DIVERSify: Designing InnoVative plant teams for Ecosystem Resilience and agricultural Sustainability

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Partner logos here?

History of Changes		
Version	**Publication Date**	**Change**
0.1	12th March 2021	Initial version sent to reviewers
0.2	19th March 2021	Updated version with revisions in response to reviewers' comments
1.0	19th March 2021	Final version

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Executive Summary

We report here on two connected pieces work, both considering how to analyse and present results from combined datasets of multiple crop mixture trials.

First, we describe a meta-analysis based on 153 trials from across 14 sites which shows a clear positive significant relationship between Land Equivalent Ratio – a measure of the yield benefit of crop mixtures – and temperature. It also shows that crop mixtures at these study sites generated overall gains in terms of crop productivity, and that the composition of the crop mixture can impact on crop mixture benefits.

Second we describe a prototype web-based platform called 'DIVERSiplotter' which has been designed and developed to help efficiently store, visualize and query the types of results obtained from multiple complex field trials generated as part of the DIVERSify project. This is linked to a database constructed using datasets from trials conducted in the project.

Finally we consider the benefits of in future drawing these two strands of work together, delivering a web-based platform enabling stakeholder (e.g. participatory farmer) data entry associated with automatically-updated analyses and graphical visualisation of the data and analysis results.

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1. Introduction

Through its participatory farmer approach, as well through as trials on project partners' core experimental platforms, DIVERSify has accrued a wealth of information on the types of intercrops being grown across Europe and beyond, and the consequences of these mixture combinations and their associated management for crop yield. Challenges for such large datasets include finding clear over-arching patterns within the data, and making the datasets more easily visualised by a wide range of stakeholders interested in intercrops. These are the challenges addressed by the work reported here.

Section 2 presents a meta-analysis of data from a large number of large scale crop mixtures trials. As well as setting out briefly the data gathering and management process, we provide an overview of the results of the meta-analysis and consider their implications for the future use of crop mixtures. We also lay out areas where further future analyses could build on this initial assessment.

Section 3 describes a prototype web-based platform called 'DIVERSiplotter' which has been designed and developed to help efficiently store, visualize and query the types of results obtained from multiple complex field trials generated as part of the DIVERSify project.

Section 4 provides some brief conclusions drawn from the above work and also considers possibilities for drawing these two parallel lines of work together.

2. Meta-analysis

2.1. Aims

The aim of meta-analyses is to combine data from multiple separate studies into a single analysis. This provides researchers with higher statistical power and precision, and the ability to address a broader scope than the combined primary studies (Vetter et al. 2013 and references therein). This approach is well suited to the DIVERSify project where we have multiple separate trials but a certain level of standardisation in the way in which trials are conducted. By combining data from separate trials into a single analysis we can ask questions about how larger scale drivers such as climate can influence the success of intercrops, a question which cannot be addressed by a single-site study.

This question of the impact of climate is particularly pertinent to intercrops. Intercrops rely on beneficial plant-plant interactions. Studies from natural and semi-natural environments have demonstrated how the impact of beneficial plant-plant interactions can vary with changes in the abiotic environmental conditions, for example along gradients of temperature or other drivers of environmental severity (see, for example, Callaway et al. 2002, He et al. 2013). Such studies have led to the development of the Stress Gradient Hypothesis (see Brooker et al. 2008 for an overview), which predicts that the frequency of, and benefits from, beneficial plant-plant interactions should be greater in more severe environments. Although meta-analyses of cultivar mixtures (e.g., Kiær et al., 2009) and

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intercrops have been undertaken, these have explored the impacts of only some potential drivers of large-scale variation in LER (land equivalent ratio – a measure of intercrop success calculated as the ratio of the area under sole cropping to the area under intercropping needed to give equal amounts of yield at the same management level – FAO 1985). In particular the substantial study by Martin-Guay et al. (2018), although looking at the impacts of aridity and nutrient inputs, did not look independently at the impacts of temperature. Developing this knowledge is a crucial part of understanding where and when intercrops might be a beneficial farming technique (and conversely where they might not offer any clear benefits over conventional crops).

