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Automated Geometrical Field Boundary Delineation Algorithm for Adjacent Job Sites

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Abstract.

Establishing farmland geometric boundaries is a critical component of any assistive technology designed towards the automation of farming systems. Observing farmland boundaries enables farmers and farm machinery contractors to determine; seed purchase orders, fertiliser application rate, and crop yields. Farmers must supply acreage measurements to regulatory bodies, who will use the geometric data to develop environmental policies and allocate farm subsidies appropriately.

Agricultural parcel delineation is the process by which land parcels are geofenced into their individual field geometric boundaries. The problem scenario addressed in this paper is to automatically discern when a tractor towing a) a silage baler b) a mower implement, moves between adjacent fields while the towed implement remains active. We present a novel method for automated agricultural field segmentation. When towed implements are considered, their power drive (usually from a Power-Take-Off shaft) can often remain active when the machine operator traverses between multiple sites that are in proximity. The solution herein automatically discerns between adjacent sites, solves for field geometric boundaries and applies a job context to machinery operational data on a field-by-field basis. The method uses historical coordinate data, coupled with a PTO activation signal, recorded on agricultural harvesting implements over several months.

The algorithm shows how adjacent fields in a land parcel, which cannot be distinguished using machinery sensors, can be spatially segmented with an accuracy of 92.6% on a baler dataset and 80.9% on a mower dataset. Data was aggregated from a full season of silage baling in East Galway, Ireland. The method is shown to outperform the state of the art within the literature at a fraction of the cost, and the technique can be applied to several agricultural implements or self-propelled machines. No aerial surveillance or undesirable land traversal is required to produce the results shown, offering an efficient, environmental and cost-effective geofencing method to agricultural stakeholders around the globe.

Keywords.
Agricultural Parcel Delineation, Field Segmentation, Agricultural Machinery Trajectory Data, Towed Implement Machinery, Field Efficiency Analysis, GNSS, GPS

1. Introduction

Agricultural parcel delineation is a necessary component in modern agricultural systems. In the EU, for example, all member states are signed up to a Land Parcel Identification System (LPIS) database to record agricultural boundaries for auditors (European Court of Auditors, 2016). This information is, in turn, used to help set environmental policies and inform subsidy management bodies such as the Common Agricultural Policy (CAP) (European Commission, n.d.). These institutions rely on accurate acreage measurements to appropriately allocate resources to farmers. A significant proportion of Precision Agriculture (PA) systems, designed towards farm and land management require accurate geofencing to function. These systems will require agricultural machinery data, that must also be segmented for information management (Mulla, 2013) and data post-processing (Matthias et al., 2003).

Geo-referenced time-series agricultural machinery data is a form of spatio-temporal data in which the entire positional history (spatial locations with timestamps) of the moving object is recorded (Kisilevieh et al., 2010). In the context of this paper, a "site" is a recorded data session capturing a machinery's trajectory in performing a single episode of work. Within a site, there may be one or several co-located fields. Segmentation is the process of labelling spatio-temporal site data as belonging to a particular field. Agricultural data mining algorithms may segment machinery trajectory data roughly using a coarse filter (timestamps, speed, Power take-off (PTO) activation). However, the problem becomes significantly more complicated when fields are adjacent (share a common boundary). In the EU, over 60% of farms are classified as "small", spanning under five Hectares in area (Eurostat, 2016). Farmers with smaller holdings may not have the financial means to afford state-of-the-art machinery and will use a third-party contractor who will lease both machinery and a skilled operator to carry out mechanised functions on the land. These contractors will often visit multiple adjacent sites in a single day, where they continue to activate the PTO, despite traversing into new job site belonging to a new landowner. Researchers may resort to segmentation by manual methods for once-off cases, at the expense of a significant labour and time cost. However, to make data capture on agricultural machinery practical for industry application, agricultural machinery trajectory segmentation must be performed automatically.

Methods exists in literature to delineate field boundaries using remote sensing methods. Approaches include hierarchical pixel clustering (García-Pedrero et al., 2017); deep learning (Aung et al., 2020); object-based image analysis (Xu et al., 2019); directional edge filters (North et al., 2019) and pixel textural classification (da Costa et al., 2007). Segmentation by remote sensing offers the advantage to batch segment fields, which is useful for large land parcels, on the provision that images are updated frequently.

In comparison, a coordinate based solution, like the one presented in this paper, is a significantly more cost-effective alternative to acquiring remote sensing images. Coordinate based methods are integrated directly onto the agricultural machinery which already traverse the field. No additional machinery or labour is required, the only cost is in the initial deployment of a GPS receiver and event sensors on the machinery. Incorporating a solution directly onto the operating machinery also offers the advantage of job-specific segmentation data.

Coordinate based methods are typically based on trajectory segmentation or clustering. A significant proportion of trajectory segmentation methods are based on establishing policies and exploiting gaps in the raw data (Biljecki, 2010; Schuessler & Axhausen, 2009; Waga et al., 2012; Yan et al., 2010). Policies may be based on speed, direction, start-end, stop-move, time intervals and predefined geo-fenced regions. Policy based segmentation methods, however, are not suitable to segmenting agricultural machinery trajectory data. Such policies, such as start-end and stop-move do not crossover to agricultural applications where start-end locations cannot be known a priori and stop-move locations depend on assumptions about operator driving behaviour and implement operation. Probabilistic logic methods found in (Guo et al., 2018) use repetitive driving schedules by which to group trajectories. Agricultural machinery operators, however, usually have irregular schedules and driving routes. Map-matching based segmentation methods (Zhu et al., 2017) rely on correlating trajectories to road network databases. This is only useful for cases of agricultural machinery travelling on roads between fields, not for adjacent fields connected by short, off-road pathways (when the operator does not switch off the PTO).

