meet global goals such as Zero Hunger. However, there is no advantage in sharing data without addressing data quality. For this reason, it is necessary to continue developing metrics such as the one proposed by F-UJI and methodologies such as the one proposed in this study that favour not only the availability of data but also that they are really useful to use, share, and reuse.

Regarding F-UJI, as mentioned by its creators, it is a continuously developing tool. Automatic testing of research data objects is based on the FAIR ecosystem, and its success depends on automatic testing with clear criteria that can be evaluated using machines.

Using F-UJI and conducting this study was possible because its creators made the code necessary to evaluate a large number of datasets quickly and automatically available to the scientific community, without having to enter each identifier individually. Therefore, we were able to install our own server using the latest version of the code available on GitHub. In this way, compliance with the FAIR principles of 6288 datasets related to the agricultural field was evaluated, and the results indicated that, from highest to lowest, compliance with the principles followed the same alphabetical order as the principles themselves, with findability being the highest rated and reusability the lowest. None of the repositories analysed reached 50% of the score for the reusability principle; therefore, it is important to investigate the causes of this low score and, at the same time, seek mechanisms for improvement. Finally, the datasets published in the Zenodo and Dryad repositories had the best results in terms of the FAIR principles, with Ag Data Commons (an institutional repository in the agricultural area) being rated third-best.

Regarding the audiences to whom this work could be of interest, it is worth highlighting the professionals behind the repositories and other dataset management and maintenance resources (including the WoS DCI) as it can guide them along the lines of improvement in compliance with the FAIR principles. In addition, it is relevant to the research staff, for whom the use of tools, such as the F-UJI, can provide guidance on compliance with the four principles in the datasets that they handle on a daily basis. Finally, software developers, both those behind F-UJI and others who are exploring similar lines of evaluation of FAIR principles, can provide an example of a specific case of the use of this type of tool and detect possible shortcomings and options for improvement.

In conclusion, as a concrete proposal for F-UJI, additional documentation on the use of the tool is valuable when installing the server. Although it had a vast description of the metrics used, a more precise documentation of the code was missing. Regarding proposals for future work, we believe that it would be interesting to address two main points.

First, the methodology proposed in this study, which combines the process of obtaining datasets and their subsequent evaluation, can be used to investigate the degree of FAIRness of datasets in disciplines other than agriculture. This would allow comparisons to be made between areas of science and to understand the current scope of FAIR principles six years after their creation. On the other hand, it would be interesting to further apply the proposed methodology and artificial intelligence models such as neural network techniques (or self-organising maps (SOMs)) (Van Hulle, 2012) to the database already evaluated by the F-UJI to obtain a classification of the established clusters and detect patterns in the results. Second, this study did not explore the differences between the different types of data (image, sequential data, geoscientific information, audiovisual) in terms of the level of FAIRness. However, it could be interesting to address this issue in future studies to determine whether there would be a greater or lesser degree of compliance depending on the type of material.

Credit authorship contribution statement

Luiza Petrosyan and Andrea Sixto-Costoya: conception and design of study, acquisition of data, analysis and/or interpretation of data, and writing—original draft.

Juan Carlos Valderrama-Zurián, Rafael Aleixandre-Benavent, Antonia Ferrer-Sapena, and Fernanda Peset: conception and design of the

study and writing—review and editing.

Declaration of Competing Interest

The authors declare that they have no competing financial interests or personal relationships that may have influenced the results of this study.