In this study we compiled a large dataset based on the results of DIVERSify trials and asked the following questions concerning the benefits from intercropping as measured by the average site level LER:

- Is LER affected by large scale climate drivers?
- Is LER influenced by the species composition of the intercrop?

2.2. Method

Details of data compilation have been set out in the milestone report MS52 and associated annex. In brief, the meta-analysis dataset is based on DIVERSify WP4 participatory farmer and core platform datasets collected in trials conducted in 2018 and 2019 in particular. The compiled dataset includes data from just over 200 separate trials (in some cases multiple trials were run at a single site), and also includes the trial location, crop mixtures grown, length of the growing season, ratio of crops in the mixture, harvest metrics (averages at the site level across any replicated plots), and additional treatments such as the application of fertilisers, whether the site was ploughed or direct drilled, and whether the farm in question is organic. In addition, daily meteorological data were extracted for each of the locations (0.1° grid cell resolution) for the growing period from the E-OBS database (Cornes et al., 2018).

Preliminary analyses were conducted, and some sites removed from the database as they were clear outliers in terms of reported LER values. In particular the very large size of their LER values suggested these were data recording/entry errors, and so the raw data need checking with the relevant project partner or participatory farmer, a potentially lengthy process that we could not do ahead of report production. The final dataset contained 153 separate observations (data from 153 trials) from across 14 sites (**Figure 2.1**). It is worth noting that we had in the final database no studies from intercrops that had not used legumes; hence our exploration of the impact of intercrop composition could not explicitly consider the effects of legumes, only the type of legume. All analyses were performed using linear mixed models with REML (restricted maximum likelihood) regression modelling, with trials nested within sites, and using the R statistical package version 4.0.3 (R Core Team 2020).

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2.3. Results

Across all studies the average LER was 1.22 (± 0.04 95% confidence interval), which is not far removed from the mean relative land output ratio of 1.38 found by Martin-Guay et al. 2018 and shows on average a clear yield benefit from growing intercrops.

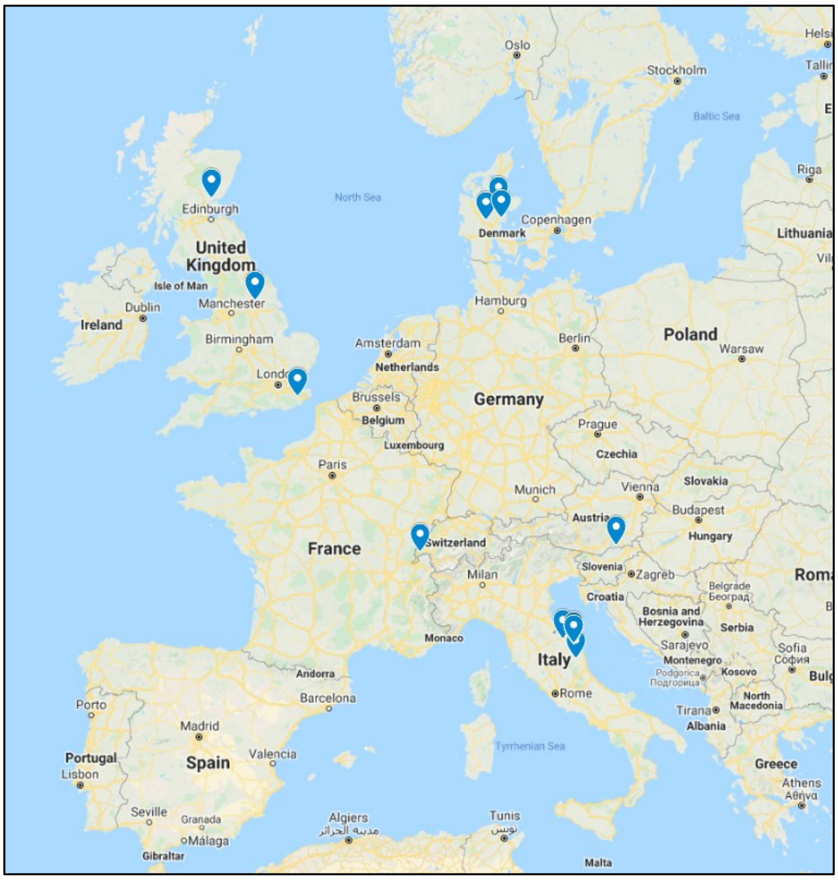

Figure 2.1 Location of field trial sites providing data for the metanalysis.

