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1 Knowledge discovery and unsupervised detection of within-field yield 2 defective observations

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10 Abstract

11 Suspicious observations, or the so-called outliers, are always present, to a greater or lesser extent, in agronomical
12 and environmental datasets. Within field yield datasets are no exception. While most filtering approaches use
13 expert thresholds and dedicated filters to remove these defective observations, more general and unsupervised
14 methods will be required to process a growing number of yield maps. However, by using these last approaches,
15 outliers would be solely identified and would remain unlabeled. This study proposes a methodology to provide a
16 label to these defective observations so that users can better characterize the harvest process, e.g. functioning of
17 the machine, driving of the operator, and provide guidelines for future improvements of equipment and operations
18 processes. Here, it is assumed that outliers have already been detected by a non-parametric and unsupervised
19 published approach. Clusters of outliers are first identified in the data to gather outliers with similar yield outlying
20 characteristics. Once detected, these clusters are given a first-order label which describes the general yield outlying
21 characteristics of the observations that belong to these clusters. Then, within each cluster, each outlier is given a
22 second-order label to provide more information on the origin of the defective observation. Yield simulated datasets
23 with known characteristics and labelled outliers were used to test the methodology. The proposed approach was
24 then applied on real yield datasets with unlabeled outliers. This study shows that it might be conceivable to label
25 outliers detected with an unsupervised approach but that some labels are more accurate than others, especially
26 those related to an unknown cutting width of the harvester or to narrow finishes within the fields. Outlying
27 observations behaved similarly between simulated and real datasets which made it possible to infer more precisely
28 the label of defective observations. By labelling outlying observations, it was possible to provide an appropriate
29 correction to one of the real yield dataset and to restore almost 15% of the outlying observations instead of
30 removing them. This study is a first attempt to provide a label to yield outliers detected from an unsupervised
31 manner.

32 **Keywords:** Intentional knowledge, knowledge discovery, outliers clustering, outliers labelling, yield

33

34 1. Introduction

35 The agricultural sector faces an impressive and still increasing flow of data arising from multiple platforms, i.e.
36 satellites, UAV, drones, or embedded and in-situ sensors (Baluja et al., 2012; Debuisson et al., 2010; Oliver, 2010;
37 Santesteban et al., 2013). All these data are very helpful for the decision-making process but come along with
38 varying degrees of quality or reliability. More specifically, defective observations, i.e. the so-called outliers, are
39 likely to be present within these data (Simbahan et al., 2004; Sudduth et al., 2007). Those suspicious observations
40 must be carefully considered before involving the datasets in complex agronomic processes or decisions. This is
41 particularly the case for within-field yield datasets which are a valuable tool to highlight the within-field spatial
42 variability and understand the underlying factors affecting this variability (Pringle et al., 2003). Yield datasets are
43 negatively impacted by a noticeable amount of defective observations widely reported in the literature, e.g. filling
44 and emptying time, speed changes, unknown cutting width when entering the crop, GNSS positioning, harvest
45 turns and narrow finishes (Arslan, 2002; Lyle et al. 2013). It must be clear that these defective observations are
46 not erroneous measurements from the yield monitors. These defective observations are problematical because they
47 do not correspond to the yield that should be observed in the field. They are rather biased by the fact that a combine
48 harvester passes through the field. In the case of within-field yield monitor data, Griffin et al. (2008) have shown
49 that in half of their experiments, the quality of the filtering procedure would have supported different field
50 management recommendations.

51 For the past twenty years, several approaches have been proposed in the literature to tackle the issue of yield
52 defective observations (Blackmore and Moore, 1999; Leroux et al. 2017; Simbahan et al. 2013; Sudduth et al.
53 2007; Sun et al. 2013). All these methodologies have come up with one single objective, which is to remove all
54 the outliers from the datasets. This way of thinking is legitimate because (i) these suspicious observations influence
55 the overall quality of the data, and (ii) yield datasets contain lots of yield records which means that these datasets
56 can handle a loss of data. Among the multiple approaches that were published in the literature to filter yield
57 datasets, most of them rely on manual expertise and/or dedicated expert thresholds and filters. With these
58 approaches, the labelling of outlying observations, i.e. the fact of attaching information with respect to the origin
59 of the outlier, is directly provided as each empirical or semi-automatic threshold/filter is specific to a type of
60 defective observation. However, with the growing number of yield maps that will need to be processed in the near
61 future, non-parametric and automatic methodologies might be preferred (Leroux et al., 2017; Spekken et al. 2013).
62 In this latter case, as the filtering is thought from a holistic perspective, the labelling of each outlier is not known
63 when defective observations are identified. There is effectively no information or description attached to the
64 outlier, i.e. the origin of this outlying information, e.g. speed change, filling and emptying time, is not known.

65 The labelling of outlying yield observations is especially relevant since there exists a lot of expert knowledge on
66 (i) the types of defective observations and on (ii) the attributes associated to the yield records to help explain the
67 origin of the errors (Arslan, 2002; Blackmore and Moore, 1999; Lyle et al. 2013). From a more general perspective,
68 the labelling of observations has multiple interests such as the possibility to (i) explain what is causing these
69 outliers, (iii) characterize the working of a machine or the driving of an operator, (iii) correct outlying observations
70 instead of removing them or (iv) provide guidelines for future improvements of equipment and operations
71 processes (Colaço et al., 2014). Once outliers are detected inside yield datasets, it seems therefore possible to
72 provide a detailed description or at least a labelling of the suspicious observations. However, even though an
73 expertise is available, it can sometimes be quite difficult to assess with a strong confidence whether a detected
74 outlier is truly one. By performing a visual inspection on the field, it can be argued that some outliers are clearly
75 visible, but this is not always the case. Moreover, such a visual inspection is cumbersome and may remain
76 subjective when dealing with large amounts of data to analyze. To improve the identification and labelling process,
77 one solution could be to use simulated datasets in which each observation would be labelled either as a normal or
78 defective observation (Leroux et al. 2018). As the location and labelling of outliers would be known in advance,
79 it would be much easier to validate a proposed procedure.

80 Assuming that a person's noise is another person's signal, several studies, though much less than those related to
81 outlier detection, have intended to provide a label to outliers so that users can better understand their characteristics
82 and origin (Anguilli et al. 2012; Ertoz et al. 2004; Knorr and Ng, 1999; Marques et al. 2015; Micenková et al.
83 2013). These studies have been either dedicated to categorical (Anguilli et al. 2009; Ertoz et al. 2004) or numerical
84 data (Knorr and Ng, 1999; Micenková et al. 2013). Given that within a dataset, an observation is characterized by
85 a set of m attributes, most of these works seek to provide a subset of k attributes ($k \leq m$) that best explain the
86 'outlierness' of each defective observation, i.e. the attributes which make the query observation most outlying.
87 Outliers are generally given a score of 'outlierness' in each possible subset of attributes to record how much these
88 suspicious points deviate from the rest of the data (Duan et al. 2015; Micenková et al. 2013; Vinh et al. 2016). For
89 a given outlier o , the subset of attributes for which the outlying score of o is the highest is generally chosen to be
90 the best descriptor of o . As suggested by Micenková et al. (2013), a reliable and valuable subset of attributes should
91 highlight the 'outlierness' of the defective observations but at the same time be minimal in the number of attributes.

92 The main contribution of this study is to propose a framework to label outlying within-field yield observations. It
93 is considered that these outliers have already been detected by an unsupervised filtering approach, but they are still
94 missing a label. To the authors' best knowledge, very few unsupervised approaches have been dedicated to outlier
95 detection in within-field yield datasets and none of them have been further extended to give a label to these
96 defective observations once detected. Here, a procedure is proposed to provide outlying observations with a label
97 so that users can extract and gain knowledge with regard to their data. The approach is first validated on simulated
98 yield datasets with known labelled outliers and then tested on real yield dataset with unlabeled outliers.

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102 **2. Material and methods**

103 *2.1 Theoretical considerations*

104 An important pre-requisite of this study is that outliers are already detected within the yield datasets. The aim is
 105 not to provide a way to find outliers but rather to help qualify and describe these defective observations. In this
 106 work, it is considered that yield outliers have been identified by a holistic and unsupervised filtering methodology
 107 proposed by Leroux et al. (2018). As stated in the introduction section, most of the existing filtering approaches
 108 provide a direct labelling of the outlying observations as empirical filters and expert thresholds are involved in the
 109 detection process (Simbahan et al., 2004; Sudduth et al., 2007). If the filtering process was to be made from a
 110 general, non-parametric and automation perspective, outlying observations would be identified but not labelled.
 111 These pre-requisites are becoming essential as more and more yield maps will need to be processed in the future.
 112 The objective here is to intend to provide a label to these outlying observations once they are spotted in the datasets.
 113 A brief summary of the approach of Leroux et al. (2018) is provided in the next section.

114 *2.1.1 Detection of spatial defective observations using a density-based clustering algorithm*

115 This approach is based on a spatial outlier detection problem in which the authors consider that an observation is
 116 defective if this latter is inconsistent with the observations in its neighbourhood. The methodology is divided into
 117 three major steps. Firstly, each observation x_i is given two different neighbourhoods. (Fig. 1). The first one is a
 118 spatio-temporal neighbourhood (ST), which regroups the spatial observations near in space to x_i and which belong
 119 to the same harvest row as that of x_i (Fig. 1). The other is a spatio-not-temporal neighbourhood (SNT), which
 120 gathers the spatial observations near in space to x_i and which belong to adjacent harvest rows to that of x_i .