Data availability

The raw data used for this study are available through the following link: https://doi.org/10.6084/m9.figshare.21558930.v2

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References

Abadal, E., 2012. Acceso abierto a la ciencia. Editorial UOC.
Ali, B., Dahlhaus, P., 2022. The role of FAIR data towards sustainable agricultural performance: a systematic literature review. Agriculture 12 (2). https://doi.org/10.3390/agriculture12020309.
Berghmans, S., Cousijn, H., Deakin, G., Meijer, I., Mulligan, A., Plume, A., Rijcke, S., Rushforth, A., Tatum, C.T., van Leeuwen, T., Ludo, W., 2017. Open Data: The Researcher Perspective. https://doi.org/10.17632/bwrnfb4bvh.1.
Borgman, C., 2012. The conundrum of sharing research data. J. Am. Soc. Inf. Sci. Technol. 63 (6), 1059–1078. https://doi.org/10.1002/asi.
Clarivate Analytics, 2017. Recommended Practices to Promote Scholarly Data Citation and Tracking (The role of Data Citation Index).
Clarivate Analytics, 2022. Data Citation Index. https://clarivate.com/webofsciencegroup/solutions/webofscience-data-citation-index/.
Coalition for Advancing Research Assessment (CoARA), 2022. Agreement on Reforming Research Assessment (Issue July). https://coara.eu/app/uploads/2022/09/2022_07_19_rra_agreement_final.pdf.
Confederation of Open Access Repositories, 2021. Input to "Data Repository Selection: Criteria that Matter.". https://www.coar-repositories.org/news-updates/input-to-data-repository-selection-criteria-that-matter/#:~:text=Data. Repository Selection: Criteria that Matter are a,repositories, generalist data repositories and institutional repositories.
Devaraju, A., Huber, R., 2021a. F-UJI - An Automated FAIR Data Assessment Tool. [Computer Software]. https://github.com/pangaea-data-publisher/fuji.
Devaraju, A., Huber, R., 2021b. An automated solution for measuring the progress toward FAIR research data. Patterns 2 (11). https://doi.org/10.1016/J.PATTER.2021.100370.
Devaraju, A., Huber, R., Mokrane, M., Herterich, P., Cepinskas, L., de Vries, J., L'Hours, H., Davidson, J., White, A., 2020. FAIRsFAIR Data Object Assessment Metrics. Zenodo. October. https://zenodo.org/record/4081213. October.
Devaraju, A., Mokrane, M., Cepinskas, L., Huber, R., Herterich, P., De Vries, J., Akerman, V., L'hours, H., Davidson, J., Diepenbroek, M., 2021. From conceptualization to implementation: fair assessment of research data objects. Data Sci. J. 20 (1), 1–14. https://doi.org/10.5334/dsj-2021-004.
Dryad, 2023. Frequently Asked Questions. https://datadryad.org/stash/faq#cost.
Enis, M., 2013. Figshare debuts repository platform. Libr. J. 138 (16), 21–22.
FAIRsFAIR, 2020. F-UJI DEMO: An Automated Assessment Tool for Improving the FAIRness of Research Data. https://youtu.be/VIIixieZWck?t=786.
Global Open Data for Agriculture and Nutrition, 2019. Agriculture. https://www.godan.info/pages/agriculture.
Hansson, K., Dahlgren, A., 2022. Open research data repositories: practices, norms, and metadata for sharing images. J. Assoc. Inf. Sci. Technol. 73 (2), 303–316. https://doi.org/10.1002/asi.24571.
He, L., Han, Z., 2017. Do usage counts of scientific data make sense? An investigation of the Dryad repository. Library Hi Tech 35 (2), 332–342. https://doi.org/10.1108/LHT-12-2016-0158.