Large scale climate drivers

There were strong trends towards impacts of the average mean daily temperature and average maximum daily temperature during the growing season on LER (P = 0.053 and P = 0.071, respectively), and a significant impact of average minimum daily temperature (P = 0.035) on LER; LER increased by 0.07 for every 1°C increase in mean minimum daily temperature. In all cases the trend was towards an increase in LER with increasing temperature (**Figure 2.2**). Total rainfall during the growing season did not significantly affect LER (P = 0.237)

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Composition of the intercrop

There was no effect of the number of species components (2 or 3) in the mixture (P=0.975), although the occurrence of oats as a cereal had a significant positive effect on LER (P=0.037). There were no interactions between climate drivers and intercrop composition.

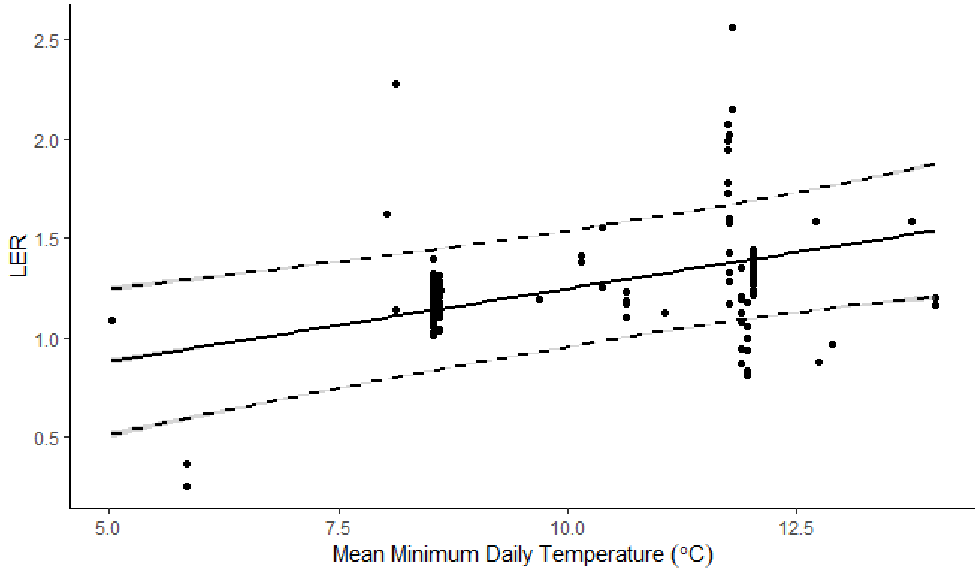

Figure 2.2 Relationship between LER (land equivalent ratio) and mean minimum daily temperature across the growing season. The fitted relationship is shown as a solid line and 95 % confidence intervals as dashed lines.

2.4. Conclusions

We found a very clear impact of temperature – particularly minimum temperatures - on LER, but no effect of rainfall. In demonstrating an overarching climate effect our results differ from those of Martin-Guay et al. (2018) who found "Irrigation and the aridity index in non-irrigated intercrops did not affect land equivalent ratio, thereby indicating that intercropping remains beneficial, both under stressful and non-stressful contexts concerning moisture availability." There may be several reasons for this disparity. First, our study may encompass climatic areas not captured by the analysis of Martin-Guay et al. (2018). Second, we may be focussing on a different range of crop types, with our study focussing in particular on cereal-legume mixtures, thereby reducing the amount of variation created in the LER data (resulting from variability in crop mixture composition) and enabling climate effects to be more easily detected.