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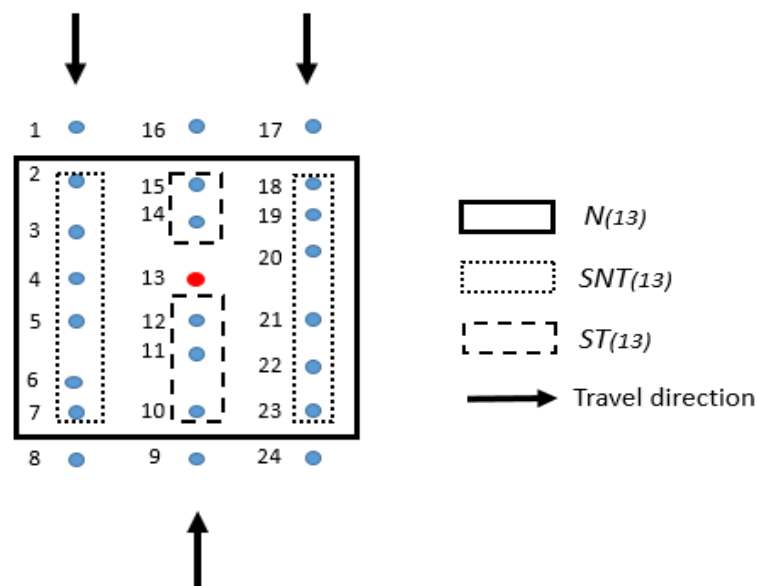
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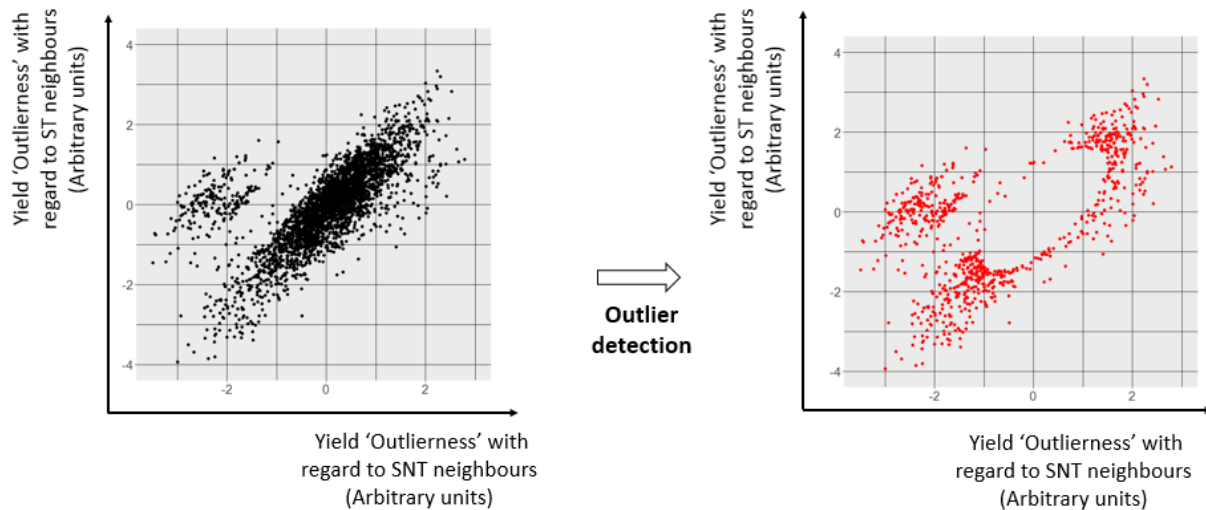
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133 **Fig. 1.** ST and SNT neighbourhoods of an observation. Each observation x_i has a $ST(x_i)$ neighbourhood
 134 (observations are acquired in a short time interval) and a $SNT(x_i)$ neighbourhood (observations belong to different
 135 passes). Source: Leroux et al., 2018)

136 Secondly, a robust metric of ‘outlierness’ which evaluates the degree of inconsistency between the yield of x_i and
 137 that of the observations in both its ST and SNT neighbourhoods is computed. This step enables to create a bivariate
 138 plot of ‘outlierness’ which reports, on the x-axis, the ‘outlierness’ of each observation with regard to its SNT
 139 neighbours and, on the y-axis, the ‘outlierness’ of each observation with regard to its ST neighbours (Fig. 2, left).
 140 For instance, an observation in the top-right hand corner of the plot has a higher yield value than both its ST and
 141 SNT neighbours. Similarly, an observation in the bottom-left hand corner of the plot has a lower yield value than
 142 both its ST and SNT neighbours. Finally, a density-based clustering algorithm, i.e. DBSCAN, is used to identify
 143 outlying observations in the bivariate plot of ‘outlierness’ according to an automatic thresholding (Fig. 2, right).



144

145 **Figure 2.** Left – An example of bivariate plot of ‘outlierness’ with all the observations (black dots on the online
146 version). Right – An example of bivariate plot of ‘outlierness’ with solely defective observations identified by the
147 method of Leroux et al. (2018) (red dots on the online version).

148

149 2.1.2 Making value of the available expertise on yield defective observations

150 For the past twenty years, there has been a considerable amount of work towards the understanding of the sources
151 of defective observations in yield datasets (Arslan, 2002; Lyle et al. 2013). The latter authors have provided users
152 with a categorization of yield technical errors into four major groups: (i) harvesting dynamics of the combine
153 harvester, e.g. lag time, filling and emptying times, (ii) continuous measurements of yield and moisture, e.g.
154 global/local yield and moisture outliers, (iii) accuracy of the positioning system, e.g. loss of signal, observations
155 outside the field boundaries and, (iv) harvester operator, e.g. speed changes, unknown cutting width when entering
156 the crop, harvest turns, narrow finishes (Lyle et al. 2013). All these errors, except those related to the positioning
157 system, originate changes in the yield value of each defective observation. Given that the approach of Leroux et
158 al. (2018) evaluates the yield outlying characteristics of each observation with respect to its spatial neighbours (ST
159 and SNT) and that each type of error originates specific yield variations, these errors should theoretically have a
160 specific location within the bivariate plot of ‘outlierness’.

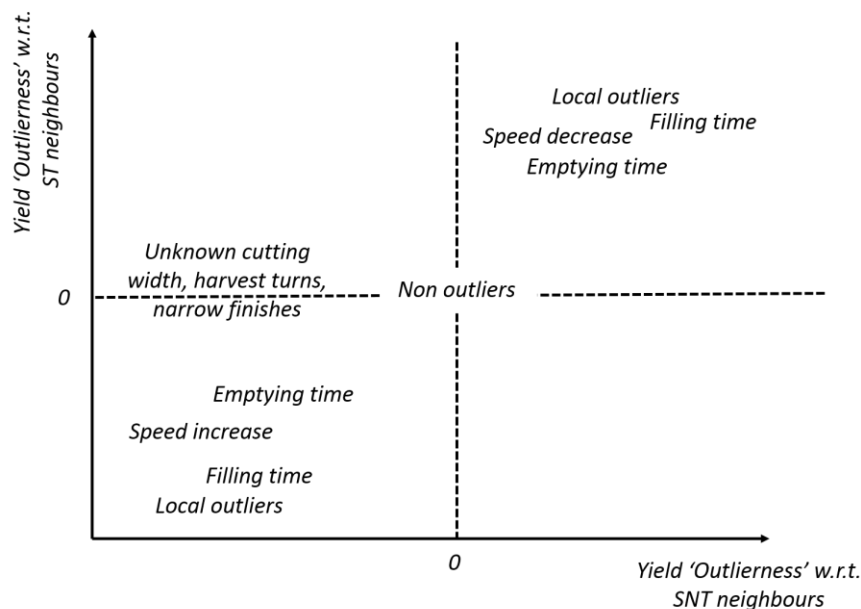
161 Given the available knowledge with respect to these defective observations, let us infer the location of these main
162 yield technical errors within the bivariate plot of ‘outlierness’ (Fig. 3). Filling and emptying times induce a yield
163 underestimation at the beginning and end of each harvest row either because the grain flow has not reached a
164 plateau or because the grain still continues to flow while the header is up. It can be therefore considered that the
165 yield of an observation acquired during these periods of time should not be consistent with that of both ST and
166 SNT neighbours. Filling and emptying times should mainly lead to observations located on the bottom left-hand
167 corner of the plot, i.e. bottom and left-hand because this observation should have a lower yield value than both ST
168 and SNT neighbours (Fig. 3). However, it must be said that at the end of the filling time or at the beginning of the
169 emptying time, the grain flow is still relatively close to the permanent regime of the machine. This aspect means
170 that some of these outlying observations might have a higher yield than that of the outlying observations at the
171 beginning of the filling time or at the end of the emptying time. As such, it might be possible to also find (in a
172 relatively small proportion though) outliers related to filling and emptying time in the top right-hand corner of the
173 plot (Fig. 3). Another specification could be added. It has been shown that the underestimation was stronger at the
174 beginning than at the end of the row (Simbahan et al. 2004). As such, observations collected at the end of a harvest
175 row should be closer to the centre of the plot than observations collected at the beginning of the row.

176 The accuracy of yield and moisture sensors along with local harvest circumstances can influence the accuracy of
177 yield measurements (Lyle et al. 2013). It might happen that yield records are effectively much higher or lower than
178 expected and consequently that they significantly vary from those of their ST and SNT neighbours. Abnormal
179 higher values should therefore be located on the top right-hand side of the bivariate plot of ‘outlierness’ while
180 abnormal lower values should appear on the bottom left-hand side of the plot (Fig. 3).

181 Speed changes originate yield under or overestimates depending on if the speed of the harvester increases or
182 decreases. In fact, during a speed change, the considered harvested area is flawed which impacts the quality of the
183 resulting yield records and creates yield biases with respect to their ST and SNT neighbours. Accelerating would
184 cause the observations to be located on the bottom left-hand part of the plot (a similar grain flow for a larger
185 harvested area originates a decrease in yield) while a speed reduction should lead to observations appearing on the
186 top-right hand side of the bivariate plot of ‘outlierness’ (Fig. 3).

187 Unknown cutting width, harvest turns and narrow finishes lead to strong yield underestimates because the
188 harvested area is much lower than actually considered. However, in that case, the underestimation is propagated
189 throughout the whole section of the row harvested under these conditions. In other words, it means that yield
190 records are lower than those of their SNT neighbours but are consistent with their ST neighbours. All these
191 observations should therefore be located in the left-hand portion of the plot but relatively close to the horizontal
192 axis (Fig. 3).

193 It must be understood that Figure 3 is theoretical and has been created with the available knowledge on the main
194 yield technical errors. The location of these errors will be validated later on with simulated and real datasets. Note
195 that this figure could be complemented with other sources of defective observations and might help see interesting
196 trends in the data.



197

198 **Figure 3.** Theoretical location of the main sources of yield technical errors on the bivariate plot of ‘outlierness’ of
199 Leroux et al. (2018).