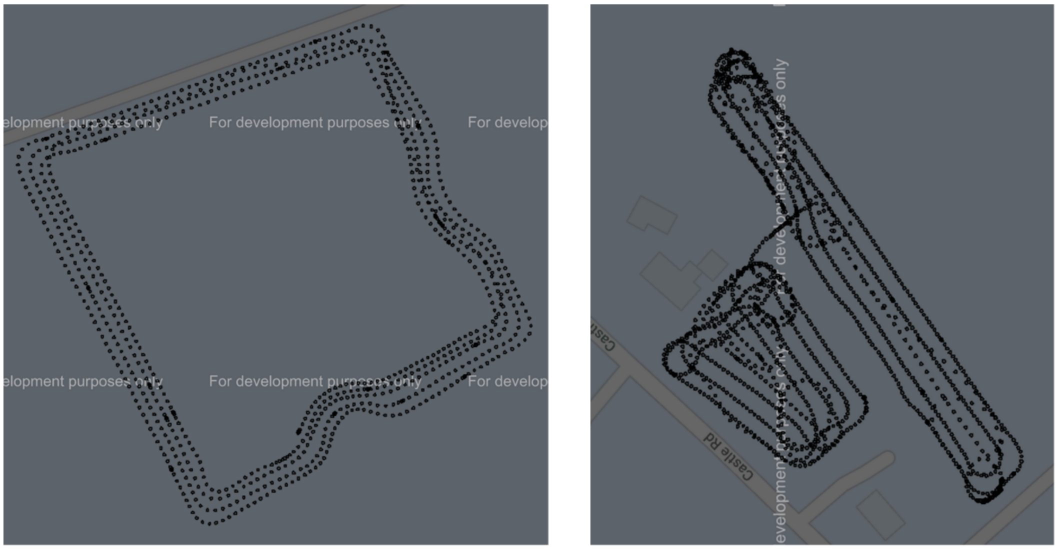


Figure 1 (a): Example of a hollow, single field site. It is not uncommon in round silage baling for the machinery operator to only bale the field perimeter. The central region of the field may be left for hay, weather dependent of course.

Figure 1 (b): Example of a conjoined site. The fields are adjacent, they share a common boundary and are connected by an off-road pathway. Visually, the divide between fields is clear, but this is not apparent in the raw trajectory data.

Clustering is a method of dividing a population of data points into groups. Clustering has already been utilised in trajectory segmentation research for both road vehicles and agricultural machinery. Both (Gong et al., 2015) and (Hwang et al., 2017) propose using versions of DBSCAN (Density Based Spatial Clustering Algorithm applications with Noise) on spatio-temporal data to identify vehicle stop points. The authors in (Chen et al., 2021) develop a field-road trajectory segmentation algorithm using DBSCAN and direction-based inference rules. The developed method shows improved performance when compared to using DBSCAN alone. However, the test cases shown do not include adjacent fields, rather isolated fields with a road between. The challenge in field segmentation is not road-to-field cases, rather field-to-field cases. Road-to-field segmentation problems for towed implement machinery can be solved using ISOBUS ECU messages or a PTO pulsed digital sensor on the shaft. This is sufficient to detect when the machine is powered, and thus whether it is on the road or not. Moving between adjacent fields remains a challenge. Figures 1(a) and 1(b) illustrate sample fields captured on machinery trajectory data for a hollow and adjacent fields job site. To the best of the authors knowledge, these types of challenging sites have not been addressed existing methods in existing trajectory based or clustering solutions.

The extent of work completed in field segmentation literature shows there is a need for an accurate adjacent field segmentation algorithm. Additionally, there are limited examples within the literature where field segmentation is performed using machinery coordinate data. This is despite the fact GPS is a reliable, cheap and globally accessible technology. Clustering machinery coordinate data is one approach to delineating farmland boundaries but training a robust model is a challenge given nature of the problem; proximity of adjacent fields, irregular field geometries and unpredictability in operator driving patterns behaviour. A novel solution to automatically segment adjacent agricultural fields is required.

This paper proposes a novel technique to automatically segment adjacent job sites where operational activation data is unreliable. To the authors knowledge, it is the only contribution in the literature to address this problem. A diagram in Figure 2 illustrates the algorithmic solution to field segmentation that segments machinery spatio-temporal data into labelled fields. Data acquired over an entire season, from a silage forage harvesting contractor, based in Galway, Ireland, is used to evaluate the proposed method. The contributions herein are:

1) The algorithm obtains field geometric boundaries from agricultural machinery data requiring GNSS (global navigation satellite system) data, ISObus ECU messages or a PTO pulsed digital sensor (as a backup in lieu of ISOBus availability.)
2) The algorithm applies a job context to machinery sensor data, unlike existing remote image sensing based methods for field segmentation.
3) The algorithm is tuned, but not trained, to segment agricultural machinery trajectory data without machine learning methods. Which to the best of the authors knowledge, is the only version of which that exists within literature.
4) The method is shown to outperform the state of the art within the literature at a fraction of the cost.
5) No additional surveillance or land traversal is necessary to produce the results shown, offering a bolt-on solution to existing mechanised practices.