Huber, R., D'Onofrio, C., Devaraju, A., Klump, J., Loescher, H.W., Kindermann, S., Guru, S., Grant, M., Morris, B., Wyborn, L., Evans, B., Goldfarb, D., Genazzio, M.A., Ren, X., Magagna, B., Thiemann, H., Stocker, M., 2021. Integrating data and analysis technologies within leading environmental research infrastructures: challenges and approaches. Ecol. Inform. 61 (February), 101245 https://doi.org/10.1016/j.ecoinf.2021.101245.
Kinkade, D., Shepherd, A., 2021. Geoscience data publication: practices and perspectives on enabling the FAIR guiding principles. Geosci. Data J. 9 (1), 177–186. https://doi.org/10.1002/gdj3.120.
Laurin, G.V., Francini, S., Luti, T., Chirici, G., Pirotti, F., Papale, D., 2021. Satellite open data to monitor forest damage caused by extreme climate-induced events: a case study of the Vaia storm in northern Italy. Forestry 94 (3), 407–416. https://doi.org/10.1093/forestry/cpaa043.
Mey, L., Ayala, L.M., Lokers, R., 2019. Open Data Impact Narratives Stories of Impact of Open Data in Agriculture and Nutrition (Issue March). https://doi.org/10.7490/f1000research.1117566.1.
National Institutes of Health, 2023. Data Management & Sharing Policy Overview. https://sharing.nih.gov/data-management-and-sharing-policy/about-data-management-and-sharing-policies/data-management-and-sharing-policy-overview.
Nature Communications, 2018. Data sharing and the future of science. Nat. Commun. 9 (1), 9–10. https://doi.org/10.1038/s41467-018-05227-z.
Peters-Von Gehlen, K., Höck, H., Fast, A., Heydebreck, D., Lammert, A., Thiemann, H., 2022. Recommendations for discipline-specific FAIRness evaluation derived from applying an ensemble of evaluation tools. Data Sci. J. 21 (1), 1–21. https://doi.org/10.5334/dsj-2022-007.
Petrosyan, L., Peset, F., Ferrer, A., Aleixandre-Benavent, R., Valderrama-Zurián, J.C., Sixto-Costoya, A., 2022. Dataset of the paper entitled "FAIR degree assessment in agriculture datasets using the F-UJI tool". Figshare. https://doi.org/10.6084/m9.figshare.21558930.v2.
PLOS One, 2019. Data Availability. https://journals.plos.org/plosone/s/data-availability.
Pommier, C., Michotey, C., Cornut, G., Roumet, P., Duchêne, E., Flores, R., Lebreton, A., Alaux, M., Durand, S., Kimmel, E., Letellier, T., Merceron, G., Laine, M., Guerche, C., Loaec, M., Steinbach, D., Laporte, M.A., Arnaud, E., Quesneville, H., Adam-Blondon, A.F., 2019. Applying FAIR principles to plant phenotypic data management in GnpIS. Plant Phenom. 2019 https://doi.org/10.34133/2019/1671403.
Quay, A.N., Fiske, P.S., Mauter, M.S., 2022. Recommendations for advancing FAIR and open data standards in the water treatment community. ACS ES&T Eng. 2 (3), 337–346. https://doi.org/10.1021/acsestengg.1c00245.
Restrepo, D.S., Pérez, L.E., López, D.M., Vargas-Cañas, R., Osorio-Valencia, J.S., 2022. Multi-dimensional dataset of open data and satellite images for characterization of food security and nutrition. Front. Nutrition 8 (January), 1–13. https://doi.org/10.3389/fnut.2021.796082.
Sales, L., Henning, P., Veiga, V., Costa, M.M., Sayão, L.F., da Santos, L.O.B.S., Pires, L.F., 2020. Go fair brazil: a challenge for brazilian data science. Data Intellig. 2 (1–2), 238–245. https://doi.org/10.1162/dint_a_00046.
Sansone, S.A., McQuilton, P., Cousijn, H., Cannon, M., Chan, W.M., Callaghan, S., Carnevale, I., Cranston, I., Edmunds, S., Everitt, N., Ganley, E., Graf, C., Hrynaszkiewicz, I., Khodiyar, V., Leary, A., Lemberger, T., MacCallum, C., McNeice, K., Murray, H., Threlfall, J., 2020. Data repository selection: criteria that matter. Zenodo. https://doi.org/10.5281/zenodo.4084762.