200

201 2.2 Finding knowledge in outliers

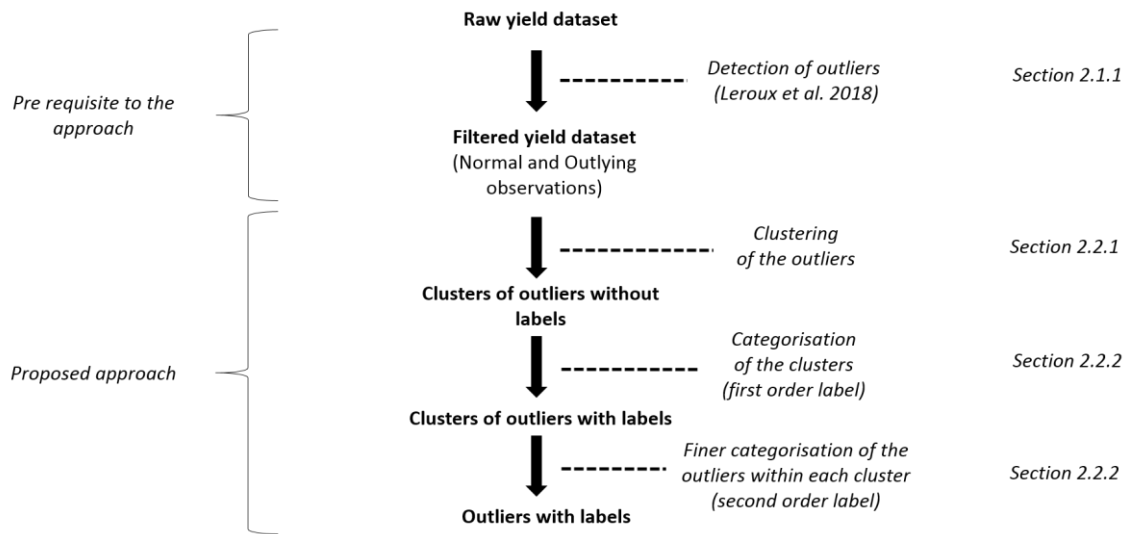
202 The objective of the present study is to intend to explain why the outliers diverge from the rest of the population
203 so that users can decide what to do with these defective observations. In this study, it is proposed to deal with these
204 outliers using a two-step process: (i) the clustering of outliers so that defective observations that behave similarly
205 are gathered, (ii) the categorization of outliers which aims at providing firstly a label to the clusters of outliers and
206 secondly a label to the outliers within each considered cluster. These steps are described in the two following
207 sections. A flowchart of the proposed methodology is proposed in Figure 4.

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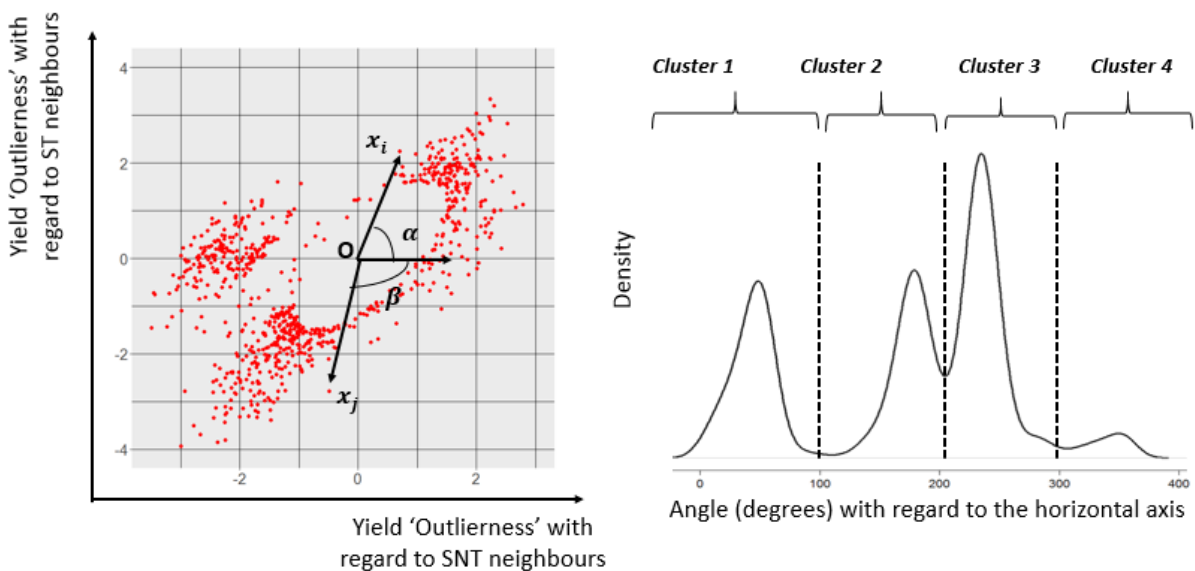


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213 **Figure 4.** Flowchart of the methodology.

214 *2.2.1 Automatic clustering of outliers*

215 In the bivariate plot of ‘outlierness’, yield defective observations are clustered in specific portions of the plot (Fig.
 216 2). In this study, an automatic clustering of observations is proposed because it is considered beneficial for the
 217 future labelling of observations. Indeed, within each cluster, observations share the same yield outlying
 218 characteristics with respect to their spatial neighbours. Grouping observations might help depict general trends or
 219 behaviours in these data. To automate the clustering of outliers, an angle-based methodology was put into place.
 220 For each outlying observation x_i , the angle that is formed between the horizontal axis and the vector \vec{Ox}_i was
 221 computed; O being the point of coordinates (0,0) in this plot (Fig. 5, left).



222

223 **Figure 5.** Left – Location of outliers using an angle-based methodology. Right – Clustering of outliers. *Outliers*
 224 x_i and x_j have respectively an angle α and β with respect to the horizontal axis.

225 A kernel density estimation (KDE) was then used to model the distribution of angles within the plot (Fig. 5, right).
 226 The number of clusters was chosen as the number of local minima in this distribution (Fig. 5, right). Each cluster
 227 was then set to contain all the observations lying between two consecutive local minima (Fig. 5, right). Within this
 228 methodology, an attention was paid to avoid the discrepancy between 360° and 0° (observations with these angles
 229 would be put in different cluster).

230 2.2.2 Categorization of outliers

231 Labelling the clusters of outliers: the first-order label

232 As the bivariate plot of ‘outlierness’ solely relies on the yield attribute, each cluster of outliers contains
233 observations that have similar yield outlying characteristics with respect to their ST and SNT neighbours. As a
234 primary description, these clusters can therefore be associated with a first-order label related to the yield
235 component which expresses how this behaviour diverges from that of the cluster of normal observations (Fig. 6).
236 The first-order label regarding the ST and SNT neighbours will be referred to as *Yield ST* and *Yield SNT*. For this
237 first-order label, three classes are provided:

- 238 (i) “Low” if the ‘outlierness’ of the centroid of a cluster of outliers is less than the first 20th
239 percentile value of the distribution of the ‘outlierness’ values of the cluster of normal
240 observations, e.g. *Low Yield SNT*,
241 (ii) “Average” if the ‘outlierness’ of the centroid of a cluster of outliers lies between the first 20th
242 and last 80th percentile values of the distribution of the ‘outlierness’ values of the cluster of
243 normal observations, e.g. *Average Yield ST*,
244 (iii) “High” if the ‘outlierness’ of the centroid of a cluster of outliers is more than the last 80th
245 percentile value of the distribution of the ‘outlierness’ values of the cluster of normal
246 observations, e.g. *High Yield ST*

247 For instance, in Figure 6, cluster n°3 is given the following first-order label: “*Low Yield SNT and Average Yield*
248 *ST*”.

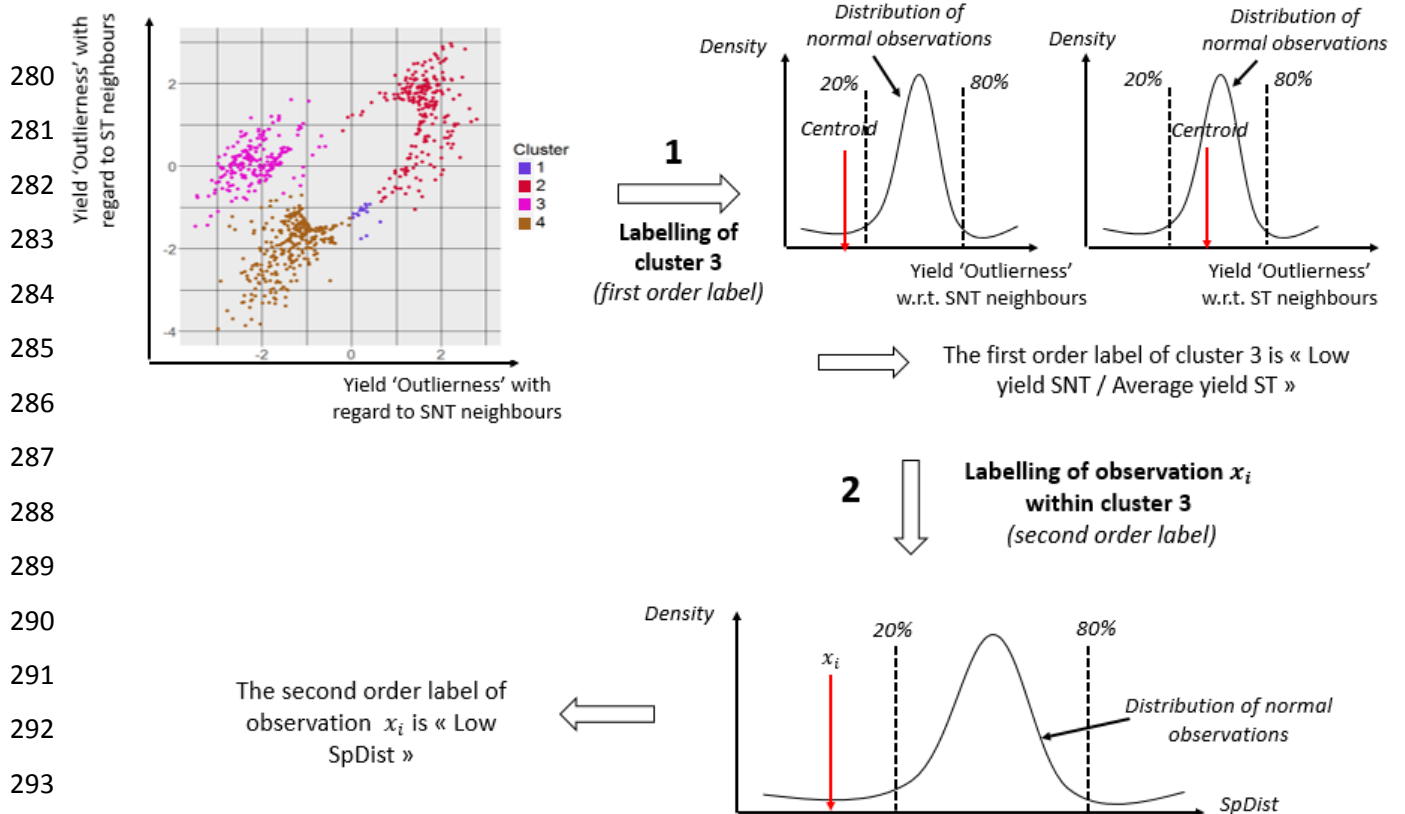
249 Labelling the outliers inside each cluster: the second-order label