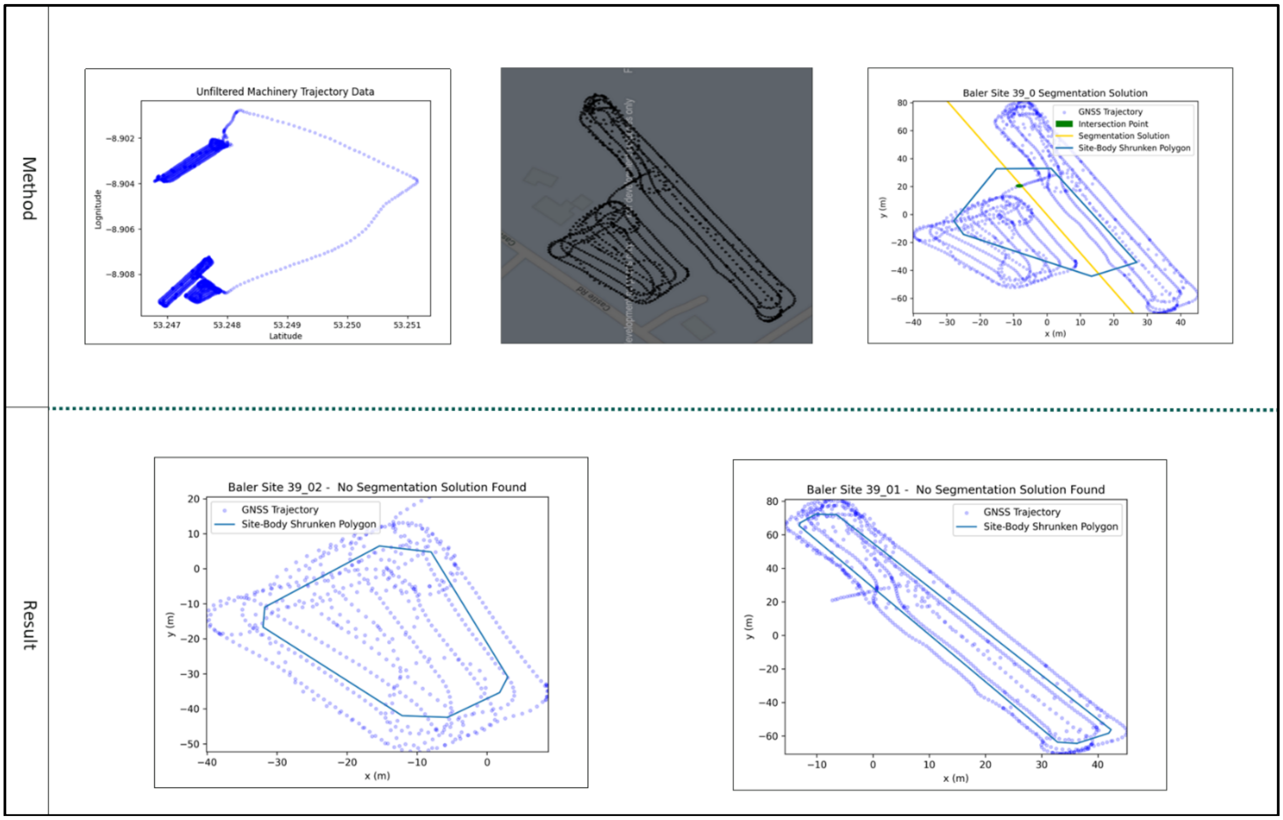


Figure 2: Algorithm Overview. A day's work of machinery trajectory data is *coarse* filtered into site data, and subsequently *fine* filtered for processing. The algorithm segments the conjoined site by imposing a straight-line solution. The result is the individual fields.

1. Materials and Methods

This section reviews the origins and implementation of the proposed automated geometrical field boundary delineation algorithm. The approach shown in this paper applies to any agricultural machine that carries out an agricultural process using a towed implement.

2.1 Data Capture

Geo-referenced time series data (*latitude, longitude, timestamp*) was collected on a McHale Fusion 3 Plus Baler-Wrapper (McHale Engineering Ltd., n.d.-a) and McHale Pro Glide R3100 mower (McHale Engineering Ltd., n.d.-b). The machinery was owned and operated by a machinery contractor based in County Galway, Ireland. Data was collected between April and November 2020. Collected data includes 145 baler and 173 mower sites. Tables 1 and 2 give an overview on number single and conjoined field sites in the Baler and Mower datasets respectively.

Table 1: Baler dataset metadata – Number of fields within unique sites.

Sites	Number of Fields Present
125	1 field
18	2 fields
2	3 fields
0	4 fields
145	

Table 2: Mower dataset metadata.

Sites	Number of Fields Present
163	1 field
9	2 fields
0	3 fields
1	4 fields
173	

Data targeted for collection included Latitude and Longitude coordinates, tractor ISObus data to register PTO speed and a PTO pulsed digital sensor on the shaft (as a backup in lieu of ISOBus availability on the tractor). For machinery coordinates, NEO-M8 GNSS positioning chips with wideband GPS antennas were fitted to both machines (Emlid, n.d.). The data was stored locally in a document-based database operating on an 8th generation Intel Nuc (Intel i3 processor and 4 GB of RAM) running Ubuntu 16.

2.2 Propsed Solution

The proposed solution is as follows. The algorithm is divided into two stages. The first stage pertains the data pre-processing where data is coarsely, and subsequently finely, filtered described in section 2.3. The second and final stage is called the LineFinder which delineates conjoined labelled sites shown in section 2.4. The algorithm is fed both conjoined and single fields sites, it has no prior knowledge whether a site contains single or conjoined fields. The developed algorithm is deterministic and recursive, segmenting site data until it determines only single fields remain.

The method diagram displayed in figure 3 will be referred to throughout. The desired solution can be observed in step 5 with the result shown in step 6. Step 5 shows the segmentation (golden line) solution which segments the machinery coordinate data into its respective fields. By intersecting the path between adjacent fields, points which fall either side of this line are appropriately labelled as belonging to either field.

2.3 Data PreProccessing

The machinery trajectory data filtering process in this paper is divided into coarse and fine filtering. The coarse filter divides the machinery data into sites. At this stage in the process, it is acceptable for the coarse filter to label several fields from a single work episode as belonging to one site. The coarse filter steps are listed below.

1. New site between when the PTO is active.
2. New site if there exists time difference of 120 minutes between the previous and current data capture.
3. New site when the recorded speed exceeds 35 km/hr.

The fine filtering process applies two filters:

1. *Moving*: Coordinate data where the vehicle is not moving *(speed = 0)* is filtered. This is a regular occurrence in the baler dataset when wrapped bales are tipped from the rear of the machine.
2. *Outlier Coordinate points*: Outlier coordinate points are removed*. e.g. erratic positions registered from GPS cold starts.*

After filtering the raw data, the algorithm converts the GNSS data to Cartesian coordinates and moves onto the second stage, LineFinder. This stage identifies and segments conjoined fields sites.