We need to investigate these possibilities further, but it is clear that our meta-analysis provides two important pieces of information. First, and irrespective of the effect of temperature across the study sites, the average LER is positive. This is not simply because the studies tend to be located in warmer conditions where potential productivity might be higher, as can be seen from **Figure 1** which

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demonstrates the large number of studies from cooler northern Europe. Second, however, our study also shows that intercropping does not generate clear productivity benefits in cooler environments. This may be because the growing season is shorter and the net radiation influx lower. This could drive a couple of mechanisms reducing beneficial effects in cooler sites. First productivity is overall lower at these sites, and consequently the net level of plant-plant interactions may be lower, necessarily meaning the benefits of intercropping are lower. Alternatively, it may be that there are still strong interactions between the crops, but the low overall productivity means the benefits of the intercrop might not outweigh competitive effects such as light interception (in contrast to the highly productive intercrops often found in tropical areas with long growing seasons and high levels of solar radiation).

Looking in more detail at the composition of the crops, the presence of oats had a significant positive effect on LER. This is an interesting result as oats were used in only a small number of trials (14). It is not the case that oats tended only to be grown in certain (i.e. warm) environments, as trials including oats were conducted in both Spain and Denmark. So there may be something about oats – for example beneficial interactions with soil organisms or low competitiveness – that makes them particularly suited to being grown in an intercrop.

Our next steps will include integrating the impact of land management – for example the use of inputs such as fertiliser or tillage/management regimes – into the analysis, bolstering the dataset with results from 2020 and other studies, and exploring in more detail the possible reasons for the beneficial effects of oats on LER

3. DIVERSiplotter data visualization tool

3.1. Aims

Information visualization is a powerful tool in the discovery of hidden knowledge in data. The brain has an incredibly high capacity for pattern recognition and therefore the presentation of information in digestible chunks allows a deeper understanding of the underlying complexity and composition of datasets. Interactive visualizations and query interfaces that aid in the visual exploration of data help facilitate knowledge discovery by aiding in the recognition of patterns which are difficult, if not impossible, to see in raw data. Effective visualizations can therefore help uncover interesting features, or indeed underlying issues, with datasets, both of which are important in analysis.

The primary aim of this work was to create custom interactive user interfaces using standard technologies that would be primarily tailored to the DIVERSify WP2 trial datasets. These interfaces could be used by DIVERSify scientists to help gain a deeper understanding of the underlying data from monoculture and intercropping treatments.

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3.2. Method

DIVERSify WP2 project data was collected (2017-2019) and collated using standardised Microsoft Excel spreadsheet templates that we designed to hold data from DIVERSify intercropping trials. These datasets covered different years, plant teams (cereals: durum wheat, barley, oat, common wheat, sorghum and maize; and legume: pea, common bean, styrian scarlet runner bean, grasspea and faba bean) and seven locations covering Scotland, Sweden, Denmark, Germany, Austria, Italy and Spain. Data cleansing and sanity checking was then undertaken using custom R scripts (Pappagallo et al., n.d.). The processed data was loaded into a custom MySQL (https://www.mysql.com) database which we designed and implemented not only to ensure the long-term structured, queryable and searchable storage of the project data, but also to act as the underlying data resource providing information to a bespoke web-based visualization and query interface.

The database comprises 11 tables, seven views and two stored procedures enabling the storage of the DIVERSify crop teams data at three levels: plot, species and individual plant. Custom Java code was written to help upload the outputs from the R data cleansing process.

In order to allow access to the underlying data, not only to DIVERSiplotter but also any other tools which may be developed, we implemented an application programming interface (API) access. This conforms to representational state transfer (REST) specifications and has been implemented in Java. Developing an API has a number of advantages such as allowing programmatic access to data to project partners through common standard interfaces and maintaining a programming language agnostic interface on which other tools can be developed in the future.

The DIVERSiplotter user interface (https://ics.hutton.ac.uk/diversify) (**Figure 3.1**) has been developed using current web standards and is based on the Vue.js (https://vuejs.org) JavaScript library. Vue brings tangible benefits including rapid prototyping and reduced development lifecycles. These are important as the development of DIVERSiplotter focused on iterative design principles where continual feedback was gained from users. All interactive visualizations use the open-source graphing library Plotly (https://plotly.com/javascript/) and use colour blind safe palettes. DIVERSiplotter has been designed and developed to use open-source tools to ensure it is freely and openly available to interested groups.