250 However, this first-order label might not be sufficient to discriminate each type of error, especially if some of the
251 errors induce similar yield changes with respect to the ST and SNT neighbours of outliers. For instance, in Figure 3,
252 even if the location of errors is theoretical, multiple sources of errors might risk to be mixed up. As such, within
253 each cluster, the objective was also to propose a second-order label so that each defective observation could be
254 identified more clearly (Fig. 6). To do so, a set of attributes, different from the yield component, was chosen to
255 improve the labelling of outliers. The selection of these attributes was driven by the available knowledge on yield
256 defective observations and by the typicity of spatial observations collected from on-the-go vehicle-based datasets,
257 i.e. yield datasets in that case. Before introducing these attributes, one may question why these variables were not
258 taken into account directly within the process of detecting of outliers. Those reasons are multiple. First,
259 incorporating several new variables makes the detection of outliers more difficult because those defective
260 observations are likely to have outlying characteristics with respect to one variable but not with respect to others.
261 This problem is also referred to as the curse of dimensionality (Beyer et al., 1999). Secondly, multiple attributes
262 are used to compute the yield, e.g. speed, grain flow, width of the cutting bar, which means that if the values of
263 these attributes were to be abnormal, this should be reflected on the yield records. It can also be added that, given
264 the expertise and knowledge available on yield technical errors, it might be better to first detect outlying
265 observations and then to try to explain their origin. Finally, it could be argued that yield datasets are often in
266 different formats and do not necessarily contain the same attributes which may be problematical for creating a
267 general methodology to detect outliers. Something certain is that they contain at least the basic information
268 required to compute the yield.

269 For each observation x_i , three features were selected: (i) the change in speed between x_i and the
270 previously collected observation x_{i-1} (*Var_Speed*), (ii) the spatial distance between x_i and the nearest harvest pass
271 (*SpDist*) and, (iii) the number of ST neighbours of x_i (N_{ST}). The numbers of ST neighbours were evaluated within
272 a distance of twice the length of the cutting bar. The attribute *Var_Speed* was selected because it should help
273 discriminate the outliers that arise from an abrupt speed change. *SpDist* should bring insight into the operator-
274 based outliers, e.g. narrow finishes, unknown cutting width when entering the crop, harvest turns because those
275 types of errors are very often located close to adjacent passes. Finally, N_{ST} could be helpful to label delay-based
276 outliers as these latter are expected to have lower ST neighbours than the remaining dataset, i.e. these errors are
277 located at the beginning and end of harvest rows.

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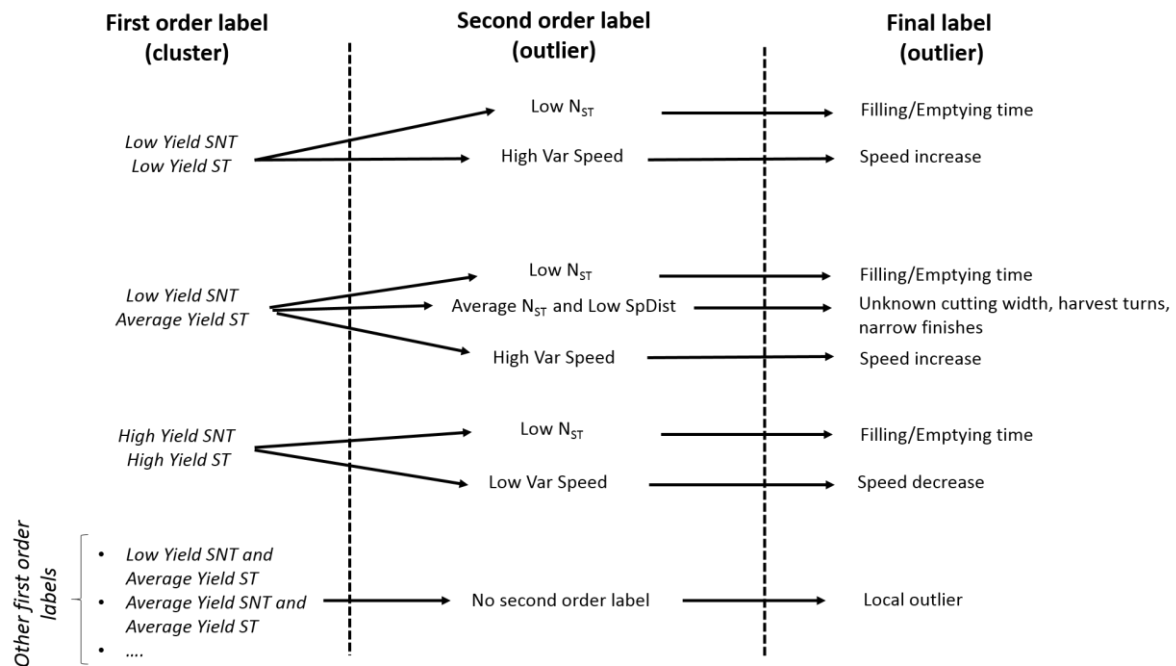


294 **Figure 6.** An example of the proposed methodology to label outliers in cluster n°3. First, each previously defined
 295 cluster is given a first-order label. Then, within this cluster, each outlier is given a second-order label.

296 To improve the labelling of outliers inside each cluster, the second-order (*Var_Speed*, *SpDist*, *N_{ST}*) labels
 297 were compared to those of the cluster of normal observations (Fig. 5). More specifically, for each attribute, three
 298 classes were provided:

- 299 (iv) “Low” if the attribute value of the outlier within the considered cluster is less than the first 20th
 300 percentile attribute value of the distribution of normal observations, e.g. *Low SpDist*,
- 301 (v) “Average” if the attribute value of the outlier within the considered cluster lies between the first
 302 20th and last 80th percentile attribute values of the distribution of normal observations and, e.g.
 303 *Average SpDist*,
- 304 (vi) “High” if the attribute value of the outlier within the considered cluster is more than the last
 305 80th percentile attribute value of the distribution of normal observations, e.g. *High N_{ST}*

306 For instance, in Figure 6, the observation x_i within cluster n°3 is given the following second-order label: “*Low*
 307 *SpDist*”. Given the first- and second order labels that were put into place, Figure 3 can be improved to provide a
 308 classification of the main sources of errors as proposed in Figure 7. An accuracy index was put into place to
 309 evaluate whether the proposed classification was able to provide accurate labels to the defective observations.
 310 Considering a first and a second-order label, the accuracy index is the ratio of the number of true labels to the
 311 number of total observations labelled. In other words, the accuracy reports on the ability of the decision rules to
 312 identify a given type of observations. Once again, Figure 3 and Figure 7 are theoretical but will be tested and
 313 validated on simulated and real yield datasets. Be aware that all the outlying observations that would not be labelled
 314 with our proposed methodology, i.e. that do not belong to our theoretical clusters (Fig. 7), will be solely considered
 315 as local outliers.



316

317 **Figure 7.** Decision rules to label outlying observations in within field yield datasets.

318

319

320 *2.3 Evaluation of the proposed approach*

321 *2.3.1. Simulated datasets with labelled outliers*

322 The approach was first validated on simulated datasets with known outliers' labels. The first objective was to
 323 locate the main types of outliers within the bivariate plot of 'outlierness' to see whether they could be
 324 differentiated. The second goal was to identify the most relevant features of these defective observations.
 325 Simulated yield datasets were generated according to the methodology of Leroux et al. (2017). The simulation
 326 process starts with the creation of a spatially structured yield dataset to which are added specific yield defective
 327 observations reported in the literature (Fig. 8). Yield datasets were created with a mean of approximately 7 T/ha.
 328 The magnitude of variation, represented by the coefficient of variation, *CV*, was set to 30%. Spatial structures (*S*)
 329 were modelled with exponential semi-variogram models. These datasets were set to contain 20% of outliers
 330 distributed between the different types of defective observations according to general findings in the literature and
 331 in personal datasets (Tab.1). Two yield datasets were simulated (Simu1 and Simu2), differing by the level of
 332 variance associated to the outliers to generate a diversity of case studies (Tab. 1) This variance can be understood
 333 as the influence of the outliers within the dataset. A low variance associated to the outliers would mean that outliers
 334 are relatively similar to their normal neighbours, and as such, are more difficult to identify (Simu1). On the
 335 contrary, a higher variance would mean that outliers have more diverging values from those of their normal
 336 neighbours (Simu2). In this case, outliers should be more easily identifiable.