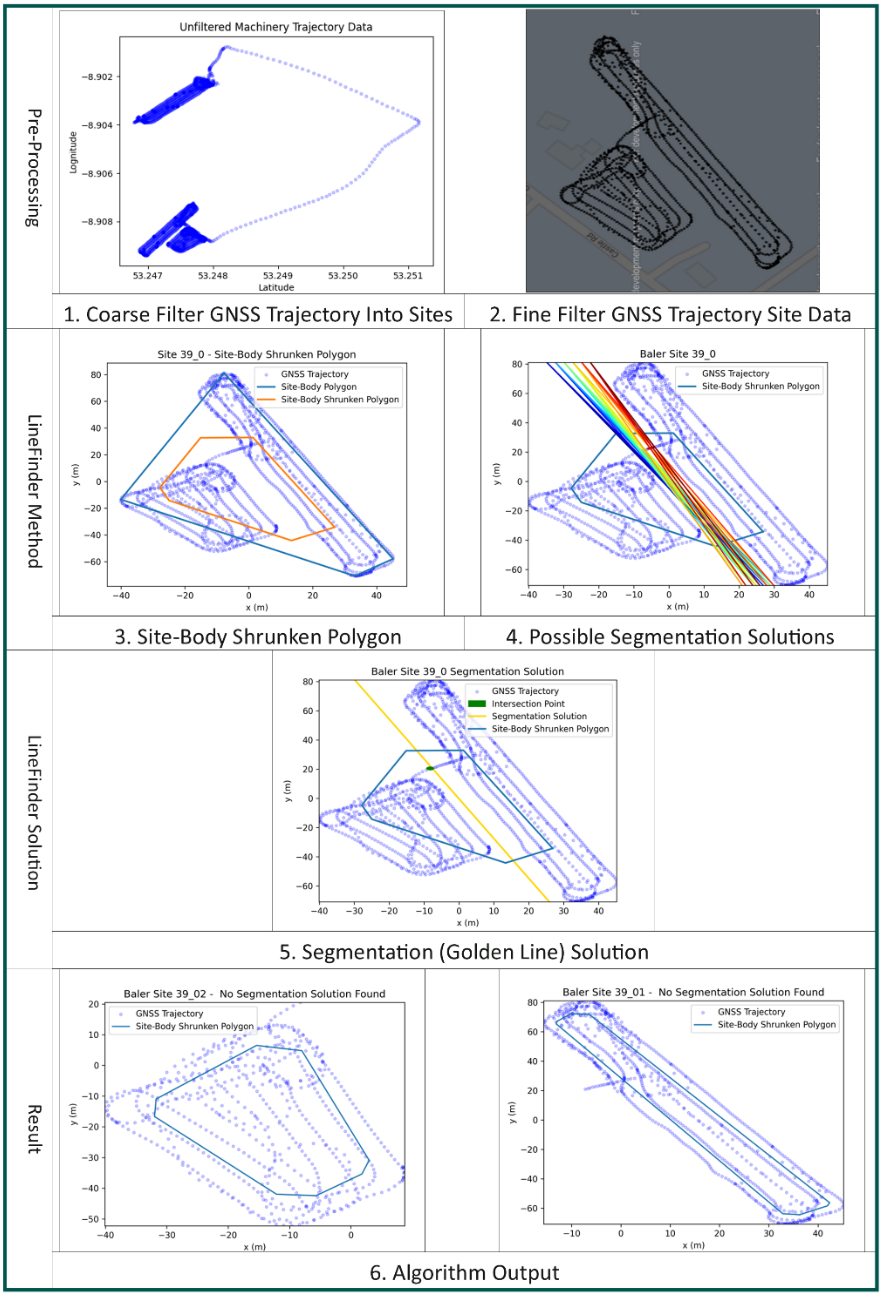


Figure 3: Algorithm operation illustrated in a step-by-step visual. The machinery trajectory data is filtered and passed to LineFinder for segmentation. Valid segmentation solutions must intersect the site-body shrunken polygon. The algorithm has no prior knowledge if a site contains single or conjoined fields.

2.4 LineFinder

LineFinder attempts to find a straight line through the conjoining path between two adjacent fields. The algorithm achieves this by manipulating two points, *A* and *B* around the site rectangular bounding box. The general equation of a straight line is calculated, given as:

$$Dx + Ey + C = 0 \; (1)$$

Points *A* and *B* are updated by either a vertical or horizontal distance to move along unique paths around the rectangular bounding box. Point *A* is iteratively stepped by 2.5 and point *B* is stepped by 1. For each point *A* update, point *B* completes its designated path. On completing its path run, *B* is reset to its starting position for the next point *A* step. For every point update, The slope m and y-intercept C of the line between the points is calculated and rewritten in the form (1). Next, each line solution generated from (1) must be validated.

LineFinder is built on the assumption that a dividing line delineating two fields should intersect **only one point** on the trajectory path. Figure 4 is an illustrative diagram to show how a valid line solution captures a single point. The point is permitted to fall within a set tolerance of 1 metre to the line. This distance is calculated as the horizontal residual from the point to the line. Points within this threshold are said to be *"on the line"*. If the threshold is:

- Too small - no point on the path is considered to be on the line OR LineFinder determines there is a potential field delineation line through the agricultural machinery's working coordinate measurements intersecting a point inside a field.
- Too large - lines intersecting the path between fields capture more than one point on the path so the solution is invalid.

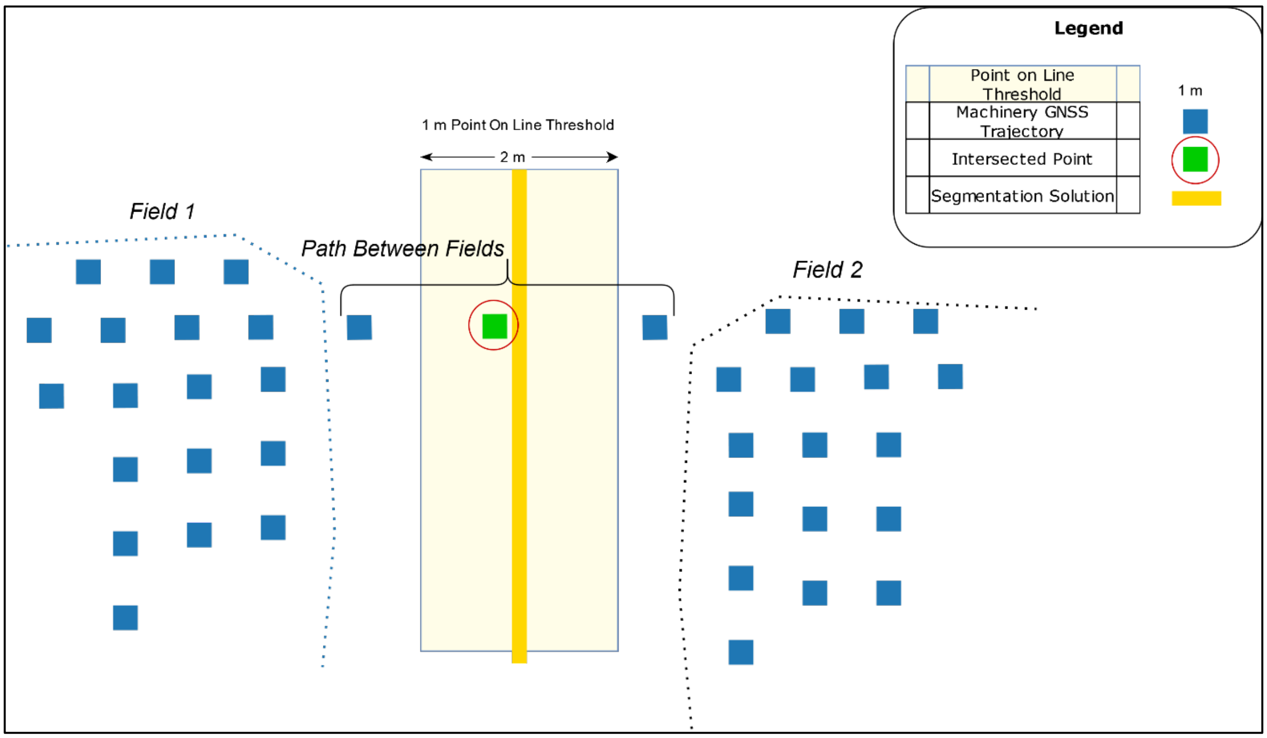


Figure 4: Illustrative diagram depicting the LineFinder assumption. The blue points represent machinery site positional data. The segmentation solution intersects a single point on the connecting pathway between adjacent fields. The green, intersected point may lie within a metre of the segmentation solution, to qualify as being intersected.