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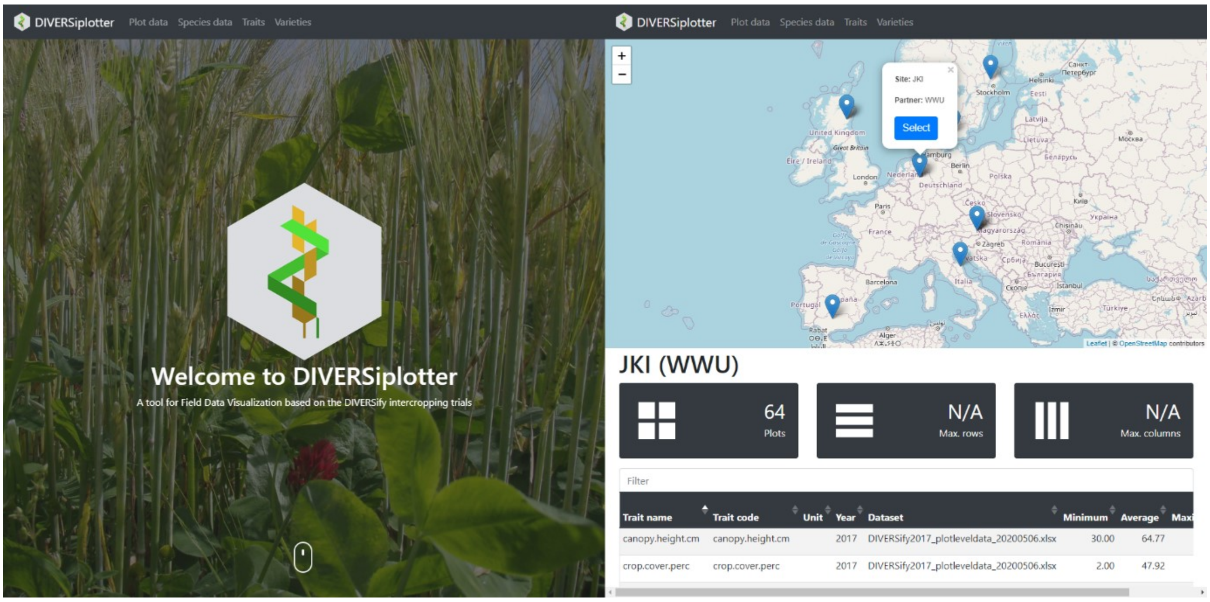

Figure 3.1 The DIVERSiplotter user interface and example showing data from the field trial site in Germany. Trial sites are represented on a map allowing a graphical selection of datasets.

3.3. Results

The web-based interface of DIVERSiplotter offers four primary types of visualisations: plot-level data looking at traits recorded across plots (**Figure 3.2**), species-level data describing the performance of individual species within a plot (**Figure 3.3**), variety-focused visualisations looking at the differences between cultivars grown as either monocultures or teams (**Figure 3.4**) and finally trait-focused visualisations comparing traits and providing tools to help identify patterns like correlations between traits (**Figure 3.5**).

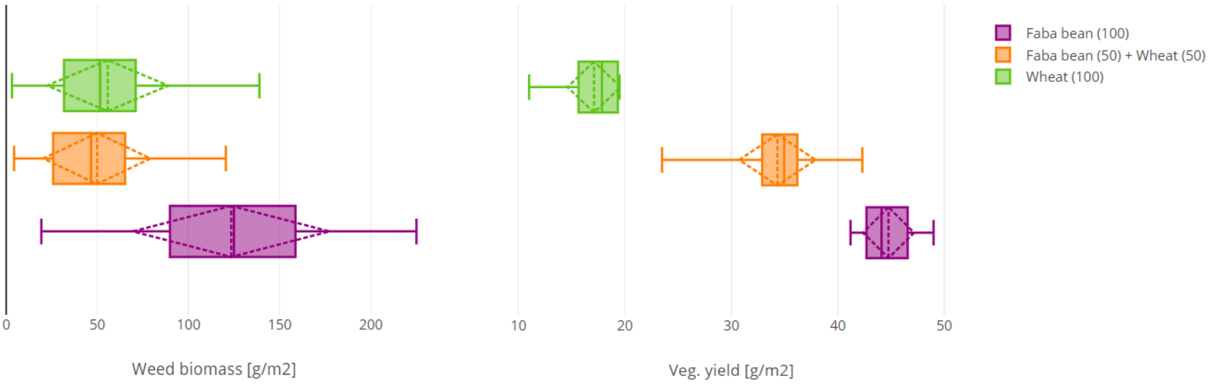

Figure 3.2 Monoculture versus intercropping: Weed biomass and vegetative yield plotted for faba bean and wheat monocultures compared to the intercropping result of growing both crops together. The intercropped plot shows a low weed biomass compared to the faba bean monoculture and exhibits a vegetative yield between that of faba bean and wheat monocultures.