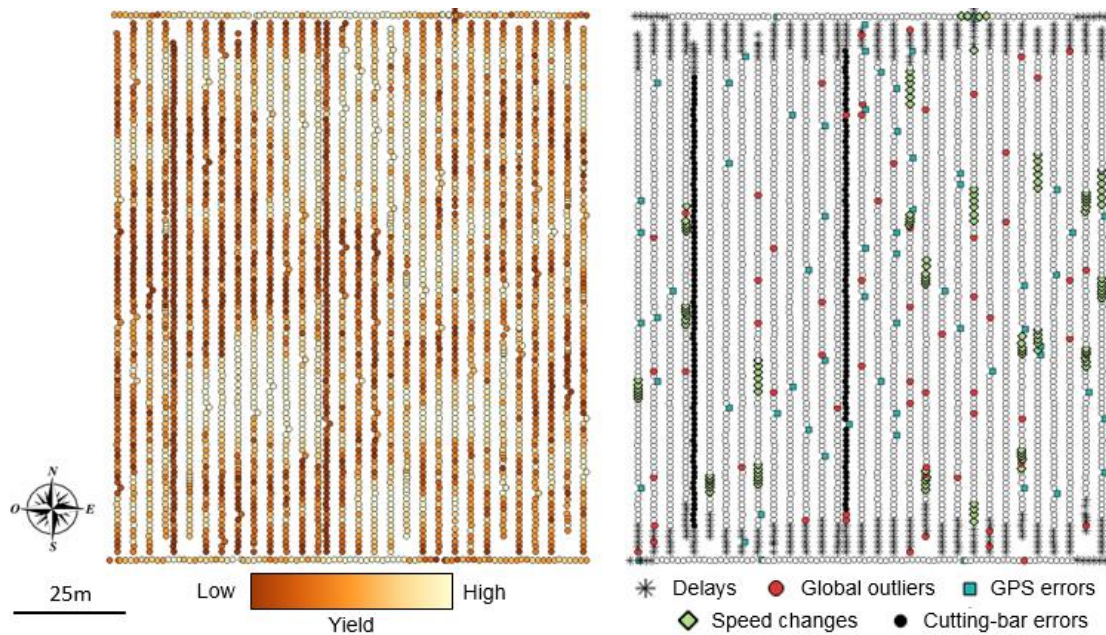


Figure 8. Example of yield simulated dataset (left) along with corresponding simulated errors (right). *These datasets were generated according to the methodology described in Leroux et al. (2017).*

2.3.2 Real datasets with non-labelled outliers

The proposed approach was then tested on four real yield datasets from fields located near Evreux in the North-western part of France. Fields were cropped in wheat and harvested with combines of different brands, especially New Holland (Turin, Italy) and Claas (Harsewinkel, Germany) combines. These datasets were selected for containing (i) different sorts of suspicious observations and (ii) outliers in different proportions (Tab. 2). Indeed, the filtering approach of Leroux et al. (2018) identified between 15 and 48% of outliers in the datasets. Defective observations were found responsible for lowering the mean yield and substantially increase the variability (CV) and skewness of the yield distribution (Tab. 2). Dataset 1 was considered as a typical yield dataset with a strong yield spatial structure, well harvested with mainly delay-based errors. Dataset 2 contains a couple of rows harvested with a not fully-used cutting width in the centre of the field. Dataset 3 was chosen because the wheel passages of a former fertilizer are very visible over the whole field and induced a decrease in yield. Dataset 4 contains two specific features. First, there are multiple narrow finishes within the field. Secondly, when entering the field, the width of the cutting bar was not set appropriately, i.e. lower than it actually was. This width was corrected after a few minutes inside the field. The objective was to see whether these specificities could be observed within the bivariate plot of ‘outlierness’ and labelled correctly.

Table 1. Description of the two simulated datasets Simu1 and Simu2 with their associated outlying yield observations. *Readers are referred to Leroux et al. (2017) for further details regarding the simulation process.*

		<i>Yield technical errors</i>				
		Filling and emptying times	Sensor errors	GPS errors	Speed changes	Not fully-used cutting bar
<i>Amount of errors (Percentage of the total number of outliers)</i>		50%	10%	10% (it can be single or groups of observations)	10%	20 % (all the observations inside a same harvest row are affected)
<i>Simulated dataset</i>	Simu1	Yield underestimation of 40% at the beginning and 20% at the end of the rows [B_k parameter in Leroux et al. (2017)]	20% noise	Lag of 10% of the inter-row distance	20% speed variation	80% of the cutting bar is used
	Simu2	Yield underestimation of 60% at the beginning and 40% at the end of the rows [B_k parameter in Leroux et al. (2017)]	50% noise	Lag of 20% of the inter-row distance	50% speed variation	50% of the cutting bar is used

363 The whole methodology was developed using the R statistical environment (R Core Team, 2013).

364 **Table 2.** Descriptive statistics of the four raw and filtered real yield datasets.

Dataset	Surface (ha)	Raw dataset (with outliers)			Filtered dataset (without outliers)			
		Mean (t.ha ⁻¹)	CV (%)	Skewness	Mean (t.ha ⁻¹)	CV (%)	Skewness	Outliers detected (%)
1	14.5	7.1	28.1	-0.6	7.5	12.1	0.1	15.3
2	20.5	7.74	34.1	6.5	8.3	10.2	-0.3	32.5
3	30.9	9.6	28.7	8.4	9.9	6.0	-0.3	34.5
4	2.2	8.7	47.3	0.05	9.5	9.1	-0.5	48.7

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366 3. Results and discussion

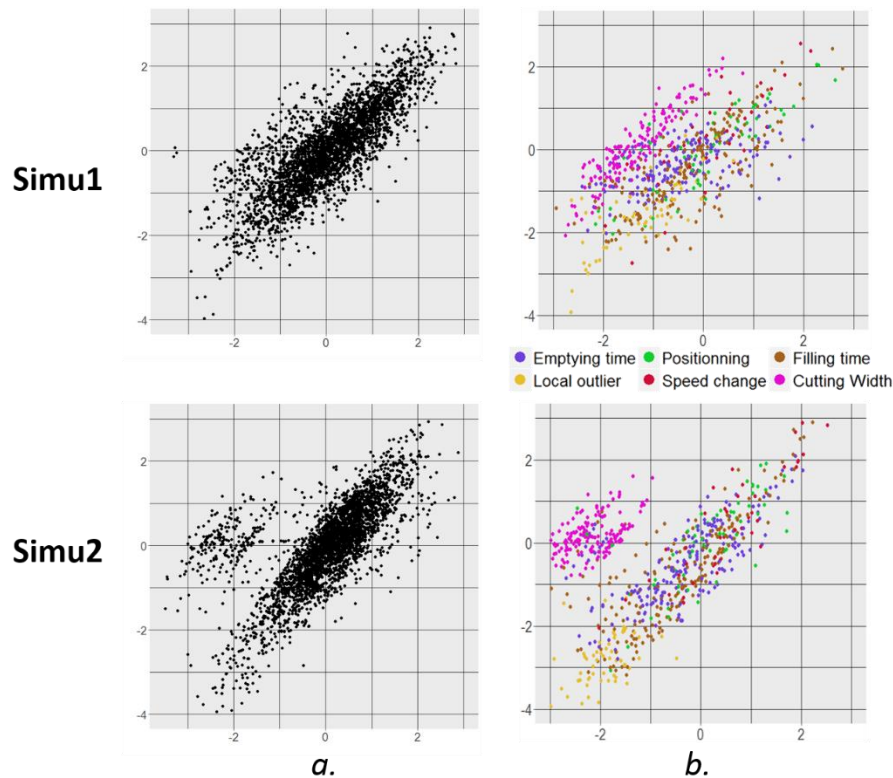
367 3.1. A first insight into the simulated datasets

368 3.1.1 Location of labelled outliers within the bivariate plot of 'outlierness' for simulated datasets

369 In simulated datasets, the label of each observation, and more especially that of the outliers along with the type of
 370 defective observation, is known. This means that it is possible to locate each outlier generated in the bivariate plot
 371 of 'outlierness' to explore how they behave. This will also be a first way to evaluate the veracity of the theoretical
 372 location of yield technical errors that was provided in Figure 3. Figure 9 displays the location of all the observations
 373 in the simulated datasets within the bivariate plot of 'outlierness' (Fig. 9, left) and also that of all simulated outliers
 374 (Fig. 9, right). The two simulated datasets Simu1 and Simu2 are presented. From a general standpoint, it appears
 375 that several defective observations have effectively a specific location within the bivariate plot of 'outlierness'.
 376 This position within the plot appears relatively consistent with what was proposed in Figure 3 but is also much
 377 fuzzier. The bivariate plot of 'outlierness' appears to be clearly impacted by the level of divergence between
 378 normal and defective observations (Fig. 9, right). Indeed, for Simu2, one can distinguish much more easily several
 379 groups of observations through a visual inspection of the plot. It can be noted that when outliers are more deeply
 380 rooted in the dataset, i.e. outliers are more similar to normal observations (Simu1), the bivariate plot of 'outlierness'
 381 seems more homogeneous without strong deviations from the centre of the plot.

382 As expected, observations collected with a not-fully used cutting bar ("Cutting Width") are mostly located
 383 on the left-hand part of the plot, i.e. they are very consistent with their ST neighbours but exhibit relatively different
 384 values to those of their SNT neighbours (Fig. 9, right). Local outliers can be spotted on the extremities of the plot,
 385 i.e. on the bottom-left hand corner because, in this simulated dataset, global outliers were generated with a low
 386 yield value. Suspicious observations collected within the filling and emptying time periods, or during a speed
 387 change appear on the main diagonal of the plot. However, several observations of these last types of error appear
 388 also near the centre of the plot of "outlierness" (Fig. 9, right). The thing is that all the outlying observations do not
 389 have the same influence on the dataset quality. For instance, within the filling time period, the underestimation
 390 associated to the first few observations will be much stronger than that associated to the last observations collected
 391 during this filling time. The primary observations within the filling time will therefore strongly deviate from the
 392 normal population while the last ones will be much closer to the distribution of the normal population. To put it
 393 simple, observations with the major impact on the yield local distribution will be located far from the centre of the
 394 bivariate plot of 'outlierness'. Finally, by observing more carefully the shape drawn by the outliers, it seems that
 395 several populations can be depicted within the plot. Indeed, it seems possible to fit straight lines with similar slopes
 396 but different intercept, especially for the observations collected with a not-fully used cutting bar with respect to
 397 the rest of the data. The change of cutting width, which originated a strong decrease in the yield values, have
 398 produced a substantial change in the yield distribution of these specific outliers that is highlighted by a shift in the
 399 bivariate plot of 'outlierness'.