If a machinery operator is to traverse to-and-fro between two fields within the same work episode, this negates the LineFinder assumption that a valid line solution intersects only one point on the path. This scenario is accounted for by detecting for similar points around the intersected path point. Points are deemed similar by the algorithm if they fall within a radius tolerance of *0.7* metres to the intersected path point. Points on the other side of the line solution are transposed across to check for similarity.

Figure 3 step 5 shows many possible line solutions for intersecting the path between fields. A single solution must be chosen from this set. To achieve this, all the possible solutions are grouped and ordered based on their value for line slope *m*. The selected solution is selected based on the median slope value registered. This method proved a reliable mechanism to pick the most common intersecting path solution. The segmentation (golden line) solution picked from the set of possible solutions is shown in Figure 3 step 6.

LineFinder is recursive and will continually segment sites until no more field segmentation solutions are found. The only other breaking case where LineFinder ends its recursive calls is if a site does not meet a *minimum point requirement* of having 150 coordinate points. If a solution results in a split where one body of coordinate points does not meet this requirement, the algorithm will disregard that body and proceed with the other split body to determine if a further solution can still be found.

2.4.1 Built-in Error Checking

LineFinder has its own built-in error-checking abilities to curb over-segmentation. The algorithm creates a *site-body shrunken polygon* for sites as seen in step 3 Figure 3. The polygon extending to the field(s) four extremities/corners is created by finding the maximum and minimum for *x* and *y* Cartesian coordinate points. The polygon is subsequently buffered, shrinking it by a factor of 10%, and the corners are bevelled. Only line solutions which intersect the site-body shrunken polygon are considered valid. This ensures solutions must intersect the main body of a site's coordinate measurement data. The rule reduces the rate of false positive cases in LineFinder intersecting isolated coordinate points on the edge of fields in a site. This scenario of isolated coordinate points may occur when, for example, a vehicle takes a wide turn at the edge of a field.

In the next section, the outlined method will be evaluated on harvest implement data, recorded over a full harvesting season.

3. Experimental Results

The algorithm was validated against two data sets, originating from; *1) McHale Fusion 3 Plus Baler-Wrapper; 2) McHale R3100 Pro Glide Mower*. The generation of the data sets is described in section 2.1. The baler dataset contains 22 conjoined fields and the mower dataset contains 12 conjoined fields. The remaining sites contain singular fields. It is important to note that the baler and mower may have traversed the same harvest sites, however, both implements will traverse the field differently. Historical knowledge for geofencing sites was not considered for this study. Coordinate measurements from each site are treated as unique data. Any user defined variables are set consistently throughout and are described in Section 2.

The results are presented in the form of Confusion Matrices (CM). There are two CMs in total, one for each dataset. Each CM presents the algorithm's ability to segment conjoined fields sites (true positives) and rightly not segment single field sites (true negatives).

3.1 Baler Field Segmenation Results

The algorithm performance on the baler dataset is shown in table 3 below.

Table 3: Algorithm performance on Baler dataset represented as a confusion matrices.

		Actual Values	
		Positive (Conjoined)	Negative (NOT Conjoined)
Algorithm Values	Positive (Segmented)	22	15
	Negative (Not Segmented)	0	167

Overall accuracy: (TP+TN / total)	92.6%

The results in Table 3 show that out of 22 conjoined fields, 22 are correctly segmented. An example result of segmenting a three field site is shown in Figure 5. There are no cases of false negatives recorded. The algorithm is effective at segmenting conjoined fields sites, however there are 15 cases of false positives. These are single field sites to which the algorithm incorrectly segmented. The overall accuracy on the dataset is given as *92.6%.*

Figure 6(a) shows a false positive case for conjoined fields site 135. The algorithm incorrectly intersects a point in the field entry path. In the next recursive call, the algorithm finds the correct line solution to segment the field as seen in Figure 6(b). Further validation checks could be implemented to avoid intersecting field entry paths. One approach could be to include a *minimum area* requirement to first validate delineated fields as sensible. Rather than find all possible line solutions, and indiscriminately select the median solutions slope value *m* as the line solution.