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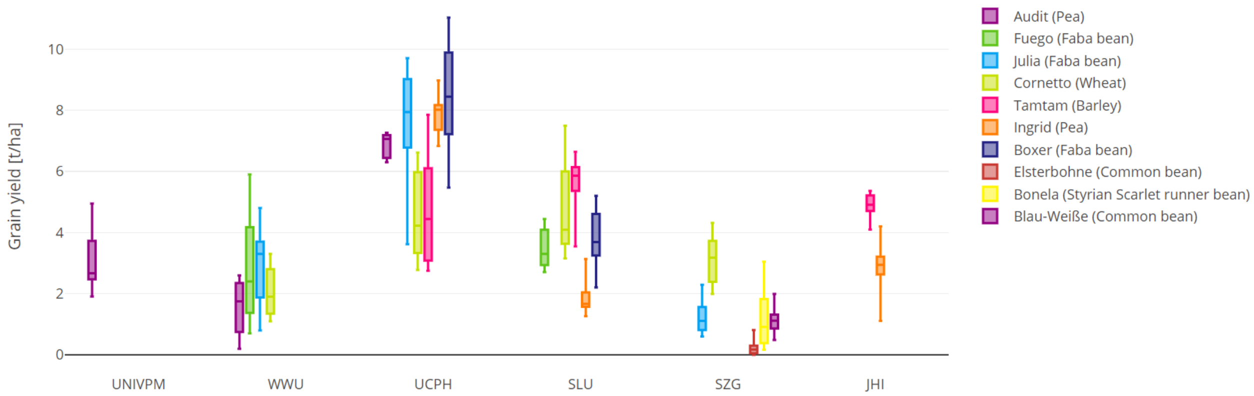

Figure 3.3 Plant cultivar grain yield across different locations: Grain yield of different species and crops is grouped by location and suggests an impact of climate or soil on plant performance. Hovering over a box plot reveals the quartile values of the respective cultivar and location.

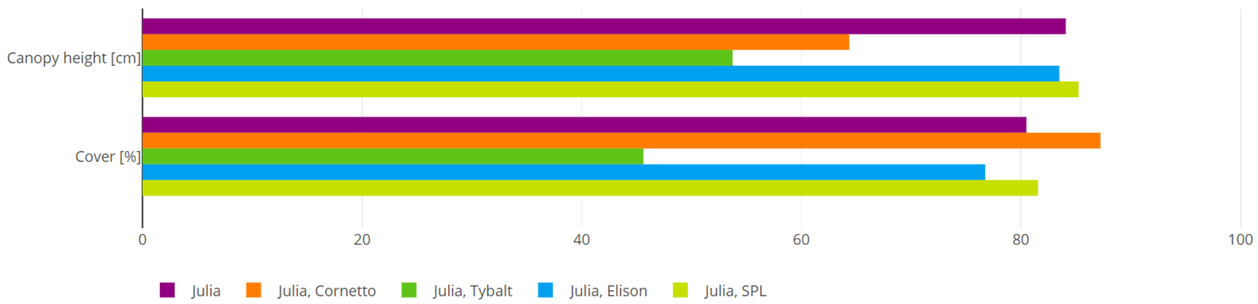

Figure 3.4 Crop varieties in monoculture versus intercropped: Average trait values are plotted per trait (y-axis grouping) where each individual bar represents either a monoculture or an intercropping plot with the monoculture always on top.