400



401

402 **Figure 9.** Location of simulated-based outliers in the bivariate plot of ‘outlierness’. In Simu1, outliers are relatively
403 similar to normal observations. In Simu2, outliers are more diverging from normal observations. *a. Unlabelled*
404 *observations. b. Labelled observations*

405 3.1.2 Automatic detection and clustering of outliers in simulated datasets

406 Figure 10 reports how outliers are handled by the proposed approach, i.e. detection of outliers (Fig. 10, left) and
407 clustering of outliers (Fig. 10, right). First, it can be seen that multiple outliers are not detected by the approach of
408 Leroux et al. (2018). As discussed in the previous section, these suspicious observations appear near the centre of
409 the plot where observations are considered normal in the aforementioned methodology. These outliers, i.e. much
410 more similar to the normal observations, are more difficult to detect and can be referred to as false-negative
411 outliers. From a practical standpoint, by considering the example of the delay-based outliers, it is much more
412 important to remove the observations at the beginning of the filling period, i.e. outliers that lay far from the centre
413 of the plot, than to remove those when the filling time is almost finished, i.e. outliers that are located in the centre
414 of the plot. In other words, it is more interesting to focus on removing the variance associated to the outliers than
415 a specific number of defective observations.

416 By using the proposed angle-based methodology, several groups of outliers were identified automatically
417 (Fig. 10, right). The proposed approach has generated two and three major clusters for the simulated datasets
418 Simu1 and Simu2. It appears that this delineation comes out more robust when outliers are relatively different to
419 the normal population, i.e. Simu2 (Fig. 10, bottom right). In this case, clusters effectively correspond to major
420 sources of yield errors. For Simu1, cluster n°5 seems relatively wide as it gathers several types of outliers.
421 However, for Simu1, the relative consistency that exists between outliers and normal observations makes it
422 difficult to properly split the cluster by solely relying on the yield attribute. In both simulated datasets, relatively
423 small clusters are being identified, e.g. clusters n°1,2 and 4 for Simu1. Those clusters will not carry much
424 information as they contain very few data.

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Simu1

Simu2

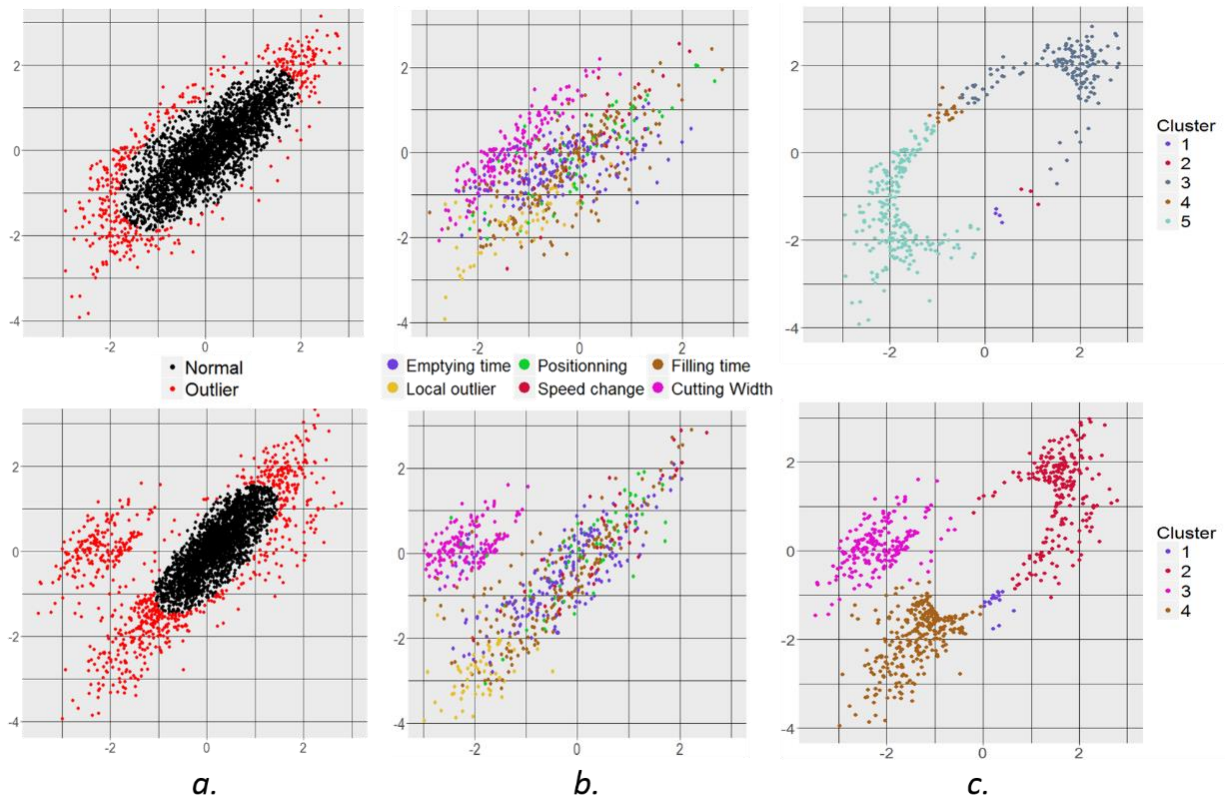


Figure 10. Analysis of outliers in the simulated datasets with low outlier variance (top) and moderate outlier variance (bottom). *a.* Identification of outliers by the approach of Leroux et al., (2018). *b.* Known labelling of the outliers within the dataset. *c.* Clustering of the outliers within the dataset

3.1.3 Labelling of outliers in simulated datasets

For both simulated datasets, Table 3 reports: (i) the first-order label associated to each cluster, (ii) the second-order label associated to each outlier within the previously-defined clusters, (iii) the final label associated to each outlying observation and (iv) the accuracy of the labelling (ratio of the number of true labels to the number of total observations labelled). Unsurprisingly, it appears that the labels' accuracy is better for Simu2 because in that case, outliers are more different to the normal population. From a general perspective, the labelling of outliers is relatively accurate. Note that when the first-order label did not match any of the theoretical outlying clusters that were proposed in Figure 7, the respective outlying observations were simply labelled as local outliers. As all types of errors can be considered as specific forms of local outliers, the accuracy index for the label *local outliers* does not make much sense.

Be aware that the labelling is generally bad when it comes to detecting observations acquired during the filling and/or emptying times with a first-order label "High yield ST/SNT" (top right-hand corner of the bivariate plot of 'outlierness'). For the remaining clusters, the accuracy is relatively high enough meaning that the outlying observations can be automatically labelled given the first- and higher-order labels that are provided. This classification, i.e. that of Figure 7, will therefore be used to analyze the real datasets (see next section).

469 **Table 3.** Labelling of outliers in simulated datasets.

Simulated Dataset	Cluster	First-order label	Second-order label	Final label	Accuracy (%)	
Simu1	1	Average yield SNT Low yield ST	-	Local outliers	-	
	2	Average yield SNT Average yield ST	-	Local outliers	-	
	3	High yield ST/SNT	Low N_{ST}	Filling/Emptying times	5	
			Low Var_Speed	Speed decrease	35	
	4	Average yield SNT Average yield ST	-	Local outliers	-	
	5	Low yield ST/SNT	Low N_{ST}	Filling/Emptying times	45	
			High Var_Speed	Speed increase	100	
	Simu2	1	Average yield SNT Low yield ST	-	Local outliers	-
		2	High yield ST/SNT	Low N_{ST}	Filling/Emptying times	13
				Low Var_Speed	Speed decrease	78
3		Low yield SNT Average yield ST	Low N_{ST}	Filling/Emptying times	61	
			Average N_{ST} and Low $SpDist$	Partially-used cutting bar	97	
			High Var_Speed	Speed increase	100	
4		Low yield ST/SNT	Low N_{ST}	Filling/Emptying times	91	
			High Var_Speed	Speed increase	80	

470

471 It must be understood that, here, the accuracy shows whether an outlying observation is given a good final label
 472 considering the first and second-order labels that are defined. However, it does not specify if, within the whole
 473 dataset, all the observations that should have been given a specific label actually received it. For instance, one can
 474 be pretty sure that the outlying observations in Simu2 that were given the label “Partially-used cutting bar” are
 475 observations that were collected when the width of the cutting bar was not used entirely. Nevertheless, one cannot
 476 be entirely sure that all the observations collected with a partially-used cutting bar were found in the whole dataset.

477 To provide users with a more comprehensive overview of the reliability of each label, the ratio between accurate
 478 labelled outliers and the total number of outliers of each type in the whole dataset is presented in Table 4. As
 479 should be expected, ratios are lower for Simu1 than for Simu2 given the construction of both datasets. From a
 480 general perspective, by looking at Table 4, ratios seem to be relatively low, especially for Simu1. Note also that
 481 no observations collected with a partially-used cutting bar could be found in Simu1 given the clusters that were
 482 identified in Figure 10 and the associated labelling rules. Obtaining relatively low ratios should not be very
 483 surprising given that several outliers were not identified by the filtering approach of Leroux et al. (2018), i.e., those
 484 are located near the centre of the bivariate plot of outlierness. As the labelling procedure solely labels observations
 485 that were identified as outliers, not all the outliers could be labelled. Be aware that the ratios would have been
 486 higher if solely the detected outliers had been considered (and not all the outliers in the dataset). On top of that, it
 487 must be clear that those ratios represent solely a percentage of outlying observations and do not convey any
 488 information regarding the variance associated with these outliers. For instance, only 43.5% of the observations
 489 acquired during a filling or emptying time were correctly labelled for Simu2 but those observations accounted for
 490 most of the variance associated to the filling/emptying time label (data not shown). The outlying observations near
 491 the centre of the bivariate plot of outliers (that were not labelled) are not that different from their neighbours (the

492 influence of these outliers is expected to be relatively low) while those far away from the centre of the plot are
493 much more influencing (Fig. 10b). This last statement echoes some of the points that were addressed in section
494 3.1.1 where it was discussed that not all the outlying observations had the same influence on the quality of the
495 dataset. The same reasoning can be applied to the other outlying observations, e.g. those collected during a speed
496 change. Indeed, some very slight speed changes can also be found near the centre of the bivariate plot of outlierness
497 (Fig. 10b). From a general perspective, the labelling outputs on the simulated datasets necessarily depend on the
498 way yield datasets were simulated (Leroux et al., 2017).