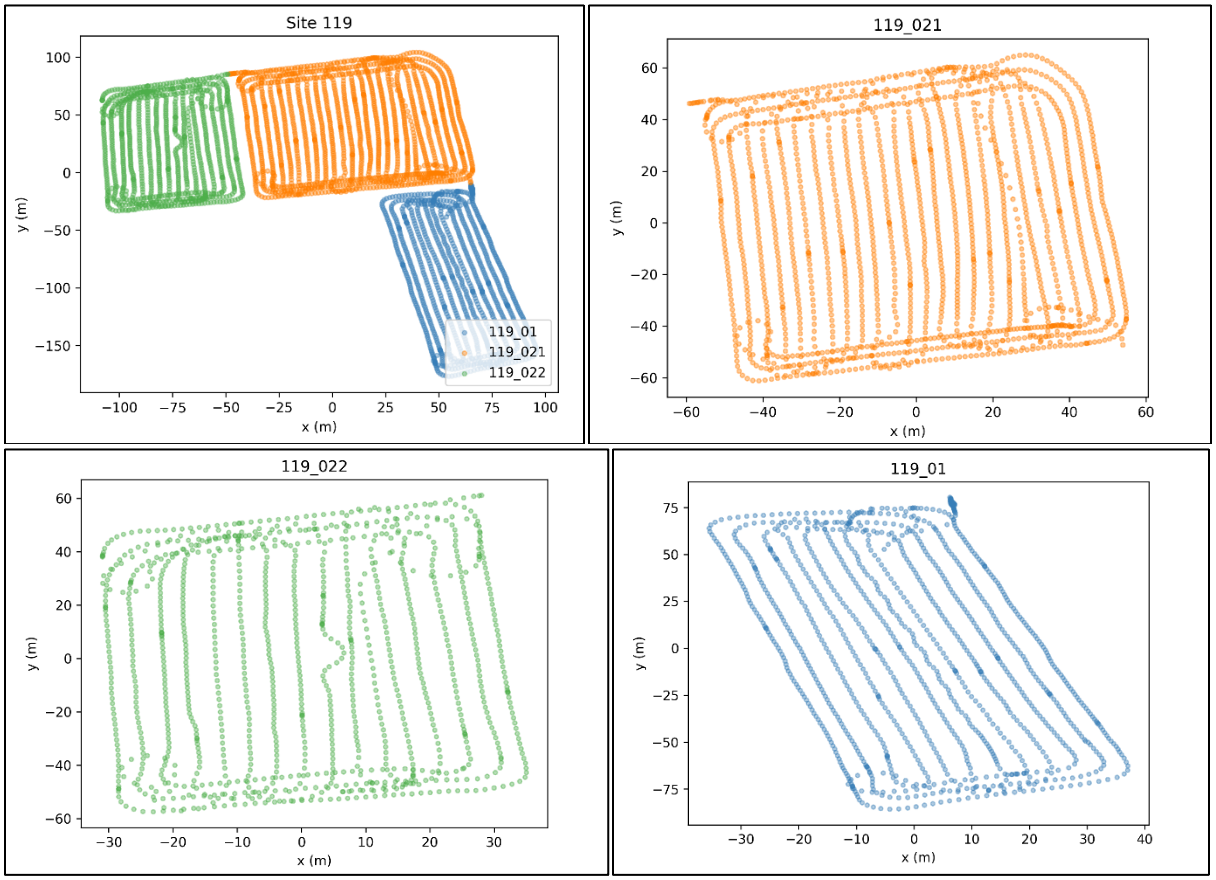
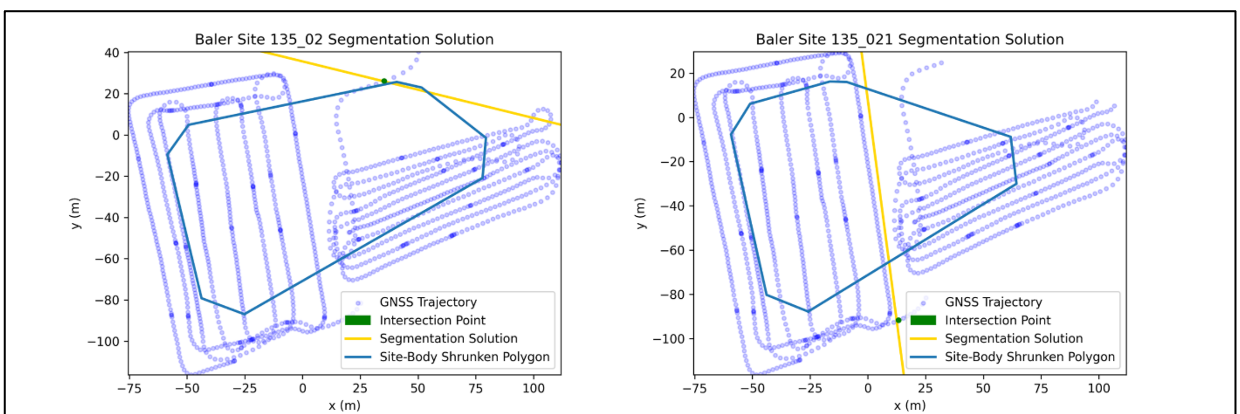


Figure 5: Algorithm output for segmenting a three-field adjacent site. The original site data shown in the top left corner is colour-coded to match the segmented field result. Epochs are defined by extracting the time from the line intersection point.



(a) Site 135 — Algorithm intersects the field entry path. False Positive. **(b) Site 135 — Algorithm intersects the conjoined field path. True Positive.**

Figure 6: Site 135 false positive case in the baler dataset. The algorithm incorrectly segments the field entry path. On the next recursive call, the algorithm finds the correct delineating solution. The algorithm segments sites recursively until no further line solutions are found.

3.2 Mower Field Segmenation Results

The algorithm performance on the mower dataset is shown in Table 4 below.

Table 4: Algorithm performance on Mower dataset represented as a confusion matrices.

		Actual Values	
		Positive (Conjoined)	Negative (NOT Conjoined)
Algorithm Values	Positive (Segmented)	12	46
	Negative (Not Segmented)	0	183

Overall accuracy: (TP+TN / total)	80.9%

The results in Table 4 again shows a high accuracy segmenting 12 out of 12 conjoined sites. However, there are 46 false positive cases. Two of these cases are shown in Figure 7. The overall accuracy on the dataset is given as *80.9%.* One possible reason for relatively higher false positive cases in the mower dataset is the extended width of the rear mower implement, extending from the side of the GNSS acquisition point. This subsequently, halved the number of GPS coordinates in the dataset when compared to the combi-baler data.

The results have shown that while the algorithm is superior in handling conjoined field sites, it's performance on handling single field sites is only adequate. The majority of false positive cases arise from a) long, narrow fields b) hollow fields and c) field entry paths. A relative padding or interpolation, along a perpendicular axial direction to the implement's motion will be considered in future work.

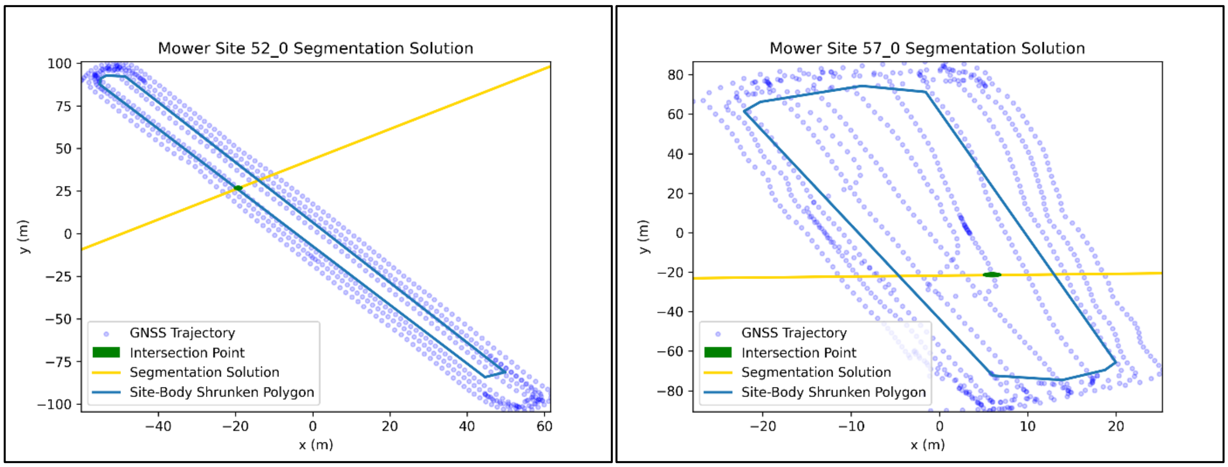
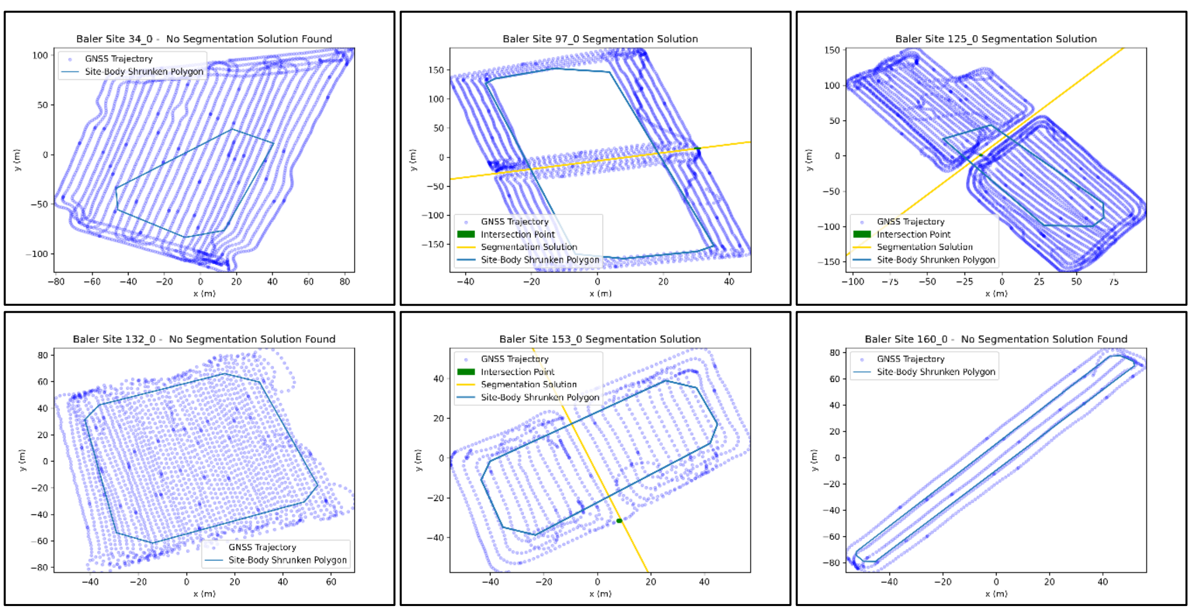