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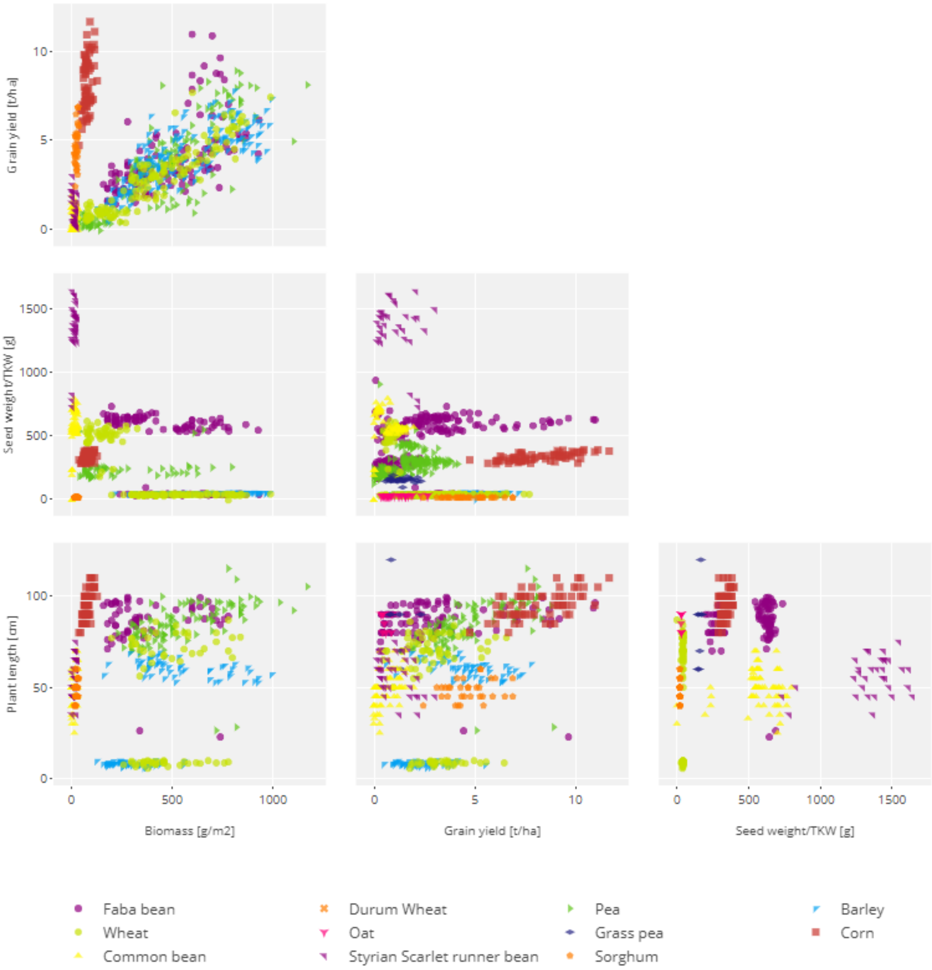

Figure 3.5 Trait scatter matrix: Four traits plotted against one another to highlight correlations, clusters and outliers in the data. The colouring is based on the crop present in the plot and emphasises their individual characteristics. Hovering over data points reveals the trait values and the crop underlying the data point. Selections made using the rectangle or lasso mechanism highlight the selected data points in all other trait combinations for easier identification of the same groupings.

3.4. Conclusion

We have developed an open source, web-based platform for the storage, querying and visualization of intercropping data over several years and across multiple locations. This is available to use from https://ics.hutton.ac.uk/diversify. As new features and updates are released, they will be available from this URL.

All code for DIVERSiplotter is freely available from our GitHub page (https://github.com/cropgeeks/)

DIVERSiplotter has use outside of the immediate DIVERSify community and we would encourage groups to download and contribute to the application.

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4. Future outlook

Above we have demonstrated the new knowledge that can be derived from compiling multi-site datasets based on standardised trials, as well as new techniques for visualising the resulting data. An obvious opportunity moving forward would be to bring these two work areas together by combining the underlying databases and linking the data visualisation tools to data analyses such as meta-analysis. An outcome from such an approach would be a web-based platform enabling stakeholder (e.g. participatory farmer) data entry associated with automatically-updated analyses and graphical visualisation of the data and the analysis results.

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