499 **Table 4.** Reliability of the labelling in simulated datasets. *The table presents the ratio between accurate labelled*
500 *outliers and the total number of outliers of each type.*

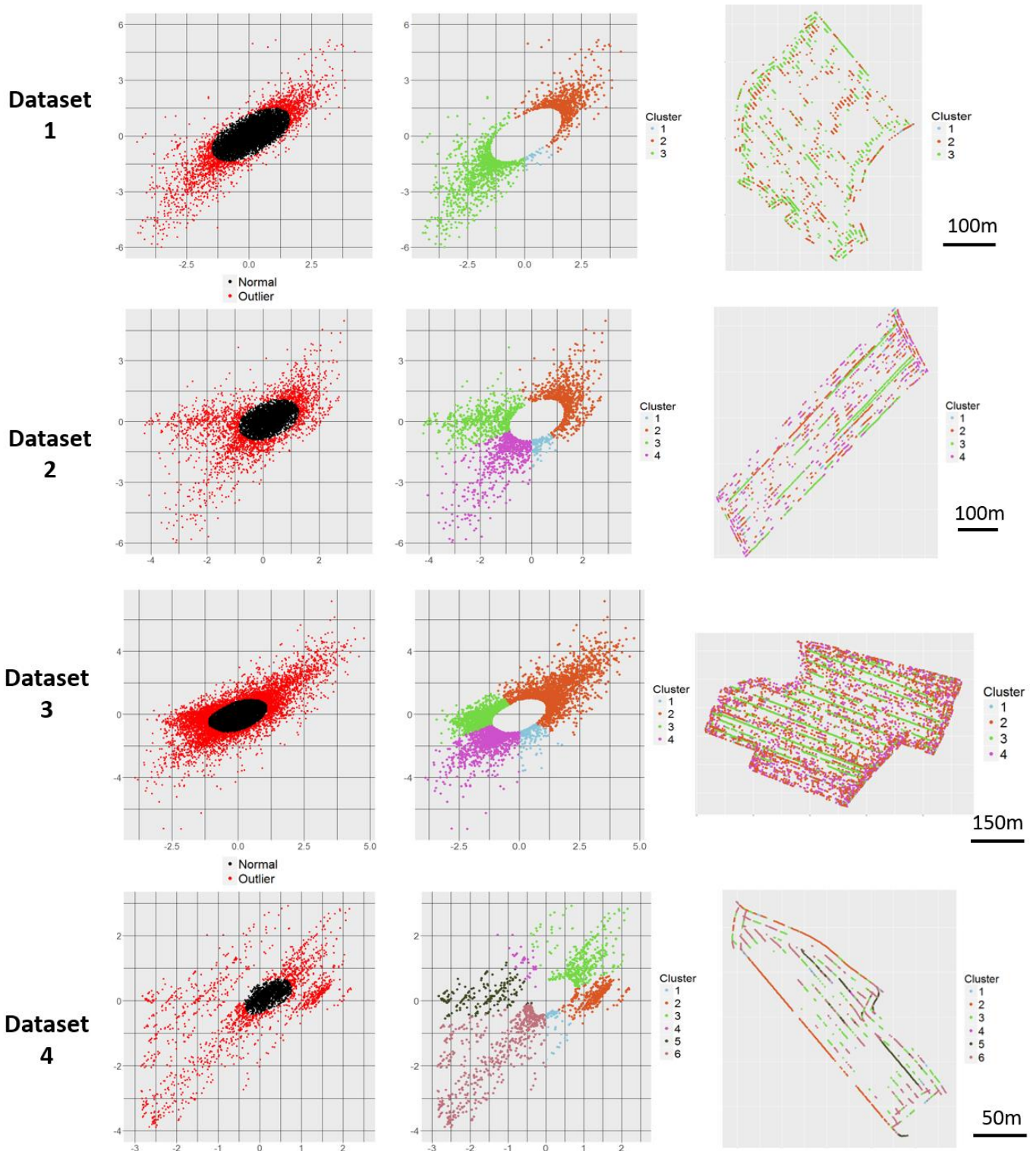
	Filling/emptying times	Speed changes	Partially used cutting bar
Simu1	16.8	8.7	0
Simu2	43.5	18.6	91.1

501

502

503 3.2. Clustering and labelling of suspicious observations in real yield datasets

504 The defective observations that were identified in the real datasets by the filtering approach of Leroux et al., (2018)
505 are depicted and clustered in Figure 11. First of all, it can be seen that the structure of the bivariate plots of
506 ‘outlierness’ shares many similarities with that of the simulated datasets (Fig. 11, left and middle). More
507 specifically, multiple observations expand towards either the top-right, bottom-left or left-hand part of the plot.
508 This aspect is satisfying because it proves the interest of the theoretical data to study and help label outliers. Note
509 that all the datasets seem to have similar types of clusters (the angles that are formed between the cluster and the
510 horizontal axis are very similar). Each dataset also has its own specificities as the number of outliers’ clusters
511 varies across the yield datasets, from two to five main clusters between datasets 1 and 5. These groups of outliers
512 are relatively well identified especially for datasets 1, 2 and 4. The delineation of the clusters appears more abrupt
513 for dataset 3, e.g. for instance between clusters n°3 and 4, but there effectively seems to be two different
514 populations in the data. It is acknowledged that the clustering using the proposed angle-based approach can be
515 considered quite brutal at the edges of the outliers’ clusters. Some confusion might effectively remain, but it must
516 be noted that the main groups of outliers are being spotted. Interestingly, the aspect of different statistical yield
517 distributions that was previously discussed with respect to simulated datasets, i.e. the impression of parallel straight
518 lines that could be fitted to the data, is particularly visible on dataset 4.



519

520 **Figure 11.** Labelling of outliers in the real yield datasets. *Left. Detection of outliers. Middle. Clustering of outliers.*
521 *Right. Location of the clusters within the field.*

522 Given the findings in the simulated datasets and the location of each outlier's clusters within the field
523 (Fig. 11, right), yield outliers could start being labelled. For the four datasets under study, the clusters located on
524 the diagonal of the bivariate plot of 'outlierness' (Low yield ST/SNT and High yield ST/SNT) are relatively well
525 identified. Observations inside these clusters were labelled as filling/emptying times, speed changes and local
526 outliers following the decision rules that were used for the simulated datasets (Fig. 7). Regarding dataset 1, some
527 observations lying within the clusters n°2 and n°3 appear to be located in the centre of the field. These observations,

528 that were labelled as local outliers according to the proposed methodology (data not shown), are in fact due to the
529 presence of a change in soil conditions which originated a short-range variation in yield. These observations are
530 therefore not outlying observations but rather expected yield records. Note that without a soil map, this distinction
531 is relatively difficult to make.

532 In the case of simulated datasets, the cluster on the left-hand side of the plot (*Low yield SNT* and *Average*
533 *yield ST*), i.e. cluster n°3, was mostly standing for observations collected with a low cutting width. This is why the
534 second-order label “*Low SpDist*” was put into place for this specific cluster. However, when looking at the
535 observations in cluster n°3 within dataset 3, many of these observations appear to be regularly spaced within the
536 field, which is not particularly a feature of passes harvested with a low cutting width (Fig. 11). These observations
537 could be spotted by the second-order label “*Average SpDist*”. These observations were found to represent the
538 wheel passages of a former fertilizer or other agricultural machinery. It must be clear that this labelling was not
539 proposed in the initial labelling framework (Fig. 7). Without using the second-order label “*Average SpDist*”, these
540 regularly spaced observations would be given the final label ‘local outliers’. To provide a better labelling of these
541 observations, it was therefore decided to add a new rule to the labelling framework (Tab. 5). This rule was
542 specifically applied to this dataset, but could certainly be used in a more general perspective in the proposed
543 approach.



544

545 **Figure 12.** Analysis of cluster n°3 in datasets 2 and 3. *The attribute SpDist helps improve the labelling of*
546 *observations inside this cluster.*

547 A last interesting aspect to consider was the relatively large cluster n°2 of dataset 4 that expands towards the right-
548 side (*High yield SNT* and *Average yield ST*) of the bivariate plot of ‘outlierness’ (Fig. 11, dataset 4). In the case
549 of dataset 4, these observations have effectively a somewhat questioning behaviour because they can be found
550 mostly on the edges of the field. It was found that this cluster n°2 corresponded to the operator’s error in setting
551 the appropriate width of the cutting bar when he started harvesting the field. The cutting bar was effectively set
552 lower than it actually was, which led to an overestimate of the yield (see material and methods section 2.3.2). This
553 dataset enabled to propose an additional rule to the initially proposed labelling framework (Tab. 5). Here again,
554 this rule was specifically applied to this dataset, but could certainly be used in a more general perspective in the
555 proposed approach.

556 Table 6 sums up the results of the labelling process, i.e. an estimate of the proportion of each type of outlying
557 observations, on the four real datasets using the initial labelling framework (Fig. 7) to which additional rules were
558 joined (Tab. 5). These summary statistics are obviously not perfect and depend on the methodology that was used
559 in this work. Be aware that global outliers (header up, zero yield values, very abnormal yield value...) are not
560 accounted for in Table 6, because they were removed before the spatial outlier detection process in Leroux et al.
561 (2018). Note also that some of these global outliers might have been labelled with one of the main sources of
562 technical errors but these outliers were found so diverging from the normal population that they were removed
563 prior to applying the spatial outlier detection algorithm. Table 6 highlights that all datasets are unique in the sense
564 that they all have different outliers and those latter are present in different proportions. It must be reminded that
565 the label “Local outliers” contains the outlying observations that could not be labelled in any of the other classes
566 of technical yield errors. This is why the percentage of observations having this label is quite high. The labelling
567 of filling and emptying time errors seems slightly low, especially for datasets 2 and 3, when comparing with the
568 literature. This may be due to the removal of such errors with the global filter introduced in Leroux et al. (2018)
569 or because some of these errors were mixed up with others and were labelled as local outliers.