Figure 7: Mower false positive cases. The algorithm is susceptible to segmenting long, narrow single field sites, like site 52. Site 57 is another false positive case, the increased false positive rate may be because of extended width of the mower.

3.3 Field Segmenation Results

Figure 8 includes several algorithm results on the mower and baler data sets.



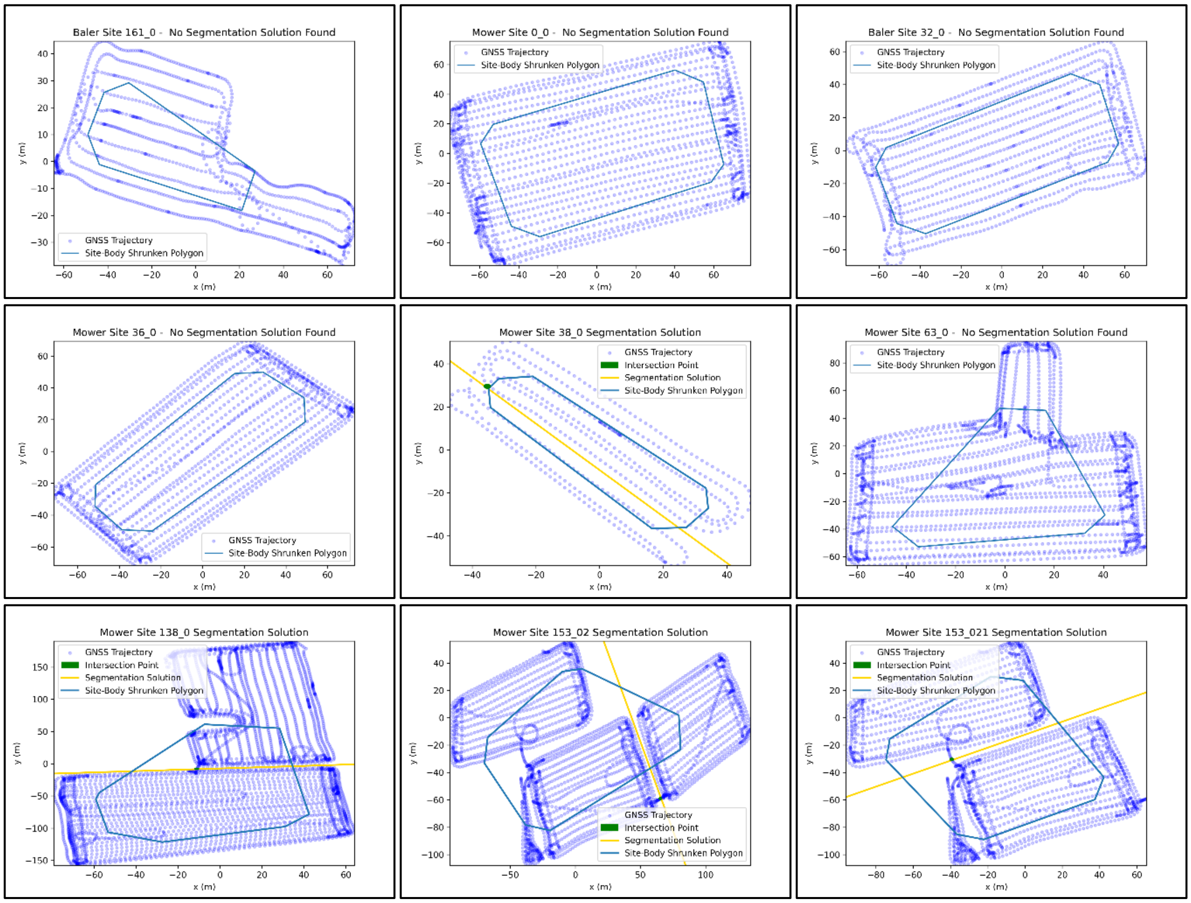


Figure 8: More segmentation results from both mower and baler datasets.

4. Conclusion

This paper presents an *Automated Geometrical Field Boundary Delineation Algorithm* which delineates machinery implement associated job site data into individual fields. The algorithm was evaluated on a baler and mower dataset obtained from a machinery contractor, throughout 2020. The sites were segmented using the algorithm presented registering an accuracy of *92.6%* and *80.9%* on a baler and mower dataset respectively.

This algorithm offers a novel, cost-effective and fully automated technique to field segmentation. Benefits to farmers and farm machinery contractors include the ability to determine: seed purchase orders, fertiliser application, crop yields and conduct job work-time analysis. Regulatory bodies can benefit by attaining accurate and up-to-date acreage measurements. It also presents the opportunity in precision agriculture and fleet management applications through increased resolution into machinery progress on a site.