Schatz, M.C., Philippakis, A.A., Afgan, E., Banks, E., Carey, V.J., Carroll, R.J., Culotti, A., Ellrott, K., Goecks, J., Grossman, R.L., Hall, I.M., Hansen, K.D., Lawson, J., Leek, J. T., Luria, A.O., Mosher, S., Morgan, M., Nekrutenko, A., O'Connor, B.D., Walker, J., 2022. Inverting the model of genomics data sharing with the NHGRI genomic data science analysis, visualization, and informatics lab-space. Cell Genom. 2 (1), 100085 https://doi.org/10.1016/j.xgen.2021.100085.
Scott, R.T., Grigorev, K., Mackintosh, G., Gebre, S.G., Mason, C.E., Del Alto, M.E., Costes, S.V., 2020. Advancing the integration of biosciences data sharing to further enable space exploration. Cell Rep. 33 (10), 108441 https://doi.org/10.1016/j.celrep.2020.108441.
Sicilia, M.A., García-Barriocanal, E., Sánchez-Alonso, S., 2017. Community curation in open dataset repositories: insights from Zenodo. Proc. Comp. Sci. 106, 54–60. https://doi.org/10.1016/j.procs.2017.03.009.
Sieber, J., 2015. Data sharing in historical perspective. J. Emp. Res. Human Res. Ethics 10 (3), 215–216. https://doi.org/10.1177/1556264615594607.
Sofi-Mahmudi, A., Raittio, E., 2022. Transparency of COVID-19-related research in dental journals. Front. Oral Health 3 (April), 1–6. https://doi.org/10.3389/froh.2022.871033.
Sun, C., Emonet, V., Dumontier, M., 2022. A comprehensive comparison of automated FAIRness evaluation tools. CEUR Workshop Proc. 3127, 44–53.
Top, J., Janssen, S., Boogaard, H., Knapen, R., Şimşek-Şenel, G., 2022. Cultivating FAIR principles for Agri-food data. Comput. Electron. Agric. 196 (February) https://doi.org/10.1016/j.compag.2022.106909.
United Nations, 2022. End Hunger, Achieve Food Security and Improved Nutrition and Promote Sustainable Agriculture.
United States Departament of Agriculture, 2023. About the Ag Data Commons. Retrieved September 18, 2022, from. https://data.nal.usda.gov/about-ag-data-commons.
Van Hulle, M., 2012. Self-organizing maps. [Book]. In: Handbook of Natural Computing, vol. 1. Springer.
Wilkinson, M.D., Dumontier, M., Aalbersberg, I.J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J.W., da Silva Santos, L.B., Bourne, P.E., Bouwman, J., Brookes, A.J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C.T., Finkers, R., Mons, B., 2016. Comment: the FAIR guiding principles for scientific data management and stewardship. Sci. Data 3, 1–9. https://doi.org/10.1038/sdata.2016.18.
Wilkinson, M.D., Dumontier, M., Sansone, S.A., da Silva, Bonino, Santos, L.O., Prieto, M., Batista, D., McQuilton, P., Kuhn, T., Rocca-Serra, P., Crosas, M.E., Schultes, E., 2019.

Evaluating FAIR maturity through a scalable, automated, community-governed framework. Sci. Data 6 (1), 1–12. https://doi.org/10.1038/s41597-019-0184-5.
Wise, J., de Barron, A.G., Splendiani, A., Balali-Mood, B., Vasant, D., Little, E., Mellino, G., Harrow, I., Smith, I., Taubert, J., van Bochove, K., Romacker, M., Walgemoed, P., Jimenez, R.C., Winnenburg, R., Plasterer, T., Gupta, V., Hedley, V., 2019. Implementation and relevance of FAIR data principles in biopharmaceutical R&D. Drug Discov. Today 24 (4), 933–938. https://doi.org/10.1016/j.drudis.2019.01.008.
Wiseman, L., Sanderson, J., Wiseman, L., Sanderson, J., 2018. Embedding the FAIR principles into a National Agricultural Data Governance Framework: an Australian perspective, F1000Research, 7.