570

571

572 **Table 5.** Additional decision rules arising from the analysis of the real yield datasets.

Dataset	Cluster	First-order label	Second-order label	Final label
3	3	Low yield SNT and Average yield ST	Low SpDist	Unknown cutting width
			Average SpDist	Wheel passage of a former fertilizer
4	2	High yield SNT and Average yield ST		Error in setting the width of the cutting bar
	5	Low yield SNT and Average yield ST	Low SpDist	Unknown cutting width / Narrow finishes

573

574 **Table 6.** Summary of the technical errors within each real dataset. *The total number of outliers is the sum of the*
 575 *number of each type of outliers.*

Dataset	Filling/Emptying time	Speed change	Unknown cutting width / Narrow finishes	Local outliers	Others (wheel passages, error in settings)	Total number of Outliers
1	4.8%	1.9%	-	8.6%	-	15.3%
2	1.5%	3.7%	5.5%	21.8%	-	32.5%
3	0.7%	5.4%	1.5%	19.6%	7.3%	34.5%
4	12.4%	2.8%	5.3%	18.6%	9.6%	48.7%

576

577 From a general perspective, by looking at the labelling rules that are proposed in this study (Fig. 7), one could
 578 suggest that the second label alone would be successful to separate each error. It is effectively acknowledged that
 579 the second-order labelling could be efficient in itself but it is also stressed that the clustering and first-order
 580 labelling of outlying observations have also their interest. First, it is clear that defective yield observations are
 581 clustered in specific portions of the bivariate plot of outlierness (Fig. 2, right; Fig. 10, Fig. 11). When looking at
 582 these figures, one might be very tempted to intend to group these outliers in terms of their yield behaviour with
 583 respect to neighbouring observations to see whether specific patterns can be identified. The approach to
 584 automatically split outlying observations in different clusters was done in that sense. Secondly, when focusing on
 585 the real yield datasets, it should become clearer that this first order labelling was relevant. In fact, for dataset 3, if
 586 cluster n°3 with the first-order label ‘*Low yield SNT and Average yield ST*’ is not separated from the rest of the
 587 outlying observations, it would not have been possible to identify the wheel passage of a former fertilizer or
 588 agricultural machinery. Indeed, these observations have a second order label “Average SpDist”. If this labelling
 589 rule was used on all the outlying observations, many specific observations would have been mixed. Same goes for
 590 cluster n°2 in dataset 4, the settings error in the cutting bar width would not have been clearly separated from the
 591 other types of outlying observations.

592 The proposed approach enables to provide users with a clearer interpretation and analysis of their yield datasets.
 593 Some of these results might be used to improve the quality of the datasets by correcting some of these errors
 594 instead of removing them (see next section). Another possibility would be to analyze the way operators drive
 595 within the fields (speed changes, operator-based outliers) or to characterize the functioning of the harvester.
 596 Economic considerations might also come up such as whether investing in systems that measure in real-time the
 597 width of the cutting bar is relevant if the outlying-related observations can be spotted and corrected. Once again,
 598 these results come along with a given uncertainty, but they might be used to depict general trends in the data. Be
 599 aware that the proposed method is a first attempt to provide a label to yield outliers. This approach can be sensitive
 600 to the thresholds that have been set, more especially the 20th and 80th percentile values that were used to help label
 601 the clusters of outliers and the outliers within each cluster. The choice of these thresholds would require further
 602 investigation. One possibility could be for instance to test the sensitivity of the method to the values of these
 603 thresholds through a Monte Carlo approach, but this is beyond the scope of this work. Note however that these
 604 thresholds are relatively easy to parametrized.

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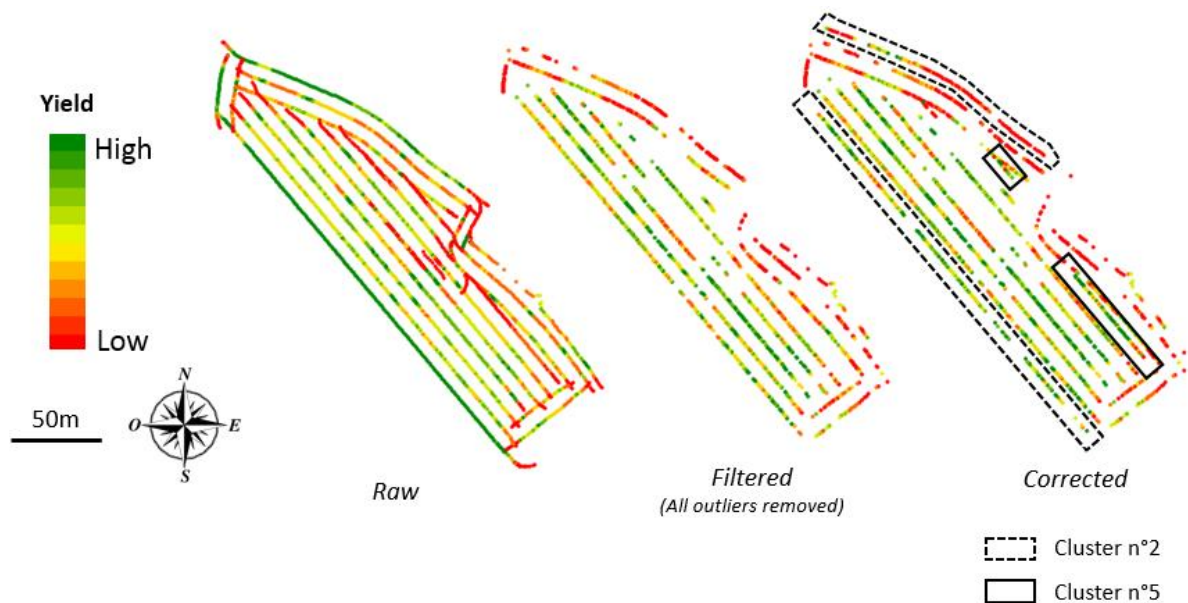
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608 3.3 What can be done with the labelled outliers ?

609 When outliers are labelled and described with a proper subset of attributes, they become meaningful and
610 understandable. As such, it becomes possible for users to make a decision with regard to these suspicious
611 observations. Two major case studies can be observed. In the first case, outliers can be considered as noise meaning
612 that these observations are not reflecting a real phenomenon and as a consequence should not have been generated.
613 This noise can have multiple causes such as the process of data acquisition in itself, e.g. the pass of the combine
614 harvester within the field, or a technical failure, e.g. loss of positioning signal. To tackle this noise, defective
615 observations can be either corrected or removed. Performing a correction on a defective observation is conceivable
616 when the phenomenon which originated the outlier is fully known and controlled. Here, it is suggested that, when
617 possible, the correction should be preferred to the removal of outliers because the final dataset would contain more
618 information and should therefore be more accurate. If the origin of an outlier is known but the accuracy of the
619 correction could be questioned, the outlier should be removed to make sure the quality of the dataset is not affected.
620 This was especially considered for technical errors such as speed changes or filling and emptying times which
621 have a complex influence on the yield output. In the second case, the outlier might really shed light on a
622 phenomenon of interest which could be either expected or unexpected. In such situations, users should be warned
623 so that they can intend to get a deeper understanding of this specific phenomenon.

624 Here, the output of the processing that was applied to dataset 4 is displayed in Figure 13. In this case study, more
625 specifically, a correction was applied to the outliers in clusters n°2 and 5 while other defective observations were
626 removed. Indeed, most suspicious observations of cluster n°2 are due to bad settings in the cutting width of the
627 harvester, which can be corrected by weighing the yield values with an appropriate factor depending on what was
628 set by the operator (this information was available in the yield dataset). The outliers belonging to cluster n°5
629 especially reflect passes harvested with a low cutting width. For these specific observations, a weighing factor,
630 related to the spatial distance to the previously harvested pass, can be applied to calculate the yield that should
631 have been found with the portion of the cutting width that was used.



632

633 **Figure 13.** Making value of the labelling of outliers to propose a correction for dataset 4. *Dashed polygons contain*
634 *the observations that were restored.*

635 This correction helped retrieve lots of yield observations within the dataset (almost 15%) to improve its quality
636 and reliability (Fig. 13, right). Note for instance that most of the yield information on the edges of the fields were
637 restored. However, it was decided not to propose any correction for the remaining clusters. One effectively knows
638 the general impact that a speed change or the delay-time might cause on the yield attribute, i.e. an increasing or
639 decreasing trend, but it is much more difficult to evaluate it precisely. Some convolution filters might be proposed
640 to cope with that issue, but they were considered relatively complex to put into place as the parameters of the
641 model convolution are not easy to define properly (Arslan and Colvin 2002). Nevertheless, it must be said that
642 yield datasets contain quite a large amount of information which means that removing outliers is not too critical if

643 a proper and accurate correction cannot be proposed. Be aware that this case study is an application example of
644 the proposed methodology and that applying this methodology would require having a discussion with the operator
645 to validate the origin of the errors.

646 4. Conclusion

647 This study proposes a methodology to cluster and label outlying observations in yield datasets after that these latter
648 have been detected by a holistic and unsupervised filtering approach. Defective observations are first labelled in
649 terms of yield characteristics with respect to their spatial neighbours. They are then further labelled with
650 appropriate spatial and non/spatial attributes so that they can be classified more accurately into the main types of
651 yield technical errors, e.g. filling/emptying times, speed changes, unknown cutting width when entering the crop,
652 narrow finishes. While some observations are more accurately classified (speed changes or unknown cutting
653 width), others are slightly more complex to be given an appropriate label (filling/emptying times). The proposed
654 labelling approach also enabled to identify specific observations in real yield datasets, i.e. the wheel passages of a
655 former fertilizer or agricultural machinery and settings errors in the cutting bar width. The proposed methodology
656 provides users with a set of interpreted outlying observations which can then be used for multiple purposes: (i)
657 understanding of the main sources of errors in each user's yield dataset, (ii) correction of the outliers instead of
658 removing them if possible, (iii) characterization of the way the operator drives within the field or how the combine
659 works during harvest, and (iv) provision of guidelines for future improvements of equipment and operations
660 processes. Future work will focus on improving the ability of the proposed methodology to properly label outliers
661 and testing the approach on more datasets, i.e. not only related to yield.

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663 5. References

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