The algorithm was designed to be application generic which it achieves by using non-specific machinery sensor data. The method relies on coordinate data, speed, a digital sensor to indicate Power Take-Off activity, and cost-effective hardware that can be abstracted to segment spatio-temporal data from a variety of self-propelled machines or towed implements.

The algorithm is superior in segmenting conjoined field sites, however, it is noted by the authors that the algorithm performance on single field sites is only adequate. Perhaps a pre-processing stage to determine whether a site contains conjoined fields could be employed. Image pre-processing methods should be considered. Additionally, performance-based analysis may be conducted to illustrate advantages on obtaining field-level resolution when analysing machinery trajectory data. Future work will involve the expansion of these proposals and the evaluation of the algorithm with additional agricultural vehicle trajectory datasets.

To the best of the authors knowledge, existing parcel delineation techniques which offer similar performance use remote sensing-based methods, which are neither cost-effective or accessible to small time operators. The algorithm solves for field geometric boundaries and applies a job context to machinery sensor data on a field-by-field basis, providing a cost-effective and reliable method to delineate implement associated job sites.

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5. References

Aung, H. L., Uzkent, B., Burke, M., Lobell, D., & Ermon, S. (2020). Farm parcel delineation using spatio-temporal convolutional networks. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, *2020-June*, 340–349. https://doi.org/10.1109/CVPRW50498.2020.00046

Biljecki, F. (2010). Automatic segmentation and classification of movement trajectories for transportation modes. *Delft University of Technology*. https://doi.org/10.4233/uuid:654587d2-6e93-4619-ab9a-29d95f843f35

Chen, Y., Zhang, X., Wu, C., & Li, G. (2021). Field-road trajectory segmentation for agricultural machinery based on direction distribution. *Computers and Electronics in Agriculture*, *186*, 106180. https://doi.org/10.1016/j.compag.2021.106180

da Costa, J. P., Michelet, F., Germain, C., Lavialle, O., & Grenier, G. (2007). Delineation of vine parcels by segmentation of high resolution remote sensed images. *Precision Agriculture*, *8*(1–2), 95–110. https://doi.org/10.1007/s11119-007-9031-3

Emlid. (n.d.). *Reach M2 and M+ – RTK GNSS/GPS modules for high precision mapping | Emlid*. Retrieved February 11, 2022, from https://emlid.com/reach/

European Commission. (n.d.). *Common agricultural policy | European Commission*. Retrieved February 9, 2022, from https://ec.europa.eu/info/food-farming-fisheries/key-policies/common-agricultural-policy_en

European Court of Auditors. (2016). *The Land Parcel Identification System A useful tool to determine the eligibility of agricultural land – but its management could be further improved* (Issue 25). https://doi.org/10.2865/19472

Eurostat. (2016). *Archive:Small and large farms in the EU - statistics from the farm structure survey - Statistics Explained*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Small_and_large_farms_in_the_EU_-_statistics_from_the_farm_structure_survey&oldid=357625

García-Pedrero, A., Gonzalo-Martín, C., & Lillo-Saavedra, M. (2017). A machine learning approach for agricultural parcel delineation through agglomerative segmentation. *International Journal of Remote Sensing*, *38*(7), 1809–1819. https://doi.org/10.1080/01431161.2016.1278312

Gong, L., Sato, H., Yamamoto, T., Miwa, T., & Morikawa, T. (2015). Identification of activity stop locations in GPS trajectories by density-based clustering method combined with support vector machines. *Journal of Modern Transportation*, *23*(3), 202–213.

https://doi.org/10.1007/s40534-015-0079-x

Guo, S., Li, X., Ching, W. K., Dan, R., Li, W. K., & Zhang, Z. (2018). GPS trajectory data segmentation based on probabilistic logic. *International Journal of Approximate Reasoning*, *103*, 227–247. https://doi.org/10.1016/j.ijar.2018.09.008

Hwang, S., Evans, C., & Hanke, T. (2017). Detecting stop episodes from GPS trajectories with GAPS. *Springer Geography*, *October*, 427–439. https://doi.org/10.1007/978-3-319-40902-3_23

Kisilevieh, S., Mansmann, F., Nanni, M., & Rinzivillo, S. (2010). *Spatio-temporal c1ustering*. 855–874.

Matthias, Dipl.-I. A., Demmel, M., & Auernhammer, H. (2003). *Methods and Services of Data Processing for Data Logged by Automatic Process Data Acquisition Systems Crop Production Engineering in Turin, Italy Technik im Pflanzenbau*. https://mediatum.ub.tum.de/doc/1232084/file.pdf

McHale Engineering Ltd. (n.d.-a). *McHale Fusion 3 Plus Product Page*. Retrieved February 1, 2022, from https://www.mchale.net/products/mchale-fusion-3-plus/

McHale Engineering Ltd. (n.d.-b). *McHale Pro Glide R3100 Rear Mower*. Retrieved February 1, 2022, from https://www.mchale.net/products/mchale-pro-glide-r3100-rear-mower/

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

North, H. C., Pairman, D., & Belliss, S. E. (2019). Boundary Delineation of Agricultural Fields in Multitemporal Satellite Imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *12*(1), 237–251. https://doi.org/10.1109/JSTARS.2018.2884513

Schuessler, N., & Axhausen, K. (2009). Processing raw data from global positioning systems without additional information. *Transportation Research Record*, *2105*, 28–36. https://doi.org/10.3141/2105-04

Waga, K., Tabarcea, A., Chen, M., & Franti, P. (2012). Detecting movement type by route segmentation and classification. *CollaborateCom 2012 - Proceedings of the 8th International Conference on Collaborative Computing: Networking, Applications and Worksharing*, 508–513. https://doi.org/10.4108/icst.collaboratecom.2012.250450

Xu, L., Ming, D., Zhou, W., Bao, H., Chen, Y., & Ling, X. (2019). Farmland extraction from high spatial resolution remote sensing images based on stratified scale pre-estimation. *Remote Sensing*, *11*(2). https://doi.org/10.3390/rs11020108

Yan, Z., Parent, C., Spaccapietra, S., & Chakraborty, D. (2010). A hybrid model and computing platform for spatio-semantic trajectories. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *6088 LNCS*(PART 1), 60–75. https://doi.org/10.1007/978-3-642-13486-9_5

Zhu, L., Holden, J. R., & Gonder, J. D. (2017). Trajectory segmentation map-matching approach for large-scale, high-resolution GPS data. *Transportation Research Record*, *2645*(1), 67-75. https://doi.org/10.3141/2645-08